Self-paced treadmill as a rehabilitation tool for recovering functional gait in people with stroke

Eunice D. Ibala

This thesis is submitted in partial fulfilment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Department of Biomedical Engineering
University of Strathclyde
Glasgow
2020

Declaration

This thesis is the result of the author's original research. It has been composed by the author and has not been previously submitted for examination which has led to the award of a degree.

Signed:

Date:

Acknowledgements

I first want to thank my supervisors Andrew Kerr and Sylvie Coupaud for their guidance and how they helped me stay on track with my work.
I want to show my appreciation to my PhD candidate colleague especially: Tom Gerards, Cheral Govind, Caleb Gambrah, Matteo Menelotto, Carine Yanze-Njiki, Sara Gómez Arnais, Esraa Aldayil, Amneh Alshawabka. We helped one another, laugh the adversities out and this made the hard times somewhat easier to bare. I want to express my gratitude to Sosthène Ibala for his advice on the software development that was necessary to complete my project. I want to thank Karen Chase and Nicholas Smith for their collaboration to my final experiment. I must express my thankfulness towards my family for their prayers and care during this PhD season. I am grateful for my siblings who are great listeners and sometimes challenged me. I would not be able to achieve this work without acknowledging the tremendous impact of my extended Scottish family, who, I am pretty sure, without knowing, provided me so much by just making themselves available, be inviting and exercising hospitality. This goes a long way. I am grateful to my friend Lewis for his insights, proofreading efforts, commend of the English language, as well as for his support and encouragements to pursue my purpose.
Finally, I want to thank my Father, who has carried me through all this season, always besides me, an ever-present help in times of trouble.

Abstract

Background

The underlying mechanism operating during the rehabilitation of walking after a stroke is not fully understood. Treadmill training is a rehabilitation tool used to improve the walking capacity of people affected by stroke with evidence of improvement to fitness and walking speed. These changes are not, however, translated to improved ability or participation in community walking which is an important goal of rehabilitation. When combined with an immersive virtual reality environment, self-paced treadmill (in which the belt speed automatically adapts to the user's intended speed) training can be used to simulate an overground community walking experience with the potential to train more complex walking skills such as speed adaptation, obstacle avoidance and dual tasking which are essential components of successful independent community walking.

The electrical activity of muscles (electromyograms) can reveal the underlying motor control strategy employed when walking in different contexts, for example indoors or community walking. Mathematical tools such as the variance ratio and the occurrence frequency provide a means of quantifying this muscle activity including variability and phasic activity. These tools may help to understand the potential of walking simulators (self-pacing treadmills synchronised with virtual reality) as tools in the rehabilitation of community mobility following stroke.

Methods

Two studies were conducted; an initial study to explore the motor control and biomechanical differences across overground, standard (fixed pace) treadmill and self-paced treadmill walking in able-bodied adults and a second study further exploring these differences in a post stroke population and including outdoor and gradient walking.

Data collection for both studies included EMG and kinematic data during treadmill (standard and self-pacing), indoor and outdoor gait of varying speeds and gradients and required the development of bespoke software and novel algorithms to identify the underlying differences in motor control and muscle activity variability in particular.

Results

Using the variance ratio, self-paced (SP) treadmill walking and overground outdoor walking presented similar value during level walking for both the able-bodied and stroke participants. Variance ratio values during self-paced treadmill walking ranged from 0.36 to 0.51, and from 0.38 to 0.77 during outdoor walking. A variance ratio value close to 1 represents low repeatability of the muscle pattern. The results suggest that SP treadmill walking, which allows natural speed variability, is a closer analogue to outdoor walking, in terms of muscle activation consistency, than fixed pace treadmill walking. For the able-bodied participants, fixed pace treadmill walking and indoor presented similar low VR values (0.26 and 0.22 respectively), which indicated a highly repeatable (cycle to cycle) EMG patterns.

Discussion

It was found that it is possible to use quantitative measures of EMG variability to characterise the differences of muscle recruitment strategies between different walking situations such as treadmill walking at a fixed pace, treadmill walking in self-pace and overground walking indoors and outdoors. The self-paced treadmill walking and overground outdoor situations presented the most similarities in muscle activity variability. The number of participants, especially stroke survivors (n=2) was limited and cannot be generalised. Nonetheless, the use of self-paced treadmills coupled with an immersive virtual environment and, targeting community walking training present a promising platform for gait adaptability training.

Conclusion

The use of the self-paced treadmills within an immersive virtual environment, present similarities to outdoor walking. Using these treadmills as a complementary rehabilitation tool, have potential for the training gait adaptability for community walking after a stroke.

List of publications and conference presentations

Literature

L2. Ibala E, Coupaud S, Kerr A (2019) Comparison of the Muscle Pattern Variability during Treadmill Walking (Fixed and Self-Pace) and Over Ground Walking of Able-Bodied Adults. J Ann Bioeng 2019 (1): 1-11

L1. Online Case Study 03. Ibala E., "Comparison of the pattern of muscle activation during treadmill and overground walking" in Kerr, A., Rowe, P. (2019) An introduction to human movement and biomechanics - Elsevier eBook on VitalSource, 7th Edition.

Communication

C1. Ibala E., Kerr A., Coupaud S. (2017) Variability of muscular activity between overground and treadmill (fixed and self-paced) walking. Movement conference 9-11 July 2017, Oxford, UK

Posters

P4. Ibala E., Chase K., Smith N., Kerr A. (2019) Comparison of muscle activity during level straight walking on treadmill (Fixed and Self-paced) and overground (Indoor and Outdoor) among Able-bodies and Stroke participants. SRR conference 5 February 2019, Nottingham, UK.

P3. Ibala E., Chase K., Smith N., Kerr A. (2018) Observations of the Motor control differences between treadmill (fixed and self-paced), indoor and outdoor walking (WIP). SSAHPF conference 13 June 2018, Dundee, UK.

P2. Ibala E., Kerr A., Coupaud S. (2017) Variability of muscular activity between overground and treadmill (fixed and self-paced) walking. Movement conference 9-11 July 2017, Oxford, UK.

P1. Ibala E., Kerr A., Coupaud S. (2016) Self-paced treadmills as a rehabilitation tool for recovering functional gait in people with neurological conditions. Research Presentation Day, 22 June 2016, Glasgow, UK.

Contents

List of Figures and Figures Titles

List of Tables

Abbreviations

VR: Variance ratio

EMG: Electromyogram

GA: Gastrocnemius

TA: Tibialis anterior

FP: Fixed pace

SP: Self-paced

IN: Indoor (walking)

OUT: Outdoor (walking)

SD: Standard deviation

AB: Able-Bodied

BW: Body weight

BWSTT: Body-weight-supported treadmill training

S: Stroke group

DALY: Disability adjusted life year

YLL: Years of life lost

YLD: years lived with disability

CI: Confidence Interval

TIA: Transient Ischemic Attack

SENIAM: Surface Electromyography for the Non-Invasive Assessment of Muscles

Chapter 1

1. Introduction

1.1. Stroke: a worldwide problem

Stroke is the primary cause of adult disability across Europe [1] as well as in the United Kingdom (UK) [2]. It is the second main cause of death worldwide [3], and the third cause of death in the UK [2]. In the UK alone the cost of this illness represents about 5.5% of the entire healthcare budget, representing approximately £4 billion [2].

The European Register of Stroke Investigators (EROS) [4] reported stroke incidence rates (adjusted to the European population) of 141.3 per 100 000 (95% CI, 118.9 to 166.6) in men and 94.6 per 100 000 (95% CI, 76.5 to 115.7) in women. The survey was carried out between 2004 and 2006 in six European countries: France; Italy; Lithuania; Poland; Spain and the United Kingdom. In Scotland, the incidence is reported to be higher, according to Scottish Stroke statistics (2017-2018) [5] the incidence of stroke was 177 per 100,000. Stroke incidence increases as people age and is higher in men than women. In Scotland, the rate of incidence was 85 per 100,000 population stroke for the under 75 years old and 1,106 per 100,000 population of the over 75 years old in 2017-2018 [5]. The number of hospital discharges following a stroke were of 514 per 100,000 population for men and 408 per 100,000 population for women in 2017-2018 [5].

The majority of people surviving a stroke are left with a motor impairment. According to Li et al (2018) [6] more than 80% of stroke survivors are affected by walking dysfunction and Jonsdottir and Ferrarin (2017) [7] reported that 65% of stroke survivors have weakness on one side of their body, known as hemiparesis (mild weakness) or hemiplegia (severe weakness or total paralysis). In this thesis, the term hemiplegia, will be used.

The recovery of walking function is ranked in the top ten priorities for research by stake holders in stroke rehabilitation (therapists, patients and carers) Pollock et al. (2012) [8] and is consistently highly prioritised by therapists and patients [8]–[11].

1.2. Risk factors and outcome

The occurrence risk of a stroke can be the result of genetic factors, heart and cardiovascular disease as well as a history of Transient Ischaemic Attack (TIA). These risk factors are intrinsic to each individual and not much can be done to prevent stroke in these cases. However, there are a much larger number of stroke risk factors that are modifiable, and therefore, should be taken into consideration. These are presented in the following Table 1.1.

Non modifiable	Modifiable
Age Sex Genetic factors Previous TIA and Hearth condition other Cardiovascular disease	High blood pressure Diabetes Cigarette smoking Atrial fibrillation* Other forms of heart disease Dietary factors and obesity Sedentary lifestyle Hypercoagulates states Sickle cell disease Elevated cholesterol Heavy alcohol use (for subarachnoid haemorrhage) Drug abuse

Table 1.1: Modifiable and non-modifiable factors of stroke, adapted from Stroke by Jonathan a Edlow (2008) *[12]*

*Atrial fibrillation is characterized by a fast, irregular heartbeat which, can lead to several heart-related complications as well as the creation of emboli which may result in a stroke. This can be treated with surgery, medication and electrical implants [12].

The outcomes from stroke are varied. Each year over 13.7 million new strokes cases occur globally [13]. Over 5.5 million people will die from their stroke each year [13], [14]. For those that survive, 80% will be left with some degree of motor and sensory impairment [11]. Post-stroke impairments, much like the outcomes, also vary. Some impairments affect the communication abilities of the survivor (for example aphasia and dysarthria) [15], vision (visual neglect) [16], [17], reading (hemianopia), writing (agraphia) [18], deglutition (dysphagia) [19], [20], perception and emotions (depression, anxiety) [21] and other such as fatigue, cognition, memory loss [21], [22].

The most commonly reported impairments post-stroke relate to the motor system, in particular a loss of muscle strength and motor control. The following are common motor impairments:

Paresis/plegia which is the loss of higher centre control of muscle activity. Paralysis usually affects an entire body part or region, but it can also affect a single muscle. Paralysis can also affect the muscle's resting tone, which is the level of resistance to movement within the muscle [23].

Paresis following stroke can be distributed in different ways and it is an important indicator of the location the damaged area of the brain. The following terms describe common distribution patterns.

- **Quadriplegia** is where all four limbs and the trunk are affected [24]–[27].
- **Paraplegia** affects both legs and at least some of the trunk [24]–[26].
- **Hemiplegia** (hemiparesis) is a type of paralysis that affects one side of the body [24]–[27].
- **Diplegia** affects both sides of the body, the same body region [24]–[26].
- **Monoplegia** affects one limb only [24]–[26].

Spasticity or High tone is manifested by an increased stiffness of the muscle. A spastic muscle will present increased resistance to passive stretch that is dependent to the velocity and enhanced tonic stretch reflexes [28], [29]. Theses outcomes are the consequences of changes in the muscle’s contractile properties and in the viscoelastic properties of the muscle-tendon unit, originating from impaired descending motor control pathways [28], [29].

Low tone also called 'flaccidity' or 'hypotonia' usually involves little resistance to passive movement and reduced strength on the muscles. Flaccidity leads to low muscle tone but is different to low muscle strength [30].

Overall muscle weakness is the most common outcome from stroke affecting 80% [6] with and 65% experiencing weakness on one side of their body, hemiplegia [7].

1.3. Factors influencing gait recovery and suitability for rehabilitation

The degree of recovery after a stroke has been noted to be influenced by the following factors:

- Pre-stroke lifestyle, health, genetics [31].
- Post-stroke lifestyle, fitness, cardiovascular, muscular or respiratory condition. [32]–[35].
- Stroke type, location and severity [32], [34], [36], [37].
- Time elapsed between stroke occurrence and hospital care [32], [38], [39].
- The treatment administered and its timing of administration [32], [38], [40]–[42].
- The impairments and medical complications consequences of the stroke [32], [34], [37].
- The rehabilitation training administrated after the stroke and its dose [32], [43]–[45].
- The patient's access to social support and family [32], [46]–[48].
- The patient's access to assistive technologies and/or adaptation [32], [48].

The impact of these different points is presented in more details in the following table *(Table 1.2: Factors influencing stroke recovery training*

)

Factor	References	Impact
Pre-stroke lifestyle, health, genetics	[31]	Genetic predispositions and unfavourable lifestyle increase the risks of stroke incidence [31].
Post-stroke lifestyle, fitness, cardiovascular, muscular, or respiratory condition	[32]–[35]	Poor functional condition at hospital admission is linked to poor post-stroke outcome [34]. Stroke patients are often unfit due to deconditioning and need fitness training to improve their cardiovascular health, to have enough strength and endurance to go back to their everyday life setting and activities.
Stroke type, location, and severity	[32], [34], [36], [37]	Higher death rate for haemorrhagic stroke in contrast to ischemic stroke

		[34]. Severe strokes usually lead to poorer rehabilitation outcome.
Time elapsed between stroke occurrence and hospital admission	[32], [38], [39]	Delay in stroke treatment can be fatal. Time can be lost in transports and/or diagnosis (recognition of symptoms, access to imaging equipment) [39].
The treatment administered and its timing of administration	[32], [38], [40]–[42]	Thrombolysis treatment for ischemic stroke is the most effective if administered early and appropriately [38], [42] (between 1.5 to 4.5h since stroke onset [38]).
The impairments and medical complication consequences of the stroke	[32], [34], [37]	Spatial neglect, aphasia, spasticity and other complications are indicators of poor rehabilitation outcome [37].
The rehabilitation training administered after stroke and its dose	[32], [43]–[45]	Long treatment duration leads to better gait rehabilitation results [44]. Repetitive, task—oriented and intensive training is recommended [43], [45].
Patient's access to social support and family	[32], [46]–[48]	Solitude and low independence at the early stage post-hospital results in poor rehabilitation results [48]. Unmarried people benefit from getting more rehabilitation than married people who tend to have more care giver's help [47].
Patient's access to assistive technology and/or adaptation	[32], [45]	Access to assistive technology can have positive impact on stroke rehabilitation [45].

Table 1.2: Factors influencing stroke recovery training

These factors have been used to develop predictive models to determine whether rehabilitation training will be beneficial to the patients with stroke [32]. While the evidence for lack of rehabilitation potential is not the same as having a lack of evidence for rehabilitation potential, it is considered that the most severe cases of stroke, where both physical impairment and cognitive impairment are important, consist of cases where the effects of rehabilitation training is expected to be less important and slower [32], [33].

Rehabilitation potential of severely disabled stroke patients is not primarily related to severity of the patient's loss of independence but mostly related to the ability of the carer and patient's to adapt [22], [32], [46], [49], [50]. Consequently, it is possible for stroke patients with severe disability to become independent and benefit from early stage rehabilitation training, adapted to their situation and the use of strategies and devices for improving their quality of life [32], [47], [51]. However, it is usually the survivors who are already able to walk before community reinsertion that attain enough independence to be independent walkers in challenging community environments such as a shopping mall or a street [52]. The decision on whether stroke patients are to undergo rehabilitation training or not is usually made by a multidisciplinary team [32]. This decision is influenced by several factors such as the resources available in the clinical setting, the availability of community support and the availability of community rehabilitation [32], [47]. A patient identified as likely to benefit from rehabilitation will be recommended for appropriate training. The patients identified with no rehabilitation potential might be left without access to any form of rehabilitation training, which, if wrongly identified, will likely limit their ability to improve [32]. Being able to make the appropriate decision regarding the potential implementation of rehabilitation training is crucial, not only for the patient's health and autonomy but also as a more cost-effective long-term treatment plan. A correct assessment of the appropriateness of rehabilitation training should allow long-term savings for the healthcare and social care environments as well as for the individuals and their families; this is known as tailored rehabilitation [32].

There are existing factors that support the prediction of the outcome after a stroke [53]–[55]. Kwok et al. (2012) [54] conducted a retrospective analysis of 14437 stroke patients (mean age 75.4 ± 12.1), 52.9% were female and 82% were admitted for a ischemic stroke. The objective of this study was to assess the effect of the presence of disability before the occurrence of the stroke over the patient's mortality and the length of their hospital stay. The estimated modified Rankin score before stroke (pre-morbid modified Ranking score), were collected prospectively to determine pre-stroke disability, was an indicator of risk of mortality with a higher score associated with a greater risk of death evolving linearly ($p < 0.001$) [54]. They also found a relationship between age and the modified Rankin score scale for which each point increase was equal to five supplementary years old. Kwok et al. (2012) [54] concluded that the presence of disability before a stroke and the length of their hospital stay are predictors of the patient's risk of mortality, independently of the patient's sex, age, stroke type and severity. Wagle et al. (2011) [55] analysed the data of 163 stroke rehabilitation patients two to three weeks following their hospital admission and re-evaluated

them 13 months after. They found that a model combining age ($p = 0.001$), neurological impairment (National Institute of Health Stroke Scale; $p < 0.001$), post-stroke cognitive function (Repeatable Battery of Neuropsychological Status; $p = 0.001$) and pre-stroke activities of daily living (Barthel Index; $p = 0.002$) was a good predictor of the long-term post-stroke functional outcome. An average Barthel index score of 19.5±0.9 (range=17–20) led to no significant disability when an average Barthel index score of 18.4±2.4 (range=13–20) led to severe disability. Coupar et al. (2012) [53] reviewed 58 studies in order to assess which factors were the best indicators of good upper-limb recovery after a stroke. They found that the strongest predictors of upper-limb recovery were the initial measure of stroke severity and related impairment (odds ratio: 14.84 with 95% confidence intervals (CI): 9.08–24.25) as well as other neurophysiological results (odds ratio: 38.62 with 95% CI: 8.40–177.53)) at the initial assessment post stroke [53].
Stinear (2010) [56] identifies the use of magnetic resonance imaging (MRI) [57], [58] and Transcranial magnetic stimulation (TMS) [59] as potential methods to predict stroke recovery outcome. However, more studies are needed to assess they reliability, feasibility and cost-effectiveness [56].

Currently, the models used to predict rehabilitation potential have not been properly and fully tested. The existing models, based on clinical variables, were able to explain the reason for only 47% of the variance in post-stroke recovery, 53% of the parameters responsible for the outcome for stroke recovery remains unexplained [32], [60]. In their paper, Bates et al. (2013) [47] used a retrospective cohort analysis to look at patient characteristics that would lead to the administration of rehabilitation during the acute phase of stroke recovery. The population analysed was composed of 9681 American army veterans (mean age 68.7 years old, 97.4% of men) discharged from hospital following a stroke. The study outcome evidenced those in receipt of inpatient rehabilitation training of any type compared to those with no form of formal rehabilitation training [47]. Bates et al. (2013) [47] observed that patients already admitted to hospital for extended care (59.2%; $p<0.001$), patients admitted for subarachnoid haemorrhage (34.4%; $p<0.001$) and patients who were married ($p<0.001$), and therefore could receive help at home, were less likely to receive rehabilitation training than other patients. The observations of Bates et al. (2013) show that not only the clinical state of the participant but also the living circumstances are factors determining the administration of rehabilitation training [47].

There is evidence that the timing of rehabilitation after stroke, early when the patient is medically stable (after 24h post-stroke), can lead to better stroke rehabilitation outcome [32]. Enderby et al. (2017) [32] proposed that the question of whether the patients have rehabilitation potential shifts to: which rehabilitation training would be the most effective for any given patient, specifically when, at what amount and by whom [32].

In their study, Franceschini et al. (2018) [34], showed that there are early predictors of favourable outcome of postacute stroke rehabilitation.
The study was a year-long multi-centre project. In total, 310 patients (mean age 75.0 years old and age range 65.0 to 81.0 years old) who experienced a stroke for the first time were analysed. The participants were assessed three times (beginning of the study, post-acute phase, and 6 months post-stroke). They concluded that out-of-bed mobilisation within the 48 hours post-stroke, absence of incontinence, absence of total anterior circulation infarct (TACI) syndrome and younger age, were the main four factors of influence to predict recovery over 6 months post-stroke.

A better understanding of early motor control ability that is more accessible to clinicians could help to determine the need and potential for rehabilitation as well as inform its intensity and content.

1.4. Stroke care phases

According to the literature, 80% of recovery occurs during the first three post-stroke months [32], [61]–[63]. However, the literature also reports that recovery continues over a longer time period for many stroke survivors [32], [64]. Despite this continued potential for recovery, researchers tend to focus on the acute rehabilitation phase (first 3 months) where recovery is considered to be more rapid due to the neuroplastic process [22].
There are four phases described in the literature [65] that follow the occurrence of a stroke, 1) the hyper acute phase, 2) the acute phase, 3) the subacute phase and 4) the community reinsertion phase.

Hyper acute phase

Phase 1 is the hyper acute phase corresponding to the first 24 hours following stroke. It is during the hyper acute phase that the patient is taken into emergency care, diagnosed and treatment considering the severity of the stroke is assessed and implemented [40], [41], [65].

This primary assessment phase includes brain (computed tomography (CT) or magnetic resonance imaging (MRI)) and vascular imaging (computed tomography angiography (CTA) or magnetic resonance angiography (MRA)). Liu et al. (2011) [41] reported the importance of early thrombolysis administration (to dissolve the blood clot in ischaemic presentations), as it diminishes stroke morbidity. It is important that the patient's stroke severity and type is diagnosed in the 4.5 hours following stroke onset [40], [65] as it promotes early treatment and allows an initial approximation of the speed and degree of recovery [65].

Acute phase

Following the first 24 hours post stroke, the patient enters phase 2, the acute phase. The acute phase lasts approximately one week, provided the individual becomes medically stable [65]. It is during the acute phase that the patient is transferred to a stroke unit, where a multidisciplinary team of healthcare professionals will confirm the stability of the patient and decide on the implementation of early rehabilitation training for the patient [65]. The decision of the implementation of the early or later rehabilitation training is decided according to the severity of the stroke, medical stability and whether the patient is likely to benefit from it [65]. The optimal time for a patient's mobilisation after a stroke is still to be defined and requires further investigation [66], [67]. While there are some recommendations for the implementation of rehabilitation training as early as possible [66], it might not be beneficial in the case of stroke. Maulden et al. 2005 [68], Sawabe et al. (2018)[69] and Chen and Xiao (2019) [70] all observed that starting the rehabilitation training sooner after the onset of stroke led to better functional outcome than delayed rehabilitation training. Bernhardt et al. (2015) [67] compared rehabilitation outcomes 3 months post stroke in 2104 stroke patients, comparing those who were mobilised early (≤24h after stroke occurrence) with stroke patients following the usual mobilisation protocol (>24 after stroke occurrence). They observed more favourable outcome for the participants who followed the usual protocol [67]. Moreover, more deaths occurred in the early mobilisation group (88 patients death), in comparison with the group provided with usual care (72 dead patients) [67]. A detailed report of this multicentre international intervention is described by and Langhorne et al. (2017) [71]. Interestingly, Chippala and Sharma (2016) [72] in their study of 86 stroke patients (mean age: = 59.95±10.55 years old), found substantial ($p=0.136$) Barthel Index improvement within the group of patients who underwent early mobilisation (median=35, IQR=30-38.75) in comparison with the group of patients who underwent the usual care (median=17.50, IQR=10-30). The early mobilisation group also exhibited significantly ($p<0.01$) better follow up result after three months (three months follow up minus admission

score) (median=42.50, IQR=35-55) in comparison with the group of patients who underwent the usual care (median=30, IQR=20-35). Chippala and Sharma (2016) [72] was a single centre study and had a much smaller sample of participants in comparison to Bernhardt et al. (2015) [67] and Langhorne et al. (2017) [71].

Predicting a patient's response to rehabilitation, therefore, will help guide the intensity and nature of rehabilitation. One of the methods used to assess the patient's likely benefit from rehabilitation is the use of the functional independence measure (FIM) scores [73], [74]. Its shortened version, the AlphaFIM® instrument (AlphaFIM), relies on six out of the eighteen FIM tasks to deduce the functional status of the acute stroke patient [75]. More assessment tools used for stroke care are presented in Annex I.

Subacute phase

In the case of medically stable patients, the subacute phase (phase 3) starts about a week after stroke [65]. There is evidence in the literature that starting rehabilitation within the first two weeks of a stroke has a positive impact on the patient's recovery [43], [76]–[78]. The eligible patients are trained according to their level of impairment. The training is adapted to their need and functional goals to achieve or facilitate through the course of rehabilitation exercises [22].

Community reinsertion

Following the subacute phase is the phase of community reinsertion (phase 4). At this stage, the patient returns home and continues the rehabilitation process through an outpatient rehabilitation program (or community rehabilitation team) relying on the help from stroke support group, home care services and other community support systems [65]. The duration of this phase depends on access to support, the caregiver's support, the re-evaluations of the patient's situation, the opportunity for the patient to participate to meaningful activities [79]–[83] and the overall health of the patient [65]. Mayo et al., (2002) [79] used telephone questionnaires at a time-interval of six months, to follow up for over two years with a group of community-based stroke survivors (434 participants , 68.4±12.5 years, average Barthel Index score 90.6/100) and controls (486 participants, 61.7±12.4 years), they observed that about half of the community-based stroke participants expressed a lack of meaningful activity, needed organised support from able-bodied care-giver and would benefit from participation in a stroke support group. Rehabilitation should be designed to help the patient achieve their goals and gain more independence in conjunction with participation in their targeted meaningful activities of choice [82]–[84].

1.5. Gait after stroke

While the majority of stroke survivors have impaired walking ability most people do recover some walking function by the time of hospital discharge. After a week, about two third of the patients recover mobility but are unable to walk without support [85]. The mean walking speed of people with a chronic hemiplegia has been reported to be 0.53 m/s [9]. Walking function clearly covers a wide range of abilities and several authors have attempted to provide categories of walking ability.

Perry et al. (1995) [86] classified walkers into six categories using indoor walking speed as cut-offs. These categories were: 1) Physiological walker (0.1 m/s); 2) Limited household walker (0.23 m/s); 3) Unlimited household walker (0.27 m/s); 4) Most-limited community walker (0.4 m/s); 5) Least limited community walker (0.58 m/s) and 6) Community walker (0.8 m/s).

Li et al. (2018) [6] similarly reported four categories of gait impairment. These were: 1) Fast walker, able to walk at approximately 44% of normal walking speed, 2) Moderate walker ∼21% of normal walking speed, 3) Slow-Extended walker, ∼11% of normal speed and usually requiring a walking aid, mainly due to weakened upper-leg muscles, and 4) Slow-Flexed walker, with even more weakened upper-leg muscles and requires assistance to walk at around 10% of a normal walking speed. Normal speed is typically between 1.1 and 1.3 m/s for able-bodied elderly individuals [7]. Dickstein (2008) [9] reported a speed of 1.34 m/s.

Fulk et al. (2017) [87] classified ambulation after stroke into four categories of ability levels. These levels were differentiated by the number of steps performed per day and the walking speed. The four functional abilities were as follows: 1) Household Ambulators, who perform 100 to 2499 steps per day, at a speed of 0.4±0.3 m/s, 2) The Most Limited Community Ambulators who perform between 2500 and 4999 Steps per day at a speed of 0.7±0.3 m/s, 3) The Least Limited Community Ambulators, who perform 5000 to 7499 steps per day, at a speed of 0.8±0.2 m/s and 4) The Unlimited Community Ambulators, who perform more than 7500 steps per days and walk at a speed of 0.9±0.2 m/s.

It is important to note that most stroke survivors do not return to independent community walking. Jonsdottir and Ferrarin (2017) [7] reported that, of the patients recovering any walking ability only 40% successfully recovered speeds associated with independent community walking (0.8 m/s). As can be been seen in the methods for classifying walking

ability, a commonly used predictor of community walking ability is indoor gait speed. When it is greater than 0.8 m/s the person is generally expected to be able to move independently outdoors [86], [88], this compares with average speed of 0.53 m/s at discharge [9]. It is important to note that, a walking speed below 1.2 m/s remains below the required minimum speed to safely walk safely across a pedestrian crossings in the UK as presented by Asher et al. (2012) [89], which limits the independence of the older adult population in the context of community ambulation, physical activities and per extension other social interactions.
Apart from the loss of physical ability, one important obstacle to confident community walking is the fear of falling [90]–[92]. The experience of multiple falls or even the development of anxiety can lead to confinement in the house. This is important because the direct consequences of a house-bond life is the isolation experienced as well as the effects on the mood leading in some cases in depressive states [93]–[96]. Hong (2015) [93] reported that for stroke survivors engaging in daily community walking the quality of life was better than for those only walking 1 to 3 times per week. In support of this, Alzharani et al. (2012) [94] reported that more physical activity was correlated with better mood in stroke survivors. The recovery of walking function is therefore a desirable outcome of rehabilitation but remains disappointing with most patients failing to achieve the walking speeds needed for community walking.

1.6. Stroke rehabilitation and treadmills training

Dobkin (2016) [43] describes the aims of stroke rehabilitation as "*to lessen physical and cognitive impairments, increase functional independence, lessen the burden of care provided by significant others, reintegrate the patient into the family and community, and restore the patient's health-related quality of life.*"
Another definition from Canadian Best Practice Recommendations for Stroke Care [97] Dawson et al. (2013) [98] defines rehabilitation as follows : "*a progressive, dynamic, goal orientated process aimed at enabling a person with impairment to reach their optimal physical, cognitive, emotional, communicative, and/or social functional level."*
In both definitions, stroke rehabilitation aims to lessen the effects of the impairment and to reintegrate patients into community life. The process of rehabilitation usually starts during the hospital stay once the individual has stabilised medically and continues when the patient returns to the community.

In Scotland, the Scottish Intercollegiate Guidelines Network (SIGN) 118 provides guidelines for practice and recommendations for rehabilitation after stroke [99], [100]. SIGN 118 recommends early mobilisation after stroke (under 48 hours), if medically possible, the patients are positioned to prevent pressure ulcers [99], [100]. Training for Activities of Daily Living (ADL) is provided by occupational therapists during in-patient rehabilitation program and continues when in the community [99], [100]. Treadmill training is recommended as a means to improve gait speed for patients who are independent walkers at the start of the rehabilitation training [99], [100]. The SIGN 118 doesn't recommend treadmill training as a routine exercise [99], [100]. To support gait and balance, repetitive task training, Functional Electrical Stimulation (FES), Ankle-foot Orthoses (AFO), fitness training, muscle strength training are recommended according to the patient's need [99], [100]. The average recommended therapy time is of 45 minutes of physiotherapy and 14 minutes of occupational therapy per day [99], [100]. However, this dose of treatment is not achieved by many [101], [102]. Since evidence were found that 16 supplementary training hours led to improved rehabilitation outcome, the SIGN 118 recommend to safely increase the intensity of training over time for improved gait [99], [100]. The SIGN 118 recommends that a pre-discharge home visit is done by a healthcare professional, often an occupational therapist, to identify what the likely challenges would be for the patient and help them and the carers can mitigate them [99], [100].

A review on the efficacy of stroke rehabilitation protocols (French et al. (2010)) [103] reported that lower-limb rehabilitation benefits from repetitive, task-specific training. Stroke rehabilitation is complex and requires the intervention co-ordinated of several professionals (physiotherapists, occupational therapists, speech therapists, etc) as part of a multidisciplinary team. The effects of rehabilitation appear to be highly dependent on the motivation of the patient and their family. Rehabilitation with high intensity training as a mean for better outcomes is commonly accepted [22]. Treadmill walking presents the obvious advantage of enabling this intensive training for the lower limbs [104]–[106] and has been successfully in several research trials (Globas et al. (2012) [106], Outermans et al. (2010) [107]).

1.7. The problem with treadmill training

Although a promising therapy, treadmill training has, some drawbacks. These, can be generally summed up in the differences with overground walking and its simplification of the natural walking pattern observed in everyday walking [108]. Notably, it differs with generally slower self-selected walking speeds and reduced range of joint motion reported [108]–[111]. There are also kinetic differences with smaller joint moments and powers reported at the hip and knee joints during treadmill walking compared to overground walking, even when speed has been standardised [109], [112]. Observations of increased muscle activity during treadmill walking has led to conclusions of higher energy consumption compared with overground walking [111], [113].

Perhaps more importantly, for recovery of community walking ability, traditional treadmills are not adapted to everyday walking challenges such as frequent changes in velocity and dual tasking such as obstacle avoidance and visual perturbations [114].

1.8. The importance of understanding the motor control pattern

The moments needed to create motion and control posture during gait are created by the voluntary action of muscles, under control from the motor cortex and supplementary areas [115], [116]. After a stroke, motor control can be impaired [22]. The muscle's activity is a direct reflection of the motor control strategy used to perform the movement [117]–[120]. As the muscle activity pattern reflects the muscle control strategy, its observation could lead to a better understanding of what makes an effective community walker within the stroke survivor population. This understanding could also inform the optimisation of gait rehabilitation and, in particular, the use of treadmills.

The integration of camera-based motion capture technologies with force sensors, body worn sensors (accelerometers, gyroscopes) and electromyography (EMG) can describe the complexity of walking in fine detail so that this understanding can be gained. The development of self-paced treadmills (ones capable of automatically adjusting belt speed according to the user's speed) allows natural speed variation to be an implicit part of the walking experience [121]. Combined with virtual reality environments and better analogy of community walking can be simulated. Virtual reality provides the user with an interactive experience, in an enriched environment involving visual, auditory and tactile feedback [122]. The use of virtual environments impacts the cortical reorganisation in patients with chronic stroke [123], [124]. It has presented good evidence as a rehabilitation intervention [125] as,

to leading to more activity engagement of the patients [126], [127] and should, therefore, be considered in regards to community walking rehabilitation training.

1.9. Research question and hypothesis

Primary research question:

Does self-paced treadmill walking within a virtual environment produce a motor control strategy that is a better analogue to everyday overground walking than fixed pace treadmill walking and would therefore be a better training modality for the recovery of community walking?

Hypothesis: The use of a self-paced treadmill linked with a virtual walking environment will create a walking experience that produces a motor output (muscle activation pattern) that is more similar to (statistically significant) overground walking than traditional fixed pace treadmill walking within a virtual environment.

Objectives:

- Conduct a review of the literature.
- Design an observational study to compare the motor control of indoors overground walking and treadmill walking using EMG data.
- Design an observational study to compare the motor control of indoors and outdoors overground walking and treadmill walking using EMG data.
- Compare the muscle control across different walking conditions using parameters of uncomplicated interpretation.
- Observe if the different walking conditions impact differently the able-bodied participants compared to the chronic stroke participants.

Chapter 2

2. Literature review

This chapter is broken down into three sections. The first section will present the rehabilitation process for recovering independent walking ability following a stroke, which is a priority for survivors. As an antecedent, some predicting factors of recovery are outlined in the first section. In the second section the literature review will explore the validity of treadmill training, its potential for extensive use in gait rehabilitation and how it can impact the community walking setting.

The third and final section, considers motor control to better understand the science underpinning the use of treadmill training for recovery of community walking. Starting with an overview of Nikolai Bernstein's theory of motor control, the discussion will proceed to more recent developments in motor control research and theory and look specifically at the decomposition and interpretation of the electromyograms produced by muscle synergies.

The review will conclude by presenting methods of analysing surface EMG signals to better understand motor control. One is the variance ratio, which has been previously used to investigate the repeatability of the EMG pattern. The second is the occurrence frequency, previously used to investigate muscle contraction patterns.

2.1. Stroke rehabilitation principles

2.1.1. Motor training after a stroke

In a paper, Krueger et al. (2012), reported the potential of optimal stroke care in Canada and how it would lead to substantial cost reductions [128]. One of the parameters considered is the early home-supported discharge of the patient. In the case of early home-supported discharge post-stroke, the patient leave the hospital earlier so that part of the rehabilitation training that would usually be done in hospital is carried on at home supervised and administered by a team of healthcare professional specialised in stroke rehabilitation [128], [129]. The practice of early home-discharge is associated with a lower incidence of dependency and death, especially with patient with mild to moderate stroke [130], reduction of the duration of hospital stay and reduction of the overall cost of stroke care [128]. Early home-discharge requires the organisation of a team able to implement intensive

rehabilitation training at home and/or in community-based centres, to provide the patients with the appropriate tools. This can present challenges in contexts with less infrastructures, such as rural areas where the distance to the facilities can affect the administration of the treatment [131].

The two following sections will present the main approaches to motor training and some of the tools necessary to achieve optimal rehabilitation post-stroke in the community.

2.1.1.1. Approaches of motor training

Motor rehabilitation training is based on four approaches [43].

1) Repetitive task-oriented training. This approach relies on motor learning principles and focuses on repetitive practice of movement tasks in order to challenge the patient and help the patient achieve limb movement consistent with the task needing performed [43], [103], [129]. Task oriented training "*focuses on practicing the specific movements that are impaired and that clients want to improve*" [132]. For example, task-oriented gait training will involve over ground or treadmill walking and/or functional tasks related to walking such as walking balance exercises [132]. French et al. (2010) [103] reviewed studies involving 23 to 60 minutes of exercising, 3 to 5 times a week in a systematic review and meta-analysis. The training programs were composed of whole therapies, targeting different tasks [133], [134], circuit training and/or mixed tasks practice [135]–[138] and single task training such as sit to stand [139], trunk control [128], [129]. Significant improvement ($p<0.05$) were observed in walking speed (standardized mean difference (SMD) 0.29, 95% CI: 0.04, 0.53); for walking distance (mean difference 54.6, 95% confidence interval (95% CI: 17.5, 91.7); sit-to-stand (standard effect estimate 0.35, 95% CI: 0.13, 0.56), and activities of daily living (SMD: 0.29, 95% CI: 0.07, 0.51).
2) Sensory facilitation. This focuses on stimulating the sensory system and mitigating muscle spasticity, to allow normal movement. In the context of movement rehabilitation, transcutaneous electrical nerve stimulation (TENS) is used to reduce spasticity [142]–[144]. Mahmood et al. (2019) [144] conducted a systematic review and meta-analysis of the effect of TENS on the muscle spasticity of adults with a stroke. They found that compared to physical therapy with placebo TENS, patients who underwent physical therapies with TENS presented significant ($p=0.0001$) improvement of muscle spasticity (SMD =0.64;

95% CI: -0.98 to -0.3; I^2 =17%). When compared to physical therapy alone, TENS combined with physical therapy also presented significant (P=0.02) improvement of muscle spasticity (SMD =0.83; 95% CI: -1.51 to -0.15; I^2 =27%).

3) Compensation. This allows the patient to adapt to the disability, even in case of diminished sensorimotor control [43]. Compensation training consists of teaching the patient to substitute a previously learned strategy to perform a given task with a new strategy that will help the patient perform the same task. Using this approach, new strategies are developed by person to overcome the underlying impairments. It can involve the use of the unaffected limb to carry out a task or can look at adapting the use of the affected side [43]. For example, someone with hemiplegia will learn to dress single-handedly [145]. Without compensatory training compensatory strategies that are ineffective to achieve the intended task can be developed by patients [146]–[148]. This approach can rely on the use of devices (e.g. use of assistive technology, walking aids) and methods that reduce spasticity and develop synergistic movements, which are abnormal movement combinations on the affected side of the stroke survivor (i.e.: movement of hand and shoulder when the intended movement is a forearm movement only) [43], [149]. The use of ankle-foot orthosis provides support to the patient's ankle and foot for stability and helps in lifting the toes during the swing phase of gait [132]. Ankle-foot orthosis improve balance and walking immediately [150]. They improve gait speed and help their users to stand more symmetrically [132], [150]. Walk aids such as canes (single point or quad cane), walker and rollators can be prescribed to patients who are suffering from impaired balance and gait [132]. However, people who usually use these types of walking aids generally walk slower, use more energy and have worse balance than the people who don't [132], [151]. Similarly to ankle-foot orthoses, functional electric stimulation improves the walking speed of people whose stroke incident has produced an impaired walking gait [132], [152].
4) Fitness and strength training. This approach uses exercises, fitness training and strength training to improve the patient's mobility [43]. Following a stroke, up to 85% of the patients are deconditioned due to the reduced activity induced by hemiparesis [43], [153]–[155]. Strength and fitness training after a stroke is part of both the early stage and later stage of stroke rehabilitation [43], [156]–[158]. Fitness or cardiorespiratory training comprises of, for example, treadmill

training [159], training in water [160]. For the patients with enough motor control aerobic exercises on bicycles or treadmills is possible [106], [161], [162]. Strength training can include the use of an exercise machine, weights, body weight or elastic resistance bands [160]. While there is little evidence of the benefits of strength training only [163], fitness training involving treadmill walking led to improved walking speed (mean difference = 6.71 metres per minute, 95% Confidence interval (CI) 2.73 to 10.69), improved walking capacity (mean difference = 30.29 metres in six minutes, 95% CI 16.19 to 44.39) and preferred walking speed (mean difference = 4.28 metres per minute, 95% CI 1.71 to 6.84) at the end of the training program [156], [160]. Mixed training, which involved both fitness walking and strength training, also presented improved increased walking capacity (mean difference = 41.60 metres per six minutes, 95% CI 25.25 to 57.95) and preferred walking speed (mean difference = 4.54 metres per minute, 95% CI 0.95 to 8.14) [156], [160].

In order to improve fitness, mobility and to reduce the risk of recurring stroke, the patient will be encouraged to keep walking daily and progressively increase distance and duration of their walks [43]. In their review paper, French et al. (2010) [103] observed that the use of repetitive task training led to a small to moderate statistically significant improvements of walking speed (n=263: standardized mean difference 0.29; 95% Confidence interval (CI): (0.04, 0.53)), walking distance (n= 130; weighted mean difference: 54.59, 95% CI: (17.50, 91.68)) and sit-to-stand motions (n= 346; standardized effect: 0.35, 95% CI: (0.13, 0.56)). The ten trials relating to gait and balance reviewed in this paper consisted of 476 participant's data [103]. Four out of the ten trials recruited participants within the first three months post-stroke. Apart from two, the trials included less than 20h of practice time [103]. The differences in practice time may have influence on the results as one might expect more opportunities for repetition in the case of longer practice time. However, the results of this review did not provide conclusive evidence on whether a higher dose of practice leads to improved patient outcomes. This review also does not consider the long-term effect that training in this way has on these patients.

In the UK, stroke rehabilitation training based on task-specific exercise has not been the most commonly used [103]. Instead, a 5th approach, the Bobath method, also called the neurodevelopmental treatment [164] which aims at restoring

normal movement under the guidance of the therapist and minimises movement repetition, has been favoured by UK therapists [103]. In their paper, French et al. (2010) [103] did a systematic review and meta-analysis to compare the impact of repetitive task training to usual care or attention control. They found statistically significant (p=0.04 overall effect) improvements in lower limb outcome measures. The walking speed (standardized mean difference= 0.29, 95% CI 0.04, 0.53), walking distance (mean difference= 54.6, 95% confidence interval (95% CI): 17.5, 91.7), sit to stand (standard effect estimate= 0.35, 95% CI: 0.13, 0.56), and in activities of daily living (standardized mean difference= 0.29, 95% CI: 0.07, 0.51) improved significantly. Improvements were also observed in global motor function (standardized mean difference= 0.32, 95% CI –0.01, 0.66) and walking abilities (standardized mean difference= 0.25, 95% CI 0.00, 0.51). No significant improvements (p=0.31) were observed for the upper limb [103].

Bhalerao et al. (2011) [165] compared the outcome of patients who underwent either the Bobath methods training (n= 8, 6 males, age= 53.67±8.46, time post-stroke= 5±2.3 weeks) or task-specific movement training (n= 10, 8 males, age= 52.27±8.06, time post-stroke= 4±1.5 weeks) over a period of six weeks. They found a greater improvement in outcome for the people who underwent task-specific training (Motor Relearning Program) as significant improvement was reported by the Functional independence measure (52 versus 34.25, p= 0.004), Functional ambulation category (4.6 versus 3.5, p= 0.0084), Motor Assessment Scale (24.8 versus 16.8 points, p= 0.0001), Barthel index (69.5 versus 47.5, p= 0.0014), and Dynamic gait index (9.6 versus 1, p= 0.004). It appears that the Bobath approach presents inferior results to the over movement training (task-specific). Bhalerao et al. (2011) [165] proposed that the reason for better outcomes of the task-specific training compared to Bobath was that it involves training in different environments (on level surface, on an uneven surface, with some cognitive activity), whereas Bobath focussed more on postural control and the correct execution of the movement. Another possible reason for better outcome of task-specific training is the active learning process that is necessary to regain mobility as the therapist gives more feedback on the patient's performance and encourages them to figure out how to correct their movement by themselves. Also, Bhalerao et al. (2011) [165] pointed at the necessity of task-specific training to encourage cortical reorganisation. The participants in

Bhalerao et al. (2011) [165] were all at an early stage post-stroke (from 2 weeks post-stroke, still in the acute phase), it is possible that similar observations wouldn't be available if the rehabilitation training started later or if it was continued on a longer term (beyond 3 months post-stroke).

Bhalerao et al. (2013) [166] compared the outcome on stroke participants of Bobath (n= 15) versus Task-specific training (n= 17) on the Activities of Daily Living and walking abilities over a six week long training program. In total 32 patients took part (19 males, age= 54.0±10.9, time post-stroke= 2 weeks). They observed that Task-specific training led to significantly greater improvements of the Activities of daily living over six weeks of training in comparison with the Bobath (Functional Independence Measure 118±9.32 versus 77.17±14.96, $p<0.05$; Barthel Index score=90.21±10.02 versus 58.2±1, $p<0.05$). All participants of the task-specific training group reached independent walking on a flat surface (Functional Ambulation Category grade= 5.87±0.5), when 50% of the participants who followed the Bobath training achieved independent walking (Functional Ambulation Category grade= 3.7±0.62) ($p<0.0084$). Here again, the Bobath method presents inferior outcome than the task-specific training at an early-stage post-stroke (two weeks).
The findings from these last papers point at better outcome results in walking rehabilitation within the time frame of two weeks to three months.

2.1.1.2. Motor training and biomechanical support

Task-oriented motor training can be initiated as soon as the patient is medically stable [43]. There is evidence that very early mobilisation after a stroke (within the first 24hrs) is detrimental to the patient's rehabilitation [71], [167]. Rethnam et al (2020) [167], observed that usual care mobilisation (median time post-stroke= 23h) led to better outcome (modified Rankin Scale score 0–2, $p = 0.005$) than very early mobilisation (median time post-stroke= 20h). Rethnam et al (2020) [167] therefore recommend rehabilitation should commence no earlier than 24h post-stroke.

At the beginning of the rehabilitation intervention, the affected limb's range of motion is maintained by means of limb positioning, the use of splints, slow rotation movements and stretching repeated for all joints several times a day and

complemented with added weight as soon as possible [43]. These types of exercises are useful to prevent an excess of hypertonicity in the muscles [43].

When the patient can stand independently, they can start training standing in parallel bars and practice gait training with the help of the therapist. The therapist's role will involve encouraging the rectification of deviations from a normal gait observed during the patient's walk. These will, for example, involve encouraging more weight-bearing exercises on the hemiplegic leg, promoting longer step lengths with greater deeper hip extensions [43]. Patients who lack control over their ankle or knee flexion can benefit from the use of ankle-foot orthosis (AFOs) [168]–[171]. Tyson and Kent (2013) [150] reported improved mobility from the use of AFOs post-stroke, using the Functional Ambulation Category (n=65; standardised mean difference: 1.34, 95% CI: (0.95,1.72) ; $p<0.001$), improved walking speed (n=250; mean difference: 0.06 m/s, 95% CI: (0.03, 0.08) ; $p<0.0001$) and improved balance, using the Berg Balance Scale (n=122; mean difference: 48.90±4.8 using an AFO vs 46.2±5.5 ; $p=0.001$). The participants in the study were mostly people with chronic stroke who had completed their initial rehabilitation. Patients within the subacute or acute stages may not see the same results as the fitness and strength of the participants might be affected by the closeness to the stroke occurrence, which could mean substantial physical deconditioning [172]. All these studies compared the use of AFO against no use of AFO and it should be noted that none of them looked at the long-term effects of AFOs for these patients. All participants received AFO treatment and the studies were randomised crossovers in structure. Different AFO designs were used within the different studies. It is not possible to detect how the varying designs impact the patients [150]. The long-term effect of wearing AFOs lacks evidence [150].

Bethoux et al. (2015) [173] compared the long-term effects of the use of functional electrical simulation against the use of AFOs over one year. A group of 384 stroke patients (≥6months post-stroke) joined the study with 204 using AFOs. There was a significant improvement in gait speed 12 months after the initiation of the use of AFO (mean difference= 0.172 m/s, $p<0.001$) [173]. The absence of other long-term analysis of the impact using AFOs can have renders it difficult to project their long-term benefit in the context of a life-long impairment. Using a year-long assessment as an indicator for long-term usage presents a good initial pool of data but longer-term studies might reveal more about body adaptation to AFOs and long-term

rehabilitation process of the impaired gait. Maybe longer-termed observation going beyond a year (e.g. 3 to 5 years) might be worth the investigation.

The assessment of walking adaptability and gait variability could be supported using instrumented treadmills. The following section presents an overview of some of the current use of treadmills in gait rehabilitation training and possible new ways of utilizing this device.

2.1.2. Gait rehabilitation

Three months after a stroke, around 80% of patients still experience walking impairments [174]. A study reported that out of 800 subjects, 50% were able to walk independently, with or without walking aid, after rehabilitation training. 11% were able to walk with assistive devices and 18% were unable to walk at all [174], [175]. Gait rehabilitation increases gradually by therapists as part of a treatment plan, according to the severity of the stroke and patient tolerance, from the early stage post-stroke (patient's mobilisation from ≥ 24 hours post-stroke treatment or even within the first 24 hours post-stroke [66], [67]) when the patient is transferred from the emergency unit to the stroke unit [67] (see section 1.4). The healthcare team will set specific recovery goals, increase incrementally the appropriate therapy and deliver the different elements of rehabilitation training (including repetition of specific functional tasks) [22]. In the last decade, the ability to diagnose and treat patients, such as early thrombolysis administration after an haemorrhagic stroke, has had positive impact on the severity of stroke [176]. The early care, the transfer of the patient into multi-disciplinary stroke unit and the early mobilisation and rehabilitation training all contribute to improved rehabilitation outcomes and early supported discharge which result in cost savings and cost effectiveness of the health and social care cost of stroke [176].

Current gait training protocols put an emphasis on stepping repetition, stepping symmetry [177]–[181] and balance [177], [180], [182]–[186]. In their paper, Balasubramanian et al. (2014) [187] presented a neural control model for walking that is composed of three interconnected components: stepping, equilibrium and adaptability (see Figure 2.1). A combination of these three components is considered

to be needed to achieve independent safe walking.

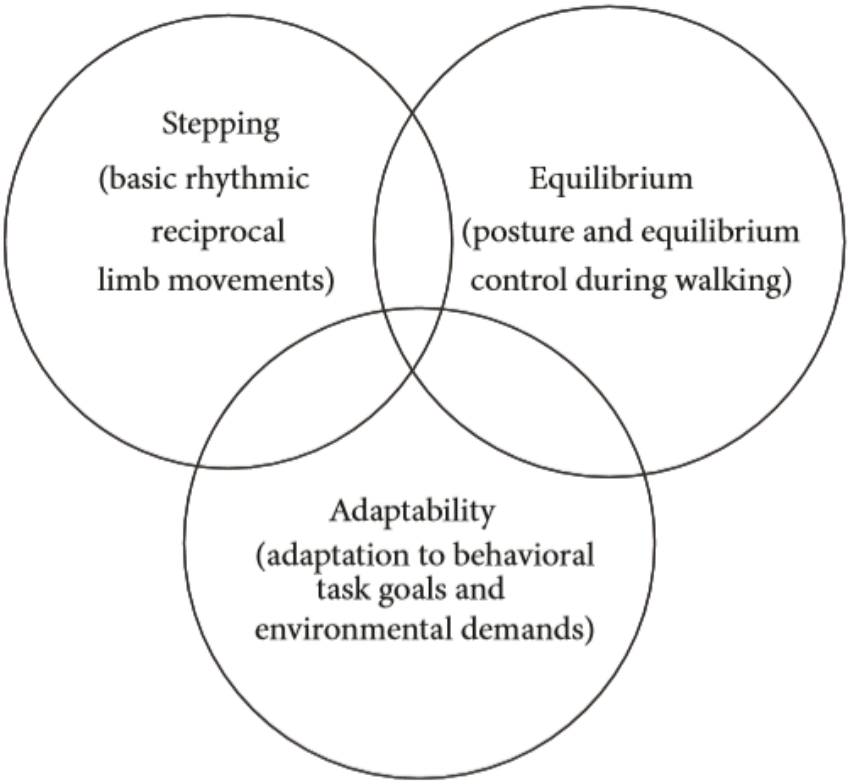


Figure 2.1: Neural control model of functional walking. Extracted from Balasubramanian et al. (2014) *[187]*

Two out of the three components (stepping and equilibrium) are commonly considered in current walk rehabilitation training protocol [185], [188], [189], however, more attention needs to be turned towards adaptability as it is also a component of functional walking requiring training. The ability to adapt gait is a key component of safe, independent community walking, which is one of the desired goals of gait rehabilitation after a stroke [8]–[11].

Balasubramanian et al. (2014) [187] reviewed the different means of assessing walking adaptability. They described walking adaptability as *"The ability to adapt walking to meet behavioural task goals and demands of the environment"*[187]. They proposed nine dimensions of walking adaptability to environmental demands applicable to every ambulatory situation. Seven of those, noticeable by stars next to their titles in *Table 2.1*, were adapted from the work of Patla and Shumway-Cook (1999) [190] who produced a conceptual framework defining dimensions of mobility for community walking. These nine environmental domains are listed in *Table 2.1*. According to the environment of walk, these domains are required at different level of intensity.

Domain	Definition
Obstacle negotiation*	Negotiating obstacles in the environment to prevent a collision between the lower limb and the obstacle, such as stepping over and obstacle avoidance
Temporal*	Time constraints imposed on walking, such as needing to walk faster to cross a street or slow in a crowded mall
Cognitive dual tasking	Walking while attending to cognitive task, such as engaging in conversation while walking
Terrain demands*	Walking on compliant or uneven surfaces that are not flat and firm, such as stairs, ramps, grass, and so forth
Ambient demands*	Factors such as level of lighting, temperature, weather conditions, noise levels, and familiarity with surroundings
Postural transitions*	Varying posture during walking, such as turning, bending down to pick an object while walking, and so forth
Motor dual-tasking	Walking while attending to additional motor tasks, such as holding a glass of water while walking, picking up an object from the floor, and so forth
Physical Load*	Carrying or interacting with a weighted object while walking, such as carrying a loaded backpack, walking to open a heavy door, and so forth
Manoeuvring in traffic*	Avoiding collision with static and dynamic objects by manoeuvring the entire body, such as walking around other people, pets, vehicles, and so forth

Table 2.1: The nine domains of walking adaptability as presented by Balasubramanian et al. (2014) *[187]*. *: the domains adapted from the work of Patla and Shumway-Cook (1999) *[190]*.

These domains have different degree of influence according to the setting. This can be observed practically, in two contrasting environments, as follows. Walking in a familiar indoors environment requires less unpredictable obstacle negotiation, temporal demand, cognitive dual-tasking, physical load and manoeuvring of traffic than postural transition demands. Also, the need to move from sitting to standing and move to grab and displace household object, may be higher when walking in a familiar indoors environment, in comparison to walking on a busy street. In a busy street, domains such as obstacle negotiation, temporal demand, the manoeuvring of traffic will be in higher demand than physical load and the motor dual-tasking domains as the environment is less predictable.

Testing walking adaptability [187], [191] is described in different ways in the literature, for example: obstacle crossing [192], obstacle negotiation [185], obstacle clearance [193], gait or walk adaptability [174], [185] or walk variability [187]. Walking impairments following a stroke make real-life walking adaptation tasks such as turning [194], [195] and obstacle negotiation difficult [186], [193], [196],

[197] and will require the development of compensatory strategies to achieve the task safely and independently [193].

Burke et al. (2008) [198] observed the recovery of walking of participants who had a stroke (n= 13; 6 males; age= 56 ± 13.5 years old) from 3 to 24 weeks post-stroke. The walking ability was quantified by measuring the self-paced comfortable walking speed and using the Functional Ambulation Categories, Rivermead Mobility Index, Motricity Index, Barthel Index, Trunk Control Test. Surface EMG was also recorded on eight muscles on both legs. At the time of the first measurements, most of the participants were unable to walk. Apart from the Trunk Control Test (p value ranged from 0.135 to 0.194), all the functional ability measures improved over time (walking speed ($P < 0.003$); Rivermead Mobility Index ($P < 0.000$); Motricity Index ($P < 0.000$); Functional Ambulation Categories ($P < 0.002$); Barthel Index ($P < 0.001$)). When observed over time, no significant changes were observed on the muscle's on-off actuation timings. Both the affected and the non-affected leg presented abnormal muscle recruitment and did not improve over time. The author proposed that the abnormal muscle patterns act to compensate the loss of stability of the patients with stroke.

Hashiguchi et al. (2016) [199] recorded surface EMG data from 8 lower limb muscles from the hemiplegic leg of patients following a stroke (n= 13; 10 males; age= 58.8 ± 13.2; time post- stroke: 66.8 ± 24.2 days) in order to compute their number of muscle synergies (muscle synergies will be discussed in section 2.3.2.4.), and their structure using a nonnegative matrix factorization (NNMF) method. The EMG data were collected twice, with a month interval. The patient's abilities were measured by recording their walking speed, balance (Timed Up and Go test (TUG) and the Short-Form Berg Balance Scale (SFBBS)), and the functional outcome of their activities of daily living (Barthel index (BI)). Between the two data collection sessions, eight patients presented a merging of their muscle synergies, which was associated with a change in the range in the joint angle and change of muscle strength [199]. Ten participants presented fractionation (separation into smaller synergies) of the muscle synergies, which was associated with an improvement in activities of daily living (BI) [199]. The participants' gait speed also increased ($p < 0.01$), as well as their muscle strength ($p < 0.05$). The paper did not inform on the exact values of post-study gait speed and muscle strength.

The findings from both these papers, [198], [199], point to improvements in functional abilities of the stroke patients which are independent of muscle recruitment strategies and changes to the muscle synergies employed.

Everyday walking requires a combination of these different domains with different degrees of importance. The following sections will present methods of measurement of walking adaptability including balance and obstacle crossing.

2.2.2.1. Walking adaptability, balance, and obstacle crossing

Park and Kim (2016) [186] observed the changes in balance (using the Berg Balance Scale, BBS), walking speed (10-meter walking test) and functional mobility (Timed Up and Go Test, TUG) of 6 adults with stroke who underwent 12x 30 minute obstacle course training sessions over the course of three weeks. The obstacle avoidance training included straight walking, slalom, up and down stair climbing and box passing. In a control group six stroke participants, acting as controls, received a program of simple, obstacle free flat overground gait training. At the end of the program, the group who trained with the obstacle course experience significant ($p<0.05$) improvements in gait speed (10-meter walking test pre: 22.7 ± 7.7s, 10-meter walking test post: 18.2 ± 6.5s), balance (BBS score pre: 43.7 ± 6.0, BBS post: 45.2 ± 5.3) and functional mobility (TUG timing pre: 20.3 ± 7.7, TUG timing post 18.6 ± 5.2). The outcome of this preliminary study points at the benefit of integrating obstacle avoidance training in order to improve gait speed, balance and functional mobility [186]. This study was conducted with a small number of participants who were already capable of independent walking and obstacle crossing and therefore needs further research to confirm results with the wider stroke community. Also, there was no detail provided on the age of the participants. Younger stroke patients are likely to be fitter than older adults with stroke, which would naturally impact their walking adaptability. The question of whether obstacle-crossing training is beneficial for the training of patients with more severe gait impairments still needs further research.

Training walking adaptability for stroke survivors is challenging not only because of the physical impairment resulting from the stroke but also because of the demand in attention required to ensure balance, prevent falling or stumbling and to complete

tasks such as walking while negotiating obstacles [192]. Smulder et al. (2012) [192] asked their stroke participants (n=8; age 57 ±15 years old; 5 males, >6 months post-stroke) and age matched healthy controls (n=8; age 54 ± 15 years old; 5 males) to walk on a treadmill at a constant speed. On the treadmill, a wooden obstacle was released in front of the affected leg (left leg of the controls) and the participants had to step over the obstacle. The obstacle-crossing task was combined with a second cognitive task (audio stroop) that required the participants to articulate at what pitch (low or high) the words "Low" and "High" were spoken. The combination of these two tasks resulted in a decrease in performance of the cognitive task, in favour of the obstacle-crossing task. The participants walked at a set speed which is not comparable with real-life walking. Also, the imposed walking speed might have forced the participants to focus on the task that might prevent them from tripping and risk falling to the detriment of the cognitive task; in a real-life obstacle avoidance setting, they might have negotiated the obstacle slower and still addressed the cognitive task. Stroke patients with limited attentional reserves may lead to a strategy that safeguards the walk, to prevent a trip or fall. Conducting the walking task on a treadmill limits the diversity of the training. It should be also noted that the obstacle was placed to in front of the affected leg only, which limits the obstacle avoidance strategy that the participant could develop. This could be improved by placing the obstacle randomly at different places along the treadmill's width.

2.2.2.2. Walking adaptability and dual tasking

Walking is of course affected by the need to carry out additional (dual) tasks [187], [194], [200]–[204] which is common during of community walking (see *Table 2.1*). When walking is challenged with an additional cognitive task (such as recalling a shopping list), this "dual-tasking" negatively impacts the walking performances of stroke survivors, i.e. by slowing down to make walking safer while answering the cognitive task [187], [202]–[204].

Bowen et al. (2001) [200] observed the dual tasking performance of 11 stroke participants (six men, age 72±9 years old, 120±48 days post-stroke). They reported a mean speed decrease superior of 4 m/min, which corresponds to 0.07 m/s (p=0.017) during the dual task execution. Hollands et al. (2014) [194] observed the dual-tasking performance of 17 stroke participants (three women, age 64±10 years old,

59±113 months post-stroke) and 15 able-bodied adults (six men, age 72±9). They reported a decrease close to 0.1 m/s in the able-bodied control group ($p<0.001$), the stroke participant's walking speed decreased in a smaller amount (under 0.05 m/s) when walking straight concluding there was no significant difference in walking speed for the stroke participants when performing dual tasks in comparison to when performing single task. There was no statistical difference ($p>0.05$) between the able-bodied and stroke participants in number of correct answers to the cognitive task (stroke: means (SD)= 0.63 (0.30) correct responses per second; able-bodied: means (SD)= 0.76 (0.23) correct responses per second). This indicated that the participants had to slow down their walk to keep up with the cognitive task's demand.

Bowen et al. (2001) [200] reported an average of 10% increase ($p=0.010$) in stride duration (indicating a slower gait), Hollands et al. (2014) [194] reported a significant ($p<0.001$) increase (about 0.20 m/s) in the able-bodied group in comparison with the group of stroke participants (< 0.1 m/s).
When it comes to stride length, Hollands et al. (2014) [194] reported lower values for both an able-bodied group and a stroke group (respectively 60.26±12.63 cm during dual task and 61.14±12.03 cm). There were no significant difference between the single and dual task condition ($p>0.001$) in Hollands et al. (2014) [194], but there was a significant increase of double support time (percentage of time in which both feet are on the floor), 18.9% to 20.9%, ($p=0.010$) in a study by Bowen et al. (2001) [200]. In the case of Bowen et al. (2001) [200], the cognitive activity consisted of responding "yes" or "no" to regular (every 3 seconds) vocalisation of the commands "red" or "blue" that were spoken in a random order.

In Holland et al. (2014) [194] participants had to walk while simultaneously subtracting 3 from a random number above 100 and verbalising the answer. The difference in nature of the exercises (answer to a verbal cue or mental calculus) probably creates different levels of difficulty to the participants.
Due to the fact that Bowen et al. (2001) [200] only observed stroke participants, the effects of dual tasking cannot be directly linked to the effects of stroke on walking adaptability.
Holland et al. (2014) [194] included participants who had a stroke and able-bodied participants, thus, comparing the two populations. The cognitive task of verbal

subtractions or even a regular answer to a question are cases of dual tasking that are unlikely to occur in everyday life; cognitive activities are generally induced by conversations which are more complex interactions.
Bowen et al. (2001) [200] instructed their participants to walk along an instrumented walkway without instructions of changes of direction. It is therefore assumed that all participant performed straight walks. Holland et al. (2014) [194] proposed a walking protocol involving a 90° turn which might be more representative of real-life community walking such as street navigation. Both protocols could benefit from the addition of diverse walk exercises including turns, obstacle avoidance and other real-life-mimicking walk situations.

2.2.2.3. Walking adaptability and the influence of the terrain

When walking, individuals have to adapt to the terrain. Walking speeds will naturally change to tackle cambers and gradients [205], [206]. People living with a stroke typically walk at slower speeds (Phan et al. (2013) [207] reported 0.77 ± 0.36nm/s for the level walking and 0.70± 0.32 m/s downhill, $p<0.001$) and reduced step length (Phan et al. (2013) [207] reported 0.53± 0.14 m for the level walking and 0.47 ± 0.13 m downhill, $p<0.001$ on the affected side and respectively 0.50 ± 0.14 m and 0.46 ± 0.12 m on the unaffected side, $p<0.001$) while walking downhill [187], [207]. Phan et al. (2013) [207] proposed that the reduced speed and step length is a strategy to compensate for the loss of muscle strength and motor control. However, no measure of muscular activity was presented. Monitoring muscle activity would give more information about the muscle recruitment strategy utilised by people with stroke when negotiating slopes.

The ability to walk up and down a flight of stairs is also affected after a stroke [207]–[210]. Novak and Brouwer (2013) [209] reported low cadence during stair walking (up and down) for stroke participants (10 participants, 7 males, age: 60.1 ± 10.3 years old, 28.1 ± 16.3 months post-stroke), in comparison to their sex and age-matched controls (mean age: 59.4 ± 8.7 years old). When walking upstairs the stroke group's cadence was of 71.11 ± 10.30 steps/min (no handrail) and 65.60 ± 10.82 steps/min (handrail) compared to the controls (94.72 ± 10.32 steps/min (no handrail) and 95.48 ± 10.84 steps/min (handrail)). When walking downstairs the stroke group's cadence was of 75.56 ± 13.43 steps/min (no handrail) and 68.13 ± 10.58

steps/min (handrail) compared to the controls (106.82 ± 16.98 steps/min (no handrail) and 102.77 ± 21.35 steps/min (handrail)). It is interesting to note here that a higher cadence is observed when going downstairs.
This study outlines the differences in speed adaptation strategies used by the stroke group in comparison to their controls. Monitoring and recording muscle activity would add to the understanding of the underlying motor control strategies between the upstairs and downstairs walks, both with and without the use of a handrail.

2.2.2.4. Walking adaptability and the influence of the surrounding environment

Balasubramanian et al. (2014) [187] also pointed out the impact of the ambient environment on walking [52], [187]. It appears that stroke survivors walk faster when they are outdoors compared to when they walk indoors [211]. These observations were done on people with chronic stroke with a mild severity that allowed community walking prior to the participation to the study (Carvalho et al. (2010) [211] and Donovan et al. (2008) [212]). Some possible factors for this difference of speed, apart from physical fitness and functional mobility level, are the motivations and confidence to take on the challenge of community walking post formal rehabilitation training [212].

Carvalho et al. (2010) [211] measured the walking speed of stroke survivors (n=36; 25 males; ≥12 months post-stroke) in three settings: a clinical setting (including clinical surrounding with over patients and healthcare professionals movement), in a basement (empty corridor indoors) and outdoors (calm neighbourhood garden). The walking speeds were measured using the thirty-meter walk tests (30 mWT) and the six-minute walk test (6MWT), to measure long and short distance performance. When walking a long distance indoors (178 ± 64 m to 471 ± 81 m) participants with recorded walking speeds ≥ 0.8 m/s (n=26; 18 males; age: 60±4; 59±27 months post-stroke) walked faster in the outdoors setting (self-selected speed outdoors= 1.31±0.22 m/s; self-selected speed basement setting= 1.306±0.23 m/s; self-selected speed clinical setting= 1.26 ±0.21 m/s). The participants with a walking speed <0.8 m/s (n=10; 6 males; age: 60±3; 69±43 months post-stroke) presented similar speeds in all settings (self-selected speed outdoors= 0.51±0.20 m/s; self-selected speed basement setting= 0.52±0.19 m/s; self-selected speed clinical setting= 0.51 ±0.18

m/s) [211]. It is therefore possible that the surrounding environment will affect the walking speed of people with less severe mobility restrictions post-stroke (speed ≥ 0.8 m/s). People with lower walking ability (speed <0.8 m/s) will keep the same speed in all circumstances because they lack the motor capacity to adapt.

Donovan et al. (2008) [212] conducted a study involving participants with stroke (n=30; 21 males; age: 61.3 ±11.1; 46.5 ±32.9 months post-stroke). They observed that when walking in a shopping mall their speed was lower (39.3 ± 11.2 m/s) than during an outdoor walk on a street (41.4 ± 12.9 m/s) [212]. The participant's walking speed was measured using the 10-metre timed walk (10MTW) and the six-minute walk test (6MWT) both measured on the context of a clinic, a street, and a mall. Donovan et al. (2008) [212] observed statistically significant slower walk in the context of a mall (-0.04 m/s, $p<0.01$). For the participants that were faster walkers (≥0.8 m/s), the environment of the walking test might have influence on the predicted walking speed in the community [86], [92], [213]–[215].
In the context of outdoor walking, especially in a mall setting, the surrounding pedestrian's activity cannot be predicted and regulated. It is therefore possible that inter-individual differences were present due to a difference of cognitive challenge.

In both Carvalho et al. (2010) [211] and Donovan et al. (2008) [212], the participants had chronic stroke with experience of walking in the community setting. Similar trials performed by post-acute patients who are just completing their course of standard rehabilitation and/or have not had yet the opportunity to walk independently in various community setting may provide further evidence on their ability to adapt to challenging environments. Donovan et al. (2008) [212] pointed at the fact that the presence of a physiotherapist during the study might have been increasing the participant's sense of confidence and safety, hence, leading to better performance.

The measure of gait speed using tests such as the 10-meter walk test and the six-minute walk test (also used for walking distance measurement) have proven to be useful tool to measure stroke survivor's speed and anticipate their community ambulation abilities. Other outcome measurements should be taken in consideration, such as the setting of the test, when considering the characterisation of community ambulation as it involves changing environment, which may include changes of

walking surfaces and different ambience (noises, reading of traffic signs and lights etc).

2.2.2.5. Measurement of walking adaptability

Bijleveld-Uitman et al. (2013) [92] compared walking speed and distance as a predictor of community ambulation ability. They found walking speed and walking distance both had the same predictive validity for a return to community walking in participants nine months after stroke who were 'mildly' to 'moderately' affected in their walking abilities. They stated that gait speed was an effective measurement tool for mild to moderate stroke survivors who can walk independently over 10 meters [92]. An et al. (2015) [215] also compared walking speed to walking distance as a predictor of community ambulation after stroke. They found that a cut-off value of 0.87 m/s and 318 meters both predicted of community walking level. They also mentioned that when one threshold was attained but not the other, it was still possible to attain community walking through the use of walking aids or compensatory gait pattern (e.g. excessive hip flexion) [215].
It is important to acknowledge that community walking can't be narrowed down to a single measure of velocity or distance as it encompasses various skills covered in the phrase walking adaptability covering skills such as: accommodating unpredictable environments, modifying gait to adapt to perturbations, as well as adapting to cognitive tasks requiring attention (i.e.: conversation, reading passing information, navigating urban streets etc) [190], [216].

While there is no unique clinical assessment that measures walking adaptability, Balasubramanian et al. (2014) [187] reviewed some related methods. Some of which have been used within stroke populations (see Table 2.2). The various methods collectively encompass the following ten domains of walking ability parameters identified by Means and colleagues [217]: multiple task test (MTT), obstacle negotiation (ON), temporal demands (TM), cognitive dual-tasking (CT), terrain demands (TR), ambient demands (AM), postural transitions demands (PT), motor dual-tasking (MT), physical load (PL), manoeuvring in traffic (TF), as presented in Table 2.2.

Test name	Purpose	Targeted population	Composition	Scoring system
Dynamic Gait Index (DGI) [218]	Assessment of the ability to change gait according to task demands	Community dwelling older adults, stroke	8 walking tasks Adaptability parameters: ON, TM, TR, PT, TF	(0-4) point/item, High score: better performance, Max score: 24
Functional Gait Assessment (FGA) [219]	Assessment of the ability to change gait according to task demands based on the DGI	Persons with vestibular disorders, stroke	10 walking tasks Adaptability parameters: ON, TM, TR, PT	(0-4) point/item, High score: better performance, Max score: 30
Modified Emory Functional Ambulation Profile (mEFAP) [220]	Timed measure of walking over a standardized set of terrains, derived from the functional ambulation profile	Individuals with stroke	5 items Adaptability parameters: ON, TR, PT, TF	Time x item's factor (based on use and type of assistive device) Total score: sum of each item's score
Community, Balance and mobility Scale (CB&M) [221]	Assessment of gait, balance, and mobility	High functioning young and middle-aged ambulatory adults with traumatic brain injury, community dwelling older adults, stroke	13 items Adaptability parameters: PT, MT, TR	(0-5) scale except one item (0-6), Max score: 96
High-Level Mobility Assessment Test (Hi-MAT) [222], [223]	Assessment of high-level mobility abilities	Traumatic brain injury	13 items Adaptability parameters: ON, TM, TR, PT. Most item's performance time and distance are recorded at the fastest safe speed and then converted for scoring	(0-4) standardised scoring, Total score: sum of each item's score, Maximum score: 54

Sensory-Oriented Mobility Assessment Instrument (SOMAI) [224]	Assessment of how sensory input are used in mobility performance		10 items "maneuvers", each is performed twice (once with normal vision, once with google eliminating peripheral vision) Adaptability parameters: PT, ON, TR	(0-3) score/item, higher score: greater impairment, Max score: 30
Walking InCHIANTI toolkit (WIT) [225]	Assessment of risk factors for mobility disability in the elderly	Older adults	14 walking tests Adaptability parameters: ON, TM, CT, AM, PT, MT, PL	
Standardized Walking Obstacle Course (SWOC) [226]	Assessment of ability to complete real-life functional mobility situations	Community-dwelling older adults	6 tasks Adaptability parameters: ON, TR, PT, MT	
Multiple Task Test (MTT) [227]	Assessment of different components of postural control	Parkinson's disease patients	8 tasks Adaptability parameters: ON, CT, TR, AM, PT, MT, TF	Task scored qualitatively and quantitatively

Table 2.2: Walking ability test and the parameters they assess. MTT: multiple task test, ON: obstacle negotiation, TM: temporal demands, CT: cognitive dual-tasking, TR: terrain demands, AM: ambient demands, PT: postural transitions demands, MT: motor dual-tasking, PL: physical load, TF: manoeuvring in traffic.

The tests presented in Table 2.2 all assess individual components of walking adaptability but do not cover all ten walking ability parameters proposed by Means and colleagues [217]. Ideally, a complete evaluation of walking adaptability ability should assess the ten parameters.
Nonetheless, all these tests present a means to assess the variability of walking and provide a quantification of the capacity to ambulate in the community.

A common method of delivering task-specific training is treadmill walking [9], [44], [228]–[230]. However, Dobkin and Dundan (2012) [230] argued that at home or community training, by involving the surrounding props of the patient may provide better media for task-specific training than treadmill training providing the patient with stepping repetition only.

The use of treadmill training and its legitimacy to support community walking are will be discussed hereafter.

2.2. Treadmill training

Treadmill training is used to rehabilitate walking as a task-oriented activity as it facilitates intensive step repetition at different treadmill speeds [43]. It not only enables the repetition of many gait cycles, but it is also used for its muscle strengthening and cardiovascular fitness improvement properties [9]. Treadmill walking is a means to practice walking in a restricted space while performing an extended number of steps in the same direction. Since it is used in the context of gait rehabilitation, this section will first present its similarity to over ground walking in order to provide support vis a vis its suitability to be used in the context of gait rehabilitation that is aimed at community reintegration. This section will then look at treadmill training for gait rehabilitation after a stroke and present some of the newly developing technologies within the field of treadmill training.

2.2.1. Fixed pace treadmill walking compared to overground walking

In their paper, Lee and Hidler (2008) [111] stressed the importance of comparing treadmill walking and overground (OG) walking, highlighting the importance of the similarity in the strategy of motor control that a patient uses in treadmill walking compared with OG walking. Establishing this similarity in the strategy of motor control is pivotal to justifying treadmill walking as an effective way to improve OG walking capability. In their protocol, Lee and Hidler set the speed of the treadmill was set to the average walking speed measured during OG walking. When treadmill walking was compared to OG walking, no significant statistical differences ($p>0.05$) were found in the temporal gait events except for stance time ($p= 0.021$) and swing time ($p= 0.0017$) that appeared to come sooner in the case of treadmill walking. Significant differences ($p=0.0037$), however, were found in the sagittal plane kinematic data for the knee's range of motion (OG: 67.7 ± 3.2 degrees, treadmill: 65.6 ± 3.3 degrees). Lee and Hidler (2008) [111] also found that, with the exception of peak ankle plantar flexion, lower limb joint moments were significantly different ($p<0.05$) between OG and treadmill walking, with differences ranging from 0.05 to 0.24 Nm/kg. They found larger knee moments (Max Extension early stance=0.63 ± 0.27 Nm/kg treadmill, 0.39 ± 0.25 OG, $p=0.0005$; Max extension late stance=$0.34 \pm$

0.16 Nm/kg treadmill, 0.22 ± 0.18 Nm/kg, OG, p=0.0010), and smaller hip extension during OG walking (Max Extension early stance =0.40 ± 0.15 Nm/kg during treadmill, Max extension late stance =0.57 ± 0.23 Nm/kg OG, p=0.0000; 0.21 ± 0.10 Nm/kg, 0.31 ± 0.11 Nm/kg, p=0.0013). While looking at the EMG, a generally higher level of muscle activity was found during the swing phase of OG walking. Tibialis anterior, adductor longus, vastus medialis and hamstrings all presented lower activity levels during the stance phase of treadmill walking compared to OG ($p<0.05$). While accepting these differences the overall conclusion from the authors of similarity led them to consider treadmill as a valid tool for gait training.

The authors of this paper suggest that the observed differences observed between treadmill walking and OG walking could stem from the lack of optical flow during treadmill walking in comparison with OG [111]. The addition of an immersed virtual reality, with a visual context matching the real walking experience, could help mitigate the effect of the visual flow differences.

The measurement of muscle activity during this study was averaged and then divided into the different stages of the walk cycle, giving a quantification of a muscle's contribution at different stages of the walk. There was no measure of walking variability applied on the kinematics or muscle activity data between treadmill and OG walking in the study, we, therefore, do not get any indication of the effect of treadmill walking on natural gait variability. Furthermore, the study was carried out with able-bodied adults, the results can therefore not be applied to populations with impaired gait.

Riley et al. (2007) [109] found that, while the kinematics showed little absolute difference between the treadmill and OG walking situation (maximum difference of 2.28°), there was still a significant statistical difference ($p<0.05$). Riley et al. (2007) also found the three-dimensional ground reaction force to be significantly greater OG compared to treadmill walking ($p<0.05$), the mean difference ranging from -3 %BW (Anterior Posterior GRF min to 5.53 %BW (Vertical GRF max). The difference between the two conditions were, according to Riley et al. (2007) within a similar range [109]. They, like Lee and Hidler [111], considered treadmill walking to be a good model to study OG walking. In the Riley et al. (2007) study, the treadmill's speed was also set to the average walking speed measured during OG

walking and the participants were all able-bodied adults, which provides reference data to compare people that have an impaired gait but the results are not directly applicable There was no visual display mentioned in the methods that would provide a visual flow, as experienced during OG walking, and no measure of the variability of the GRF data between the two walking environments was completed. We, consequently, do not get to compare the variability of treadmill walking to OG walking.

Wearing et al. (2013) [110] compared the use of instrumented OG walkways to the use of a treadmill for gait analysis. The participants walked at the same speed on each device, taking the instrumented walkway's speed as a reference. They found that treadmill walking was significantly different ($p<0.001$) as the gait cycles lasted for a longer time (walkway: 1.04 ± 0.06 s, treadmill: 1.2 ± 0.05 s) and the cadence was faster (walkway: 115.6 ± 6.4 steps/min, treadmill: 118.2 ± 5.9 steps/min, $p<0.01$). While there was a high correlation (from $r=0.79$ to $r=0.95$) between the two types of walking, the limit of agreement for the spatial data agreed to ±5 cm, and the temporal data to ±2% gait cycle. They concluded that the literature presenting temporospatial gait parameters data from OG walking is not comparable to the temporospatial data from treadmill walking [110].

In this paper there was no mention of visual environment display matching the OG walking experience in the description of the treadmill walking-related methods and no measure of the variability of the parameters observed was quantified.

Regarding energy consumption, it has been observed that treadmill walking requires more energy than OG walking. Martin and Li (2017) [113] measured the metabolic cost between the two walking scenarios and measured 2.56 ± 0.33 J/kgm for the OG walk and 3.39 ± 0.31 J/kgm for the treadmill walk. Lower-limb muscles also presented greater values of peak activity as well as Root-Mean-Square (RMS) activity in the treadmill. The medial gastrocnemius presented a significant increase in RMS ($p=0.005$) and peak activity ($p=0.048$). While semitendinosus presented an increase in RMS ($p = 0.042$) [113] only. These observations are consistent with the hypothesis that the muscle activity will change to adapt to a given kinematic pattern [111]. In this case the changes in muscle activity can be associated with the need to adapt to the more restrictive walking situation that treadmill walking represents. The

increased metabolic cost is attributed to the adaptation done by the muscle to maintain the kinetic pattern specific to treadmill walk at a fixed speed [113]. The participants were 15 young adult able-bodied males. The young men self-reported healthy lifestyles, which might not reflect the reality of people with impaired walking abilities, such as stroke survivors.

Kuys et al (2008) [231], Nagano et al (2011) [232], Riley et al (2007) [109] observed that on both young adults and older adults, self-selected gait speed diminishes while walking on a treadmill compared to when walking OG. According to the observations of Nagano et al., (2011) [232], the foot clearance is significantly smaller (around 0.2 to 0.6 cm minimum foot clearance difference; $p= 0.006$) for older individuals during treadmill walking Nagano et al., (2011) [232]. Nagano et al., (2011) focused on foot clearance because insufficient foot clearance has been identified as a reason for trip falls in older adults [114], [231]. In their paper Nagano et al., (2011) [232] found that walking on a treadmill significantly increases minimum foot clearance in older and younger adults ($p\leq0.026$) but this tendency was not present on the non-dominant side of the older participants. Therefore, it is suggested that young adults and older adults don't have the same response to treadmill walking; older adults potentially make an intentional effort to secure their non-dominant side by use of a high minimum foot clearance in the case of a challenging walking situations [232]. It is possible that a similar foot clearance technique will be observed in people with gait restrictions caused by stroke. The study relied on a small participant sample (n=22 with 11 young adults), it is therefore possible that the results are subject to statistical error.

2.2.2. Fixed pace compared to Self-paced treadmill walking

As presented before, there are differences between fixed-pace treadmill walking and overground walking. One main drawback of fixed-pace treadmills is that they impose a given speed to the user who is constrained to keep up with it. The development of self-paced (SP) treadmills allows users to overcome this constraining situation by controlling the belt's speed so that they match the user's actions and therefore lead to a gait pattern that is arguably closer to natural overground walking [233].

The principle of self-paced treadmill

During self-paced treadmill walking the belt speed is controlled using the user's position (and walking speed) on the treadmill belt as a feedback information to the control unit [233], [234]. One treadmill control strategy relies on measuring the user's position (for example using motion capture technology) on the belt and aims to keep them at the central area of the treadmill (area in green in Figure 2.2). If the patient remains within a specified central zone on the treadmill, the control system considers that the user is at a desirable position. In case of changes of position, the treadmill speed is adapted in order to keep the user within the designated central area of the treadmill [234], [235].

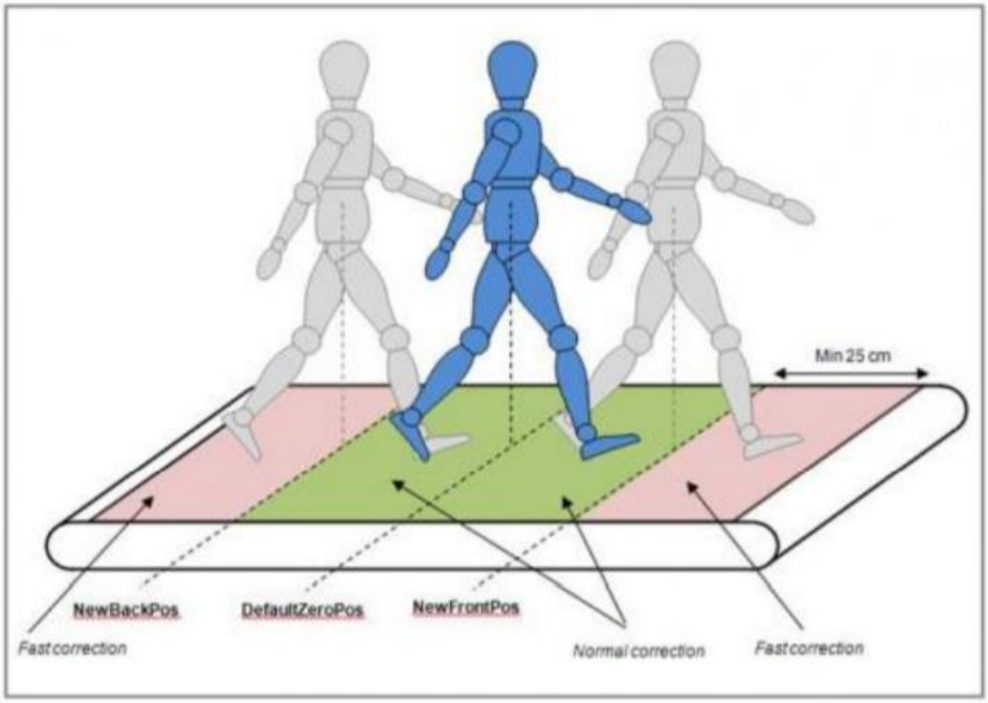


Figure 2.2: The self-pacing control of the algorithm act to keep the user in the central are of the treadmill (in green) by varying the treadmill's belt speed according to the user's position on the belt. Extracted from Motek Medical BV (2014) [236]

The self-pacing regulation algorithm

Several SP treadmill modes are designed using PID-controllers [233], [237], [238]. PID stands for Proportional Integral Derivative. It acts between the instruction applied to the system and its output response, the command (see Figure 2.3).

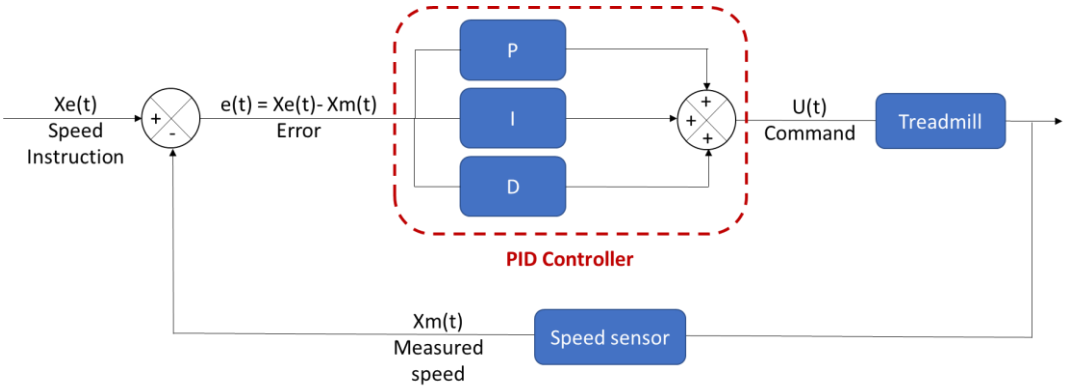


Figure 2.3: The PID controller acts on the system when it is placed between the instruction of the system to affect the command response value

The general PID equation is expressed as follow in equation (2.1):

$$u(t) = P\Delta x(t) + I\int_0^t \Delta x(t)dt + D\frac{d\Delta x(t)}{dt}$$

(2.1)

with u(t): the command, which is the controller output, e(t): the error, which is the difference between the instruction (value to reach) and the measure (the output value that is effectively reached).

The proportional (P) gain is used to adjust the error coming from the difference between the command value and the output response [239]. Its role is to improve the system's response time, that is to reach the target response with minimal delay, by correcting the error e(t), using a multiplication factor. The integral (I) component's role is to cancel the error by summation of the difference between the command and the results over a period of time dt. The aim is to have zero difference between the command and the output value. The derivative (D) response depends on the rate of change of the error. It is used to reduce the oscillations of the system [239].

Sloot et al. (2014) [233], compared three different self-pacing algorithms based on the a PD controller (PID without integral component) with FP treadmill walking. The speed of the treadmill was regulated by using the acceleration ($\ddot{x}$ in equation (2.2)) of the treadmill according to the difference in position between the treadmill user and the middle of the belt and the speed of the user. The first algorithm is expressed in equation (2.2) as follows:

$$\ddot{x} = P\Delta x - \Delta x D\dot{x}$$

(2.2)

$\ddot{x}$ is the acceleration, P the proportional gain is dependent of the difference of position Δx and serves to reach the command value (the biggest the distance, the greater the acceleration). The oscillations of the system are regulated by the derivate response D which is dependent of the speed $\dot{x}$ and the difference of position Δx of the user. It is subtracted to the proportional gain parameter as too much acceleration will destabilise the user.

The second algorithm was a variation of the previous one. It only differs by a multiplication factor of two (see equation (2.3)).

$$\ddot{x} = 2(P\Delta x - \Delta x D\dot{x})$$

(2.3)

The third algorithm is similar to (2.2). It adds a speed-related multiplication factor (see equation (2.4)).

$$\ddot{x} = \dot{x}(P\Delta x - \Delta x D\dot{x})$$

(2.4)

The acceleration $\ddot{x}$ is dependent on the speed $\dot{x}$ and the difference of position of the user Δx that are multiplied to the proportional gain P. The oscillation of the system is regulated by the derivate response that is dependent of the difference of position Δx and the squared speed $\dot{x}^2$ (energy). Because of inertia, each body tends to conserve its speed and, consequently, its energy. Therefore, a sudden break will lead the body to keep moving forward at the same speed while the entire system has stopped.

Souman et al. (2011) [240] added a feedforward term to their algorithm. The feedforward term used was the estimation of the user's speed on the SP treadmill [241]. When the user is in the central area of the treadmill, it is possible to differentiate between a slow-down to bring the walk to a stop or a continuation of the walk [241], therefore allowing a more smooth adjustment of the treadmill's speed.

The outcome of the kinematic, spatiotemporal and kinetic gait analysis by Sloot et al. (2014a) [233] was that although significant ($p<0.05$), there were only small differences found between the gait patterns found during Fixed-pace and Self-paced treadmill walking. In terms of kinematics, the range of motion was lesser during self-paced walking (difference of hip abduction RMS: 0.13°, $p<0.05$; hip flexion: 0.7°, $p<0.01$; knee flexion: 1°, $p<0.01$). The spatiotemporal analysis' outcome was that the step width increased (difference: 0.01 m, $p<0.05$) and stance length decreased (difference: 0.36 % of gait cycle, $p<0.01$) were diminished during self-paced. Regarding kinetics, self-paced treadmill walking displayed less power, with reduced hip power (-4.2% gain, $p = 0.02$) and ankle flexion power (root-mean-square (RMS) value= -6.6%, $p = 0.03$; gain = -4.7%, $p = 0.04$) across the lower limb joints. The participants walked within a 180° virtual environment display working in synchronisation with the treadmill (speed and inclination). The participants were all young (29.2 ± 5.0 years old) and healthy adults free of any mobility impairment.

Kim et al. (2017) [242] investigated dynamic stability when comparing fixed-pace to self-pace treadmill walking. Their aim was to study changes of balance during gait leading to falls and thus, prevent the occurrence of falls during treadmill walking. The dynamic stability was measured using the margin of stability as presented by Hof et al. (2005) [243]. The margin of stability is the difference between the centre of mass (its position along the x axis, X_{COM} in Figure 2.4) and the base of support (i.e. the position of the foot contact along the x axis, Base of support (BOS) in Figure 2.4) [242]. When the walk was slow, the margin of stability was significantly greater during self-paced walking than during fixed-pace walking (self-pace: $F = 276.22$, $p < 0.001$; fixed pace: $F = 262.06$, $p < 0.001$). The opposite happened when the walking speed was faster, the margin of stability was then significantly smaller ($p < 0.05$) for self-paced walking [242].

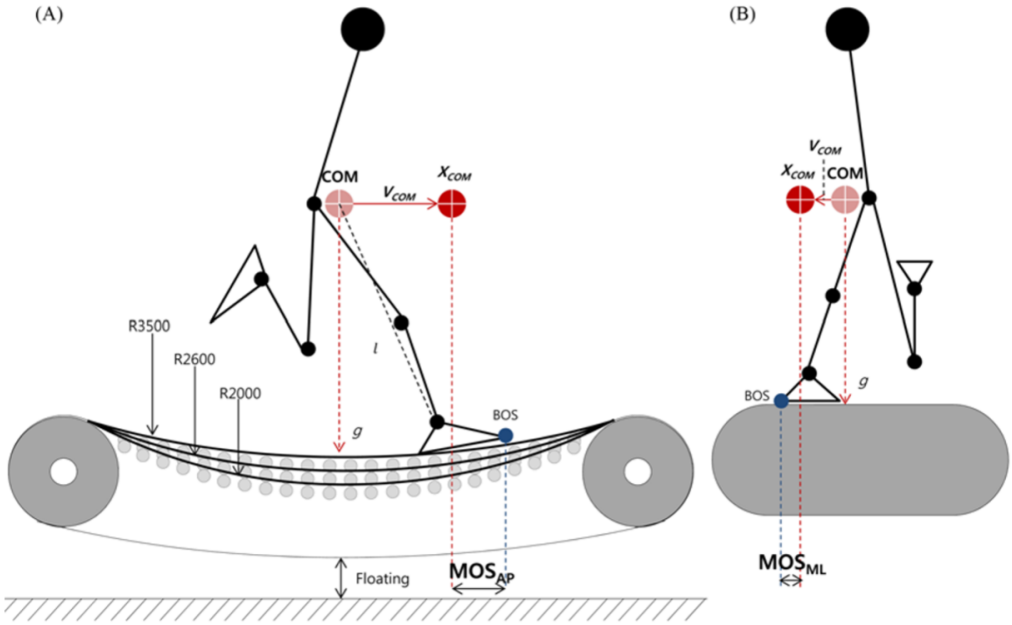


Figure 2.4: Measure of the margin of stability (MOS), (A) MOS on the sagittal plane, (B) MOS on the frontal plane, extracted from Kim et al. (2017) [242]

Kim et al. (2017) [242] used a non-motorised, curved, treadmill (see Figure 2.4) to collect these data. Compared to motorised treadmills, non-motorised curved treadmills have been demonstrated to be a better likeness to OG running because the runner can accelerate and decelerate freely, using techniques similar to OG running, as reported by Edwards et al. (2017) [244], the curve of the treadmill intrinsically provides some degree of SP. The use of non-motorised curved TDs does leads to higher cardiac efforts than OG and motorised treadmill walking [244]. Moreover, in their study Kim et al. [244] found that lightweight runners had to exert more effort

than the heavier runners in curved treadmill usage. While monitoring the effect on the quadriceps and hamstring muscles in comparison between the motorised and non-motorised treadmill, it was found that non-motorised treadmill training generates more involvement of the quadriceps than the motorised treadmill, explaining the higher effort. These results should be regarded tentatively compared with flat motorised treadmill experiment results, as the participant's BMI has an influence on the outcome of the walk. This study was conducted on young healthy male only with a normal average BMI (24 kg/m²). The influence of BMI could be re-tested by including participants with varying BMI scores in the study.

2.2.3. The effects of fixed pace treadmill training on post-stroke recovery

Treadmill training can be initiated within the first three months (acute and sub-acute phase) following a stroke [229] and may be implemented at a later time during the chronic phase [106], [245]. In a review paper, Dickstein (2008) [9] noted that patients who underwent treadmill training with or without body-weight support were able to achieve a speed gain of 0.12 to 0.3 m/s in OG walking speed when they started at low speeds (ranging between 0.2 and 0.4 m/s). These increased speeds were statistically significant (p value was not reported) but the functional walking level of the patients did not improve [9]. The functional walking levels were measured using the Functional Ambulation Categories [9], [246]. The Functional Ambulation Categories is an assessment tool with six categories of walking ability from 0: non-functional ambulation, where the subject cannot walk independently and require assistance, to 5: Independent ambulator, where the subject can walk up and down slopes and stairs as well as on levelled floor independently. The tool is administered by the observation of a subject's performance. The Functional Ambulation Categories has been reported as a reliable tool with good responsiveness with people that have post-stroke hemiparesis [247].

Treadmill training is task-oriented: it aims to recover walking capacity through repetitive practice [9], [104], [191]. Treadmill training is a form of exercise therapy [9], as it is a form of physical exercise that provides improved fitness and endurance to the user as well as improved walking skill [248]. In body-weight-supported treadmill training (BWSTT), therapists can gradually adjust the weight support to adjust the load on the legs and use different treadmill speeds to practice stepping. The therapist will verbally

feedback to the patient about their step pattern performance and use physical cues in order to optimise the patient's walk cycle in terms of kinematic, temporal and kinetic parameters [43]. Unloading the body helps the individual's focus on the gait pattern without being challenged by postural control [45]. Gait practice normally has time constraints because of the need for assistance and support during the exercise. A treadmill that is further equipped with a safety harness and/or body weight (BW) support can help overcome these constraints enabling higher intensities of stepping practice [247]. Duncan et al. (2011) [179] compared BWSTT to a home-exercise program focusing on balance and strengthening. They found no significant difference ($p=0.07$) of outcome in the walking ability of the participants when comparing the two programs [179]. In another paper, Dobkin and Duncan (2012) [230] argue that BWSTT failed to provide clinically significant improvements in walking capacity, in terms of walking speed, walking distance, strength, physical functioning–related quality of life, and dependence on assistive aids [230]. They study concluded that BWSTT should only be used as a research tool and instead, patients should be encouraged to do community walking and home-based physical therapy programs [230]. Many studies using BWSTT don't report information on sensory feedback or feedback on performance [230]. In the context of OG gait training the therapist can apply a certain amount of force on the patient's lower limb to guide movement e.g. assist knee extension. This is not necessarily replicated during treadmill training [230]. The level of a patient's mental engagement during movement learning is not assessed when performing BWSTT. It is possible that the ongoing movement of the treadmill leads the patient to disengage in the learning process and that OG training might be a better setting to study patient focus [230].

Dobkin and Duncan (2012) [230] argue that studies presenting the positive and statistically significant improvement in functional ambulation observed following BWSTT did not provide information about the improvement of walking distance in everyday activities. They point at a common tendency to mostly report data that portrays statistical significance, which could be interpreted as a source of bias [230]. Dobkin and Duncan (2012) [230] also stress that training from home and in the patient's neighbourhood provides more task-specificity, as the therapist can use what is available in the patient's home environment, such as chairs and home stairs. The lack of life-like task-specificity is an issue that treadmill training has in common with BWSTT. It is

possible that the inclusion of immersed virtual environment can provide this task specific context.

In their systematic review, Mehrholz et al. (2017) [229] observed that with or without the use of body-weigh-support (BWS) treadmill training did not make a difference to the long-term improvements of walking abilities for participants with stroke impairments in comparison with traditional physical therapies, that focusses on endurance and strength. Treadmill training for rehabilitation led to significant increases in walking endurance ($p=0.01$) and speed ($p<0.0001$), however, Mehrholz et al. (2017) [229] reported a lack of data showing how the daily living activities and the quality of life of the participants was affected. These findings of Mehrholz et al. (2017) [229] reinforces the conclusion of Dobkin and Duncan (2012) [230]. Mehrholz et al. (2017) [229] also observed that people able to walk independently after their stroke (i.e. mild to moderate strokes) are more likely to benefit from treadmill training rather than people more severely affected .
In their review paper, Abbasian and Rastegar (2018) [44] considered whether either intensity or duration of treadmill training delivered the best gait training outcome. They divided the types of training protocols into four categories.

- Category (1) protocols delivering low intensity (≤0.6m/s) and low volume (duration ≤500 minutes) training.
- Category (2) protocols delivering low intensity (≤0.6 m/s) and high volume (duration >500 minutes) training.
- Category (3) protocols delivering high intensity (>0.6 m/s) and low volume (duration ≤500 minutes) training.
- Category (4) protocols delivering high intensity (>0.6 m/s) and high volume (duration >500 minutes) training.

To compare these strategies, Abbasian and Rastegar (2018) [44] assessed the standard mean difference of the results from studies using a 95% confidence interval. The heterogeneity between multiple studies was measures using I-squared (I^2) statistic. Low heterogeneity ranged between 25% and 50%, moderate heterogeneity with I^2 ranged between 50% and 75%, and high heterogeneity ≥ 75%. While a moderate inter-study heterogeneity was evident within the groups (around 74%), the protocols presenting the best motor function recovery results were in category (2): Low-intensity (≤0.6 m/s) and high-duration (volume >500 minutes) training, this produced the highest standard mean difference, 0.75 m/s with a 95% confidence interval (CI): 0.64-0.85, this improvement was significantly different from the other three categories ($p=0.0001$) [44].

2.2.4. Virtual Reality treadmill training

In their review paper, Takeuchi and Izumi (2013) [45] pointed at the use of multi-sensory feedback to help the motor learning process. It appears that positive feedback can influence a patient's performance during stroke rehabilitation training. In their paper Dobkin et al. (2010) [249] found that informing the patients about how fast their 10 m walk was completed daily resulted in a walking speed increase of 36% at the point of hospital discharge (from 0.45 to 0.91 m/s). Their study design was a single-blinded, multicentre trial where the participants (n=179) were randomized in either a training involving feedback about their self-selected walking speed (number of participants: 88, age 62.9 ± 12.6 years old, 27.3 ± 78 days post-stroke) or without any reinforcement (number of participants: 91, age 65.1 ± 11.9 years old, 30.2 ± 53.5 days post-stroke) after the daily training [249].

Amongst the methods presented, the use of Virtual Reality or Virtual Environment (VE) has potential to enhance treadmill training [250] through visual (inclusion of an optical flow), auditory and tactile feedback [122]. There is evidence that the use of VE contributes to the cortical reorganisation in patients with chronic stroke [123], [124]. Immersive VE can either involve the use of VE goggles or headsets that allow the user to experience an entire environment, in isolation from their real-life surroundings or a large screen display allowing a large scale visual of a virtual scenery. The use of VE headsets can be a source of eye fatigue and visually induced motion sickness [251]–[254]. Sharples et al. (2008) [255] reported significant ($p< 0.01$) increase of nausea (mean difference=19.58), disorientation (mean difference=29.31) and locomotor (mean difference=15.16) scores using the Simulator Sickness Questionnaire (SSQ), following the exposure to a head-mounted VE display experience. Post-exposure to a concave screen display, only the disorientation score increased significantly ($p<0.05$, mean difference=9.65). The pre vs post exposure between the head mounted set and the concave screen display presented significant difference ($t = 3.166$; $df = 30.304$; $p < 0.005$), as well as the disorientation score difference pre vs post exposure ($t = 2.098$; $df = 34$; $p = 0.043$). Non-immersive VE relies on the use of a screens or display mounted on top of a surface and may include other devices such as joysticks or other interface devices [45]. The use of VE can be part of a task-specific, intense, and repetitive type of training, which makes it relevant to healthcare applications such as stroke rehabilitation

training. VE makes training through gaming possible [256], [257]. VE is also a training media that gives training support, delivers feedback on achievements and can be set at different difficulty levels [45], [258], [259]. It is also possible to deliver VE technology as a home-based form of training. In their review, Laver et al. (2017) [125] reported that the use of VE did not lead to significant improvement in balance and gait speed. Parameters such as quality of life, cognitive function and participation restriction are seldom reported, however, a significant improvement (standardised mean difference (SMD) 0.25, 95% CI 0.06 to 0.43, 10 studies, 466 participants) of the quality of daily living was observed in participants. The authors concluded that VE used in the context of stroke rehabilitation may be beneficial if combined with conventional therapies [125]. Ooijen et al. (2016) [188] designed a parallel-group randomised controlled trial that compared the effects of usual therapy, conventional treadmill and adaptable treadmill training in reducing fear of falling and improving the walking abilities of older adults. Both programs relied on FP treadmill walking at a comfortable pace. The primary outcome measures were walking ability and walking adaptability. Walking ability was assessed using several tests: Performance Oriented Mobility Assessment, Elderly Mobility Scale, Timed Up-and-Go test, Functional Ambulation Category, 10 m Walking Test and Nottingham Extended Activities of Daily Living. Walking adaptability was assessed using two 10-meter walking tests (one with obstacles and one with cognitive task). The secondary outcomes were the fear of falling, fall occurrence and general health [188]. Adaptability treadmill training consisted of walking on a treadmill while performing exercises aimed at guiding the user's steps on stepping targets spaced irregularly and regularly [188]. The group of older adults (n=70) were 83.3±6.7 years old and recovering from a fall injury that had led to a hip fracture. All participants were at a chronic recovery stage where they could bear weight on the affected leg, it is noted that at least six weeks passed since their hospital admission for their fall. The characteristic and baseline values between the three group of participants (usual therapy, conventional treadmill, adaptability treadmill) were analysed using a one-way analysis of variance (ANOVA). The effect of the intervention in the group were analysed using an analysis of covariance (ANCOVA). The study results presented significant improvements ($p<0.032$) in walking abilities (speed, independence, and variability) and reduced fear of falling, measured by the Falls Efficacy Scale International (FES-I) over time for the three types of interventions: usual therapy, conventional treadmill and adaptative treadmill training). The measures of walking ability measured general walking ability (Functional Ambulation Category, 10 m Walk Test) and walking adaptability (Timed Up and-Go

test, Elderly Mobility Scale, performance-oriented mobility scale, 10 m Walk Test with cognitive task, 10 m Walk Test with obstacles). Adaptive treadmill training displayed significant improvement ($p=0.046$), on the dual-task effect of walking speed in comparison to the two other interventions, usual therapy, and conventional treadmill training. The paper did not present a population recovering from a stroke, but the age of the participants and their fear of falling are characteristics that apply to a stroke population. Gait impairment following a hip fracture, however, is not comparable to that found with post-stroke gait impairment.

The adaptable treadmill training provides a means for the participant's ability to vary stepping during a walk. Such a protocol has potential for use by stroke patients with impaired gait aiming to recover the more complex task of independent walking in the community. This study did not include an immersive VE but did use a visual display showing stepping targets on the treadmill belt. This component might lead the user to look down most of the time while walking, which might not be a good representation of everyday life walking. This protocol adds to the treadmill properties of fitness and stepping repetition as well as training the patient's walk variability, leading to reduced fear of falling and helping everyday life walking feel safer for the patient. Conventional treadmill training displayed significant improvement of functional ambulation category (the minimum category score recruited was level 2: ambulator is dependent on physical assistance, see more about functional ambulation categories in section 2.2.3 and Annex B) during the training time ($p=0.003$ at first assessment, $p=0.039$ at the second assessment), in comparison to the two other interventions (usual therapy and adaptative treadmill training). It is important to note that the authors mentioned that the number of participants they had for this experiment was not enough to provide statistical power of the effect that the intervention has. Nonetheless, treadmill training is regarded as a suitable medium to training gait adaptability as it is safe, feasible and shows some evidence of efficacy rehabilitation among stroke-impaired survivors [188], [191], [197].

So far, treadmill walking within a VE has presented little significant improvement in gait abilities post-stroke [125]. It has, nonetheless, presented a means to facilitate cortical reorganisation post-stroke [123], [124], improve quality of daily living and has potential for integration to out hospital, at home gait training [125].

Investigating the impact of treadmill training associated with VE post-stroke may need to rely on other parameters than the previously reported balance and gait speed [125].

2.2.5. Training gait variability with treadmills

In addition to being a task-specific type of training, treadmill training can also be used as a context-specific training medium which could support individuals in achieving their goals of recover the more complex walking skills required during community ambulation [191].

In their paper, Timmermans et al. (2016) [191] proposed an experimental protocol to compare the outcome of an OG training program (FALLS program [260]) with a FP treadmill training program. Both type of exercise contexts, OG and treadmill exercises, can provide a variety of practice, tasks, and movements scenarios, that could contribute to the effectiveness of the training [22], [177], [191], [261], [262]. The OG training introduced several challenges of community walking including obstacle avoidance tasks. The treadmill program involved the use of a C-Mill (Motek, Amsterdam/Culemborg, the Netherlands) treadmill. The C-Mill uses an instrumented treadmill that displaying visual cues on the treadmill's belt [191]. It is used as a form of task-specific practice for walking adaptability [191]. The images displayed on the treadmill are used to represent obstacles to be avoided or provide stepping targets. Upon completion the primary outcome measure of this experiment will be the participant's walking speed [191]. A proof-of-concept was published by Timmermans et al. (2019) [263] in order to assess the C-Mill training program. The study was conducted with 64 participants: 24 healthy adults (age: 29.14 ±11.69, height: 1.76 ±0.08, weight: 71.55 ±9.24), 12 able-bodied older adults (age: 70.25 ±5.23, height: 1.76 ±0.08, weight: 84.83 ±14.26), 28 adults with gait and/or balance impairments (age: 69.96 ±11.40, height: 1.71 ±0.08, weight: 76.83 ±11.48). The objective was to assess the feasibility, the acceptability, and the clinical potential of C-Mill treadmill training. The data were evaluated over 10 sessions of training sessions (over 5 weeks) and analysed using ANOVAs (repeated-measure ANOVAs for the intra-subject analysis, or nonparametric Friedman ANOVAs followed by paired-samples T-tests or using Wilcoxon signed rank tests). The feasibility was evaluated by looking at the progress of participants. The difficulty of the exercises was automatically increased every odd or even session, according to the precedent performance of the patient. A significant increase of the belt speed over the sessions was observed ($F= 21.35$; $P < 0.01$; $\eta^2 = 0.50$) with significant differences between all odd training sessions and the successive even sessions ($t_{21} > 2.08$; $P < 0.05$; $r > 0.41$). The level of difficulty increased significantly over the sessions ($\chi^2_{22} = 36.51$; $P < 0.01$). The

acceptability of the study was evaluated using the participant's feedback. The participants reported mild discomfort due to muscle soreness, shortness of breath or fatigue during (once: n = 2; frequently: n = 5) and after (once: n = 2; frequently: n = 6) the training sessions. They also reported improvement of walking speed (n = 14), fitness (n = 19), walking safety (n = 17), confidence during indoor walking, outdoor on smooth surface, on irregular surface and/or in crowded environments (n = 20). The participants also reported the intervention as being user-friendly, motivating, fun, challenging and recommendable for their peers. The clinical potential of this intervention was determined using the data the treadmill belt speed, the 10-meter walk test, the Timed Up & Go test and Short Physical Performance Battery (SPPB) score which all improved over time (all $F_{1.53,33.75} > 5.22$; $P < .01$; $\eta^2 > 0.19$). Significant post-training improvement was observed (all T2 vs T1 $t_{22} > 2.26$; $P < 0.05$; $r > 0.43$; and all T3 vs T1 $t_{22} > 2.22$; $P < 0.05$; $r > 0.43$) as was retention of these improvements after 6 weeks (all T3 vs T2 $t_{22} < 1.40$; $P > 0.18$; $r < 0.29$). To our knowledge there is no published data on a larger scale study of gait impaired patients within a clinical environment that relies on C-Mill treadmill training. C-Mill treadmill training nonetheless presents promising results for future research and application for gait adaptability and variability training post-stroke.

2.3. Motor control

Motor control is fundamental to the organisation and control of the muscles responsible for movement and posture [264]. After a stroke, motor control can be impaired and needs to recover through restitution of the original networks or development of new networks through neuroplastic changes in order to recover function [183], [265]. A better understanding of the underlying mechanism of motor control is important to comprehend how the central nervous system can relearn specific movements such as walking [116], [266].

2.3.1. Motor control theory: Bernstein's first experiments and legacy

Studying the motor system can help develop an understanding of how movement is organised and how the process of rehabilitation works in case of neuromuscular impairment as resented in conditions like stroke [264]. Importantly, by improving this understanding, the effectiveness of physical rehabilitation can be improved.

Motor control was defined by Latash (2012) [267] as the scientific field devoted to the exploration of the laws defining how the nervous system interacts with its environment and various body parts, in order to produce purposeful, coordinated movements [267]. The motor cortex and associated areas in the brain, control the activation of skeletal

muscles. The motor system, which includes the motor cortex, the brain's supplementary control areas, neural pathways (central and peripheral), muscles, afferent sensors, afferent pathways, the cerebellum, ascending sensory pathways, and sensory cortex, controls postural changes, and thus, the musculoskeletal aspects of expression and behaviour [264]. One of the "fathers" of the study of movement and motor control was the Russian scientist Nikolai Bernstein. His work paved the way for the exploration of human biomechanics and the neural control of movement. His research motivated interest from specialists looking at different problems related to movement such as neurologists, physiologists prosthetists and even music pedagogues [268].

2.3.1.1. Bernstein's early experiments

In this section, Nikolai Bernstein's early works and how they led to a better understanding of the neuromotor control, as it is known today will be presented.

Bernstein's early work (circa 1922) was the study of manual labour tasks. During this work, Bernstein posited that the movements reflected processes happening inside the brain [269]. Bernstein analysed these processes from studying electroencephalographic (EEG) data, where the electrical activity of the brain represents the output from the motor cortex. In particular, Bernstein observed the EEG amplitude and how movements related to a state of rest or activity of the brain [270]. He deduced that there must be an underlying mechanism designed to prepare and adjust movement control of intense cyclical activities such as walking and running [270]. In 1926, Bernstein began focusing on studying human locomotion. While human gait seemed to be at first sight a highly automated and stable movement, after his preliminary studies, Bernstein concluded that the locomotor process was instead "*a living morphological object of inexhaustible complexity*". Another important take on his studies on locomotion was that movement should be described as a group of structures that are then differentiated into details rather than as a chain of simple mechanisms [268]. Bernstein's model of human movement is fashioned around the idea of a complex neural network as opposed to a chain of cells, which was the accepted understanding of human movement at the time [269]. Bernstein investigated the movements of athletes and labour workers in order to understand which underlying methods were necessary to perform efficient movements and reduce redundancy [271].

2.3.1.2. Motor redundancy

In the context of motor control, Bernstein's principle of motor redundancy refers to the fact that one given task can be achieved successfully using many different solutions, for example in the case of an arm movement in which a finger extends through space to reach a specific point. Though this seems a simple movement, the mechanical system is composed of the shoulder joint which possesses three rotations, the elbow joint has one rotation, the wrist two rotations and there is a shared rotation between the elbow and the wrist, in addition there are rotations from the finger joints. If you ignore the finger joints as well as the scapula, you have in total a system of seven degrees of freedom. A given point in space only requires three coordinates to be located, however, the joint configuration leading the finger to a specific point in space is equivalent to solving a system of three equations with seven unknowns, therefore leading to an infinite number of solutions [272].

To reduce the motor redundancy equates to reducing the number of solutions capable of achieving the movement target. In the case of the movement completion, reduction in the number of strategies used to achieve the movement [272]. It might be expected that repetitive human movement becomes more consistent (less variable) over time, as the individual becomes more skilled. What Bernstein observed, however, was that during the acquisition of motor skills, the variability of the displacements during the movement did not diminish. Which means that, even in the case of a known movement that one is accustomed to perform, the variability across repetitions of the given movement performances does not alter. Counter intuitively, it appears that a high level of reproducibility in a movement does not equate to a low level of variability in an action. To achieve a high level of repeatability on a highly skilled automated movement it is important to retain high variability in this movement to cope with unexpected external forces interfering with the intended action [268]. Bernstein proposed that the presence of high variability in automated movements reflected the search for and selection of the optimal motor control strategy, resulting in the execution of a stable movement even within a changeable environment. He theorised that, even when a very small event alters the environment, the execution of a specific movement generates a lot of reorganisation in the entire movement control.

2.3.1.3. Phases of motor learning

The learning of movement is divided into three stages, the first stage is the novice stage, during which the degrees of freedom are reduced, and the person appears stiff executing the movement. The second stage, the advanced stage, is when the degrees of freedom are increased, the person's movements are more fluid, and the execution is more efficient. The third stage is the expert stage, this is when the person uses every degrees of freedom in order to automatically perform a task with fluidity [273]. Bernstein also suggested that some repetitive skills such as swimming or bicycle riding, are acquired by a sudden jump in competence and then remain for life. Even after a long time without using the skills, a person's automation of the task can be quickly restored [274].

A repetitive movement is automated when it does not require attention during its execution. A repetitive automated movement is associated with a higher level of control in the brain which is stored in the long term memory [271]. A repetitive movement that is not automated requires attention, it is thought through and is associated with a low level of brain control. The automation of movement is, therefore, the reorganisation of central motor control in order to eliminate the redundancy in the neural processes contributing to the creation of the motion [268].

In 1962 Bernstein stated that the possibility to "*program an action with respect to a certain goal only based on an image or a model of a situation to which this action must lead and with respect to which the action is undertaken*" [275]. Recent research relying on the use of imagination to generate or retrain movement confirmed this statement [276]. A number of studies have investigated the activity of the primary motor cortex (M1) and imagining an action, brain imaging Munzert et al. (2009) [277] reported studies published between 1995 and 2008.

This vision was innovative since movement, until this point, was explained as the theory of reflexes (e.g. Sherrington) [278]. According to Sherrington's theory, smooth transitions between coordinated movement sequences are the result of a combination of reflexes keeping the body stable in the presence of external disturbances resulting in smooth movement execution [278], [279].

2.3.1.4. Motor equivalence

The analysis of natural phenomenon often requires the design of a simplified model. To study the patterns of motor behaviour, the motor-equivalence problem was raised by Bernstein in 1967 [268]. The motor-equivalence problem points at the fact that different muscle activation strategies can lead to the same movement. Limbs have several joints which result in multiple degrees of freedom that far exceed the minimum required of six, facilitating movement capable of reaching any point in space. The motor-equivalence problem is complicated by the number of potential muscle activations that cause these joint rotations. In fact, the number of muscles acting on a joint goes beyond the number of muscles necessary to perform the joint rotation. Consequently, there are many different muscle activation strategies that can produce the same joint torque. Exploring the motor-equivalence problem further, the redundant number of degrees of freedom that are found in each muscle [280] is a challenge as it is equivalent to solving a problem with more unknowns (sum of the number of degrees of freedom) than the number of equations to be solved (three sets of equations in a three dimensional context). The muscles are composed of a group of motor units with different sizes and properties. The firing of each motor unit is unique and specific to action required, but comes from a consistent input [280].

The model of muscle synergy is based on the principle that, to execute a movement, the nervous system will recruit neural modules (blocks of motor units) which co-ordinate the synchronised activity of a group of muscles so that they act as a single functional unit [281]. The muscle synergies can be considered as elementary building blocks of movement generation. When these building blocks are combined in activation, they produce various movements [282], [283]. The activation of the muscle synergies is predetermined by the neurones [284].

2.3.1.5. Abnormal muscle synergies in hemiplegic stroke

As mentioned in section 2.3.1.1, muscle synergies are groups of muscles coactivating together, as a unit when performing a movement. This model simplifies the study of motor control. When the control system is damaged, like it is after a stroke, abnormal synergies can emerge.

Three hypotheses have been presented regarding the cause of abnormal muscle synergies in people with a stroke [268], [281], [283], [285].

Hypothesis 1: *abnormal flexor synergies in hemiplegic stroke are mediated via the primitive flexion-withdrawal of reflex response*.

This hypothesis has so far not been supported by experimental research. Rymer et al. (1998) [286] observed the spatial patterns of muscle co-activation and timing relations on the unimpaired side of the elbow of the hemiplegic participants and the nondisabled control participants. They compared the EMG pattern of the response to generated flexion-withdrawal and the voluntary flexion-withdrawal movement. To generate the flexion-withdrawal responses a stimulus was administered using ring electrodes on the palmar surface of the fingers [286]. The response to the stimuli was displayed by the occurrence of a flexion torque with an actuation of the flexor muscles of the elbow and shoulder. The outcome of this experiment showed that the patterns were substantially different between the induced movement and the voluntary movement. This means that they were not controlled by the same motoneuronal routes. It was deduced from these experiments that it was not possible to mimic the abnormal synergy observed in hemiplegic stroke by generating flexion-withdrawal responses [268].

Hypothesis 2: *abnormal synergies arise because of anatomical constraints inherent in descending brain stem pathways*.

This hypothesis is based on the idea that, following a brain injury such as a stroke, the abnormal movements and/or postures are a result of an enforced use of a simpler spinal pathway [268]. To assess this hypothesis, studies have

observed the muscle activation pattern while a startling noise is generated. The idea was that the startle reflex would reflect the distribution pattern from the spine to the brain and beyond [287]. Studies on patients with Parkinson's disease and stroke showed that there were no significant differences in the reaction time caused by the startling sound, therefore rendering this hypothesis incorrect. [288], [289] Moreover, despite the involuntary nature of the movement it can still be as fast as that of a physically unimpaired person [289].

Hypothesis 3: *Abnormal synergies develop from cortical reorganisation*.

To test this hypothesis it was necessary to use functional magnetic resonance imaging to observe where the brain activation occurs during the execution of a movement [268]. The use of functional magnetic resonance imaging revealed the process of cerebral reorganisation. The reorganisation of the brain post-stroke was observed [265], [290]. The observations showed that after stroke, the neural activity increases and these changes, occurring during the first weeks following the stroke, have significant correlation with greater recovery of movement during this time period. The reorganisation of the brain is a phenomenon that is dependent on the length of time taken to learn a movement [265].

Abnormal synergies are manifested by abnormal postures during voluntary movements [268]. Over the last decades, more research on the muscle synergy pattern post-stroke has been conducted, such as Clark et al. (2010) [285], Neckel et al (2006) [291], and reviewed by Casadio et al. (2013) [281]. These studies presented cases of synergies merging and/or reduction of muscle synergies in comparison to able-bodied individual's synergies, which can explain the resulting abnormal postures.

2.3.1.6. Movement control and anatomical properties

The muscles are, from an engineering standpoint, not ideal actuators. There is no direct correlation between the force exerted by the muscle and its neural activation [268]. In fact, a muscle's force output is also dependent on its recent contraction history, its velocity, and its length [292]. Muscle consists of contractile and non-contractile elements (Hills model of muscle) [293], [294]. However, it is the contractile component that generates tension when activated by a motor unit action potential, which consists of the two interacting proteins called actin and myosin. The non-contractile component comprises of connective tissues that are parallel and in series with the contractile components, linking the muscle fibres to the bones, called the tendons. The tendon is a passive structure but it's viscoelastic properties have repercussions on motor control as the length of the tendon is dependent on the force applied on it [268], [295].

Bernstein suggested that the movements of the body segments influence each other via the joint reaction forces [296]. Consequently, each muscle will have an effect beyond the joint that it directly moves. One example of this can be observed during cycling. During cycling the extension of the knee during the downward stroke is partly achieved through the actuation of the hamstrings which normally acts as a knee flexor muscle group [268]. This outlines one of the inherent issues of motor control: When adapting the muscle actuation to perform the task required of one joint, other disturbance will arise at other joints [268], [295].

The lower limb can be considered an ensemble of connected segments, connected one to the other and able to move with relative independence. Examples of this can be found in and ensemble composed of the trunk, pelvis, thigh, shank and foot of an individual – they all represent an open chain during the swing phase – (see Figure 2.5). The movement occurring in this kinetic chain is the result of the contribution of the different articulations that lead to an intended movement. Naito et al (2010) [297], by studying the kinetics of football kicking (see Figure 2.5) observed that the moment of the kicking knee's extension was the main contributor (58.7%) of the movement's execution followed by the trunk rotation's moment (55.9%) [297]. An alteration to one of these components would impact the kinetics of the other segments of the kinetic.

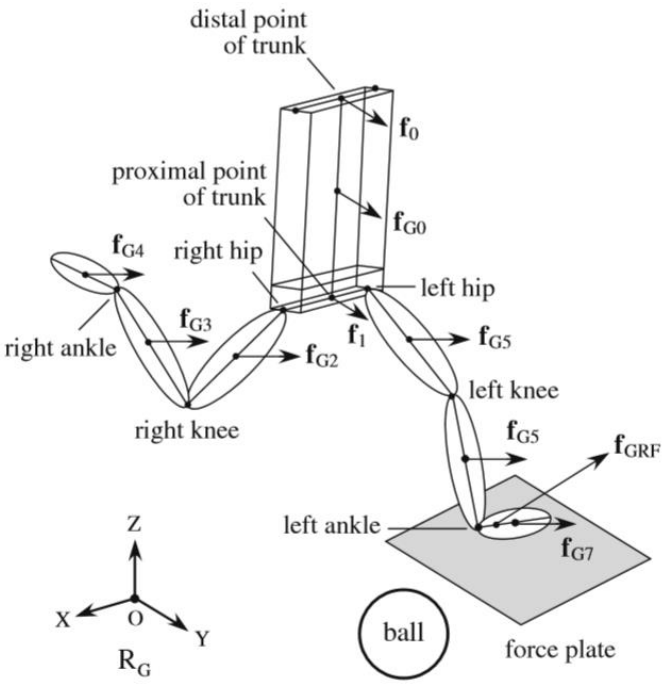


Figure 2.5: Kinematic chain example in the football kick situation. The kinematic chain is composed of trunk, thighs, shanks, and feet. f_{GRF} is the ground reaction force (source: Naito et al (2010) [297])

2.3.2. What is new in the motor control of gait?

2.3.2.1. Understanding of the role of the motor cortex

In recent studies [298]–[301] the role of the motor cortex in the execution of movements has been investigated in more detail. In the primary motor cortex (M1) neurons generates Motor Unit Activation Potentials (MUAP). A MUAP can be considered as a vector directed toward the neuron's preferred direction with the vector length matching the mean level of discharge from the neurons during a movement [298]. The neural activity of M1 presents a correlation between the movements direction, distance, speed [298]. *Figure 2.6* presents the outcome of an outward (B) and inward (A) spiralling finger pattern execution. There is a noticeable correspondence between the moment-to-moment activity of the M1 neural population (the instantaneous vectors of *Figure 2.6* represent the velocity of displacement of the finger) and the spatial kinematics of the tracing motions of the hand. The neuronal activity is represented in vectors

which correspond in direction to the neuron's preferred direction. In *Figure 2.6*, the increasing semi-circular vector pattern observed in D matches the increase of diameter of the outward spiralling pattern B.

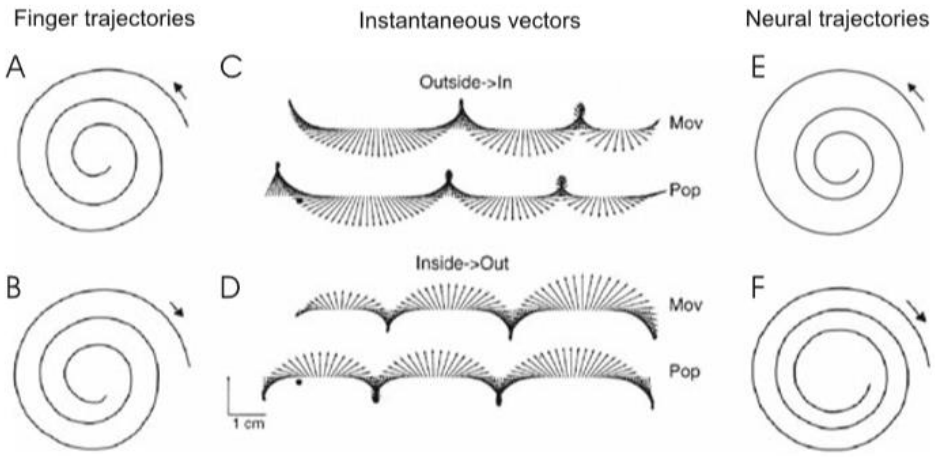


Figure 2.6: A, B represent the mean spatial path of the finger repeated trials of an inward (A) and outward (B) spiral tracing task. C, D are the vector representation of the temporal sequence of instantaneous velocity of displacement of the finger (Mov) and of the net directional population signal in M1 (Pop) at equally spaced short time intervals along the path of inward and outward spiral tracing movements, respectively. E, F are the neural trajectories during inward and outward spiral tracing movements, reconstructed by joining the instantaneous population vectors C, D tip to tail. Extracted from Kalaske et al. (2009) *[298]*.

Whilst neural activity in general reflects the resulting kinematics, the exact role of M1 as a motor controller remains unclear. The investigation into the role of M1 in muscle control is challenging because it would require knowledge as to which neuron directs which part of the spinal inter-neuronal circuit to actuate the desired muscles [298]. There is no direct link from the neurons in the motor cortex to the muscles, instead there are connecting neurons located in the anterior horn of the spinal cord, this connects to the efferent fibres of the peripheral motor efferent.

Some studies have found that the activity of M1 correlates to the activity of muscle synergies: meaning that the activity of a M1 neuron does not influence a single muscle but rather a synergy of muscles [115], [298]. Muscle synergies are formed by muscles building a functional relationship with one another to achieve a movement. There are studies that showed that M1 activation displayed signals from the neurons indicating its implication in the control of muscle activity [298]–[301]. Kalaska (2009) [298] observe that the activity of the M1 neurons related to muscle activity and movement direction (as previously presented). Townsend et al. (2006) [299] found a linear relationship between the

activity of M1 and the muscle activity of macaque monkeys during a hand gripping exercise. Santucci et al. (2005) [300] were able to extract kinematic parameters of the arm reaching movements of monkeys from their M1 activity. Morrow and Miller (2003) [301] were able to predict the muscle activity of monkeys from the M1 signal they recorded.

Motor control has been thought to be an entity in which the nervous system oversees the control of body movements, similarly to how a computer program might control the movements of a robot [298], [302]. The work of Beer (2009) [303] points to a model where motor performance emerges from the collaboration between biomechanics and the neural activity. To make another analogy with robotics, rather than representing motor control using an open-loop system in which the nervous system is the input and limb displacement is the output, a closed-loop system is more effective, where the input nervous command also receives feedback from the end-effector during the intended movement. Beer (2009) [303] used an evolutionary algorithm to characterise the biomechanical and neural constraints of a simple walking model. The evolutionary algorithms are used to analyse the brain-body-environment interactions. The walking model used in their paper was a single-legged walk with a simplified gait cycle, divided in two phases being “leg up” and “leg down”, and the movement was controlled by 3 to 5 neurons. From this simplified walk model [303], millions of neural pattern generators (networks) were realised. Exploration of the optimal motor pattern leads to the conclusion that the optimal motor pattern is degenerate. This means that the optimal motor pattern is not one trajectory but, an infinite ensemble of trajectories [303]. Conclusively, these findings support Bernstein’s observations.

Since the motor cortex (M1) is not a direct representation of the movement, EMG (measuring the electrical activity of muscles peripherally) could be used to gain a better understanding of motor control.

2.3.2.2. Understanding muscle activity

According to Latasy et al. (2010) [304], the study of motor control is the investigation of how the central nervous system contributes to the realisation of coordinated and voluntary movements in relativity to the rest of the entire body and its environment. Motor control research aims to provide a recognised, clearly defined description of the variables involved in the physiological processes generating these movements. EMG signals reflect the neuromotor control of a muscle [304].

Understanding the MUAP signals that emerge from M1 and ultimately provided to the muscle is possible by interpreting the EMG signal and how it is organised. A movement such as walking requires the co-ordinated activation of multiple muscle groups [305]. To understand how the central nervous system (CNS) coordinates this activity, it is necessary to record the activity of the muscles when contributing to a given movement. The control of the joints involved in the execution of a movement is dependent on the net torque generated by the different muscle groups, creating joint movement whilst simultaneously stabilising adjacent body segments. Analysis of the muscle activity is usually done by resolving the EMG signals into an envelope. An EMG envelope is a graph representing the boundaries within which the EMG signal is contained [306]. This envelope is usually designed during post-processing where the signal is rectified so that it does not produce a zero average and filtered and smoothed/filtered to remove noise [305]. The EMG signal can then be deconstructed and mapped onto the phases and analysed within the biomechanical context. From the resulting activity pattern of the different muscles, it is then possible to identify elementary building blocks called muscle synergies (as introduced in 2.3.1.1).

Muscle synergies might be a reflexion of the underlying characteristics of the musculoskeletal system or the underlying motor properties.

2.3.2.3. Interpreting the neural strategy from surface EMG signals

Several methods have been developed to extrapolate the motor recruitment strategies from the muscle activity signal provided by surface EMG [283], [284], [307].

Synchronous muscle synergies are used as a framework for dimensionality reduction in muscle coordination. When a task is performed, the motor control system works with the many degrees of freedom available through the different joints and muscle connections, to achieve the movement. Grouping the different muscles into coordinated entities simplifies the system by reducing the degrees of freedom, also achieving dimensionality reduction. Muscle synergies are the foundation of a variety of complex tasks requiring the coordination of several muscles, such as human arm movements [308]. Section 2.3.2.4 focuses on lower limb synergies, this section presents the techniques used to measure and understand muscle synergies.

Ajiboye and Weir (2009) [284] looked at whether a set of muscle synergies could be used to anticipate EMG activity in untrained static hand postures. The subject's forearm and hand muscle activities were recorded while they performed 33 American Sign Language (ASL) alphabet signs. A set of synergies were extracted from 11 training postures and used to anticipate the EMG pattern of the postures remaining to still be performed (the method relied on the use of non-negative matrix factorisation). Overall, the record of 11 postures led to the identification of 8 synergies. 90% of the 33 ASL sign's EMG patterns were successfully predicted (including trial-to-trial variations). The expected synergies were differentiated into two categories: subject-specific or general population synergies. The subject-specific synergies were usually dominated by a single muscle. The general population synergies were driven by a group of coactivating muscles. To make this observation, indwelling EMG electrodes were attached to 11 muscles groups that command hand movements [284]. From the 11 muscle's EMG data collected, eight muscle synergies were estimated. The muscle synergies estimated from the EMG pattern collected were compared to predictions of the EMG pattern. The outcome of the study was that the EMG data observed for the different hand postures matched the synergies extracted.

The outcome of this study showed that synergies are synchronous structures, making them an identifiable group of muscles working together to produce a movement [309], [310], and a good estimate of muscle activity patterns. The results also confirmed that the muscle synergies model is a robust predictor of EMG activity in specific hand gestures [284]. This observation has potential applications for EMG technologies such as functional electrical stimulation systems and prosthetics [284]. This paper stands out as an investigation because it uses muscle synergies to predict muscle activity rather than that to describe muscle activity. This study was performed on a small number of adult participants (seven) with no known neuromuscular disorders, all right-hand dominant and young (means age 29.1 ± 11.0 years old), with no fluency in ASL. They all used their right hand (dominant hand to perform the tasks). It is possible that an individual who is fluent in ASL will display different muscle associations. Also, as aging alters muscle properties [311]–[313] and actuation [314], data for an older adult group might result to different synergies being observed.

The observation of muscle synergies can be used as a means to evaluate the level of impairment of a patient with a stroke, as observed by Cheung et al. (2012) [283]. In this paper, the muscle activation pattern of both sides of upper-limb muscles of the participants (n=31) was assessed. In the case of the mildly impaired participants (Fugl-Meyer scores > 30) the muscle synergies of the side affected by the stroke and the contralateral side presented a similar number of synergies (7). In the case of the severely impaired group (Fugl-Meyer motor function scores <=30) there was a contrast between the affect arm and the non-affected arm. The synergies observed showed less resemblance and the number of synergies extracted from the two arm muscles was different, four synergies from the affected arm against six on the non-affected side. The smaller number of synergies found on the affected side appeared to be caused by the merging of several synergies. This observation is compatible with the reported tendency of muscles to co-contract after a stroke [285], [291]. A significant correlation was found between the synergy merging and the severity of the impairment (the three-way ANOVA analysis results gave $r=-0.51$, $p<0.01$) [283]. When the impairment is severe, it is more common to find synergies representing a merging of several synergies not only in the affected side but also, interestingly,

in the unaffected side. The authors proposed that in patients with mild and moderate stroke, the abnormal motor behaviour observed is caused by an inability of the motor control system to correctly actuate single distinct synergies since the muscle pattern were different but the synergies on both sides were similar [283].

Barroso et al. (2017) [307] explored the feasibility of combining usual biomechanical assessment tools (camera systems and force plates) and muscle synergies analysis methods in order to assess a pathological walk such as the walk of a patient with hemiplegic stroke. They argued that while biomechanical analysis provides the information related to the kinematics (joint angles), kinetics (ground reaction forces) and spatiotemporal (e.g. stride length and duration) characteristics of the paretic limb, the addition of muscle synergies data would provide information on the neural control of the impaired limb. Both biomechanical and neural control data are important in order to model rehabilitation training that can be tailored to the patient's needs and capacity [307].

2.3.2.4. The muscle synergies of lower-limb muscles

The control of human walking is a complex system to analyse. The legs are composed of more muscles (>20 excluding intrinsic foot muscles) than the amount of basic degrees of freedom necessary for its mechanical description (the basic biomechanical model counts seven degrees of freedom [315]). The role of one muscle is not linked to the actuation of a unique joint but can be useful for several lower limb motions [316]. A number of modelling studies agree on a description of human locomotor strategy using a simple five-muscle groups model [316]–[319]. These muscle groups are usually called "modules" and are in fact co-activating muscles [319]. Neptune et al. (2009) [319] presented the modules as in the following table (Table 2.3: Five Muscle Module model description adapted from McGowan et al. (2010) [316], Table 2.3).

	Muscle group involved	Occurrence and Main Function
Module 1	VAS (vastus intermedius, vastus lateralis and vastus medialis), RF (rectus femoris), GMAX (gluteus maximus, adductor magnus), GMED (anterior and posterior regions of the gluteus medius)	Early stance: body support
Module 2	SOL (soleus, tibialis posterior), GAS (medial gastrocnemius)	Late stance: body support and propulsion
Module 3	TA (tibialis anterior), RF (rectus femoris)	Early and late swing: leg deceleration, Swing: power for the trunk
Module 4	HAM (medial hamstrings, biceps femoris long head)	Late swing: leg deceleration Early stance: energy for leg propulsion
Module 5	IL (illiacus, psoas)	Swing: leg forward acceleration

Table 2.3: Five Muscle Module model description adapted from McGowan et al. (2010) [316]

The musculoskeletal model derived from this muscle synergy group is illustrated by Figure 2.7. The patterns of these muscle synergies are

presented in Figure *2.8*. The distribution of the activity of these modules is represented in Figure *2.9*.

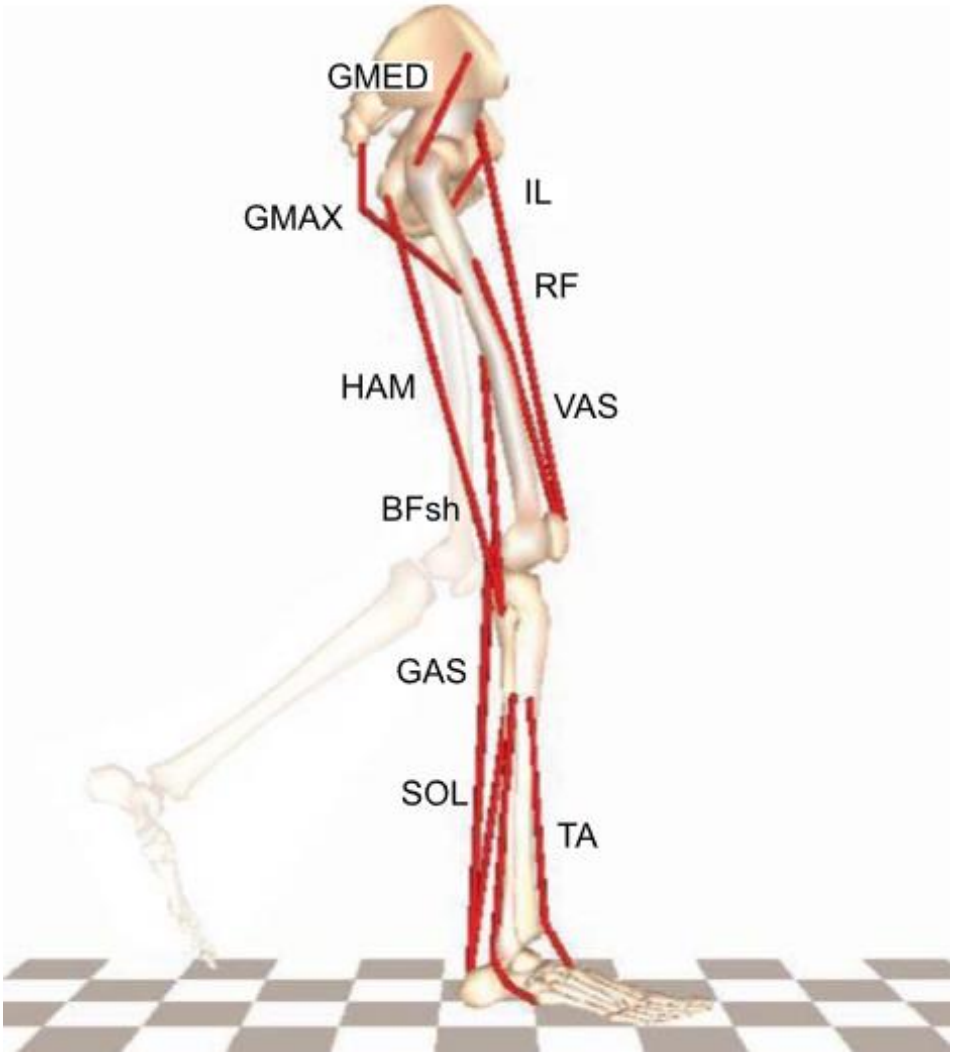


Figure 2.7: Leg muscle model taken from McGowan et al. (2010) [316]

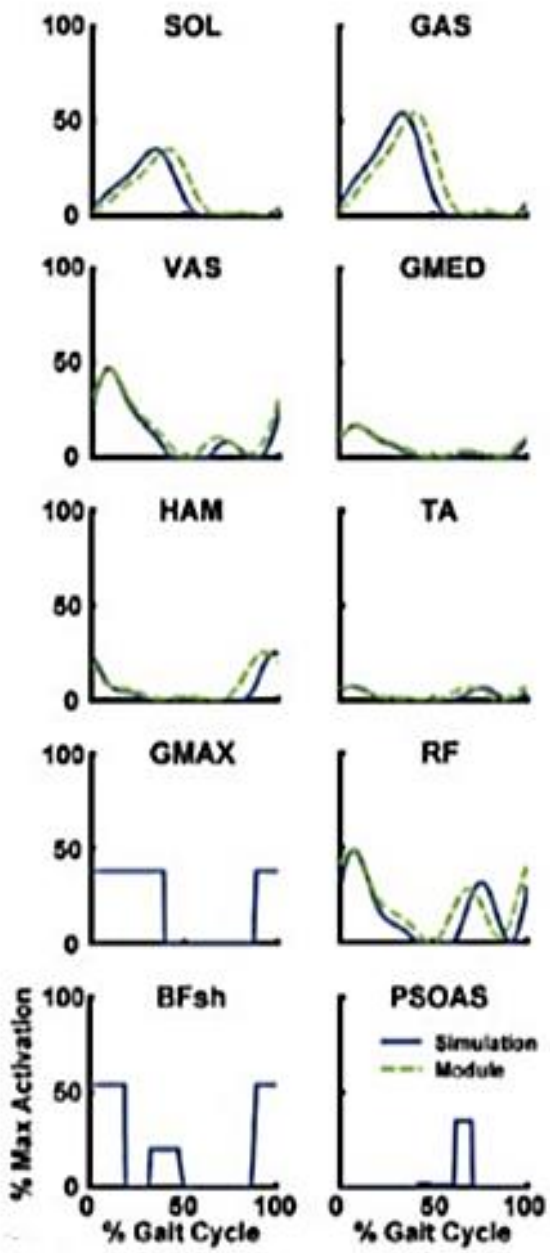


Figure 2.8: Muscle synergies module patterns, extracted from Neptune et al. (2009) *[319]*, all data normalised to peak simulation excitation magnitude.

According to Table 2.3, module 2 of the lower limb muscle synergies is composed of VAS and GMED muscles. It is therefore without surprise that the SOL and GAS muscles are actuated simultaneously, principally during the first half of the gait cycle as represented in the first row of graphs of Figure *2.8*. Similarly, the actuation pattern of the VAS and GMED, both mart of the module 1 of lower limb muscle synergies display synchronous patterns, as presented in the second row of graphs of Figure *2.8*. TA and RF (graphs on the 3rd and 4th row of the right column of Figure *2.8*) are part of module 3 and are both active at the

beginning of the gait cycle, then present two spikes of activity on after the first half of the gait cycle and the second at its very end.

The contribution of the different modules during the walk cycles is illustrated in Figure *2.9*. At early stance, the energy contribution of module 1 and 2 decreases when all the other increases, equating to an overall energy decrease when the foot is stepping on the ground. During early swing, all modules except module three present an increase of energy, which equate to overall increased energy while the foot is lifted off the ground.

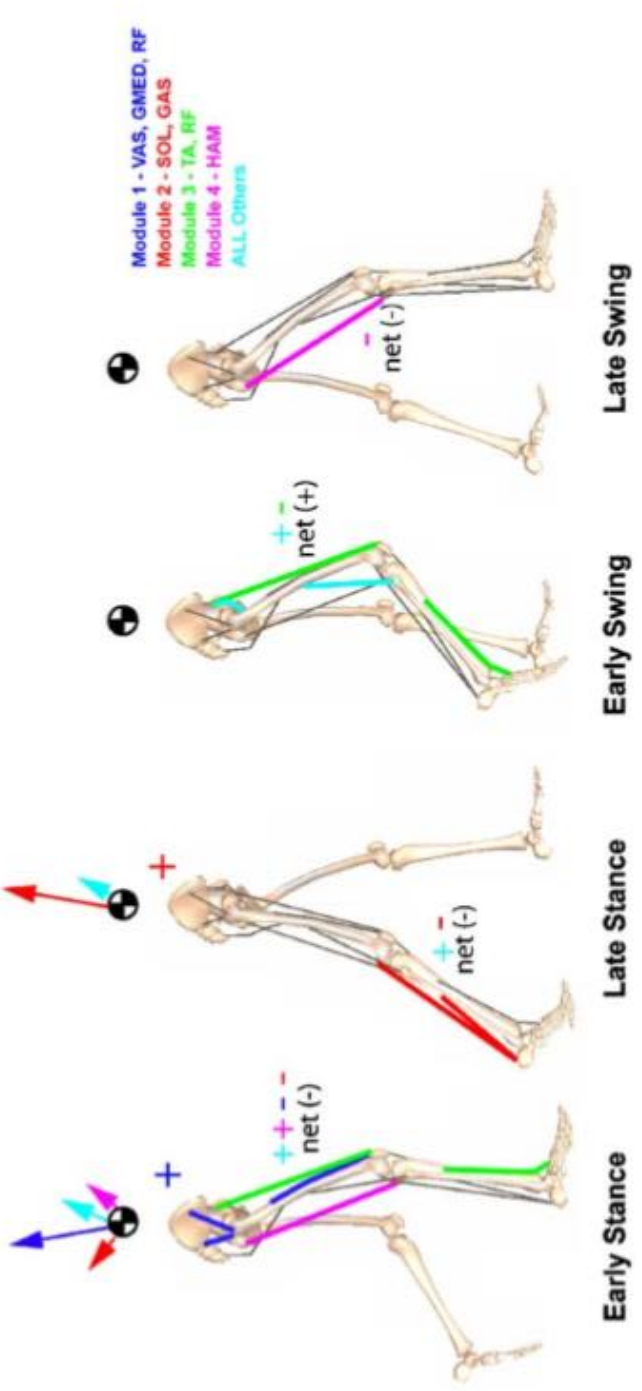


Figure 2.9: Module contributions to the walking sub-tasks of body support, forward propulsion and leg swing in the beginning of early stance. The arrows acting on the centre-of-mass symbol indicate the resultant module contributions to the horizontal and vertical ground reactions forces that act to accelerate the body centre-of-mass to provide body support and forward propulsion. Net energy flow by each individual module to the leg or trunk (‘ ‘ net’ ’ total of all modules presented for the leg) is denoted by a ‘ ‘ +’ ’ (energy increase) or ‘ ‘ -’ ’ (energy decrease). Extracted from Neptune et al. (2009) *[319]*.

The motor control pattern for walking is not complete at birth, but its basic components are present in the form of a two patterned model as presented in the left column of *Figure 2.10* (Neonate). The EMG pattern appears, for each muscle recorded, like a sine wave with a valley followed by a peak.

Later in life when the child is a toddler a more complex pattern model emerges. The EMG pattern is less smooth, with sharper peaks (see second column of *Figure 2.10*, toddlers) and is incrementally improved up to adulthood to create mature movement [318] (see *Figure 2.10*). Cheron et al. 2006 [320], demonstrated that using EMG and an optical tracking system, it was possible to replicate the main parameters of human gait on adults and toddlers using a method called Dynamic Recurrent Neural Network (DRNN). They proposed that the human learning technique for walking follows the theory of neuronal group selection. Neuronal group selection implies that the primary movement will be initiated by some group of neurons that have a general purpose but no definite connecting. If the resulting movement is successfully achieved a natural selection of the neural group will follow by synaptic reinforcement. Walking is achieved and perfected through repetition from the toddler stage to adulthood. The following figure (*Figure 2.10*) presents the changes of EMG profiles in a human walk according to age. At the adult stage, the tibialis anterior (TA) will present a clear peak at the beginning of stance whereas the neonate TA signal presents little change of amplitude over the gait cycle (*Figure 2.10*).

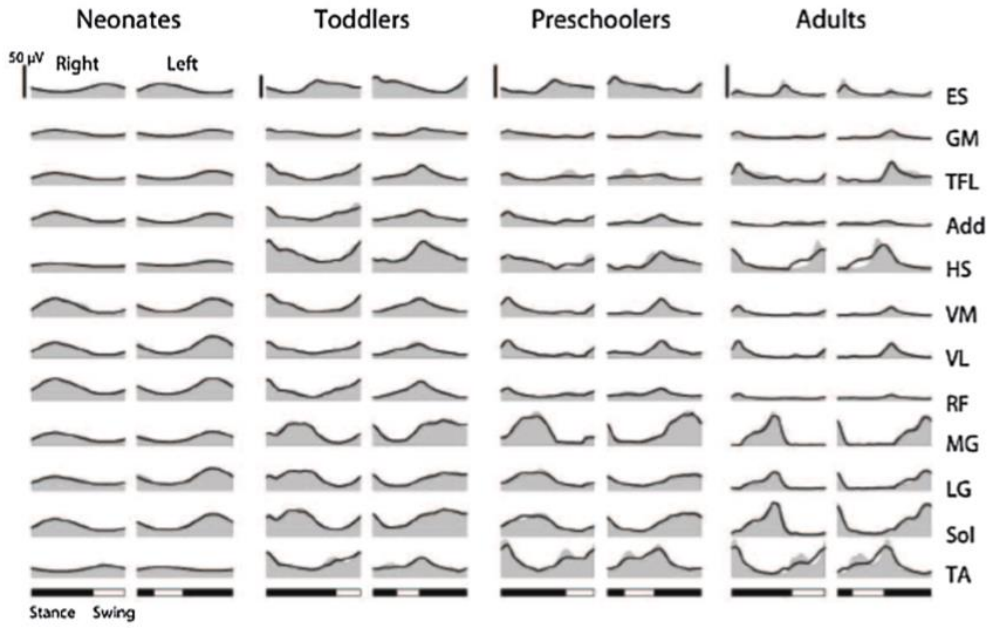


Figure 2.10: Ensemble averaged EMG profiles during gait cycle (for as sample of 39 neonates, 10 toddlers, 10 preschoolers, and 10 adults). The black traces are the profile reconstructed as weighted sum of the pattern extracted from the ensembles and the shaded areas are the experimental data ES: erector spinae, GM: gluteus maximus, TFL: tensor fascia latae , Add: adductor longus , HS: hamstrings, VM: vastus medialis, VL: vastus lateralis, RF: rectus femori, MG: Gastrocnemius medialis, LG: gastrocnemius lateralis, Sol: soleus, TA: tibialis anterior (Extracted from Ivanenko el al (2016) *[305]*).

The investigation of the motor control strategies following a neurological lesion is important since it can highlight the control strategy adopted during the rehabilitation phase. Due to the redundancy of the muscles, there are many neuromotor strategies available to the nervous system to compensate for the impaired neuromuscular route. Ideally, a closer pattern to the original would optimise the energy cost as it would involve the same synergies. It would then provide a movement performance that is visually similar to the original and would not be source of long-term asymmetry in the muscles, which are sources of pain and deformities [321]. Also, the use of the same synergy would be a manifestation of the availability of movement control adaptability. However, in the case of a damaged motor control system, the number of synergies can be reduced and, thus, lead to a reduction of variability in motor control and, consequently, movement.

Clark et al (2010) [285] reported that able bodied participants mostly required four modules to be able to walk at a self-selected speed (37.5% needing three, 55% needing four and 5% needing five). Post-stroke participants (time since stroke =57.8±64.8 months), however, required less modules on the paretic leg (45% needing two and 36% needing three modules) [285]. In the case of the participants with the lowest number of modules, the pattern was simple, with a clear actuation and rest sequencing and no co-contraction occurred between the two modules. Paretic legs that relied on three or four modules had more complex control pattern and included co-contractions. The motor control complexity of the modules reflected the locomotor performance of the individual in speed modulation between self-selected ($p=0.0002$), fast walking speed ($p=0.0008$), step length asymmetry ($p=0.02$) and propulsive asymmetry ($p=0.04$). A simpler module pattern is believed to lead to more limitations in walking performances. A simpler module pattern intrinsically reduces the number of alternatives for different muscle recruitment strategies, hence reducing the variability of walking.

Clark et al. (2010) [285] suggests that when module organisation and the qualitative amount of muscle actuation is the same between able-bodied ad post-stroke participant, the main difference lies in the degree to which the

module actuation is independently controlled by the nervous system. This impairment of the independent control of the modules after a stroke affects the complexity of the motor output to the extent that it constrains the motor output and the resulting biomechanics of the movement [285]. Clark et al. (2010) [285] stated that the more complex the locomotor output is, the better the walking performances are for people with a stroke. More skilled walking performances are reflected in a normal community walking for people with gait restriction from stroke.

Gizzi et al (2011) observed the muscle activity of sub-acute stroke participants (less than 20 weeks after stroke occurrence) and compared it to ten able-bodied controls [322] to find out if the motor modules of the stroke participants would compare to the healthy controls. They found that four modules were needed to display the motor control pattern of gait in both healthy and acute-stroke participants: this matches the previously presented study [285]. The timing of muscle actuation for the sub-acute stroke participants matched the muscle actuation timings of the able-bodied participants. This was expected in the control group originating from the CNS. However, it was not possible to obtain an accurate muscle activation pattern for the sub-acute participant group while using the same motor module as the controls [322].

2.3.2.5. EMG decomposition

There is a likely correspondence between the motor unit action potentials (MUAPs) and the motor neuron discharge observed in the muscle fibres [323] The cumulative discharge of the motor neurons that innervate the muscle is called the muscle's neural drive [323]. The decomposition of the EMG signal can be separated into individual motor unit (MU) contributions. To record MU discharges, indwelling EMG electrodes are the equipment of choice as they can directly sense the muscle fibres [323]. This procedure is, however, invasive and requires strict care, even if it is accepted in the context of clinical practices. It is not clinically appropriate to use this procedure in certain situations such as the observation on children, athletes, ergonomics and even some aspects of neurorehabilitation, to observe the

motor units properties in morphologies and functions and their adjustment to the contexts of exercise, fatigue, pain or over conditions [323].

To overcome this practical limitation, the use of surface EMG electrodes allows indirect recording of the MU discharges. The surface EMG electrode senses the electrical activity of the group of neighbouring muscle fibres that are active during the contraction of the underlying targeted muscle. The single fibre action potential (SFAP) is the electrical activity of a single fibre that is propagated from the neuromuscular junction and spreads out towards the tendons. The further the distance to the tendon is, the more the SFAP signal is attenuated. One MUAP consists of several SFAPs (see Figure *2.11*).

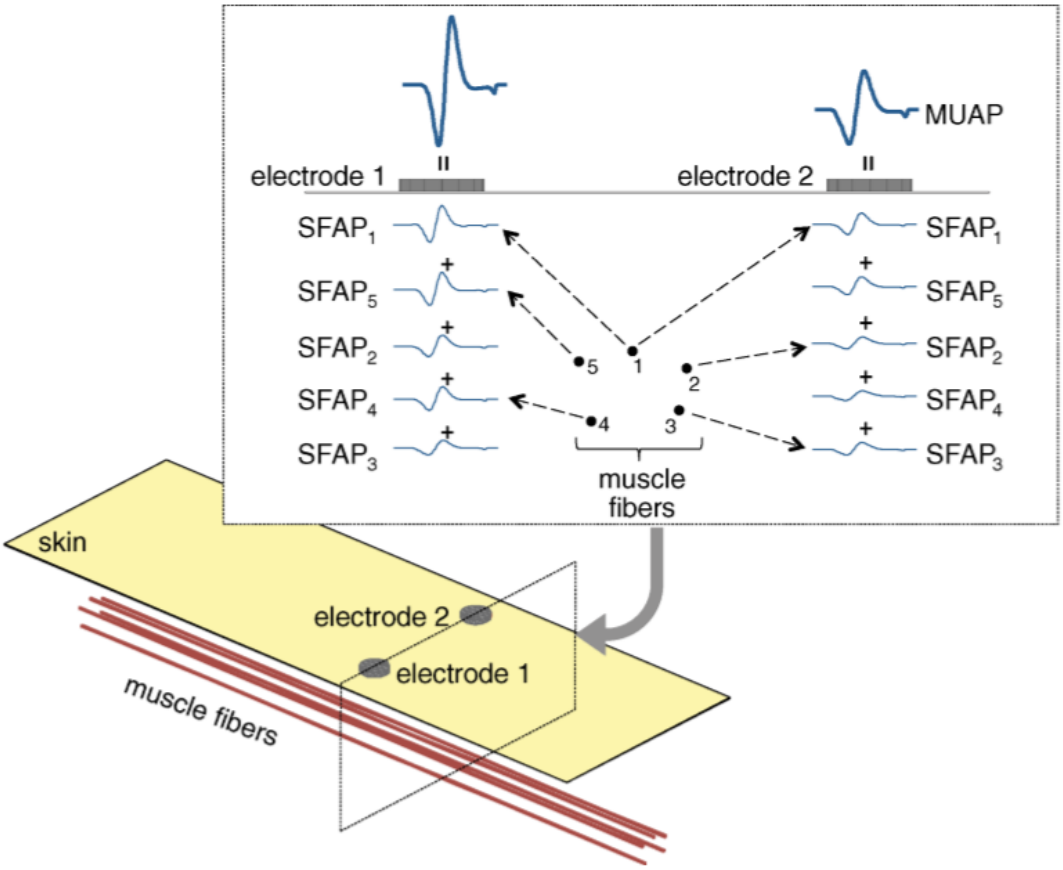


Figure 2.11: Representation of the MU fibres belonging to the same motor unit with their corresponding SFAPs, detected by two different surface electrodes, adding up to form a MUAP (extracted from Holobar et al. (2016) *[323]*)

To decompose surface EMG signals into the type of decomposition an indwelling EMG electrode might provide, a template matching approach can be used [323]. This process is composed of three stages: 1) the EMG signal

is segmented into distinguishable waveforms, 2) the MUAP templates are identified, and 3) the identified MUAPs are identified and matched to the appropriate EMG waveforms (clustering). Using this method, it is possible to investigate the MU synchronization, the cortico-muscular coupling, and the neural drive. Figure *2.12* and Figure *2.13* represent the different steps of surface EMG decomposition using the template matching approach.

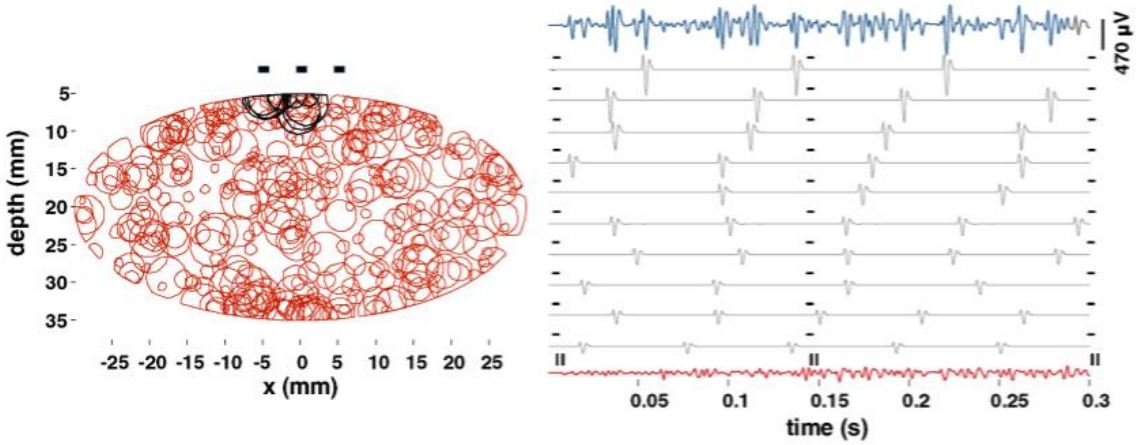


Figure 2.12: Decomposition of the surface EMG by the template matching approach in a synthetic EMG channel. A population of 388 active MU is represented in the left panel through a simulated 30% maximum voluntary contraction. The grey traces in the right side are the MUAPs identified (represented in the left side by the MUs in the black areas circled) and peeled off from the original EMG signal. The bottom traces in the right panels represent the residual after subtraction of the ten MUAP trains (grey signals on the right side) from the original EMG signal (source Holobar et al (2016) *[323]*).

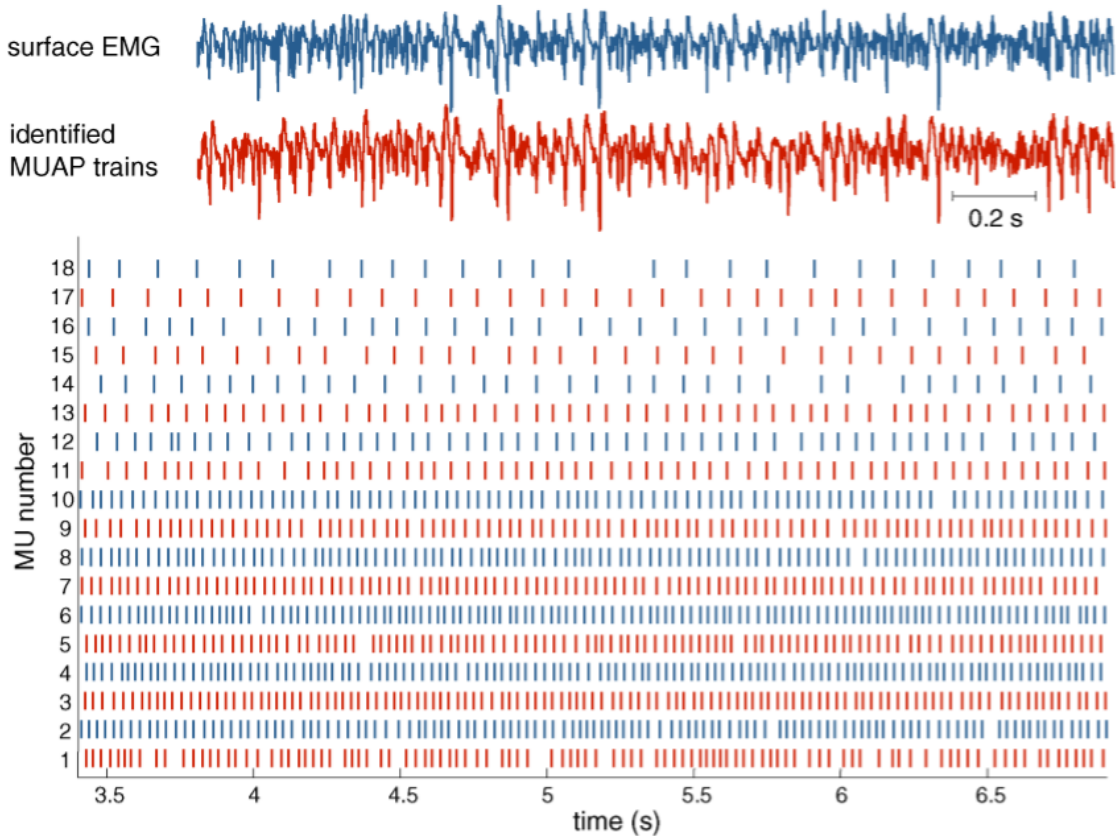


Figure 2.13: Surface EMG of tibialis anterior muscle at 70% MVC during an isometric contraction of 15 seconds (in blue on the upper graph) and the sum of MUAP trains identified from surface EMG (in red on the upper graph). Here, only one out of the 90 (10 rows ×9 columns) acquired EMG channels is presented. The lower graph displays the discharge patterns of 18 MUs from surface EMG represented in the upper graph. The vertical bars represent the MU discharges at a given instant in time (source Holobar et al (2016) *[323]*).

EMG signal decomposition is a means of non-invasive study of motor control strategies. Through EMG signal decomposition it is possible to learn about the characteristics of the MUs such as their recruitments and de-recruitment, discharge rate, individual conduction velocity and MU discharge rate (coefficient of variability for MU inter-discharge interval). For example, it is possible to show how intensive exercise of the muscle has an effect on the electrophysiological and the motor control of the motor units of bicep brachii [324]. In this study, it was found that two hours post-exercise, the mean conduction velocity of the muscle fibre decreased, and the motor unit discharge rate increased in the case of contraction levels of 50% and 75% of the maximum voluntary contraction.

EMG decomposition is a promising tool, likely to advance understanding of motor control however its accuracy is still debated and the subject of

investigations [323], [325]–[329]. Consequently, for now, the results from EMG decompositions simulations can't be generalized to interpret experimental conditions [323]. When this limitation of surface EMG decomposition can be mitigated by the simultaneous recording with indwelling EMG, it takes away the inherent advantages of the use of non-invasive surface EMG [323]. Moreover, while several methods of EMG decomposition exist, there is no standardised method available to our knowledge [323].

EMG decomposition has found to be of use in stroke research. In a preliminary report dated of 2011, two stroke participant's voluntary isometric contraction were recorded and decomposed [330]. The comparison of the paretic side with the contralateral side showed that, on the paretic side the mean motor unit firing rate was reduced and the range of force recruitment of the affected side was lesser than the contralateral side [330]. These two phenomena were associated with the incapacity of the muscle to actuate the muscle on the paretic side, leading to atypical EMG amplitudes. While observing the activity of three chronic stroke participant's shoulder abduction, elbow flexion and finger flexion, [331] compared their decomposition to controls. In the stroke group, the firing rate observed on the paretic side were significantly lower than on the controls. Also, the modulation of the firing rate was impaired on the muscles belonging to the paretic side [331]. In this case the analysis was performed in the muscles independently and not between them [331]. This means that the analysis of a movement including several muscle's action and revealing how they relate to one another was not presented. As complex movements involve the actuation of several muscles, having a method allowing the analysis of simultaneous muscle and observe the coherence of their activation pattern is desirable. Moreover, Miller et al. (2014) [331] and Suresh et al. (2011) [330] were studies performed on a small sample of participants (3 stroke, 5 control [331] and 2 stroke [330]), as these were used as a preliminary study [331] or observational study [330]. In both studies, the decrease of firing rate appear to be characteristic to the paretic muscle [330], [331]. This was also stated in another study on the observation of the behaviour of the MU firing after a stroke [332].

The EMG signal is investigated to understand the underlying control of movement during different types of exercise and in individuals of different ages and heath conditions, including stroke. EMG decomposition presents a means to learn more about the properties of the MU and how they adapt to different situations. The observation of this variability of the muscle recruitment on people who had a stroke during and after rehabilitation would be valuable information about how the body adapts to everyday walking challenges from the early stages of rehabilitation until the community reinsertion.

2.3.3. Investigating movement variability

The previously-mentioned studies on EMG decomposition were mostly conducted using constrained movements (e.g.: limb tightly strapped while performing voluntary muscle contraction at varying force level [330]). An interesting aspect of human movement, however, is its natural variability even in the case of the repetition of a given task (see section 2.3.1.1 on redundancy). During everyday walking for example, each step will differ in the angles of the joints, overall posture, foot positioning and muscle activity [333], [334]. It is, therefore, necessary to have a deeper look at the effect of muscle activity during a natural movement (i.e. the absence of constraints on speed, surface, etc which are often part of movement studies) and see how the motor control varies. It is particularly interesting to be able to characterise a situation of normal walking movement such as indoors walking in a familiar environment such as a domestic household or outdoors in a community setting.

While the study of the motor unit properties provides in depth understanding of the underlying behaviour of the muscle fibres, surface EMG provides the means to inform the variability of the motor control system using analytical tools methods such as the variance ratio and occurrence frequency.

2.3.3.1. Variance ratio

The variance ratio (VR) is a method used to compare the envelop of the surface EMG and give a quantification of the changes of pattern over consecutive muscle actuation during repetitive movement cycles. This measure has been found to be useful for both measuring the variability presented between data collection sessions and within muscle activity repetitions [335]–[338].

It revealed the variability that is naturally present in the EMG signal. This parameter is presented in more details in section 4.5.2 of this thesis.

It was first presented by Hershler and Milner (1978) [335]. They used the VR as a measure of the repeatability over a given number of footsteps, of lower-limb the EMG signal who were rectified and averaged [335].

The mathematic formula of the variance ratio is the following equation (2.1):

$$VR = \frac{\sum_{i=1}^{k}\sum_{j=1}^{n}(X_{ij} - \bar{X}_{\iota})^2/k(n-1)}{\sum_{i=1}^{k}\sum_{j=1}^{n}(X_{ij} - \bar{X})^2/(kn-1)}$$

(2.5)

In this formula, Xij is the value of the jth EMG envelope element at time i, $\bar{X}$ is the mean of the average EMG envelope signal, $\bar{X}_{\iota}$ is the average of the EMG envelope values over j cycles at time i, k is the number of points in a cycle, and n is the number of cycles.

Hwang et al. (2003) [336] used the VR to observe the effect of the use of handrail during treadmill walking for people with post-stroke hemiparesis (n=6, age range: 22-28 years old). Their results were compared with able-bodied participants (n=14, age range: 46-67 years old, time since stroke: 3 months to 1 year). The VR was collected over consecutive steps while the study participants walked on a treadmill at a self-selected speed. They found lower VR value for hemiplegic participants when walking on a treadmill, using handrail than while walking overground (for the tibialis anterior: VR= 0.3509±0.140 overground and VR=0.1959±0.045 on the treadmill with handrails; p=0.028 for tibialis anterior of the affected side). On the able-bodied participant, treadmill walking with a handrail led to smaller VR values (better EMG pattern consistency) while walking on the treadmill using the handrail than without (for the tibialis anterior, on the non-dominant side: VR= 0.4169±0.100 on treadmill without using the handrail, VR=0.1919±0.046 when using the treadmill's handrail; p< 0.0083).

Granata et al. (2005) [337] used the VR to observe within-session and between-session EMG envelope variability between children (n=11, 6.5±2.3 years old) and adults participants (n=10). They found higher VR values (more variability) in children in the case of within-session in comparison to adults.
Richards et al. (2014) [338] used the VR to compare the EMG variability of normally developing children (n=13, 10.6 ± 1.9 years old) with children with cerebral palsy (n=18, 10.8 ± 2.5 years old). Children with cerebral palsy presented significantly higher VR values ($p<0.05$) for the tibialis anterior and medial gastrocnemius muscles in comparison to their typically developing controls. The children with cerebral palsy also presented lower VR than their controls in the medial hamstrings. The authors posited that this increase of variation in the muscles responsible for the ankle movement might make the VR a useful tool for the clinical assessment of the muscle activity.
This thesis work intends, therefore, to make use of this parameter in consideration of its potential for clinical assessment of the muscle activity and help characterise the motor control strategy.

2.3.3.2. Occurrence frequency

In a couple of papers, Di Nardo et al (2015 and 2017), looked at the surface EMG signal, analysing the activation pattern and timing of the muscle while preforming the repetitive activity of walking [339], [340]. The resulting activation modality corresponded to the number of times the muscle is active during one gait cycle.
The parameter described in these papers is called the occurrence frequency. It is the frequency of muscle firing, quantified by the number of strides in which the muscle of interest is used in this given activation modality. The activation modality corresponds to the number of contractions observed within a gait cycle. For the activation modality "n", the occurrence frequency equation is as follow in equation (2.6):

$$Occurrence\ Frequency\ (n) = \frac{Number\ of\ gait\ cycles\ with\ n\ activation\ intervals}{Total\ number\ of\ gait\ cycles} \quad (2.6)$$

The use of occurrence frequency is recommended in the case of the analysis of a large number of steps (a hundred of strides and more) [340]. In the 2015 paper of Di Nardo et al., the occurrence frequency was calculated from the gastrocnemius

lateralis of four young healthy adults and two children walking freely. The mean number of steps collect was of 232 ± 27 strides. The activation modalities (the number of contractions observed per gait cycles) were of one, two or three contractions per cycles. The inter-individual analysis presented no significant differences in the onset-offset times and the duration of muscle activity of the muscle of the different modalities. However, the most used muscle modality pattern appeared to be very variable between individuals. With 16% to 74% in the case of the one-activation modality, from 20% to 45% in the two-activation modality and from 3% to 35% in the case of three-activation modality. Taking into account these results which enable the detection of differences in muscle recruitment across consecutive gait cycles, the occurrence frequency is expected to be a useful tool in the field of research and clinical studies for physiological and pathological conditions [340].

The following study by Di Nardo et al. (2017) was performed on 40 healthy able-bodied participants, comprising 20 adults (10 males) and 20 children (10 females) [339]. The EMG electrodes were attached to the gastrocnemius lateralis, the tibialis anterior, the rectus femoris and the biceps femoris. The participants walked barefooted back and forth on a straight 10 m long track. The mean number of strides collected was of 365±134 strides. This time, there were five activation modalities observed for each muscle. Overall, there were three types of activation: one-activation, two-activation, and three-activation, see *Figure 2.14* for an illustration. On *Figure 2.14*, a representation of the three modalities can be seen for the gastrocnemius lateralis of one adult participant. The adult female group presented significantly higher occurrence frequency for the three-activation modality ($p=0.0076$) and a significantly lower occurrence frequency for one-activation modality ($p=0.0019$), in comparison with the male group. When compared to the adult group, the children group presented a significantly higher occurrence frequency in the case of three-activation modality ($p=0.0123$). Here again, there was no correlation between the occurrence frequency and the EMG actuation timing nor with the duration of actuation of the muscle [339]. This means that the occurrence frequency is a measure of the muscle signal variability that could be used to differentiate age-related and gender-related characteristics of the EMG pattern, independently of the time-related information.

Since the occurrence frequency method consists of basic calculation and is independent of other major time-related parameters such as the duration of a

contraction. Occurrence frequency promises potential in the analysis of both the healthy and the disabled neuromuscular system and can be used to characterise motor control strategies by developing a greater understanding of changes to the neuromuscular system in patients with neurological conditions.

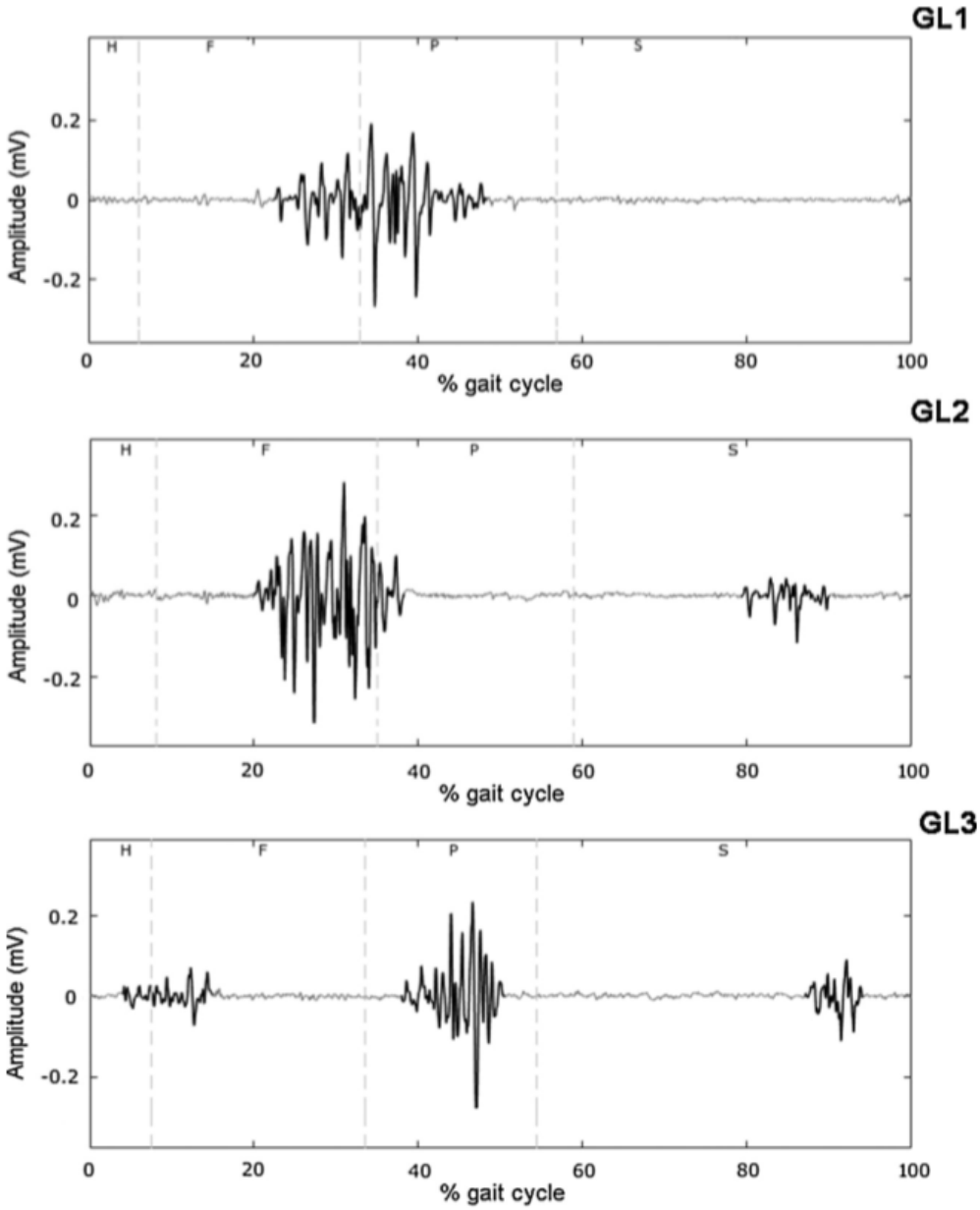


Figure 2.14: Raw EMG signal of the gastrocnemius lateralis for on participant during one walking trial, presenting one activation (GL1), two activations (GL2) and three activations (GL3) (extracted from Di Nardo et al. (2017) *[339]*)

It is interesting to note that, when it is expected of the gastrocnemius to be active during stance phase only [341], [342] (see *Figure 2.15*), the observation of the raw

contraction signals shows that the occurrence of contractions of the gastrocnemius is also possible during the swing phase, in the cases of the two and three-actuations modalities as visible in the two lower graphs in *Figure 2.14*.

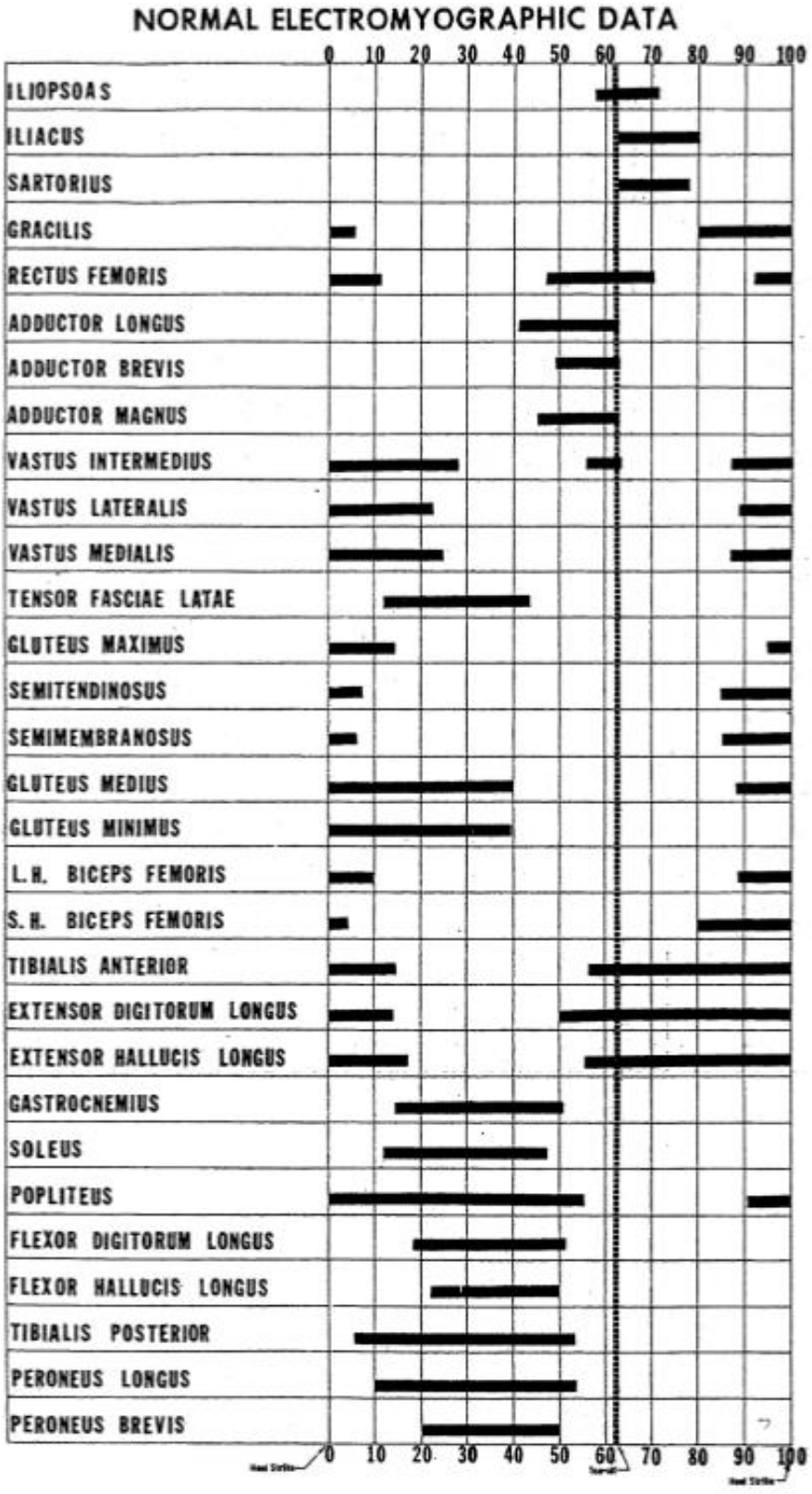


Figure 2.15: Muscle phasic activity chart of adults. The vertical dashed line represents the start of the swing phase (Extracted from Sutherland (2001) *[342]*)

A deeper understanding of the inherent variability of the muscular system would improve the understanding of the mechanism used by the neuromuscular system to fine-tune the biomechanical outcomes of walking and therefore improve rehabilitation interventions [339].

2.4. Summary

In summary, the first section of this review of the literature presented aspects of mobility training, focusing on gait rehabilitation training. While current walking rehabilitation training methods intentionally train balance and stepping, gait adaptability/variability is seldom trained and measured.
Several means to practice and measure gait adaptability exist and were used to measure walking adaptability for people who had a stroke. Most of these methods quantified gait adaptability by the success rate at performing specific tasks such as obstacle course-based tests, dual-tasking tests.

The use of treadmills as a valid means of enhancing gait training through practice intensity was presented in the following section 2.2. Overground training has proven efficacy for improving walking adaptability, the viability of using treadmills in various modalities in stroke rehabilitation was investigated in section 2.2. Treadmill training is a valid means to mimic overground walking and thus provides a means to walking while remaining indoors. The inclusion of immersed virtual realities to provide optical flow, perturbations, and self-pacing to simulate a more normal walking experience have the potential to improve the training of gait adaptability and help patients recover community ambulation capacity.

The third section presented the theory of motor control and new developments in the understanding of motor control. The relationship between surface EMG data and motor control suggested the need for its use in investigating motor control strategy during rehabilitation exercise performance. The use of a simple parameter such as the occurrence frequency has potential to provide a quantitative measure of the motor control variability and fill the knowledge gap on the characteristics of walking of able-bodied people and people with stroke.

It appears from the literature that treadmill training offers a way forward to create the intensity of rehabilitation the guideline recommends and that the inclusion of immersed

virtual realities and self-pacing function may overcome the predictable nature of traditional treadmill that, while improving general fitness, do not enable the re-acquisition of complex variable walking skills suitable for community walking.
However, before these new technologies can be justified as a training modality the motor control should be compared with overground walking using some of the new analytical tools for interpreting EMG signals, in particular variability which, as Bernstein stated, is a critical, inherent characteristic of normal repetitive movement.

The aim of this thesis is to monitor the lower-limb muscle activity of adults (able-bodied and who had a stroke) while walking on a treadmill (on fixed pace and self-pace) and overground (indoors and outdoors) to analyse their variability, using the variance ratio and the occurrence frequency.

The objective is to compare self-pace treadmill walking to community walking and thus observe whether the muscle activity behaviour, which reflects the underlying motor control, is similar between the different walking situations and thus determine which treadmill walking mode provides the closest experience to community walking.

The hypothesis is that the use of a self-paced treadmill linked with a virtual walking environment will create a walking experience that produces a motor output (muscle activation pattern) in healthy controls and stroke survivors that is more similar to (statistically significant) overground walking than traditional fixed pace treadmill walking.

Chapter 3

3. Description of Electromyography

This chapter will define the key principles of electromyography, highlighting the issues relating to data collection processes, signal processing and interpretation. This description is to provide the background for the approach undertaken to measure features of motor control. Particular attention will be given to signal interpretation, highlighting those areas which continue to be debated.

3.1. Muscles physiology and structure

3.1.1. Skeletal muscle anatomy

The skeletal muscles are composed of a group of muscle fibres attached together by a connective tissue called perimysium which forms muscles fascicles. The muscle fibres can then be subdivided into groups of myofibrils which are themselves composed of an aggregation of the elementary muscle unit, the sarcomeres, which are attached in series.

3.1.1.1. Sarcomere

The sarcomere is composed of a superimposition of protein filaments of myosin, a filament charged with negative charges and actin, a thinner type of filament with two negative charges, circling around one another [341], [343]. Because, both the myosin and actin filament are negatively charged, at the rested state they oppose one another and lay next to one another. Once a contraction is stimulated, the motor neuron releases an electric charge that leads to the release of calcium ions through the sarcomere transversally, through transverse tubules [343]. Because the calcium ions are positively charged, they attract the actin filaments. Because of the positive charge present on the actin, the myosin is then attracted to the actin. The filaments pull together towards the centre of the sarcomere, causing the sarcomere to shorten (see Figure 3.1).

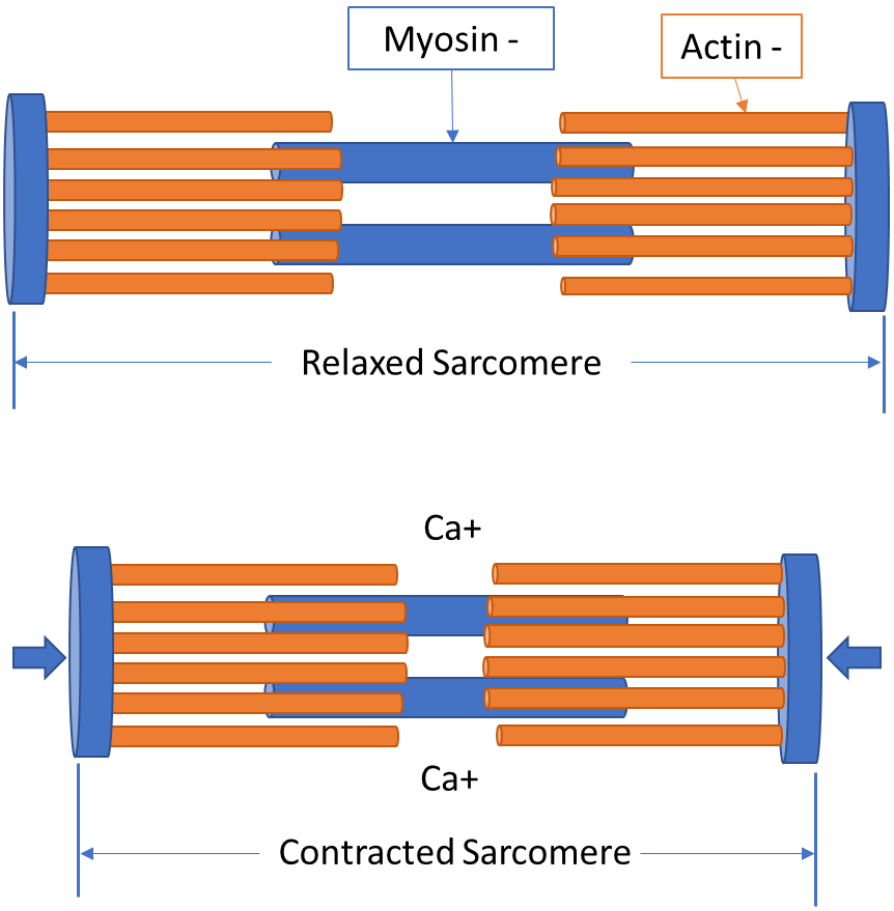


Figure 3.1: Interaction of actin and myosin filament during the contraction and relaxation of a muscle sarcomere

The myosin filaments have their tails attached to the thick filament inside the sarcomere. The myosin heads contains an ATPase, which is an enzyme that catalyses the chemical reaction of adenosine triphosphate (ATP) and allows the conversion of the energy of adenosine triphosphate (ATP) into mechanical energy [344]. The mechanical energy in store is released when the myosin head attaches to the Ca++ activated actin fibres. The crossbridge, which is the attached head, pulls the actin filaments in, creating an overlap of myosin and actin filament and shortens the muscle fibre [344]. This longitudinal sliding motion takes about 0.6µm, after what the crossbrige's stress is relieved and it detaches to get re-attached at another biding site [344].

The muscle fibres are distributed under 3 main categories based on their ability to contract quickly and their sensitivity to fatigue [343].

Fast-twitch, fatigue resistant muscles are classified as Type I. Their appearance is pale.

Fast-twitch fatigable muscles are classified as Type II. They need less than 35 m to contract or complete a polarization and depolarisation cycle. They can twitch more than 25 times in a second and can operate at a frequency comprised between 30 and 50 Hz. Their appearance is whitish.
Slow-twitch muscles need more than 35 ms to polarise and depolarise. They can twitch less than 25 times in a second at a frequency of around 10 and 20 Hz. Their appearance is reddish.

3.1.1.2. Motor units

A motor unit (MU) is composed of a group of muscle fibres and the motor neuron that excites them, and the motor nerve cell found in the spinal cord connected to this muscle group (see Figure 3.2). To create movement, it is necessary to recruit several MUs or to increase the firing frequency of the MU in order to observe more than a simple muscle twitch [341].

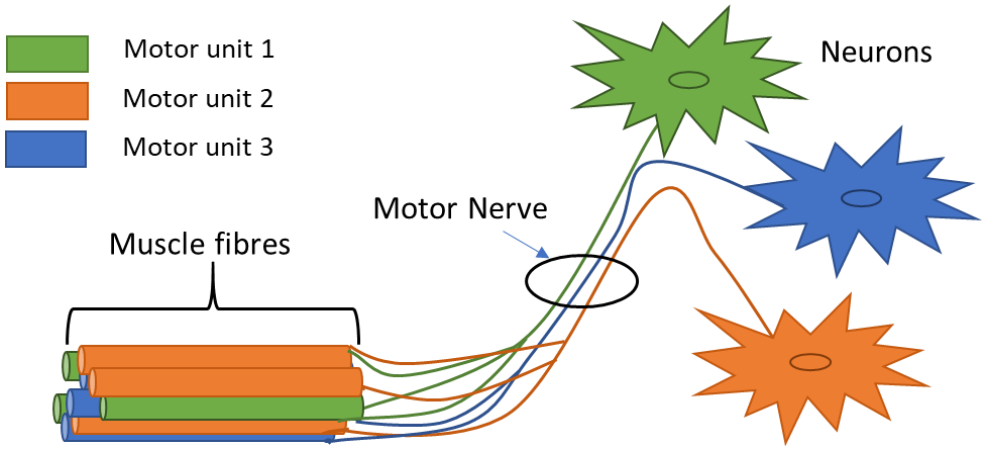


Figure 3.2: Motor units' model

3.1.1.3. Tendon

The tendons provide the muscle's attachment to the bone, they are mainly composed of type 1 collagen with some elastin and have viscoelastic properties [341].

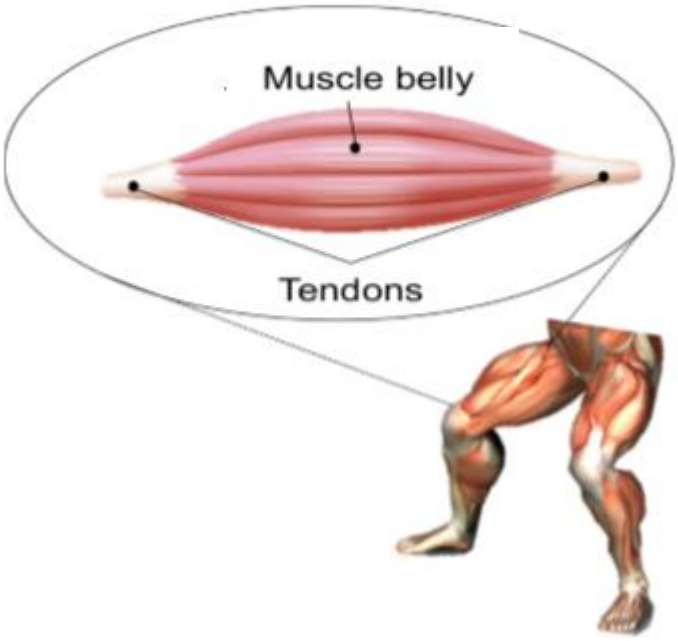


Figure 3.3: Quadriceps muscle composed of muscle fibre and tendons at its extremities. (Adapted from Mokaya et al. (2013)[345]

3.1.1.4. Functional potential of a muscle

The morphology of the muscle and its structure has repercussions on the amount of force it can produce. The functional potential of the muscle depends on the muscle's size. The physiological cross-section area (PCSA), measured perpendicularly to the muscles' fibres direction, defines the maximal tension capability of the muscle [341] (see Figure 3.4). When maximal contraction occurs, it reflects the muscle fibres reaction to this stimulation, thus the PCSA displays the muscle's maximal force potential.

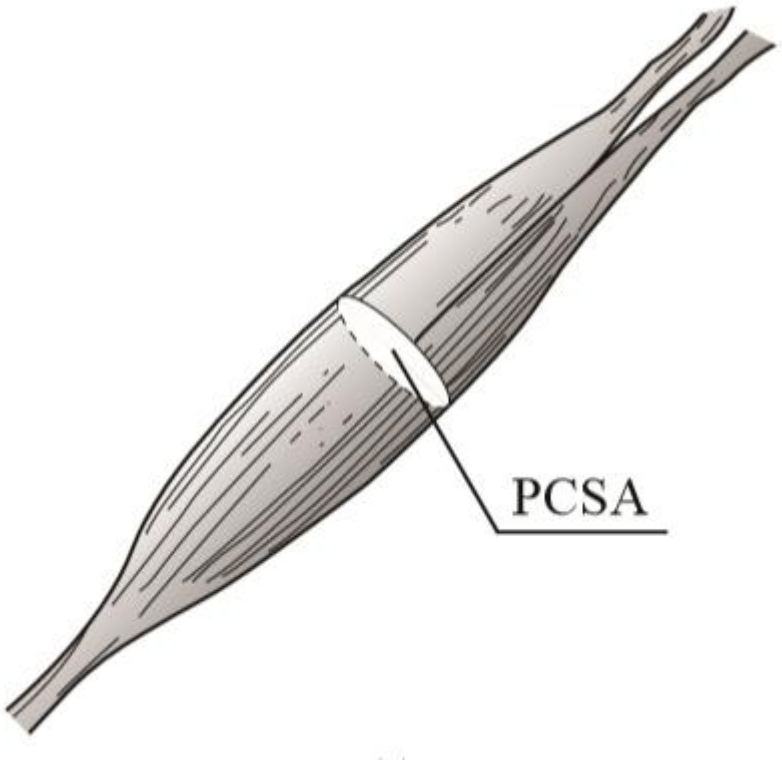


Figure 3.4: Muscle's physiological Cross-Section Are (PCSA) extracted from Ohta et al (2014) [346]

The muscle fibre's length fixes the maximum contraction velocity of this muscle. The longer a muscle, the more sarcomeres it contains. If there are more sarcomeres, they don't need to shorten as much to reach the necessary velocity and therefore less force is lost in the action [341]. One of the shortest leg muscle's fibres are found in the soleus (see Figure 3.5), located at the back of the lower leg between the ankle and the shank, with a length around 20mm.

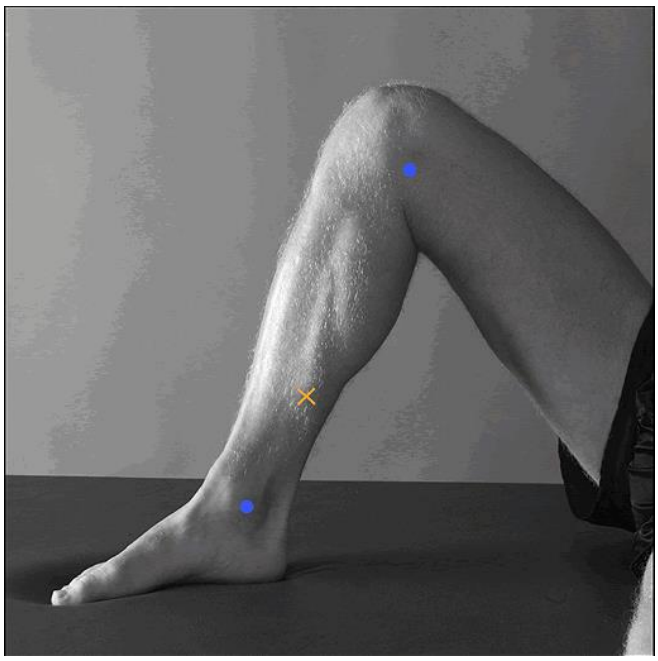


Figure 3.5: Soleus muscle EMG placement (orange cross) according the SENIAM method [344]

The muscle fibres of the sartorius (see *Figure 3.6*), located at the front of the upper leg attached between the proximal knee joint and the anterior superior iliac spine, with a length of around 455mm, which makes it the longest leg muscle [341].

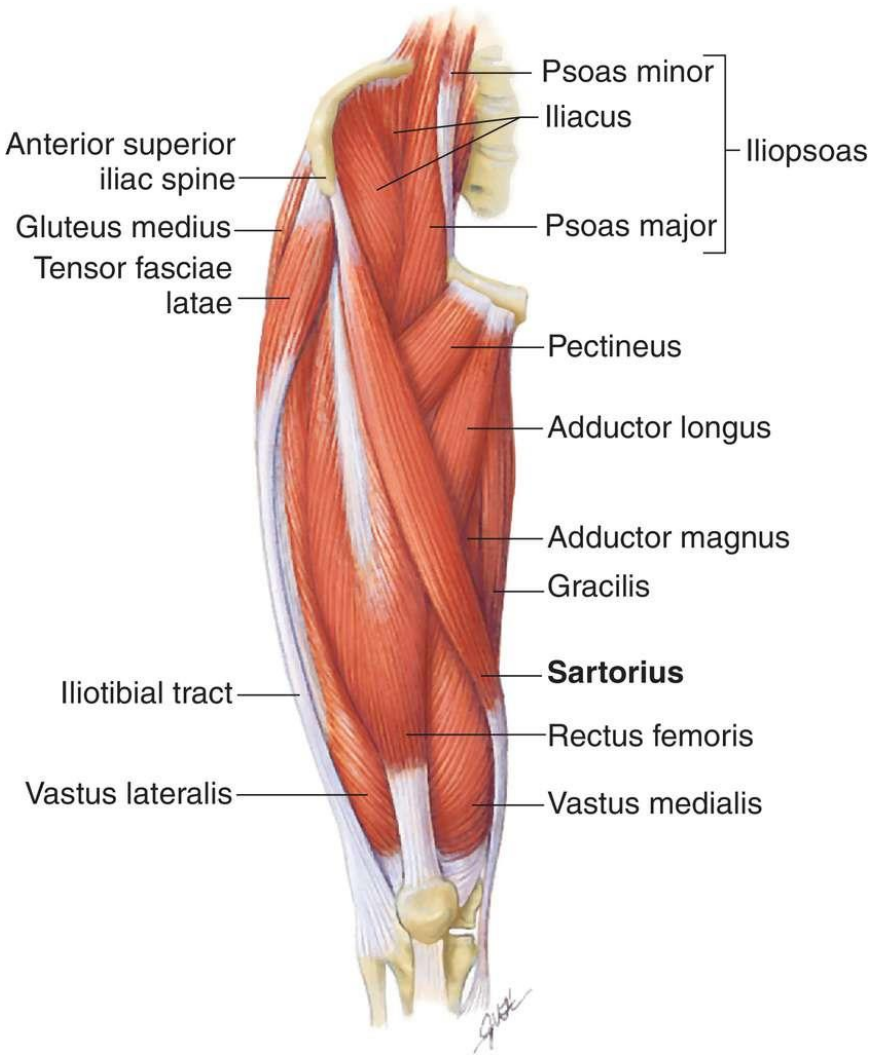


Figure 3.6: Sartorius muscle location extracted from Mosby's Medical Dictionary, 9th edition *[348]*

The longer the muscle fibre the faster the joint movement [341].

3.1.1.5. Muscle contraction modes

The word “contraction” originally means “to bring together” or “shortening” [349]. Contractions can be divided in three different categories or modes [341]. Isometric contraction is a contraction that occurs without any limb motion and zero contraction velocity. In this case, the tension and the energy are fluctuating. The muscle can therefore generate force, but the muscle length doesn’t change, no movement is involved (e.g. when pushing on an object that can’t be moved) [350].

A concentric contraction occurs when a movement is initiated. The muscle force is greater than the resistance to motion. During this type of contraction, the two ends of the muscles pull towards one another, leading to joint movement. Eccentric contraction occurs when the resistance is greater than the force exerted by the muscle, at a consequence the muscles ends move away from one another, it lengthens, while tension is developed within the muscle [350].

3.1.1.6. Motor neurons

The actuation of the muscle is made possible with the nervous system, with the exception of reflex-related actuations (e.g. tap on patellar tendon resulting in knee extension and quadriceps contraction) [351]. The motor neurons are located in the anterior horn of the spinal cord or part of the brain stem as illustrated in *Figure 3.7*. They receive descending inputs from the brain through the corticospinal tracts. Each motor neuron possesses nerve fibres called axons. The axons spread out of the spinal cord to reach the muscle fibres to which the motor neuron transmits the action potential [352]. A group of motor neurons participating to the actuation of one muscle are called a motor nucleus. The motor nucleus is gathered longitudinally on consecutive segments of the spinal cord.

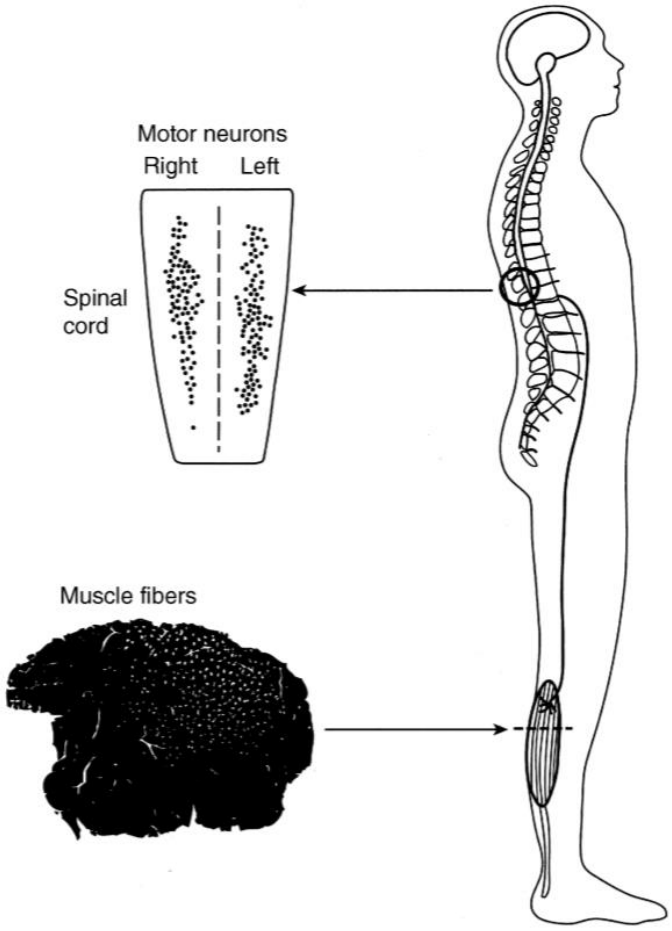


Figure 3.7: A population of motor units (motor unit pool), located in the spinal cord controls the muscle force. Each motor unit innervates a number of muscle fibres (muscle unit). Modified from Enoka *[352]*.

The motor neuron has branches with synaptic contacts able to receive and transmit electrical currents and therefore generate action potentials [352].

3.2. Electromyography

3.2.1.1. The origin of muscle activation and its transmission

To initiate a muscle contraction, the brain must first generate an action potential. This is a change in the electrical potential which is transmitted along the cortical-spinal tracts to the anterior horn of the spinal cord where it synapses with motor neurons. (see *Figure 3.7*). Eventually, it takes around 250ms [353], [354] to reach the place were nerve and muscle share "border with" and is called the neuromuscular junction (see Figure 3.8).

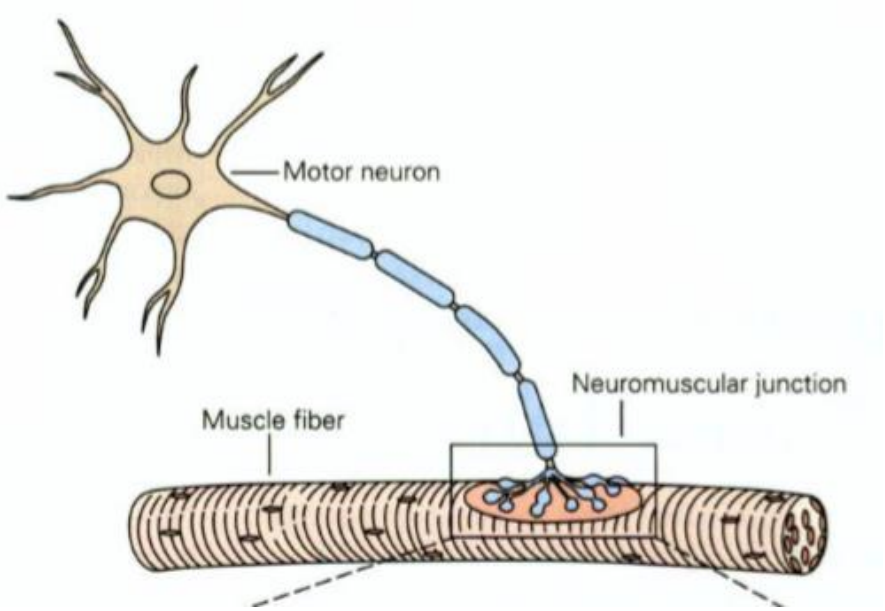


Figure 3.8: The difference of electrical potential from the motor neuron to the neuromuscular junction, Extracted from Boncompagni (2012) [355]

At this point, a neurotransmitter called acetylcholine is released to journey across the junction and activate with receptors attached to the membrane of the muscle fibre. Consequently, the membrane depolarizes. Then, the transverse tubular system transmits the action potential across the muscle fibre. As the action potential spreads, a signal spread to the release of calcium, necessary to create the difference of potential necessary to the muscle contraction (refer to Sarcomere section 3.1.1.1).

3.2.1.2. EMG instrumentation

Since surface EMG electrode will be used in this thesis, the instrumentation relating to surface EMG will be succinctly introduced here.

Due to the small amplitude of the electrical signal generated by the muscle (in the order of the microvolt (µV)), to obtain recordable signal it is necessary to have an instrumentation that can amplify this signal. Such a small signal when amplified is likely to be polluted by other electromagnetic signals belonging to the testing environment as well as the body (e.g. EEG and ECG), referred as noise [343]. To reduce the impact of this noise the surface EMG electrode is composed of a differential amplifier. The role of the differential amplifier is to amply the difference between the two input signals at its terminals and cancel any voltage that is common to the two input signals, called common-mode signal [356] (see *Figure 3.9*).

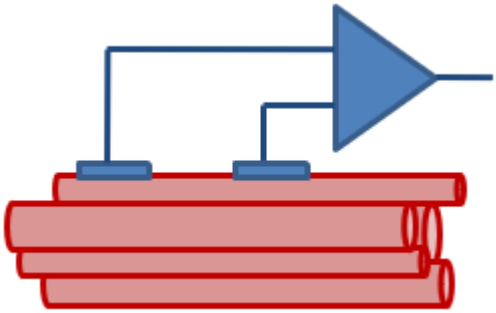


Figure 3.9: Simplified representation of the surface EMG data collection instrumentation, in blue the EMG electrode, in red the muscle.

The first obstacle to the unaltered transmission of the raw muscle signal is the body tissues present between the electrodes and the muscle motor units. The electrodes are applied on the skin, from which they record the electrical signal from the motor units. The motor units that are the closest to the electrodes are the greater contributors to the collected signal. The electrode's distance to the motor units varies from one person to another due to the presence of fat and body tissues which absorb part of the signal. It is therefore expected to observe higher amplitude of EMG signal on a person with lower body fat in comparison with a person with a thicker under skin fat layer [343].

The skin is also a barrier to the transmission of the EMG signal. Its state, namely, its moisture, the presence of dead skins or of oily layer, results in a change of resistance to the transfer of the electrical current, called impedance. It is therefore recommended practice to ensure that the skin impedance is as low as

possible [343]. To achieve low impedance, the skin is prepared, usually using abrasive paper and followed by a cleaning with alcohol pads. In some cases only a vigorous rubbing with alcohol wipes is made [343], [357].

The surface amplifier used on the surface EMG electrodes tend to be sensitive to impedance imbalance. Impedance imbalance can occur when one of the electrode is in contact with a hairy patch of skin while the other in on a hair-free area, or, if one of the electrode does not share good contact with the user's skin [343]. To avoid this type of errors, it is recommended to ensure that the area intended for EMG data collection is hairless and that the electrodes are firmly attached to the skin of the person.

EMG electrodes are composed of a conductive material usually silver, gold or in some cases nickel or even mix for example silver chloride (AgCl) [343]. To improve the conduction and in case the EMG electrode is placed on a sensitive skin area, it is possible to use electrodes coated with hydrogel. Since the property of this hydrogel matches the skin's acidity and water content it is ideal to use with no risk of damaging the skin.

To improve the EMG data collection outcome, the location of the electrode has to be appropriate, distant from the tendon's bone attachment of the muscle, oriented parallel to the muscle fibres direction, without overlapping with the location of another muscle. There are precise directive for surface EMG electrode placements and procedure designed by the Surface Electromyography for the Non-Invasive Assessment of Muscles (SENIAM) [347].

3.2.1.3. EMG Signal processing

EMG signal processing is not standardised and subject to multiple variations in the literature according to the authors choice and the information they want to extract. An example of common EMG data processing steps starting from the raw EMG signal are presented in Figure 3.10 and commented in Table 3.1 non-exhaustively. Some data processing protocols will not use all of these steps, according to the need of the research (i.e. no normalisation of EMG in case of a study looking at EMG signal amplitude, or no smoothing needed in the case of spectral analysis of the signal).

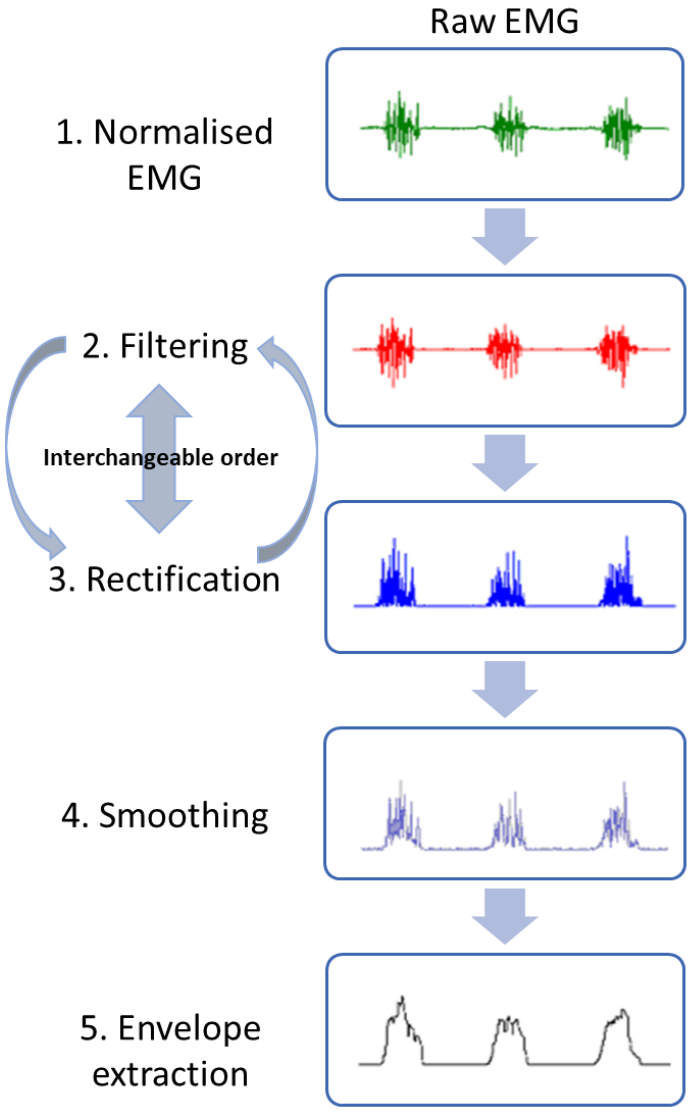


Figure 3.10: Example of EMG data processing flow. Adapted from Altimari et al. (2012) [358]

Steps	Methods
1. Normalized EMG	Normalisation to the Maximal amplitude of the signal [359], [360], peak (peak dynamic method) or the mean (mean dynamic method) of EMG signal [358], [361]–[363] during the movement. The peak dynamic and mean dynamic normalisation methods have shown to be better at reducing inter-individual variations [363], [364].
2. Filtering	Low pass filtering (i.e. Butterworth filter with given cut off frequency 6Hz [350], 5Hz [365]), Band pass filtre (5Hz to 500Hz [366], 20Hz to 500Hz [367], [368])
3. Rectification	Half wave (reject all negative values) or full wave (all negative values turned positive) rectification
4. Smoothing	Smoothing by filtering (i.e. Butterworth [359], Kalman filter [369], …)
5. Envelope extraction	Hilbert transform [369], Mean square Error [370], Waveform [371], RMS [372]–[375]

Table 3.1: Diverse methods of data processing

3.2.1.4. Timing muscle activation

The contraction timing or duration corresponds to the time partitioned by the onset of the muscle activity and its cessation. This information can be deduced from the raw EMG through visual observation or through computerized analysis [341] using threshold detection algorithms.
Several threshold detection methods exist. Most methods depend on the use of a reference value, such as a maximum contraction or a baseline resting state and use this reference value to determine on and off times with statistical techniques.

One of the most referred to is the double threshold method [376]–[380]. The first step of this method is to measure the mean and the standard deviation of the EMG signal's baseline noise amplitude coming from the rested muscle. From this, the first threshold criterion is extracted. The EMG amplitude must be above either 95%, 99% of the confidence interval or even greater if the baseline level

of activity is important. Some papers recommend two or three standard deviations above the mean baseline noise

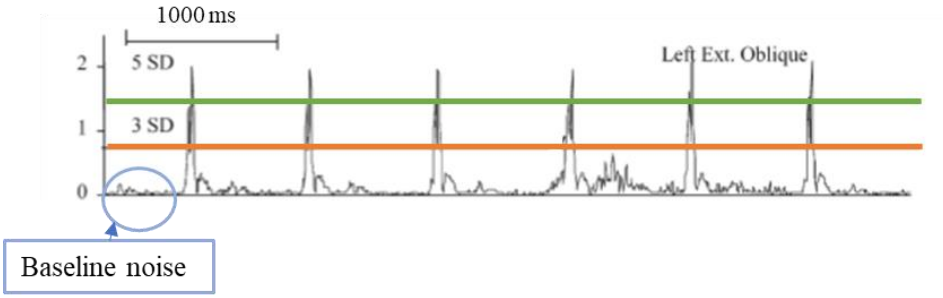


Figure 3.11: Repeated contractions of the Left External Oblique. The horizontal lines represent the 3 standard deviations (SD) (orange) and 5SD (green) thresholds from the mean baseline noise of muscle activity. Adapted from Allison (2003) [381]

With these methods, the muscle is considered contracted if the amplitude of the EMG signal goes beyond a specific threshold which can be 3 standard deviations [381]–[383] or 2 standard deviations [384] from the mean baseline noise amplitude or a percentage of the maximum value of the signal [385]. It can also go beyond 3 standard deviations as presented in [359], [381], who used 4 and 5 standard deviation thresholds too. Allison (2003) [381] looked for the optimal threshold value to detect the contraction of trunk muscles who are often subjected to ECG-induced noise. Morey-Klasping et al. (2004) [359] compared different EMG onset methods on the filtered EMG of lower limb muscles. A higher threshold value leads to less false EMG onset detection however it induces a time delay in the detection of the muscle contraction. They concluded that the measure of onset alone was not sufficient to describe EMG onset [359].

In some cases, a double threshold method is used, taking into account not only the amplitude of the signal but also how long it is above its amplitude threshold [343], [376], [386]. From this method two type of errors can emerge. Type I corresponds to the detection of the muscle contraction before it occurs. Type II corresponds to the detection of the muscle contraction after it occurs. The second threshold is used to correct the Type I error effect.
The second threshold criteria is that the EMG signal that goes above the first threshold value should also stay above it for a critical time period (t_c). This critical time period can vary between 10 and 50ms, according to the EMG signal's baseline activity level [387]. Other more complex methods exist relying

for example on fuzzy-entropy [388], wavelet transform [380] or other adaptative algorithms [367], [389].

The magnitude of the muscle EMG signal is related to the location of the electrode according to the motor units (MU) of the muscle as well as the strength of the muscle action [341].

3.2.1.5. The interpretation of the EMG signal

The area under the EMG linear envelope is obtained by integrating the area under the curve [387], [390]. The measure of the area under the EMG envelope is considered to be a measure of muscle activity or the energy of the muscle signal during a given time period [387]. The area has been used to measure the muscle energy in several papers [337], [343], [391]. The integration under the EMG curve is the also referred as IEMG (see Figure 3.12).

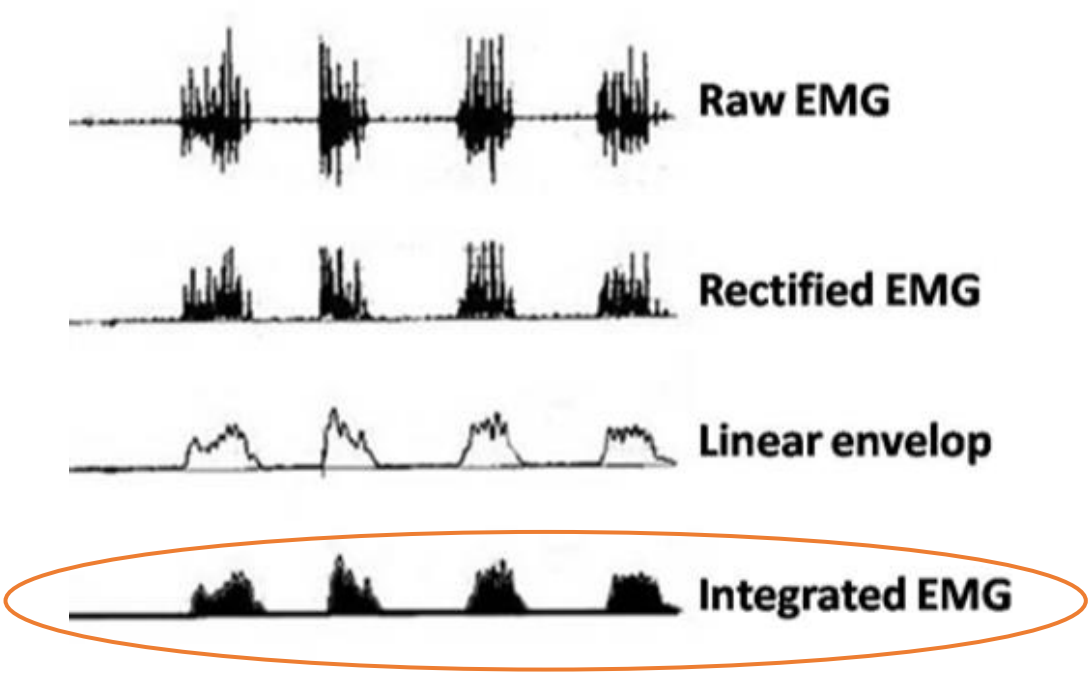


Figure 3.12: Representation of integrated EMG (in orange circle) as the integration of the linear envelope of the rectified EMG signal. Adapted from Clarys et al. (2010) [392]

The slope of the linear envelope of the EMG signal is used to quantify changes in neuromotor control when the main characteristics of the muscle remain the same through the experiment [387]. To measure the slope, the onset of the EMG

signal is first selected and then a short integration interval is selected (e.g. 30ms) so that a line is fitted to the envelope [387].

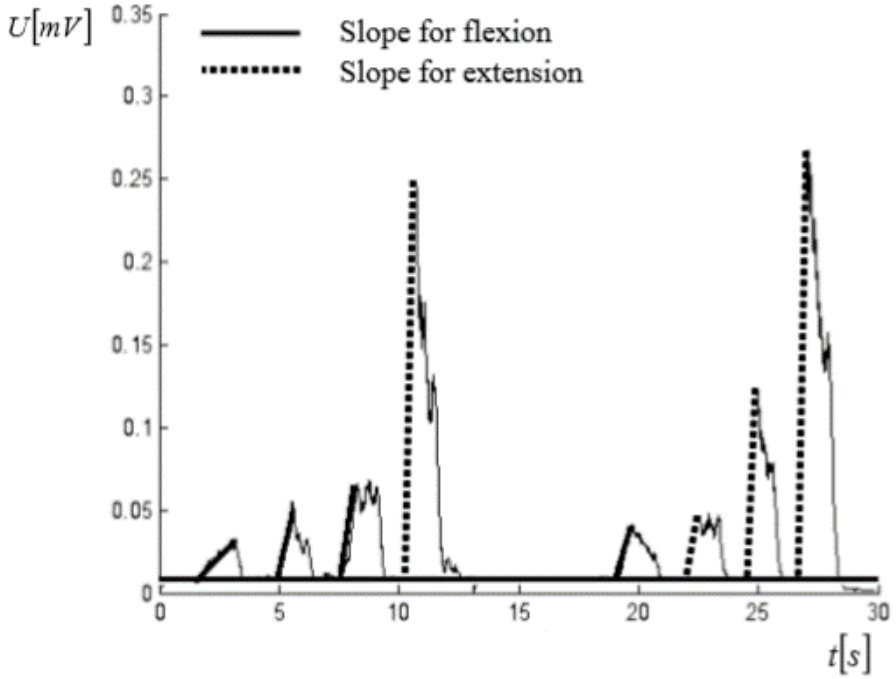


Figure 3.13: Slopes on EMG envelope signal. Extracted from Kutilek et al. (2012) [393]

Kutilek et al. (2012) [393] used the slope of the rectified EMG envelope to determine the velocity of the joint rotation of a robotic arm. The steeper the slope, the higher the muscle contraction rate is [393]. The magnitude of the slope is an indicator of the joint's direction and angular velocity of rotation [393].

EMG amplitude is used as an indirect measure of the force produced during the movement. The EMG amplitude is dependent of the motor unit's number, size and firing rate [365] therefore the higher the amplitude the higher the force. The amplitude of the signal will be dependent of the EMG placement which implies that quality of the signal is dependent of the investigator's placement skills. This can have repercussion in the case of studies comprising multiple participants of different gender and body types making the electrode placement more or less challenging according to the investigators experience [365]. Also, in the case of

multiple session recording, it might be subject to inter-session error as it would require precise and consistent electrode placement [365].

The EMG envelop is the linear representation of the EMG amplitude variation. It provides a representation of the changes of amplitude of the signal. The EMG amplitude being dependent of the muscle motor unit firing rate, size and number, the EMG envelop can be used in the context of the investigation of the motor control strategy or the muscle neuromotor control [364]. In their paper, Bojanic et al. (2011) [364] compared the normalised EMG pattern of children with cerebral palsy to a control groups gait pattern signal of lower limb muscles during walking. As can be observed in Figure 3.14, a child with cerebral palsy will have different muscle recruitment pattern, which reflect a different muscle recruitment strategy.

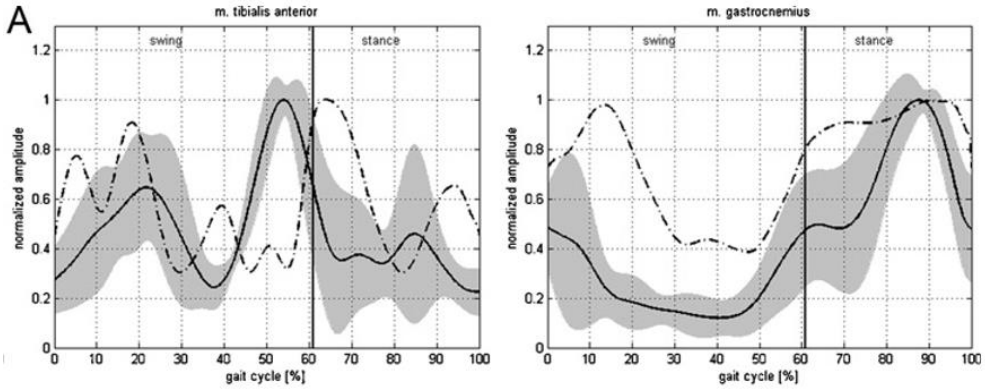


Figure 3.14: Comparison of the EMG envelope of a child with cerebral palsy (dashed curve) with the mean EMG envelope of a control group (continuous black curve) and standard deviation (grey shade) on two lower limb muscles. Left: Tibialis anterior, Right: Gastrocnemius. Extracted from Bojanic et al. (2011) [364].

Muscle fatigue is manifested by a long lasting decrease of the ability to apply force and contract the muscle [394]. Muscle fatigue leads to an increase of recruitment of the muscle motor units and slower conduction velocity [394]. It is noticeable in the EMG time domain by decreased force amplitude over time and in the frequency domain (application of Fast Fourier Transform [353]) by an decrease of high frequencies and an increase of low frequencies [363], [394] (see Figure 3.15).

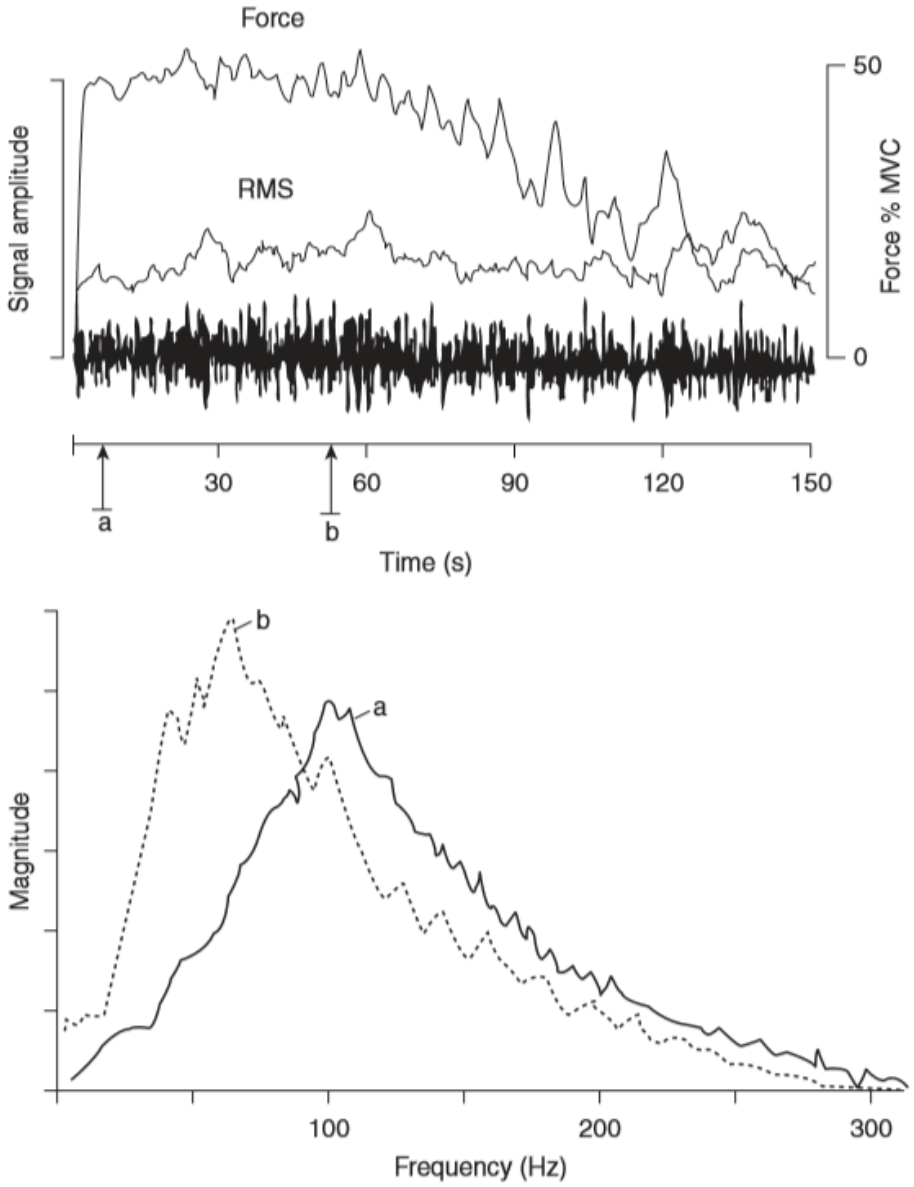


Figure 3.15: Effects of fatigue on the EMG signal. Top: In time domain, decrease of the force during the maximum voluntary contraction (MVC) of the first dorsal interosseus muscle. Bottom: In frequency domain, spectral representation of muscle signal non-fatigued (a) and fatigued (b). Extracted from Burden (2008) [353]

The definition of muscle fatigue threshold is difficult because of the inter-individual differences in muscle characteristics, as they depend on age, gender, and other variable such as caffein consumption or health habits such as smocking [394].

While different methods are available to measure fatigue from the surface EMG signal, Al-Mulla et al. (2011) [394] noted that the there is a transition state between non-fatigued and fatigued muscle and that it should be taken into consideration too.

Measuring muscle variability is a means of monitoring how much the muscle recruitment strategy changes over the multiple repetition of a given movement. It can be an indicator of changes of muscle recruitment strategy and documents intra-individual variability of the neuromotor control.

The shape of the EMG envelope and its changes over time can be used to understand neuromotor control [387]. The intra-individual variability of the EMG envelope can be quantified using the variance ratio (VR). The VR is first presented in this thesis in Chapter 2, Section 2.3.3.1. Variance ratio. The mathematical description of this tool is presented in more detail in Chapter 4 Section 4.5.2. The VR is one of the tools used to quantify the similarities of EMG signals [335], [395], [396]. The VR allows the comparison of several consecutive muscle signals and gives a measure of the variability of the muscle activity for this given repeated task. The smaller value of the VR the smaller the variability is. Jacobson et al. (1995) proposed to place a threshold of VR=0.4 as a repeatability limit when used on able-bodied subjects [397]. This implies that a VR $\leq$0.4 is an indication of small to normal variability.

3.2.1.6. EMG cross-talk

The phenomenon of cross-talk occurs when the signal detected by the surface EMG electrode is not generated exclusively by the targeted muscle but is contaminated by the electrical activity of a nearby muscle [350], [398]–[400]. Cross-talk can be a significant source of error during the analysis of EMG signals and lead to misinterpretation of the activity timing of the target muscle [400]. It occurs during surface EMG recording when the sensor's detection point is at a distance allowing the detection of the common order of magnitude from different muscles [398]. When the potential disappears when reaching the tendons, it generates far-field signals that are recorded by the sensors with the targeted muscles data [400]. Cross-talk is affected by factors such as the subcutaneous fat layer and the inter-electrode distance [400]. Farina et al. (2002) [401] concluded that cross-talk originates from non-propagated electrical potential coming from muscles nearby the target muscle. They also noticed that the signal characteristics (spectral frequency [402], amplitude [400]) of the targeted muscle is different from the signal characteristics of the cross-talk

signal. They concluded as well that the effect of cross-talk can't be reduced simply by high-pass filtering the EMG signal [398], [400].

3.2.1.7. Other sources of noise

The noise observed at the output of the instrumentation amplifier is the result of the combination of the noise from the electrode-skin contact and the current and voltage noises present at the input of the amplifier [403].

Motion artefacts

Motion artefacts are the results of the temporary loss of contact between the EMG electrode and the user's skin while moving [387]. A reduced quality of contact is responsible for the presence of low frequency noise. As the frequencies of motion-related noise is usually comprised between 1 and 10 Hz, it can be eliminated by high-pass filtering [350], [399].

Power-line interference

Power-line interference is the noise originating from the radiations of surrounding power sources. It is particularly noticeable at the frequency of 60 or 50 Hz. One way to eliminate this noise is notch-filtering [350], [399]. The notch filter acts as a noise canceller of the specified frequency.

ECG Artefacts

In case of the collection of EMG signal on the shoulder area, it is possible that the electrical activity of the heart interferes with the surface EMG signal. The ECG artefact's frequencies overlap the EMG signals, in particular, on the trunk muscles. To eliminate ECG artefacts, a 100 Hz high-pass filter is efficient [399]. In his paper, Allison (2003) used a high-pass filter of 80 Hz [381].

3.2.1.8. EMG Signal filtering

Internal noise originates from the intrinsic physiological, chemical and anatomical properties of the body [399]. The fact that there is a certain amount of muscle fibre, where they are located, their depth and the amount of tissue present between the targeted muscle fibres and the electrode have an influence on the EMG signal collected. In fact, when the layer of tissues between the EMG electrode and the muscle fibres is larger, the amplitude of the EMG signal is smaller [399], [404] . Consequently, for the recording of the same muscle and the same type of exercise, people with a thicker layer of subcutaneous fat will display EMG signals of smaller amplitude. One way to reduce some of the effect of internal noise is the use of high-pass filters [399].

The amplitude of EMG signal is quasi-random. While during a repeated movement the mean amplitude can remain the same the signal appears random due to the firing rate of the muscle units [405].

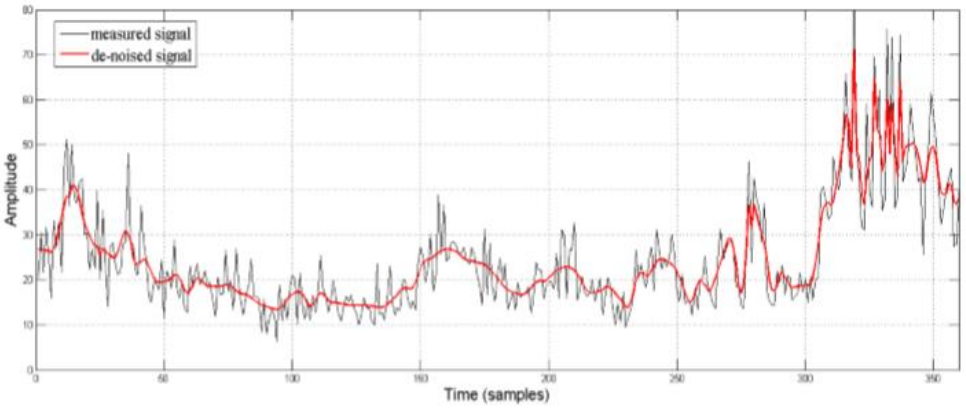


Figure 3.16: Bicep muscle EMG rectified signal during contraction (signal in black) and its filtered version (signal in red). Extracted from Gradolewski et al. (2015)[406]

Its signal is unstable in the frequency spectrum comprised between 0 and 20 Hz. The reason for these instabilities is the muscle's motor unit's fire rates. These unstable frequencies can be removed using a 20 Hz high-pass filter [350], [399]. Using this high pass filter value contributes to eliminate the motion artefact at the same time (see section 3.2.1.7)

3.2.1.9. EMG smoothing

EMG smoothing is a digital process that attenuates the randomness of the signal variation of amplitude linked to noise and the nature of EMG signal [369], [407], [408]. The EMG signal's overall shape can be a good representation of the signal when its magnitude is studied and compared through statistical analysis and ease the extraction of features of interest in applications such as bionic limbs and other [407]–[410]. It is possible to smooth the EMG signal using low-pass filtering [411]. The Root-Mean-Square (RMS) of the EMG was found to be a good estimator of the EMG signal amplitude and provide a smoother signal appearance to the signal [412]. De Luca et al. (2010) [413] recommends low-pass frequency comprised between the values of 400 to 450 Hz and used 450 Hz in their paper. Ghalyan et al. 2020 [409] used a Gaussian filter which has similar property to the low pass filter. The Gaussian filter keeps the high frequency components while reducing the distortions of the signal [409].

3.3. Summary

In this chapter, the muscle anatomy, and the origin of the electromyographic signal were first presented to understand the underlying physiological mechanism contributing to the generation of the EMG signal.

The EMG signal, its characteristics, instrumentation, processing, and interpretations were then presented, and the controversies highlighted.

The envelope of the EMG signal is the reflection of the underlying motor unit's activity and thus, is a means to retrieve indications on motor control strategies.

This technique enables researchers to study the motor control involved in movements like gait. Through this understanding, the recovery of movement can be better supported through rehabilitation training as it can informs on the variability of the motor control strategy during overground or treadmill walking, be it on a fixed pace treadmill or on a self-paced treadmill.

Chapter 4

4. Variability of muscle activity during three straight walking situations (overground and treadmill on fixed pace and self-paced) in healthy adults

This chapter will present the first study of this thesis. The aim was to collect and compare the muscle activity characteristics, using the techniques described in chapter 3, during overground and treadmill (fixed and self-paced) walking, to test the hypothesis that self-paced treadmill walking is a closer analogue to overground walking than traditional, fixed-pace treadmill, and, therefore, provides a better training environment for the recovery of walking function in people with impairments resulting from stroke. The study also served as a pilot to test the data collection and analysis processes in preparation for the subsequent study which recruited people with gait impaired by the effects of a stroke. The methods and findings will be presented and discussed in the context of existing literature.

4.1. Aim and objectives

The aim of this study is to test whether the use of a self-paced treadmill provides a closer analogue to overground walking in terms of motor control, than a traditional fixed-pace treadmill, by measuring the muscular activity of the lower limbs.

The objectives for this preliminary study were:

1. Record and process the EMG signals from selected lower limb muscles over multiple gait cycles in healthy adults walking overground, on a treadmill that is self-pacing and on a treadmill with a fixed pace.

2. Record and process the lower limb joint kinematics of healthy adults during multiple gait cycles walking overground, on a treadmill that is self-pacing and on a treadmill with a fixed pace.

3. Statistically compare the muscular and the kinematic signals across the three different walking conditions.

4. Statistically test the hypothesis that walking on a self-paced treadmill is a closer analogue to overground walking than fixed pace treadmill walking in healthy adults.

4.2. Ethics and participants

The participants were recruited from the staff and student population of the University of Strathclyde. The age ranged from 19 to 56 years old, weighed between 59.5 kg and 118.0 kg and comprised six male and five female participants (see Table 4.1 for details). Prior to participation, each participant was checked by the researcher against the inclusion and exclusion criteria listed as follows:

Exclusion criteria:

- No known musculoskeletal, neurological, or sensory deficit.
- No history of motion sickness,
- Not known to be pregnant,
- Under the age of 18,
- A skin condition that would prevent the application of surface EMG electrode on the skin.

The inclusion criteria were:

- Able bodied,
- Unimpaired sight, with or without visual aid,
- Weight under 135 kg,
- Able to walk independently without use of aids at a self-determined pace for approximately 10 minutes.

All participants read an information sheet before being invited to sign a consent form. The study was approved by the ethics committee of the Biomedical Engineering Department of the University of Strathclyde (reference DEC/BioMed/2016/79, see consent form in Annex D).

Participants number	Gender	Age	Height (m)	Weight (kg)
1	M	28	1.69	65.7
2	F	24	1.61	63.8
3	F	19	1.69	71.2
4	M	56	1.71	63.2
5	M	28	1.85	66.1
6	F	24	1.66	58.8
7	M	26	1.76	68.0
8	M	30	1.68	78.0
9	M	25	1.85	118.0
10	F	19	1.72	59.5
11	M	30	1.85	83.4
Mean		28.1	1.73	72.3

Table 4.1: Participants information

4.3. Design of the study

This was an observational study comparing the muscle activity of the lower limb muscles during different walking conditions (overground, self-paced treadmill and fixed-pace treadmill) of able-bodied adults.

4.4. Material and equipment

4.4.1. Equipment

The electrical activity of the muscles was collected using Wireless EMG surface electrodes (Delsys Trigno, Boston, USA). The kinematic data were recorded via VICON Nexus (Vicon, Oxford, UK) in two different laboratories. In laboratory one, the overground walking data were collected. The motion capture system in this laboratory comprised 12 Vicon cameras T-Series motion capture system (Vicon MX Giganet, Oxford Metrics Ltd., UK) (worst static precision 25 µm; max dynamic error 0.3863mm [414]) also used in numerous other studies [415]–[420]. Two type of T-Series Vicon cameras were used. The T160 cameras which have a resolution of 16 megapixel (4704 x 3456) with 120 frames per seconds, and T40 cameras which have a resolution of 4 megapixel (2336 x 1728) with 515 frames per seconds). In the second laboratory, the treadmill walks were collected. The treadmill used was part of the Computer-Assisted Rehabilitation Environment (CAREN) system (Motekforce Link, Amsterdam, the Netherlands) installed in the Biomedical Engineering Department, the

embedded treadmill is composed of a dual belts (forward speed up to 7 m/s, back ward speed up to -3 m/s and acceleration up to 15 m/s²) with two integrated force plates. The treadmill had self-pacing capacity and was embedded on the CAREN motion base allowing 6 degrees of freedom. The motion capture system comprised 12 infra-red Vicon Bonita cameras (Vicon Motion Systems Ltd., Oxford, UK) (max single dynamic error 1.68mm [421]) also used in numerous other studies [422]–[424]. The Vicon Bonita cameras have a resolution of 1 megapixel (1024 x 1024) with 250 frames per seconds. The treadmill walking experience was enhanced using virtual reality environment (VE) displayed on a 180° screen (see Figure 4.1). The visual VE display was projected on the screen and controlled via Motek's D-Flow software. The CAREN system has been used in several gait study research protocols [425]–[431].

Figure 4.1: Motek CAREN plateform

4.4.2. Data collection process

4.4.2.1. Anthropometric measurements and marker/sensor placement

The anthropometric measurements of each participant were recorded first. They included the participant's height, weight, leg length, knee width, ankle width and pelvis width. These parameters enabled the creation of a computer model of each participant and the calculation of joint angle. The model used was the well-established Plug-In-Gait (PIG) model [109], [415], [422], [432], [433]. The PIG model is a biomechanical body model that requires the accurate placement of markers on body landmarks [419], [434]. For an accurate application, the PIG model marker's placement is determined by the palpation of the anatomical landmarks [434]. Training and experience are needed for good inter-assessor reliability [434]. Following the anthropometric measurements, the 16 retro-reflective markers were attached according to the instructions for the Plug-In-Gait model (see Figure 4.2 and Figure 4.3). The PIG kinematic data were recorded at a 100Hz frequency via VICON Nexus.

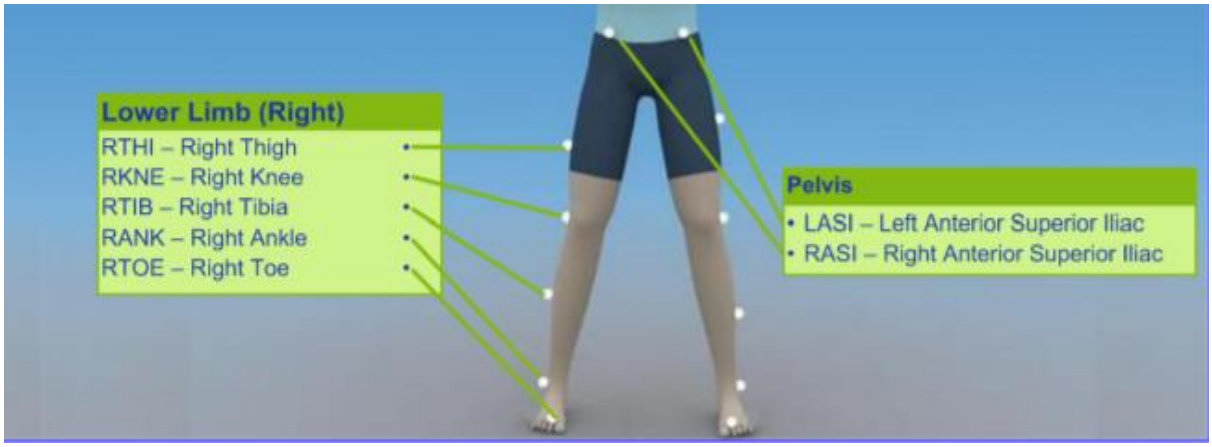


Figure 4.2: Lower limb Plug-In-Gait model markers placement frontal view (extracted from VICON online documentation) [435]

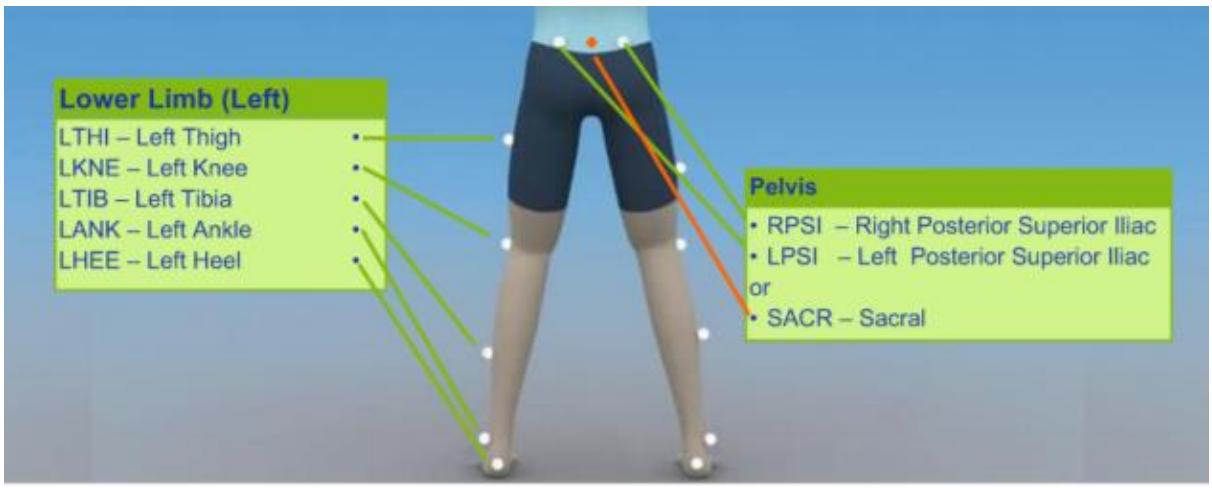


Figure 4.3: Lower limb Plug-In-Gait model markers placement posterior view (extracted from VICON online documentation) [435]

The EMG electrodes were attached to the legs after making sure that the area was free of hair, which required shaving in some cases, and cleansed with an alcohol pad. Wireless EMG surface electrodes (Delsys Trigno, Boston, USA) were applied on the hamstrings (biceps femori), quadriceps (vastus lateralis), gastrocnemius (lateral gastrocnemius), tibialis anterior, and soleus on both legs of each participant (see *Figure 4.4*). The surface EMG placement was carried out with reference to the "atlas for electrode placement" from Criswell and Cram (2011) [343], which adheres to the SENIAM approved method [347] for electrode placement. The EMG signal were recorded at a frequency of 2kHz. The digital processing of the EMG and kinematic signals are discussed later (section 4.4.4).

4.4.3. The movement task including speed variation

Each participant was asked to walk at three different, self-selected, speeds during each of the three walk conditions. One corresponded to their usual comfortable gait speed, then a fast gait speed, described as the speed they would adopt when running late to catch a bus and finally a slow walk speed, referred to as a slow stroll around a park. Each of these were performed overground over approximately 10 meters straight on a flat, well lit, surface free of obstacles, then on the treadmill at fixed speed and finally on self-paced mode. For each participant each of the selected speed completed four times to collect sufficient data to create a statistical mean and variation. The overground data were recorded from gait initiation. Treadmill data were recorded from gait initiation and from approximately 20 to 30 subsequent steps after gait initiation.

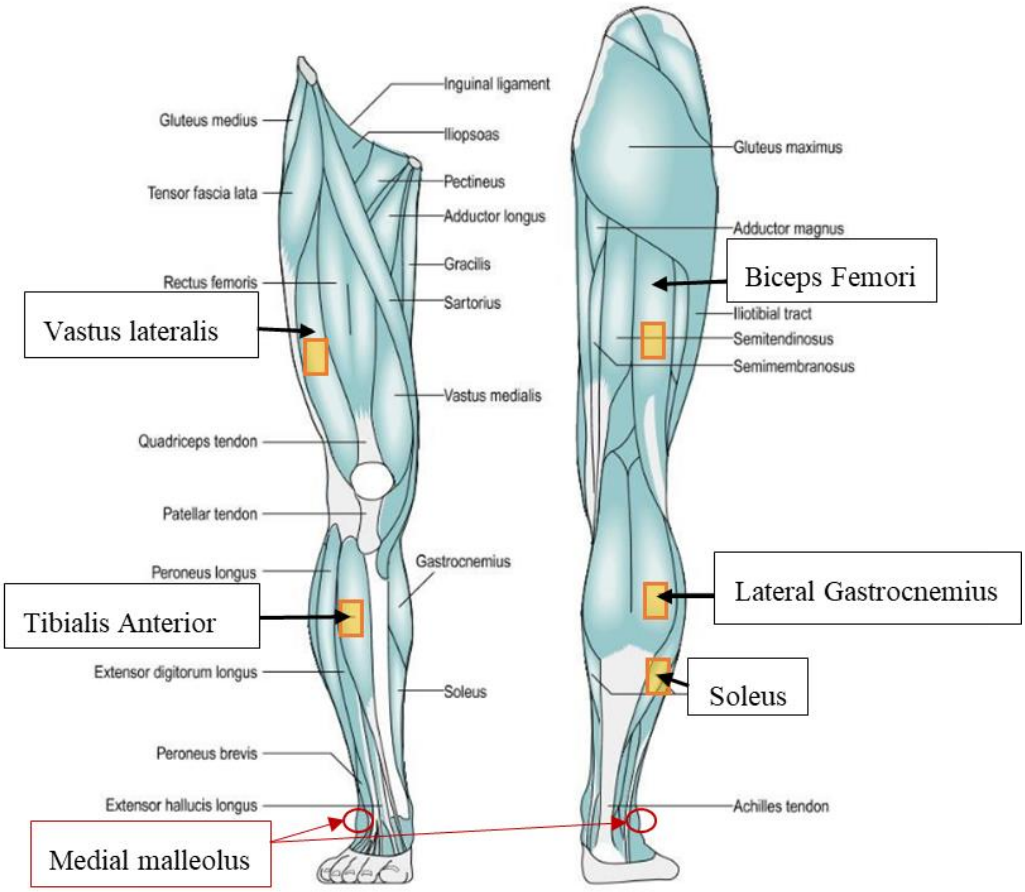


Figure 4.4: Muscles of interest and their EMG Electrodes placement (orange rectangles). Adapted from Criswell and Cram (2011) [436]

The muscles of interest were chosen for their characteristic roles in the actuation of the knee and ankle joint (as presented in Table 4.2) and for their ease of access when using surface EMG sensors.

Muscle	**Function**	**References**
Biceps femori	Knee flexion, hip medial rotation, and extension (medial or lateral)	[437]–[442]
Vastus lateralis	Knee muscle extension	[437], [440], [442]–[444]
Gastrocnemius	Knee flexion, foot plantar flexion	[437], [440], [442]
Tibialis anterior	Foot dorsiflexion	[437], [439]–[442]
Soleus	Foot flexion and inversion	[437]–[442]

Table 4.2: Targeted muscles and their function [343]

4.4.4. EMG signal processing

Once normalised to their maximum contraction value, the signal was then centred around 0 by subtracting its median value to the signal, leaving as many values over zero than below zero. The signal was then full wave rectified leaving the values of the processed signal comprised between 0 and 50.

The signal from surface EMG is inherently noisy and in order to facilitate the analysis of its pattern a means of smoothing is useful to reduce its randomness [369], [407], [408]. The smoothing of the EMG signal is usually designed by filtering the signal (i.e. Butterworth [359] or Kalman filter [369]). However, the use of low-pass or band-pass filtering is a source of delay which can affect the overall shape of the signal [445], [446]. To avoid the effects of data delay occurring in case low pass filtering of the EMG signal, the envelope of was designed as the Root Mean Square (RMS) of the EMG signal. Clancy and Hogan (1999) [412] found the Root-Mean-Square (RMS) of the EMG to be a good estimator of the EMG signal amplitude while providing a smoother signal appearance to the signal. The RMS has been used in several studies investigating feature extraction from surface EMG [372]–[375]. It was, therefore, used in this work.

The raw and normalised EMG signals are usually represented as a symmetrical signal which symmetry axis is the zero X axis. As the EMG signal obtained were not all centred around zero, the signal was centred by subtracting the median of the value of the EMG signal in order to uniformize the representation without modifying the shape and amplitude of the signal.

4.5. Data analysis

4.5.1. Placing the EMG activity into context of gait cycle

To compare several EMG signals to one another, the cycle-to-cycle reference used was the knee joint angle curve from the sagittal plane. The knee joint has the advantage of presenting a characteristic pattern that is easy to interpret and match to the walk phases. The EMG signals were normalised to the maximal recorded during each trial. To select the gait cycles the EMG signal was subdivided using the knee angle data as the reference measure, for the start and the end of each gait cycle [447], [448]. This separation was defined using the minima of the knee joint sagittal angles (see Figure 4.5).

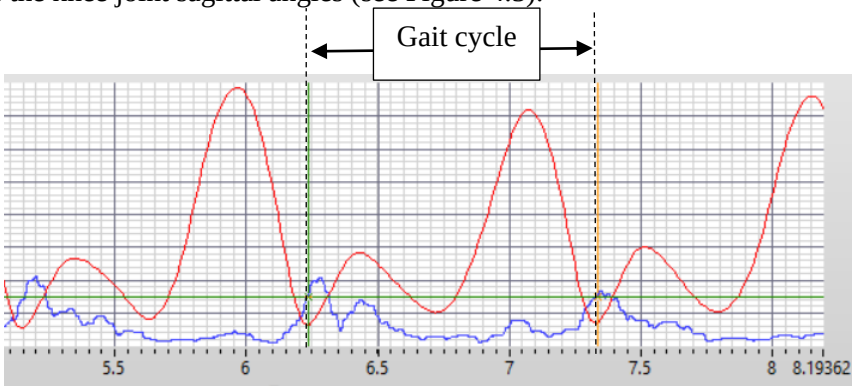


Figure 4.5: Knee angle (red and EMG envelope (blue) over time (in seconds)

Once a cycle was selected the portion of EMG signal was re-sampled into a 2000-points signal using LabVIEW as will be presented here after.

Then each cycle's time base was adapted so that each signal was expressed as a percentage of the gait cycle (0 to 100%). This method is used in the literature [336], [395] in order to normalise the stride time, as the number of frames varies from stride to stride, and present the data of each EMG corresponding to a gait stride, over a percentage of the gait cycle comprised between 0 and 100%.

Let us take a portion of an EMG envelope (Figure 4.6), corresponding to the muscle activity over one gait cycle.

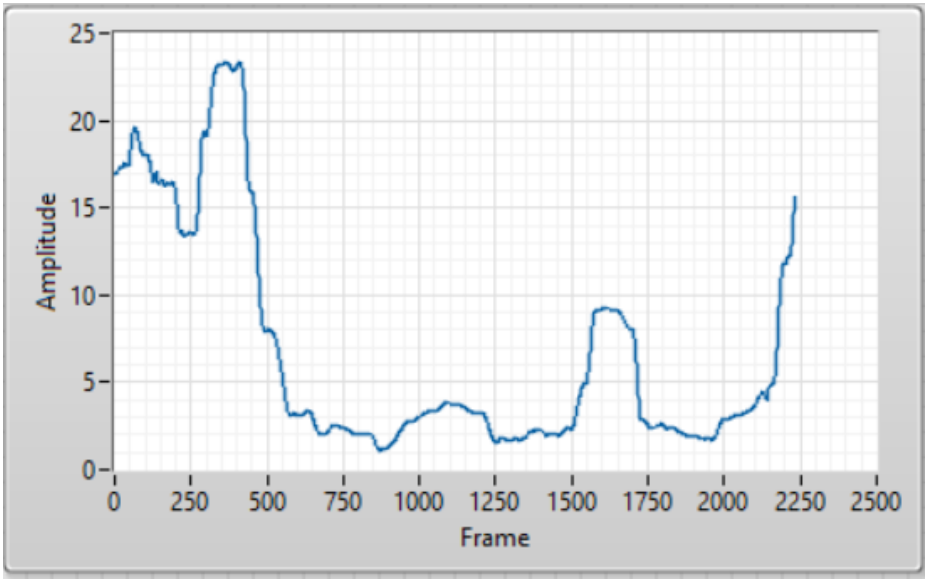


Figure 4.6: EMG envelope before resampling

The steps of this resizing operation are represented in the LabVIEW code (block diagram) in (Figure 4.7)

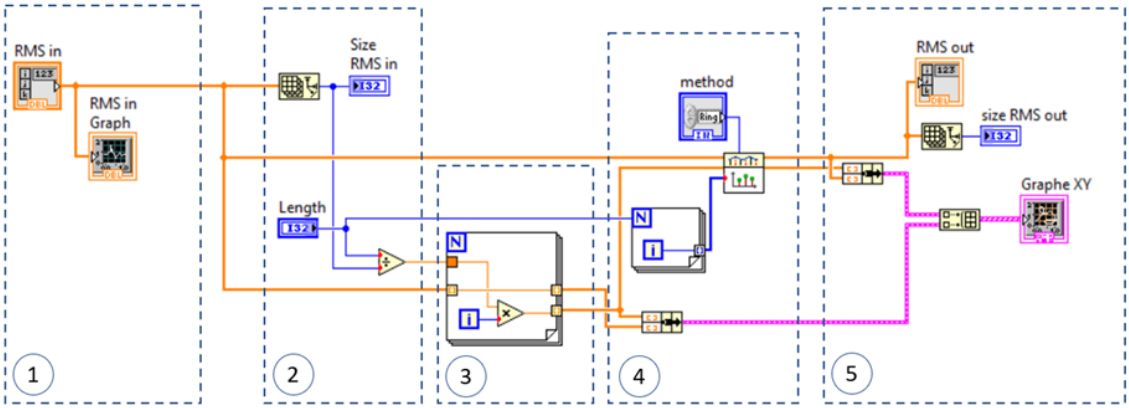


Figure 4.7: LabVIEW block diagram for the EMG envelope resampling

1. The EMG envelope signal was acquired at a frequency of 2000 Hz. The top left block named “RMS in” contains the EMG envelope data collected at a 2000Hz frequency. The block called “RMS in Graph” is the graphical representation of this signal as the signal amplitude as a function of the number of frames, in this case the size is of 2234 frames (see Figure 4.7).
2. The scale is changed to a measurement step going for 0 to 2000 no matter the step duration (see Figure 4.8). The measurement step is built by dividing the desired abscissa length by the number of frames of the entry envelope “RMS in”. “Length” is the number of frames to which we want to normalise each gait cycles, in our case

Length=2000 frames. Length is divided by the “Size RMS in” (top of section 2), which corresponds to the entry EMG envelope’s size (or number of frames). The length that we want to resize every gait cycle data is of 2000 frames. The normalised length is divided by the size of the EMG envelope “RMS in”.

3. Once we have measurement step, the next action corresponds to the construction of the new abscissa associated to the EMG Envelope. It corresponds to the construction of the new time unit associated to the array of the EMG envelope.
4. For each value of the new time unit, we search the EMG envelope amplitude which is associated to each time unit points by using the initial values and the spline interpolation function.
5. The output signal is then the EMG envelope “RMS out” with an abscissa value going from 0 to 2000 frames (see Figure 4.8).

The resulting signal is the EMG envelope (RMS out) sampled over 2000 frames.

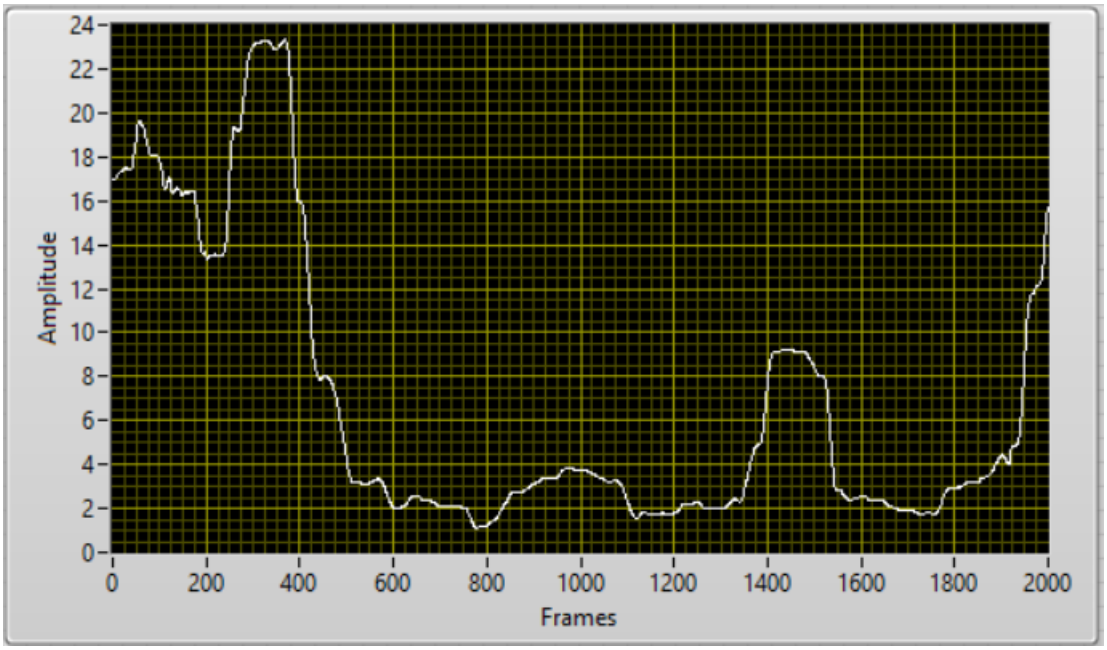


Figure 4.8: EMG envelope resampled to 2000 frames

To change the time base from seconds to a percentage of the gait cycle, each frame must correspond to a percentage of the gait cycle. To do so, the succession of operations used in this study are represented in the block diagram of Figure 4.9.

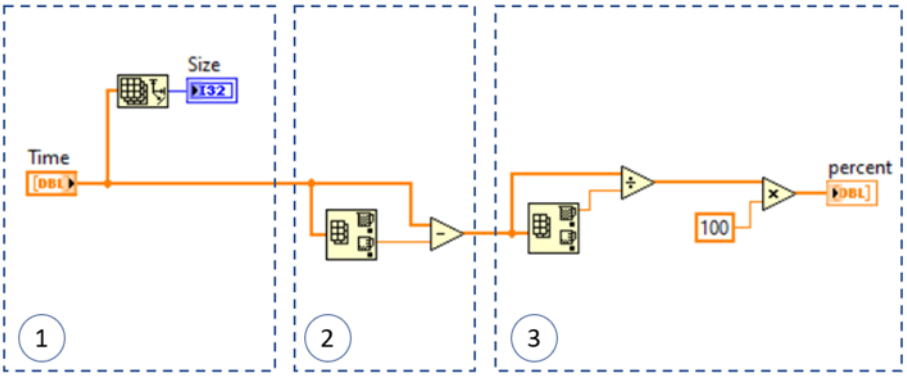


Figure 4.9: Block diagram of the conversion from frame number to percentage of gait cycle

1. The abscissa values of the EMG signal are collected over one stride. In the block diagram it is represented by the block called “Time”.
2. Then, the first element of the temporal series is put to zero by subtracting all the values of the “Time” array by the smallest value of this array.
3. Finally, the values are changed into percentages of duration of the gait cycle. It is done by dividing each element of the array by its maximal value and multiply them by 100.

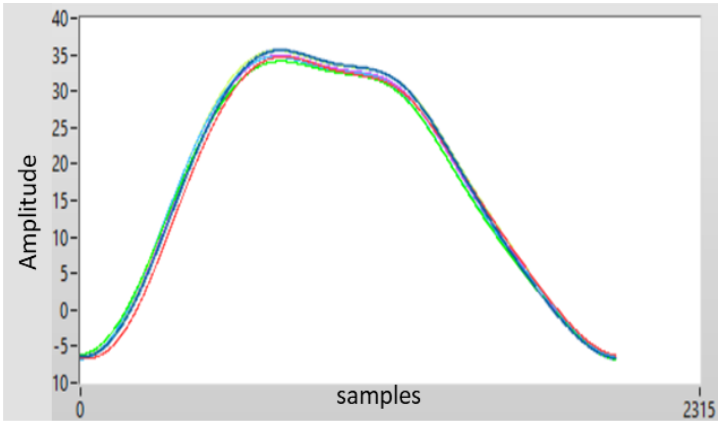
4.5.2. Muscle activation pattern

Objective 3 of this study was to quantify and characterise the muscle activity during the different walking situations (overground, fixed pace and self-pace treadmill). A parameter of key interest in understanding the control of gait is the cycle-to-cycle variability, see section 2.3.3 for further discussion. During overground and self-paced treadmill walking (compared to fixed pace treadmill walking) the control of speed is left to the individual who has the possibility to change walking cadence, step length and consequently walking speed at will. To understand whether this has an impact on movement control the EMG signal variability was analysed using a mathematical tool called the variance ratio (VR) (see section 2.3.3.1. Variance ratio, for more detail). This tool compares consecutive EMG envelopes of one participant’s given muscle and quantifies the cycle-to-cycle variability of the muscle activity. The EMG envelope was defined as the Root Mean Square (RMS) of the EMG signal (c.f. Section 4.4.4). The VR is the sum of the square of the deviation from the mean EMG envelope over a single gait cycle divided by the sum of the square of the deviation from the mean EMG envelope of all cycles. Its mathematical expression is presented in equation (4.1). A VR equal to 0 means the cycles are identical, the closer the VR comes to 1 the greater inter-cycle difference (see Figure 4.10).

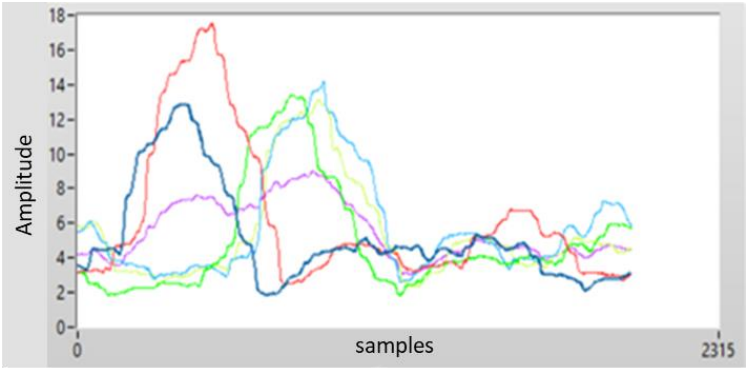
$$VR = \frac{\sum_{i=1}^{k}\sum_{j=1}^{n}(X_{ij} - \bar{X}_{\iota})^2/k(n-1)}{\sum_{i=1}^{k}\sum_{j=1}^{n}(X_{ij} - \bar{X})^2/(kn-1)}$$

(4.1)

Xij is the value of the jth EMG envelope element at time i, $\bar{X}$ is the mean of the average EMG envelope signal, $\bar{X}_{\iota}$ is the average of the EMG envelope values over j cycles at time i, k is the number of points in a cycle and n is the number of cycles.



A



B

Figure 4.10: VR over 6 cycles VR = 0.0002 (A) of Hip joint angle VR = 0.925 (B) of atypical leg muscle, each coloured line corresponds to the respective signal's envelopes during a cycle of walk of one participant.

Hershler and Milner 1978 [335] found that the VR tends to change values over the first gait cycles and then stabilizes its value by the 5th cycle onward (see Figure 4.11 and Figure 4.12) [335]. The number 1 to 3 on the graph plot corresponds to three different walking speeds of Hershler and Milner's participants.

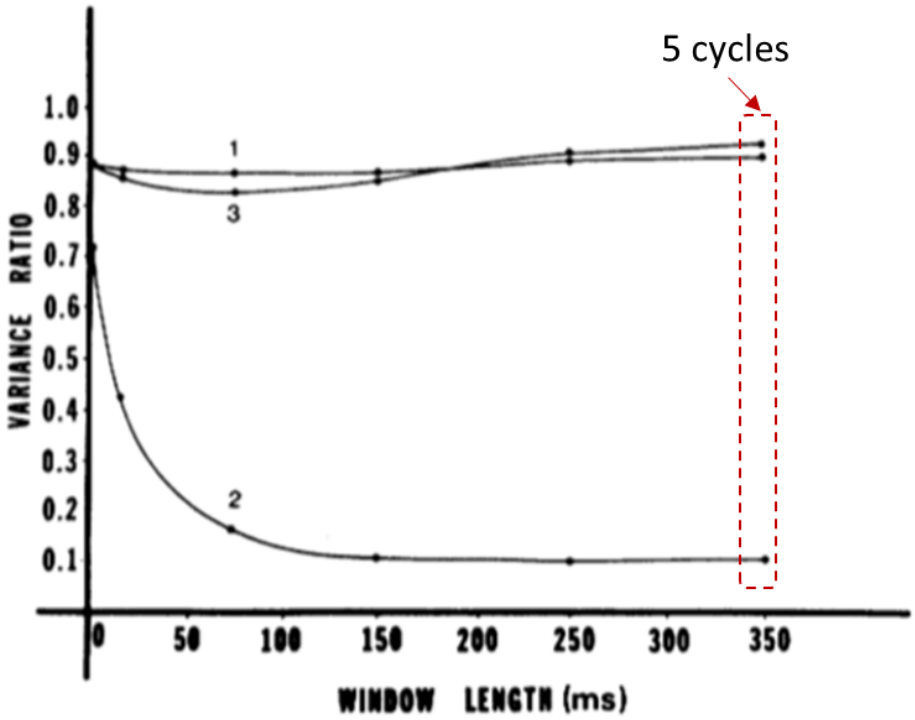


Figure 4.11: Repeatability curves (VR as a function of time in ms) over 5 cycles for three different walking speeds. Speed 1= 63.8 cm/s. Speed 2 = 90.3 cm/s. Speed 3 = 96.8 cm/s. Adapted from [335].

Therefore, it was decided, in this study, to set the amount of cycles over which the VR is calculated to a minimum of 6. Therefore, unless further mentioned, each VR value was calculated across 6 cycles for the muscles analysed. To confirm this the VR of 6 muscles was examined across at least 9 cycles, see Figure 4.12. The number of cycles used to calculate the VR is not always reported in the literature [336]–[338] and it could be an issue for the interpretation of the data since the VR is dependent of the number of iterations of the calculation as described in [335] previously mentioned.

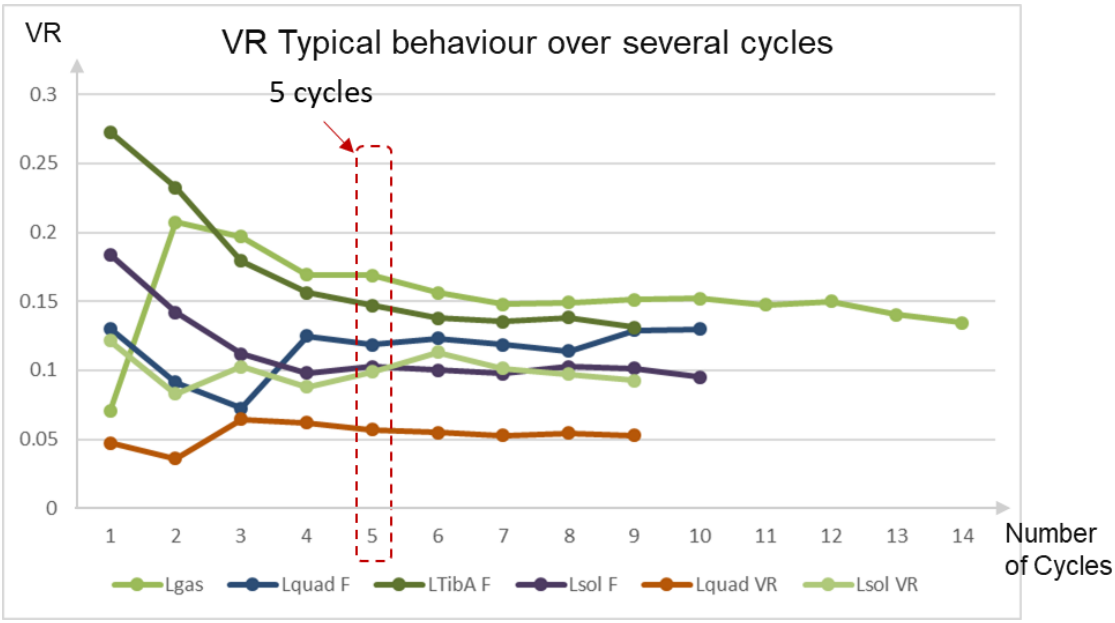


Figure 4.12: Typical evolution of the VR of different muscles over the number of cycles observed in current study data. Y-axis: VR AND X-axis: number of cycles.

The choice of 6 cycles for the analysis was influenced by the desire to select a number of iterations that was small enough to allow testing with future participants with stroke who may not have been able to provide many cycles while within the range where the VR was close to its stable value.

Another measure of variability, such as the coefficient of variation could be used, to add to the variability measure. The coefficient of variation (COV) has been used in the literature to measure the variability of the gait cycle duration [449]–[452], stance and/or swing time [449], [452], single legged or double support time or duration [449], [452] and walking speed and/or cadence [452]–[454]. However, the COV parameter will not be used in this thesis since its focus is the analysis of the muscle activity variability and the COV has, only been used, to date, for kinematics analysis. The COV was, therefore, not used in this thesis.

4.5.3. Statistical Analysis

The data was tested for normality using the Anderson-Darling normality test and the data distribution was found normal. The one-way Analysis of Variance (ANOVA) was used in this study to test the hypotheses that the variability of SP treadmill walking variability is closer to the overground walking variability in comparison to FP treadmill walking at a given walking speed. The repeated ANOVA was used to test the hypothesis that the variability of FP treadmill walking is different to SP treadmill walking and overground walking variability across the three walking speeds. The alpha level was set at 0.05. A p-value ≤ 0.05 is considered statistically significant.

4.6. Results

A minimum of 3 trials were recorded from all eleven participants in the three different conditions (overground, FP treadmill and SP treadmill) at the three different speeds (slow, comfortable, and fast) giving a total of 10764 gait cycles for 10 muscles (5 on each sides) and 6 joint angles (three on each side) per participants. The motion capture cameras' view field from the overground set up limited the extent of the kinematic data collected. Because of the different stride length of some participant the minimum of three trials was not sufficient to capture the necessary minimum of 6 complete gait cycles per side. More trials would have been necessary to ensure the capture of enough full gait cycles on both leg sides. Table 4.3 to Table 4.13 provide a summary of the number of gait cycles recorded for each participant's muscles and joints. Table 4.14 provides a summary of the walking speeds of the different participants in the three walking conditions.

N°	Participant 1				Participant 2				Participant 3			
	Speed (m/s)	Nb of cycles			Speed (m/s)	Nb of cycles			Speed (m/s)	Nb of cycles		
	Slow	Muscle	Kinematics		Slow	Muscle	Kinematics		Slow	Muscle	Kinematics	
FP	0.9	L Hams 14			1	L Hams 11			1	L Hams 14		
		L Quad 15				L Quad 10				L Quad 15		
		L Gas 15	L Hip	12		L Gas 10	L Hip	10		L Gas 15	L Hip	
		L Tib 14	L Knee	12		L Tib 10	L Knee	10		L Tib 15	L Knee	
		L Sol 15	L Ankle	12		L Sol 10	L Ankle	10		L Sol 13	L Ankle	
		R Hams 13	R Hip	12		R Hams 10	R Hip	10		R Hams 15	R Hip	12
		R Quad 14	R Knee	12		R Quad 9	R Knee	10		R Quad 15	R Knee	10
		R Gas 13	R Ankle	12		R Gas 10	R Ankle	9		R Gas 14	R Ankle	11
		R Tib 14				R Tib 10				R Tib 15		
		R Sol 14				R Sol 10				R Sol 13		
	Comfortable	Muscle	Kinematics		Comfortable	Muscle	Kinematics		Comfortable	Muscle	Kinematics	
	1.15	L Hams 8			1.2	L Hams 9			1.35	L Hams 10		
		L Quad 8				L Quad 9				L Quad 10		
		L Gas 8	L Hip	7		L Gas 9	L Hip	10		L Gas 10	L Hip	10
		L Tib 8	L Knee	8		L Tib 9	L Knee	9		L Tib 10	L Knee	10
		L Sol 8	L Ankle	7		L Sol 9	L Ankle	10		L Sol 10	L Ankle	9
		R Hams 7	R Hip	8		R Hams 9	R Hip	10		R Hams 10	R Hip	10
		R Quad 7	R Knee	7		R Quad 10	R Knee	10		R Quad 10	R Knee	10
		R Gas 7	R Ankle	8		R Gas 10	R Ankle	9		R Gas 10	R Ankle	10
		R Tib 7				R Tib 9				R Tib 10		
		R Sol 7				R Sol 10				R Sol 10		
	Fast	Muscle	Kinematics		Fast	Muscle	Kinematics		Fast	Muscle	Kinematics	
	1.6	L Hams 10			1.75	L Hams 9			1.75	L Hams 11		
		L Quad 10				L Quad 9				L Quad 11		
		L Gas 10	L Hip	11		L Gas 9	L Hip	8		L Gas 11	L Hip	11
		L Tib 10	L Knee	10		L Tib 9	L Knee	9		L Tib 10	L Knee	11
		L Sol 10	L Ankle	11		L Sol 9	L Ankle	8		L Sol 11	L Ankle	12
		R Hams 10	R Hip	10		R Hams 8	R Hip	9		R Hams 12	R Hip	11
		R Quad 11	R Knee	11		R Quad 8	R Knee	8		R Quad 11	R Knee	11
		R Gas 11	R Ankle	10		R Gas 8	R Ankle	9		R Gas 13	R Ankle	11
		R Tib 11				R Tib 8				R Tib 12		
		R Sol 10				R Sol 8				R Sol 12		

Table 4.3: Number of cycles collected during FP treadmill walking for participants 1 to 3

Participant 4					Participant 5					Participant 6				
Speed (m/s)	Nb of cycles				Speed (m/s)	Nb of cycles				Speed (m/s)	Nb of cycles			
Slow	Muscle		Kinematics		Slow	Muscle		Kinematics		Slow	Muscle		Kinematics	
1.1	L Hams	10			0.95	L Hams	11			0.85	L Hams			
	L Quad	10				L Quad	10				L Quad			
	L Gas	10	L Hip	10		L Gas	10	L Hip	9		L Gas		L Hip	
	L Tib	10	L Knee	10		L Tib	10	L Knee	10		L Tib		L Knee	
	L Sol	10	L Ankle	10		L Sol	10	L Ankle	9		L Sol		L Ankle	
	R Hams	10	R Hip	10		R Hams	9	R Hip	10		R Hams		R Hip	
	R Quad	10	R Knee	10		R Quad	9	R Knee	9		R Quad		R Knee	
	R Gas	10	R Ankle	10		R Gas	9	R Ankle	10		R Gas		R Ankle	
	R Tib	10				R Tib	9				R Tib			
	R Sol	10				R Sol	9				R Sol			
Comfortable	Muscle		Kinematics		Comfortable	Muscle		Kinematics		Comfortable	Muscle		Kinematics	
1.15	L Hams	11			1.25	L Hams	10			1.30	L Hams	9		
	L Quad	10				L Quad	10				L Quad	9		
	L Gas	11	L Hip	10		L Gas	10	L Hip	10		L Gas	9	L Hip	10
	L Tib	11	L Knee	11		L Tib	10	L Knee	10		L Tib	9	L Knee	9
	L Sol	11	L Ankle	10		L Sol	10	L Ankle	11		L Sol	9	L Ankle	9
	R Hams	10	R Hip	10		R Hams	10	R Hip	10		R Hams	10	R Hip	9
	R Quad	10	R Knee	10		R Quad	10	R Knee	10		R Quad	10	R Knee	10
	R Gas	10	R Ankle	9		R Gas	10	R Ankle	10		R Gas	10	R Ankle	8
	R Tib	10				R Tib	10				R Tib	10		
	R Sol	10				R Sol	9				R Sol	10		
Fast	Muscle		Kinematics		Fast	Muscle		Kinematics		Fast	Muscle		Kinematics	
1.75	L Hams				1.70	L Hams	11			1.80	L Hams	11		
	L Quad					L Quad	11				L Quad	11		
	L Gas		L Hip			L Gas	11	L Hip	5		L Gas	11	L Hip	12
	L Tib		L Knee			L Tib	11	L Knee	6		L Tib	11	L Knee	10
	L Sol		L Ankle			L Sol	11	L Ankle	5		L Sol	11	L Ankle	11
	R Hams		R Hip			R Hams	11	R Hip	7		R Hams	11	R Hip	11
	R Quad		R Knee			R Quad	11	R Knee	11		R Quad	11	R Knee	11
	R Gas		R Ankle			R Gas	11	R Ankle	10		R Gas	11	R Ankle	11
	R Tib					R Tib	10				R Tib	11		
	R Sol					R Sol	11				R Sol			

Table 4.4:Number of cycles collected during FP treadmill walking for participants 4 to 6

Participant 7					Participant 8					Participant 9				
Speed (m/s)	Nb of cycles				Speed (m/s)	Nb of cycles				Speed (m/s)	Nb of cycles			
Slow	Muscle		Kinematics		Slow	Muscle		Kinematics		Slow	Muscle		Kinematics	
1.10	L Hams				0.70	L Hams	10			1.10	L Hams	10		
	L Quad					L Quad	10				L Quad	10		
	L Gas		L Hip			L Gas	10	L Hip	10		L Gas	10	L Hip	10
	L Tib		L Knee			L Tib	10	L Knee	10		L Tib	10	L Knee	10
	L Sol		L Ankle			L Sol	10	L Ankle	9		L Sol	10	L Ankle	10
	R Hams		R Hip			R Hams	9	R Hip	10		R Hams	10	R Hip	10
	R Quad		R Knee			R Quad	10	R Knee	10		R Quad	10	R Knee	10
	R Gas		R Ankle			R Gas	10	R Ankle	10		R Gas	10	R Ankle	10
	R Tib					R Tib	10				R Tib	10		
	R Sol					R Sol	9				R Sol	9		
Comfortable	Muscle		Kinematics		Comfortable	Muscle		Kinematics		Comfortable	Muscle		Kinematics	
1.55	L Hams	10			0.90	L Hams	11			1.30	L Hams	10		
	L Quad	10				L Quad	11				L Quad	10		
	L Gas	10	L Hip	10		L Gas	11	L Hip	11		L Gas	10	L Hip	10
	L Tib	10	L Knee	10		L Tib	11	L Knee	11		L Tib	10	L Knee	10
	L Sol	10	L Ankle	10		L Sol	11	L Ankle	11		L Sol	10	L Ankle	10
	R Hams	10	R Hip	10		R Hams	11	R Hip	12		R Hams	10	R Hip	10
	R Quad	10	R Knee	10		R Quad	12	R Knee	12		R Quad	9	R Knee	10
	R Gas	10	R Ankle	9		R Gas	12	R Ankle	12		R Gas	10	R Ankle	10
	R Tib	10				R Tib	11				R Tib	10		
	R Sol	10				R Sol	12				R Sol	10		
Fast	Muscle		Kinematics		Fast	Muscle		Kinematics		Fast	Muscle		Kinematics	
1.80	L Hams	6			1.45	L Hams	12			1.90	L Hams			
	L Quad	6				L Quad	12				L Quad			
	L Gas	6	L Hip	4		L Gas	12	L Hip	10		L Gas		L Hip	
	L Tib	6	L Knee	5		L Tib	12	L Knee	12		L Tib		L Knee	
	L Sol	6	L Ankle	4		L Sol	12	L Ankle	11		L Sol		L Ankle	
	R Hams	6	R Hip	4		R Hams	11	R Hip	12		R Hams		R Hip	
	R Quad	6	R Knee	5		R Quad	11	R Knee	11		R Quad		R Knee	
	R Gas	6	R Ankle	5		R Gas	11	R Ankle	11		R Gas		R Ankle	
	R Tib	6				R Tib					R Tib			
	R Sol					R Sol	11				R Sol			

Table 4.5: Number of cycles collected during FP treadmill walking for participants 7 to 9

Participant 10					Participant 11				
Speed (m/s)	Nb of cycles				Speed (m/s)	Nb of cycles			
Slow	Muscle		Kinematics		Slow	Muscle		Kinematics	
1.10	L Hams	9			0.80	L Hams	8		
	L Quad	9				L Quad	8		
	L Gas	9	L Hip	10		L Gas	8	L Hip	8
	L Tib	9	L Knee	10		L Tib	8	L Knee	8
	L Sol	9	L Ankle	10		L Sol	8	L Ankle	7
	R Hams	10	R Hip	10		R Hams	10	R Hip	10
	R Quad	10	R Knee	10		R Quad	10	R Knee	10
	R Gas	10	R Ankle	10		R Gas	10	R Ankle	
	R Tib					R Tib	10		
	R Sol	10				R Sol	10		
Comfortable	Muscle		Kinematics		Comfortable	Muscle		Kinematics	
1.30	L Hams	10			1.35	L Hams	10		
	L Quad	10				L Quad	10		
	L Gas	10	L Hip	10		L Gas	10	L Hip	9
	L Tib	10	L Knee	10		L Tib	10	L Knee	10
	L Sol	10	L Ankle	10		L Sol	9	L Ankle	9
	R Hams	10	R Hip			R Hams	9	R Hip	10
	R Quad	10	R Knee	10		R Quad	9	R Knee	9
	R Gas	10	R Ankle	10		R Gas	9	R Ankle	10
	R Tib	10				R Tib	9		
	R Sol	10				R Sol	9		
Fast	Muscle		Kinematics		Fast	Muscle		Kinematics	
1.80	L Hams	10			1.90	L Hams	10		
	L Quad	10				L Quad	10		
	L Gas	10	L Hip	10		L Gas	10	L Hip	10
	L Tib	10	L Knee	10		L Tib	10	L Knee	10
	L Sol	10	L Ankle	10		L Sol	9	L Ankle	10
	R Hams	10	R Hip	10		R Hams	10	R Hip	10
	R Quad	10	R Knee	10		R Quad	10	R Knee	10
	R Gas	10	R Ankle	10		R Gas	10	R Ankle	10
	R Tib	10				R Tib	10		
	R Sol	10				R Sol	10		

Table 4.6: Number of cycles collected during FP treadmill walking for participants 10 to 11

N°	Participant 1					Participant 2					Participant 3				
	Speed (m/s)	Nb of cycles				Speed (m/s)	Nb of cycles				Speed (m/s)	Nb of cycles			
SP	Slow	Muscle		Kinematics		Slow	Muscle		Kinematics		Slow	Muscle		Kinematics	
	1.08	L Hams	15			1.165	L Hams				1.03	L Hams			
		L Quad	16				L Quad					L Quad			
		L Gas	16	L Hip	12		L Gas		L Hip			L Gas		L Hip	
		L Tib	15	L Knee	12		L Tib		L Knee			L Tib		L Knee	
		L Sol	15	L Ankle	12		L Sol		L Ankle			L Sol		L Ankle	
		R Hams	15	R Hip	12		R Hams		R Hip			R Hams		R Hip	
		R Quad	13	R Knee	12		R Quad		R Knee			R Quad		R Knee	
		R Gas	15	R Ankle	12		R Gas		R Ankle			R Gas		R Ankle	
		R Tib	15				R Tib					R Tib			
		R Sol	15				R Sol					R Sol			
	Comfortable	Muscle		Kinematics		Comfortable	Muscle		Kinematics		Comfortable	Muscle		Kinematics	
	1.37	L Hams	12			1.32	L Hams				1.32	L Hams	10		
		L Quad	12				L Quad					L Quad	10		
		L Gas	12	L Hip	13		L Gas		L Hip			L Gas	10	L Hip	10
		L Tib	12	L Knee	13		L Tib		L Knee			L Tib	10	L Knee	11
		L Sol	12	L Ankle	14		L Sol		L Ankle			L Sol	9	L Ankle	10
		R Hams	12	R Hip	14		R Hams		R Hip			R Hams	10	R Hip	11
		R Quad	12	R Knee	12		R Quad		R Knee			R Quad	10	R Knee	10
		R Gas	12	R Ankle	14		R Gas		R Ankle			R Gas	10	R Ankle	10
		R Tib	12				R Tib					R Tib	10		
		R Sol	12				R Sol					R Sol	10		
	Fast	Muscle		Kinematics		Fast	Muscle		Kinematics		Fast	Muscle		Kinematics	
	1.42	L Hams	13			1.625	L Hams	13			1.80	L Hams	10		
		L Quad	13				L Quad	13				L Quad	10		
		L Gas	13	L Hip	12		L Gas	13	L Hip	13		L Gas	10	L Hip	10
		L Tib	13	L Knee	11		L Tib	13	L Knee	13		L Tib	10	L Knee	11
		L Sol	13	L Ankle	13		L Sol	13	L Ankle	14		L Sol	9	L Ankle	10
		R Hams	12	R Hip	11		R Hams	13	R Hip	13		R Hams	10	R Hip	11
		R Quad	13	R Knee	12		R Quad	14	R Knee	14		R Quad	10	R Knee	10
		R Gas	12	R Ankle	11		R Gas	14	R Ankle	13		R Gas	10	R Ankle	10
		R Tib	12				R Tib	14				R Tib	10		
		R Sol	14				R Sol	13				R Sol	10		

Participant 4					Participant 5					Participant 6				
Speed (m/s)	Nb of cycles				Speed (m/s)	Nb of cycles				Speed (m/s)	Nb of cycles			
Slow	Muscle		Kinematics		Slow	Muscle		Kinematics		Slow	Muscle		Kinematics	
1.15	L Hams				1	L Hams	8			1.005	L Hams			
	L Quad					L Quad	8				L Quad			
	L Gas		L Hip	10		L Gas	8	L Hip	7		L Gas		L Hip	
	L Tib		L Knee	7		L Tib	8	L Knee	8		L Tib		L Knee	
	L Sol		L Ankle	10		L Sol	8	L Ankle	6		L Sol		L Ankle	
	R Hams		R Hip	9		R Hams	10	R Hip	11		R Hams		R Hip	
	R Quad		R Knee	8		R Quad	10	R Knee	10		R Quad		R Knee	
	R Gas		R Ankle	7		R Gas	10	R Ankle	7		R Gas		R Ankle	
	R Tib					R Tib	10				R Tib			
	R Sol					R Sol	10				R Sol			
Comfortable	Muscle		Kinematics		Comfortable	Muscle		Kinematics		Comfortable	Muscle		Kinematics	
1.28	L Hams	13			1.6	L Hams	12			1.28	L Hams	11		
	L Quad	13				L Quad	12				L Quad	12		
	L Gas	13	L Hip	13		L Gas	11	L Hip	15		L Gas	12	L Hip	13
	L Tib	12	L Knee	13		L Tib	12	L Knee	12		L Tib	12	L Knee	15
	L Sol	12	L Ankle	13		L Sol	12	L Ankle	15		L Sol	12	L Ankle	14
	R Hams	13	R Hip	13		R Hams		R Hip	14		R Hams	12	R Hip	16
	R Quad	12	R Knee	13		R Quad	12	R Knee	14		R Quad	12	R Knee	14
	R Gas	12	R Ankle	13		R Gas	12	R Ankle	14		R Gas	12	R Ankle	15
	R Tib	12				R Tib	12				R Tib	12		
	R Sol	12				R Sol	12				R Sol	12		
Fast	Muscle		Kinematics		Fast	Muscle		Kinematics		Fast	Muscle		Kinematics	
1.45	L Hams	15			1.9	L Hams	12			1.66	L Hams	13		
	L Quad	15				L Quad	12				L Quad	14		
	L Gas	12	L Hip	20		L Gas	13	L Hip	22		L Gas	14	L Hip	18
	L Tib	13	L Knee	19		L Tib	12	L Knee	20		L Tib	14	L Knee	17
	L Sol	13	L Ankle	16		L Sol	12	L Ankle	19		L Sol	13	L Ankle	17
	R Hams	14	R Hip	19		R Hams	12	R Hip	21		R Hams	13	R Hip	17
	R Quad	14	R Knee	20		R Quad	12	R Knee	15		R Quad	14	R Knee	16
	R Gas	15	R Ankle	20		R Gas	12	R Ankle	21		R Gas	14	R Ankle	16
	R Tib	15				R Tib	12				R Tib	13		
	R Sol	14				R Sol	12				R Sol			

Table 4.7: Number of cycles collected during SP treadmill walking for participants 1 to 6

Participant 7			Participant 8					Participant 9				
Speed (m/s)	Nb of cycles		Speed (m/s)	Nb of cycles				Speed (m/s)	Nb of cycles			
Slow	Muscle	Kinematics	Slow	Muscle		Kinematics		Slow	Muscle		Kinematics	
1.58	L Hams		0.7	L Hams	12			1.25	L Hams	11		
	L Quad			L Quad					L Quad	12		
	L Gas	L Hip		L Gas		L Hip			L Gas	12	L Hip	10
	L Tib	L Knee		L Tib		L Knee			L Tib	11	L Knee	11
	L Sol	L Ankle		L Sol		L Ankle			L Sol	11	L Ankle	12
	R Hams	R Hip		R Hams		R Hip			R Hams	12	R Hip	11
	R Quad	R Knee		R Quad		R Knee			R Quad	12	R Knee	10
	R Gas	R Ankle		R Gas		R Ankle			R Gas	12	R Ankle	11
	R Tib			R Tib					R Tib	11		
	R Sol			R Sol					R Sol	10		
Comfortable	Muscle	Kinematics	Comfortable	Muscle		Kinematics		Comfortable	Muscle		Kinematics	
1.855	L Hams		1.00	L Hams	11			1.45	L Hams	11		
	L Quad			L Quad	11				L Quad	11		
	L Gas	L Hip		L Gas	11	L Hip	12		L Gas	11	L Hip	10
	L Tib	L Knee		L Tib	11	L Knee	11		L Tib	11	L Knee	10
	L Sol	L Ankle		L Sol	11	L Ankle	12		L Sol	12	L Ankle	11
	R Hams	R Hip		R Hams	12	R Hip	12		R Hams	10	R Hip	10
	R Quad	R Knee		R Quad	12	R Knee	12		R Quad	11	R Knee	10
	R Gas	R Ankle		R Gas	12	R Ankle	12		R Gas	11	R Ankle	
	R Tib			R Tib	12				R Tib	11		
	R Sol			R Sol	11				R Sol	11		
Fast	Muscle	Kinematics	Fast	Muscle		Kinematics		Fast	Muscle		Kinematics	
2.095	L Hams		1.20	L Hams	14			1.75	L Hams			
	L Quad			L Quad	13				L Quad			
	L Gas	L Hip		L Gas	14	L Hip	15		L Gas		L Hip	
	L Tib	L Knee		L Tib	14	L Knee	15		L Tib		L Knee	
	L Sol	L Ankle		L Sol	13	L Ankle	15		L Sol		L Ankle	
	R Hams	R Hip		R Hams	14	R Hip	16		R Hams		R Hip	
	R Quad	R Knee		R Quad	13	R Knee	15		R Quad		R Knee	
	R Gas	R Ankle		R Gas	14	R Ankle	16		R Gas		R Ankle	
	R Tib			R Tib	14				R Tib			
	R Sol			R Sol	14				R Sol			

Table 4.8: Number of cycles collected during SP treadmill walking for participants 7 to 9

Participant 10					Participant 11				
Speed (m/s)	Nb of cycles				Speed (m/s)	Nb of cycles			
Slow	Muscle		Kinematics		Slow	Muscle		Kinematics	
1.15	L Hams				1.20	L Hams	10		
	L Quad					L Quad	12		
	L Gas		L Hip			L Gas	15	L Hip	15
	L Tib		L Knee			L Tib	12	L Knee	14
	L Sol		L Ankle			L Sol	12	L Ankle	15
	R Hams		R Hip			R Hams	14	R Hip	14
	R Quad		R Knee			R Quad	11	R Knee	16
	R Gas		R Ankle			R Gas	15	R Ankle	13
	R Tib					R Tib	12		
	R Sol					R Sol	15		
Comfortable	Muscle		Kinematics		Comfortable	Muscle		Kinematics	
1.30	L Hams	6			1.5	L Hams	10		
	L Quad	6				L Quad	10		
	L Gas	6	L Hip	6		L Gas	10	L Hip	10
	L Tib	6	L Knee	6		L Tib	10	L Knee	10
	L Sol	6	L Ankle	6		L Sol	10	L Ankle	10
	R Hams	6	R Hip	6		R Hams	9	R Hip	10
	R Quad	6	R Knee	6		R Quad	9	R Knee	8
	R Gas	6	R Ankle	6		R Gas	9	R Ankle	7
	R Tib	6				R Tib	9		
	R Sol	6				R Sol	9		
Fast	Muscle		Kinematics		Fast	Muscle		Kinematics	
1.80	L Hams				1.95	L Hams	13		
	L Quad					L Quad	13		
	L Gas		L Hip			L Gas	13	L Hip	14
	L Tib		L Knee			L Tib	13	L Knee	14
	L Sol		L Ankle			L Sol	13	L Ankle	14
	R Hams		R Hip			R Hams	13	R Hip	13
	R Quad		R Knee			R Quad	13	R Knee	14
	R Gas		R Ankle			R Gas	13	R Ankle	14
	R Tib					R Tib	14		
	R Sol					R Sol	12		

Table 4.9: Number of cycles collected during SP treadmill walking for participants 10 to 11

N°	Participant 1			Participant 2			Participant 3		
	Speed (m/s)	Nb of cycles		Speed (m/s)	Nb of cycles		Speed (m/s)	Nb of cycles	
OG	Slow	Muscle	Kinematics	Slow	Muscle	Kinematics	Slow	Muscle	Kinematics
	NA	L Hams		1.4	L Hams 6		1.4	L Hams 6	
		L Quad			L Quad 6			L Quad 6	
		L Gas	L Hip		L Gas 7	L Hip 6		L Gas 6	L Hip 6
		L Tib	L Knee		L Tib 6	L Knee 6		L Tib 6	L Knee 5
		L Sol	L Ankle		L Sol 6	L Ankle 6		L Sol 6	L Ankle 6
		R Hams	R Hip		R Hams 7	R Hip 6		R Hams 6	R Hip 5
		R Quad	R Knee		R Quad 6	R Knee 5		R Quad 6	R Knee 5
		R Gas	R Ankle		R Gas 6	R Ankle 5		R Gas 6	R Ankle 5
		R Tib			R Tib 6			R Tib 6	
		R Sol			R Sol 6			R Sol 6	
	Comfortable	Muscle	Kinematics	Comfortable	Muscle	Kinematics	Comfortable	Muscle	Kinematics
	1.32	L Hams 6		1.3	L Hams 6		1.42	L Hams 6	
		L Quad 6			L Quad 6			L Quad 6	
		L Gas 7	L Hip 6		L Gas 6	L Hip 4		L Gas 6	L Hip
		L Tib 6	L Knee 5		L Tib 6	L Knee 4		L Tib 6	L Knee 4
		L Sol 6	L Ankle 5		L Sol 6	L Ankle 4		L Sol 6	L Ankle
		R Hams 6	R Hip 5		R Hams 6	R Hip 4		R Hams 6	R Hip 4
		R Quad 6	R Knee 4		R Quad 6	R Knee 4		R Quad 6	R Knee 4
		R Gas 6	R Ankle 6		R Gas 6	R Ankle		R Gas 6	R Ankle 4
		R Tib 6			R Tib 7			R Tib 6	
		R Sol 6			R Sol 6			R Sol 6	
	Fast	Muscle	Kinematics	Fast	Muscle	Kinematics	Fast	Muscle	Kinematics
	NA	L Hams		1.98	L Hams 6		1.59	L Hams 6	
		L Quad			L Quad 6			L Quad 6	
		L Gas	L Hip		L Gas 6	L Hip		L Gas 6	L Hip 6
		L Tib	L Knee		L Tib 6	L Knee 5		L Tib 6	L Knee 6
		L Sol	L Ankle		L Sol 6	L Ankle		L Sol 6	L Ankle 6
		R Hams	R Hip		R Hams 6	R Hip		R Hams 6	R Hip 5
		R Quad	R Knee		R Quad 6	R Knee		R Quad 6	R Knee 5
		R Gas	R Ankle		R Gas 5	R Ankle		R Gas 6	R Ankle 4
		R Tib			R Tib 6			R Tib 6	
		R Sol			R Sol 7			R Sol 6	

Table 4.10: Number of cycles collected during OG walking for participants 1 to 3

Participant 4					Participant 5					Participant 6				
Speed (m/s)	Nb of cycles				Speed (m/s)	Nb of cycles				Speed (m/s)	Nb of cycles			
Slow	Muscle		Kinematics		Slow	Muscle		Kinematics		Slow	Muscle		Kinematics	
1.14	L Hams	6			1.07	L Hams	8			1	L Hams	8		
	L Quad	6				L Quad	7				L Quad	8		
	L Gas	6	L Hip			L Gas	7	L Hip	9		L Gas	7	L Hip	6
	L Tib	6	L Knee			L Tib	7	L Knee	7		L Tib	7	L Knee	6
	L Sol	6	L Ankle			L Sol	7	L Ankle	7		L Sol	7	L Ankle	6
	R Hams	6	R Hip			R Hams	7	R Hip	9		R Hams	6	R Hip	9
	R Quad	6	R Knee			R Quad	9	R Knee	9		R Quad	6	R Knee	6
	R Gas	6	R Ankle			R Gas	8	R Ankle	6		R Gas	6	R Ankle	9
	R Tib	6				R Tib	9				R Tib	6		
	R Sol	6				R Sol	9				R Sol	6		
Comfortable	Muscle		Kinematics		Comfortable	Muscle		Kinematics		Comfortable	Muscle		Kinematics	
1.11	L Hams	6			1.21	L Hams	6			1.43	L Hams	6		
	L Quad	6				L Quad	6				L Quad	6		
	L Gas	6	L Hip			L Gas	7	L Hip	4		L Gas	6	L Hip	6
	L Tib	6	L Knee			L Tib	7	L Knee	4		L Tib	6	L Knee	6
	L Sol	6	L Ankle	4		L Sol	6	L Ankle	4		L Sol	6	L Ankle	6
	R Hams	6	R Hip			R Hams	6	R Hip	4		R Hams	6	R Hip	6
	R Quad	6	R Knee			R Quad	7	R Knee	4		R Quad	6	R Knee	6
	R Gas	6	R Ankle			R Gas	6	R Ankle	4		R Gas	6	R Ankle	6
	R Tib	6				R Tib	6				R Tib	6		
	R Sol	6				R Sol	6				R Sol	7		
Fast	Muscle		Kinematics		Fast	Muscle		Kinematics		Fast	Muscle		Kinematics	
1.39	L Hams	6			1.33	L Hams	6			2.18	L Hams	6		
	L Quad	6				L Quad	6				L Quad	6		
	L Gas	6	L Hip	5		L Gas	6	L Hip	5		L Gas	6	L Hip	6
	L Tib	6	L Knee	5		L Tib	6	L Knee			L Tib	6	L Knee	6
	L Sol	6	L Ankle	5		L Sol	6	L Ankle	5		L Sol	6	L Ankle	6
	R Hams		R Hip			R Hams	6	R Hip	5		R Hams	6	R Hip	6
	R Quad		R Knee			R Quad	6	R Knee	5		R Quad	6	R Knee	6
	R Gas		R Ankle			R Gas	6	R Ankle	5		R Gas	6	R Ankle	
	R Tib					R Tib	6				R Tib	6		
	R Sol	6				R Sol	6				R Sol	6		

Table 4.11: Number of cycles collected during OG walking for participants 4 to 6

Participant 7					Participant 8					Participant 9				
Speed (m/s)	Nb of cycles				Speed (m/s)	Nb of cycles				Speed (m/s)	Nb of cycles			
Slow	Muscle		Kinematics		Slow	Muscle		Kinematics		Slow	Muscle		Kinematics	
1.37	L Hams	7			NA	L Hams				NA	L Hams	6		
	L Quad	8				L Quad					L Quad	6		
	L Gas	7	L Hip			L Gas		L Hip			L Gas	6	L Hip	
	L Tib	6	L Knee			L Tib		L Knee			L Tib	6	L Knee	
	L Sol	6	L Ankle			L Sol		L Ankle			L Sol	6	L Ankle	
	R Hams	8	R Hip			R Hams		R Hip			R Hams	6	R Hip	
	R Quad	7	R Knee			R Quad		R Knee			R Quad	6	R Knee	
	R Gas	7	R Ankle			R Gas		R Ankle			R Gas	6	R Ankle	
	R Tib	7				R Tib					R Tib	6		
	R Sol	8				R Sol					R Sol	6		
Comfortable	Muscle		Kinematics		Comfortable	Muscle		Kinematics		Comfortable	Muscle		Kinematics	
1.49	L Hams	6			1.35	L Hams	6			1.37	L Hams	6		
	L Quad	6				L Quad	5				L Quad	6		
	L Gas	6	L Hip			L Gas	6	L Hip	4		L Gas	6	L Hip	
	L Tib	6	L Knee			L Tib	6	L Knee	4		L Tib	6	L Knee	
	L Sol	7	L Ankle			L Sol	6	L Ankle	4		L Sol	6	L Ankle	
	R Hams	6	R Hip			R Hams	6	R Hip	4		R Hams	6	R Hip	
	R Quad	6	R Knee	4		R Quad	6	R Knee	4		R Quad	6	R Knee	3
	R Gas	6	R Ankle			R Gas	6	R Ankle			R Gas	6	R Ankle	3
	R Tib	6				R Tib	6				R Tib	6		
	R Sol	6				R Sol	6				R Sol	6		
Fast	Muscle		Kinematics		Fast	Muscle		Kinematics		Fast	Muscle		Kinematics	
2.18	L Hams	6			NA	L Hams				NA	L Hams	6		
	L Quad	6				L Quad					L Quad	6		
	L Gas	6	L Hip	4		L Gas		L Hip			L Gas	6	L Hip	
	L Tib	6	L Knee	3		L Tib		L Knee			L Tib	6	L Knee	
	L Sol	7	L Ankle	4		L Sol		L Ankle			L Sol	6	L Ankle	
	R Hams	6	R Hip	3		R Hams		R Hip			R Hams		R Hip	
	R Quad	6	R Knee			R Quad		R Knee			R Quad		R Knee	
	R Gas	6	R Ankle	2		R Gas		R Ankle			R Gas		R Ankle	
	R Tib	6				R Tib					R Tib			
	R Sol	6				R Sol					R Sol	6		

Table 4.12: Number of cycles collected during OG walking for participants 7 to 9

Participant 10					Participant 11				
Speed (m/s)	Nb of cycles				Speed (m/s)	Nb of cycles			
Slow	Muscle		Kinematics		Slow	Muscle		Kinematics	
0.65	L Hams	6			NA	L Hams			
	L Quad	6				L Quad			
	L Gas	6	L Hip	8		L Gas		L Hip	
	L Tib	6	L Knee	6		L Tib		L Knee	
	L Sol	6	L Ankle	7		L Sol		L Ankle	
	R Hams	9	R Hip	9		R Hams		R Hip	
	R Quad	9	R Knee	9		R Quad		R Knee	
	R Gas	9	R Ankle	11		R Gas		R Ankle	
	R Tib	9				R Tib			
	R Sol	10				R Sol			
Comfortable	Muscle		Kinematics		Comfortable	Muscle		Kinematics	
1.47	L Hams	6			1.34	L Hams	2		
	L Quad	6				L Quad	2		
	L Gas	6	L Hip	6		L Gas	2	L Hip	
	L Tib	8	L Knee	8		L Tib	2	L Knee	
	L Sol	8	L Ankle	5		L Sol	2	L Ankle	
	R Hams	6	R Hip	8		R Hams	2	R Hip	
	R Quad	6	R Knee	6		R Quad	2	R Knee	
	R Gas	6	R Ankle	8		R Gas	2	R Ankle	
	R Tib	8				R Tib	2		
	R Sol	8				R Sol	2		
Fast	Muscle		Kinematics		Fast	Muscle		Kinematics	
1.89	L Hams	6			NA	L Hams			
	L Quad	6				L Quad			
	L Gas	6	L Hip			L Gas		L Hip	
	L Tib	6	L Knee			L Tib		L Knee	
	L Sol	6	L Ankle			L Sol		L Ankle	
	R Hams	6	R Hip			R Hams		R Hip	
	R Quad	6	R Knee			R Quad		R Knee	
	R Gas	6	R Ankle			R Gas		R Ankle	
	R Tib	6				R Tib			
	R Sol	6				R Sol			

Table 4.13: Number of cycles collected during OG walking for participants 10 to 11

		1	2	3	4	5	6	7	8	9	10	11	Mean	Standard Deviation
FP	Slow	0.9	1	1	1.1	0.95	0.85	1.10	0.70	1.10	1.10	0.80	0.96	0.14
	Comfortable	1.15	1.2	1.35	1.15	1.25	1.30	1.55	0.90	1.30	1.30	1.35	1.25	0.16
	Fast	1.6	1.75	1.75	1.75	1.70	1.80	1.80	1.45	1.90	1.80	1.90	1.75	0.13
SP	Slow	1.08	1.165	1.03	1.15	1	1.005	1.58	0.7	1.25	1.15	1.20	1.12	0.21
	Comfortable	1.37	1.32	1.32	1.28	1.6	1.28	1.855	1.00	1.45	1.30	1.5	1.39	0.22
	Fast	1.42	1.625	1.80	1.45	1.9	1.66	2.095	1.20	1.75	1.80	1.95	1.70	0.26
OG	Slow		1.4	1.4	1.14	1.07	1	1.37			0.65		1.15	0.27
	Comfortable	1.32	1.3	1.42	1.11	1.21	1.43	1.49	1.35	1.37	1.47	1.34	1.35	0.11
	Fast		1.98	1.59	1.39	1.33	2.14	2.18			1.89		1.79	0.35

Table 4.14: Speeds for ach participants and walking situations.

4.6.1. Muscle Variance Ratio Results

The variance ratio (VR) was calculated for all five muscles of interest over the three self-selected speeds and three walking conditions, for all participants. The following section will present the VR for each individual as well as the group average at the three different speeds.

4.6.1.1. Data reduction of the Variance Ratio analysis

To understand the overall pattern of how VR differs across the walking speeds and conditions (OG, SP treadmill, FP treadmill) the data were reduced to mean, SD and range. This information is presented in the Table 4.15.

	Fixed pace treadmill			Self-paced treadmill			Overground		
	Fast	Comfortable	Slow	Fast	Comfortable	Slow	Fast	Comfortable	Slow
Mean VR	0.322	0.224	0.322	0.23	0.176	0.23	0.25	0.196	0.25
Variance (SD)	0.044 (0.147)	0.038 (0.183)	0.042 (0.197)	0.011 (0.097)	0.016 (0.121)	0.024 (0.142)	0.017 (0.12)	0.020 (0.134)	0.022 (0.142)
Range	0.146	0.190	0.309	0.140	0.168	0.240	0.170	0.153	0.210
Mean VR difference percentage between treadmill walking and overground	28. 8	14.286	28.8	-2	-10.204	-8	0	0	0

Table 4.15: Inter-individual Statistics of mean VR of muscles.

As the principally observed parameter is the variability of the EMG signal, reporting the statistical parameter describing the amplitude spread of the data is valuable. The variables selected in Table 4.15 to describe the VR are the range to present the total amplitude of the VR, the standard deviation (SD) giving the deviation from the mean of the data batch and the variance which is also an indicator of the data dispersion.

While the value of the VR range differed according to the observed muscle and the walking situation the participant was in, it appeared that, in 6 out of 11 of the participants, the range of VR was bigger (means VR difference of 0.03 and 0.05 between FP and overground and between SP and overground respectively) while walking on a treadmill at a comfortable self-selected FP than during an overground or SP treadmill walk. Exceptions to this were found on the left Hamstrings and right Gastrocnemius who presented overall VR values inferior on the SP treadmill and over ground walking. Also, on FP treadmill walking, the right

Hamstrings and right Quadriceps presented VR values inferior to SP but still superior to over ground walking.
When calculating the percentages of the difference between the treadmill walks and the overground walk, the SP treadmill presented between -2 and -10% of difference with overground walking when the FP was between 14 and 28% across the different walking speeds. This shows SP treadmill walking as a closer analogue to overground.

Another interesting observation from this inter-individual analysis is that the variability of the muscular activity apparently does not present a symmetrical behaviour between the left and the right leg. The trend of the VR values of all the participant when walking at a comfortable speed are represented in the following figures (Figure 4.13 to Figure 4.15), looking at the left (L) and the right (R) side.

On the left leg, mean VR value tends to be the highest during FP treadmill walking (see blue bars in Figure 4.13). On the right leg, the highest mean VR value is found during overground walking (see green bars in Figure 4.13).

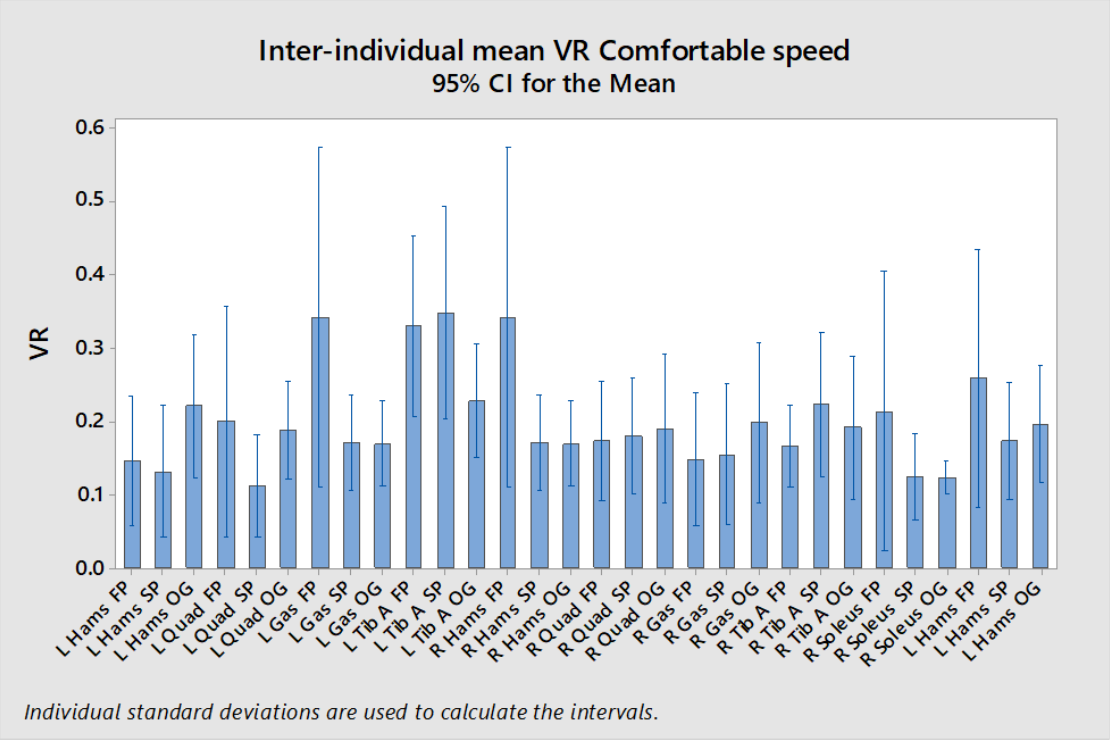


Figure 4.13: Mean Inter-individual bi-lateral VR of the muscles at comfortable walking speed (FP: Fix-paced treadmill, SP: self-paced treadmill, OG: overground); L: left; R: right.

In the case of the fast-walking speed, the highest mean VR value is mainly found during overground walking (see green bars in Figure 4.14).

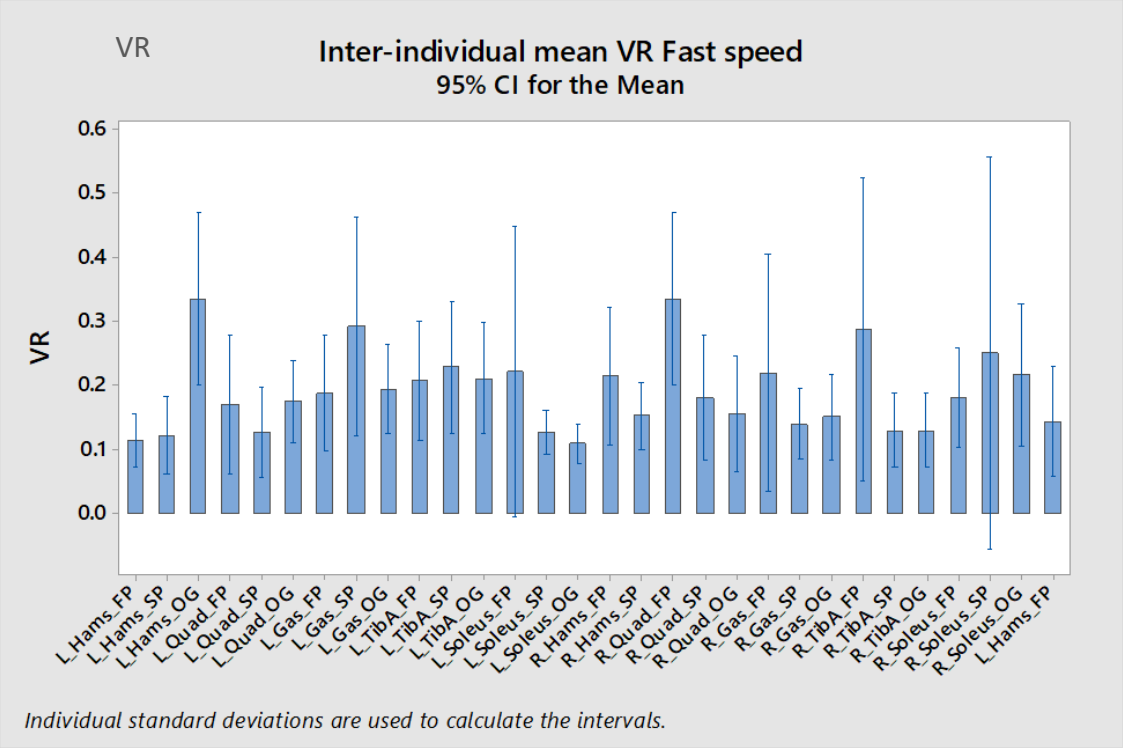


Figure 4.14: Mean Inter-individual bi-lateral VR of the muscles at fast walking speed (FP: Fix-paced treadmill, SP: self-paced treadmill, OG: overground); L: left; R: right

In the case of the slow walking speed, the highest mean VR value is mainly found during fixed pace walking (see green bars in Figure 4.15).

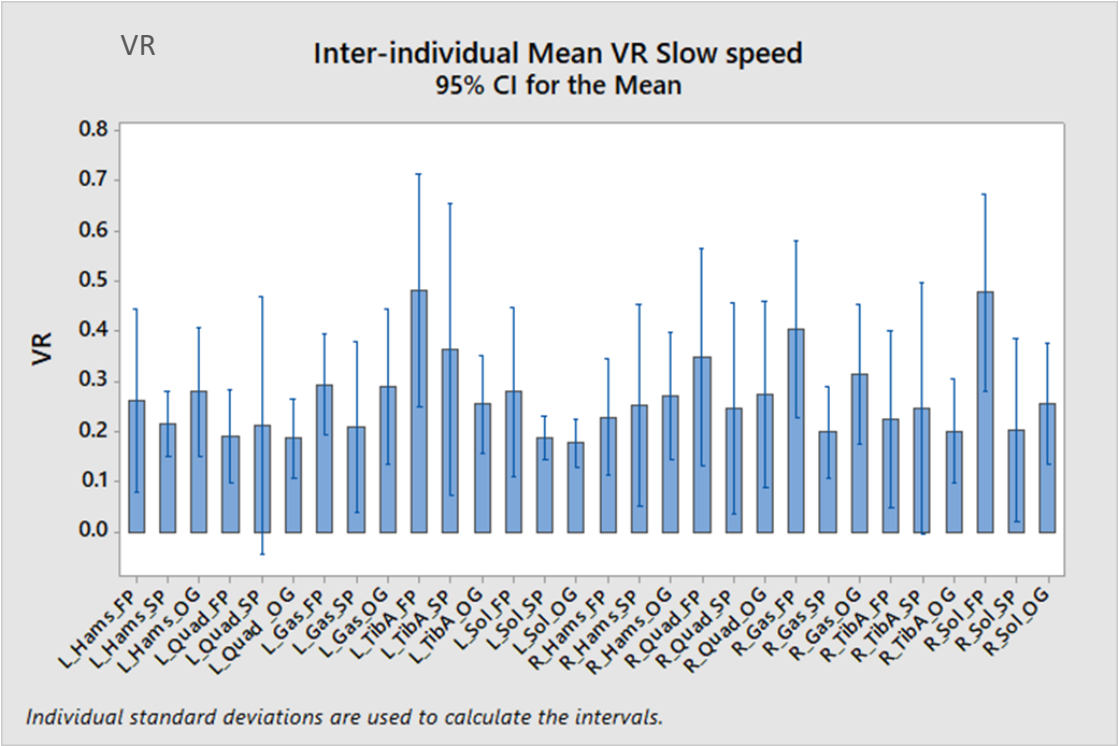


Figure 4.15: Mean Inter-individual bi-lateral VR of the muscles at slow walking speed (FP: Fix-paced treadmill, SP: self-paced treadmill, OG: overground); L: left; R: right

		FP			SP			OG		
		Fast	Comf	Slow	Fast	Comf	Slow	Fast	Comf	Slow
	mean VR	0.25	0.16	0.25	0.23	0.16	0.23	0.27	0.21	0.27
Hams	(SD)	0.18	0.11	0.18	0.11	0.12	0.11	0.15	0.15	0.15
	Variance	0.03	0.01	0.03	0.01	0.01	0.01	0.02	0.02	0.02
	Range	0.69	0.4	0.69	0.4	0.42	0.4	0.52	0.48	0.52
	mean VR	0.27	0.19	0.27	0.23	0.13	0.23	0.23	0.19	0.23
Quad	(SD)	0.21	0.18	0.21	0.18	0.12	0.18	0.17	0.12	0.17
	Variance	0.04	0.03	0.04	0.03	0.01	0.03	0.03	0.01	0.03
	Range	0.77	0.74	0.77	0.53	0.48	0.53	0.64	0.48	0.64
	mean VR	0.35	0.26	0.35	0.2	0.2	0.2	0.3	0.21	0.3
Gas	(SD)	0.18	0.24	0.18	0.1	0.12	0.1	0.17	0.15	0.17
	Variance	0.03	0.06	0.03	0.01	0.01	0.01	0.03	0.02	0.03
	Range	0.73	0.86	0.73	0.34	0.44	0.34	0.58	0.62	0.58
	mean VR	0.36	0.29	0.36	0.3	0.24	0.3	0.23	0.19	0.23
TibA	(SD)	0.27	0.24	0.27	0.22	0.19	0.22	0.12	0.15	0.12
	Variance	0.07	0.06	0.07	0.05	0.03	0.05	0.01	0.02	0.01
	Range	0.8	0.89	0.8	0.66	0.58	0.66	0.35	0.68	0.35
	mean VR	0.38	0.22	0.38	0.19	0.15	0.19	0.22	0.18	0.22
Sol	(SD)	0.23	0.18	0.23	0.1	0.09	0.1	0.11	0.12	0.11
	Variance	0.05	0.03	0.05	0.01	0.01	0.01	0.01	0.01	0.01
	Range	0.79	0.87	0.79	0.36	0.39	0.36	0.38	0.49	0.38
	Mean VR	**0.322**	**0.224**	**0.322**	**0.23**	**0.176**	**0.23**	**0.25**	**0.196**	**0.25**
TOTAL	Mean Variance	0.044	0.038	0.044	0.022	0.014	0.022	0.02	0.016	0.02
	Mean Range	**0.756**	**0.752**	**0.756**	**0.458**	**0.462**	**0.458**	**0.494**	**0.55**	**0.494**

Table 4.16: Summary of descriptive statistics of VR for each muscle in the three walking situations at the three self-selected speeds.

The repeated ANOVA analysis of the data showed that walking speed had a significant impact on the VR of four out of the five muscles (Hams $p=0.000$, $f=9.02$; Quad $p=0.026$, $f=3.85$; Gas $p=0.015$, $f=4.46$; TibA $p>0.05$; Sol $p=0.004$, $f=6.08$). All muscles presented a significantly ($p<0.05$) lower VR value when walking at the comfortable speed apart from the tibialis anterior which did not present significant differences between the three walking speeds. A summary of these observations is presented in Table 4.16.
Surprisingly, the ANOVA analysis did not present any statistically significant impact of the walking situation on the muscle VR, apart for the soleus muscle ($p=0.019$, $f=4.16$) presenting higher VR values during FP treadmill walking. The VR value, nonetheless, was lower during comfortable walking compared to fast and slow walking in each walking situations and in most muscles.

4.6.1.2. Comfortable walking speed

At the comfortable walking speed, Fixed pace (FP) treadmill walking created a wider range of VR values (Table 4.16) (mean VR: 0.224, mean range: 0.752, mean variance: 0.038) compared to overground (mean VR: 0.196, mean range: 0.550, mean variance:0.016) and self-paced (mean VR: 0.176, mean range: 0.458, mean variance: 0.014). The details of the results from individual participants are presented in Table 4.17.

	VR of Fixed pace Comfortable speed (over 6 cycles)												
Muscle	L Hams	L Quad	L Gas	L Tib A	L Soleus	R Hams	R Quad	R Gas	R Tib A	R Soleus			
Subject n°											Mean	Variance	Stand dev
001	0.13	0.22	0.25	0.38	0.4	0.17	0.45	0.26	0.2	0.18	0.264	0.01066	0.108853
002	0.1	0.24	0.14	0.76	0.19	0.13	0.49	0.46	0.29	0.22	0.302	0.039	0.208156
003	0.08	0.26	0.27	0.2	0.26	0.2	0.14	0.17	0.31	0.15	0.204	0.00454	0.071056
004	0.45	0.05	0.93	0.48	0.09	0.08	0.12	0.26	0.1	0.1	0.266	0.07092	0.280721
005	0.27	0.78	0.93	0.51	0.34	0.44	0.26	0.28	0.93	0.93	0.567	0.07764	0.293714
006	0.14	0.05	0.19	0.06	0.06	0.09	0.04	0.1	0.04	0.1	0.087	0.0021	0.048316
007	0.06	0.07	0.1	0.09	0.09	0.2	0.07	0.11	0.08	0.23	0.11	0.003	0.057735
008	0.12	0.24	0.39	0.49	0.14	0.25	0.19	0.16	0.23	0.19	0.24	0.0121	0.11595
009	0.09	0.07	0.17	0.28	0.3	0.08	0.04	0.161	0.05	0.29	0.1531	0.00964	0.103508
010	0.07	0.14	0.08	0.3	0.1	0.05	0.07	0.07	0.06	0.29	0.123	0.00796	0.094051
011	0.06	0.12	0.11	0.51	0.09	0.17	0.11	0.09	0.14	0.13	0.153	0.01498	0.129018
Mean	0.144	0.202	0.331	0.368	0.166	0.169	0.153	0.1861	0.223	0.263			
Variance	0.01386	0.0432	0.0972	0.0434	0.0091	0.01197	0.0169	0.0127	0.06444	0.05382			
Standard dev	0.12411	0.21908	0.3287	0.2196	0.1007	0.11532	0.137	0.1187	0.26758	0.24454			

Table 4.17: Muscles VR during treadmill FP at comfortable speed.

These values (see Table 4.16) can be compared to SP treadmill (Table 4.18) (mean range 0.378, mean variance 0.016). The details of the results from individual participants are presented in Table 4.18.

	VR Self pace Comfortable speed (over 6 cycles)												
Muscle	L Hams	L Quad	L Gas	L Tib A	L Soleus	R Hams	R Quad	R Gas	R Tib A	R Soleus	Mean	Variance	Stand dev
Subject n°													
001	0.13	0.34	0.13	0.2	0.17	0.18	0.5	0.19	0.08	0.13	0.205	0.013985	0.124655
002	No data available												
003	0.07	0.09	0.31	0.28	0.13	0.18	0.19	0.33	0.21	0.2	0.199	0.006989	0.088122
004	0.18	0.04	0.32	0.24	0.07	0.06	0.15	0.52	0.1	0.13	0.181	0.019469	0.147079
005	0.47	0.02	0.24	0.6	0.12	0.27	0.12	0.27	0.3	0.19	0.26	0.02636	0.17114
006	0.12	0.06	0.15	0.12	0.04	0.1	0.06	0.09	0.04	0.11	0.089	0.001269	0.03755
007	0.05	0.07	0.12	0.57	0.09	0.43	0.08	0.09	0.05	0.05	0.16	0.03032	0.183545
008	0.06	0.17	0.2	0.17	0.16	0.11	0.03	0.17	0.12	0.06	0.125	0.003065	0.058357
009	0.06	0.03	0.08	0.51	0.17	0.2	0.09	0.32	0.19	0.27	0.192	0.019076	0.145587
010	0.1	0.18	0.09	0.16	0.11	0.07	0.12	0.14	0.09	0.16	0.122	0.001196	0.036454
011	0.08	0.13	0.08	0.62	0.26	0.2	0.21	0.11	0.08	0.43	0.22	0.02852	0.178014
Mean	0.13222	0.087778	0.1767	0.3633	0.1278	0.18	0.116667	0.2267	0.1311	0.17778	0.172		
Variance	0.01571	0.003151	0.0081	0.0385	0.0037	0.01213	0.003111	0.0188	0.0065	0.0122			
Standard dev	0.13293	0.059535	0.0955	0.208	0.0644	0.11683	0.059161	0.1453	0.0855	0.1173			

Table 4.18: Muscles VR during treadmill SP at comfortable speed.

The results of over ground walking (Table 4.16) (mean range 0.418, mean variance 0.019) (see results per muscle in Table 4.15). The details of the results from individual participants are presented in Table 4.19.

	VR of Overground Comfortable speed (of 6 cycles)													
Muscle	L Hams	L Quad	L Gas	L Tib A	L Soleus	R Hams	R Quad	R Gas	R Tib A	R Soleus	Mean	Variance	Stand dev
Subject n°													
001	0.127	0.213	0.27	0.189	0.228	0.11	0.506	0.148	0.183	0.171	0.2145	0.01148	0.112926
002	0.067	0.027	0.332	0.064	0.121	0.514	0.242	0.695	0.727	0.524	0.3313	0.06455	0.267804
003	0.179	0.23	0.267	0.22	0.142	0.126	0.124	0.164	0.121	0.466	0.2039	0.0099	0.104874
004	0.234	0.33	0.218	0.335	0.072	0.11	0.199	0.542	0.135	0.183	0.2358	0.01698	0.137336
005	0.326	0.174	0.099	0.258	0.139	0.113	0.426	0.163	0.095	0.194	0.1987	0.01049	0.107959
006	0.216	0.076	0.075	0.042	0.036	0.088	0.073	0.094	0.095	0.044	0.0839	0.00236	0.051202
007	0.164	0.144	0.239	0.172	0.164	0.303	0.098	0.137	0.1	0.153	0.1674	0.00346	0.062
008	0.121	0.306	0.218	0.366	0.13	0.135	0.068	0.119	0.162	0.219	0.1844	0.00778	0.092998
009	0.551	0.127	0.099	0.138	0.155	0.482	0.236	0.136	0.105	0.273	0.1946	0.01338	0.12268
010	0.221	0.242	0.133	0.169	0.087	0.066	0.076	0.103	0.138	0.117	0.1352	0.00319	0.059542
011	No data available					No data available							
Mean	0.2206	0.1869	0.195	0.1953	0.1274	0.2047	0.2048	0.2301	0.1861	0.2344			
Variance	0.01677	0.00837	0.0069	0.0098	0.0026	0.02525	0.0213	0.0394	0.03329	0.02042			
Standard dev	0.1365	0.09644	0.0877	0.1046	0.0534	0.16749	0.1537	0.2091	0.19233	0.15062			

Table 4.19: Muscles VR during overground walking at comfortable speed

The one-way ANOVA did not reveal any significant differences ($p > 0.05$) between the different types of walking. However, in such a small sample it is worth looking at individual participants.

A one-way ANOVA was conducted on each participant to compare the different walks at comfortable speed. Two male participants (n°5 and n°8) behaved differently to the rest of the group. While the other participants presented VR values which were close to one another in all walking situations participant n°5 had a significantly higher ($p=0.001$) value of VR during the FP treadmill walk (see Figure 4.16)

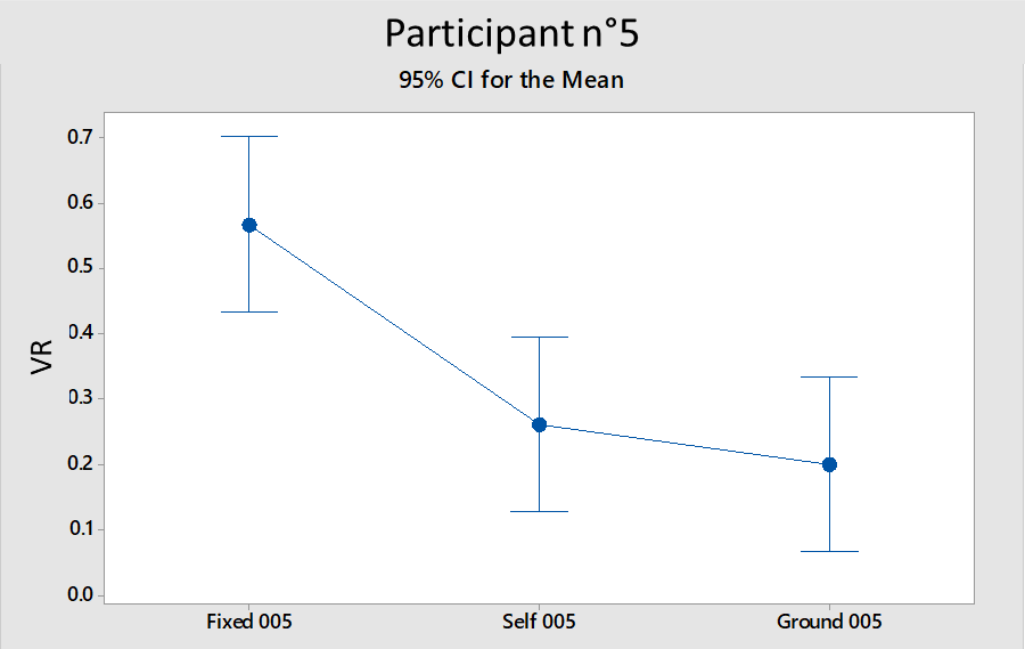


Figure 4.16: Interval plot of participant n°5 VR value during FP (Fixed), SP (Self) and Overground (Ground) walking

Participant n°8, also presented a p value <0.05 ($p=0.03$), although the VR value observed were less obviously different (see Figure 4.17).

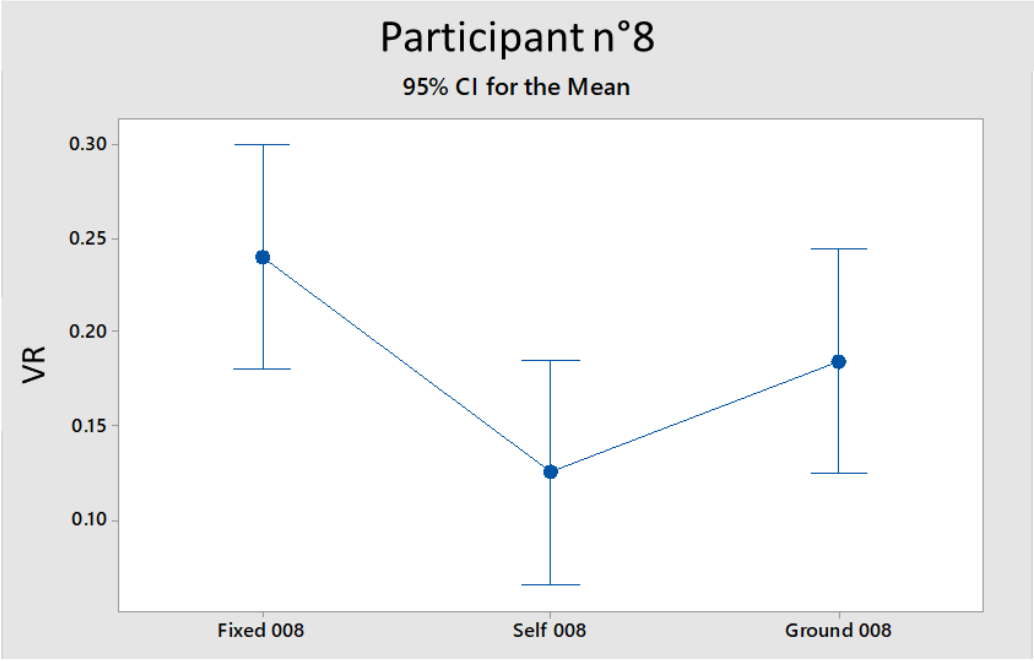


Figure 4.17: Interval plot of participant n°8 VR value during FP (Fixed), SP (Self) and Overground (Ground) walking

4.6.1.3. Fast walking speed

The same general finding was observed at the faster walking speed leading as reported for comfortable speed. The fast walk speed led to a VR mean of 0.322, a range of 0.435 and mean variance of 0.044 on the FP treadmill (Table 4.16), mean VR: 0.23, mean range: 0.458, mean variance: 0.022 on the SP treadmill and on the OG data mean VR: 0.25, mean range: 0.464, mean variance: 0.02. The details of the results from individual participants are presented in Table 4.20.

	VR Fixed Pace Fast speed (over 6 cycles)													
Muscle	L Hams	L Quad	L Gas	L Tib A	L Soleus		R Hams	R Quad	R Gas	R Tib A	R Soleus			
Subject n°												Mean	Variance	Stand dev
001	0.1556	0.5409	0.1411	0.4532	1		0.209	0.3369	0.2431	0.1347	1	0.4214	0.10004	0.33339
002	0.0343	0.0489	0.1391	0.3071	0.1628		0.3522	0.3741	0.0942	0.082	0.1643	0.1759	0.01409	0.12511
003	0.0386	0.1542	0.4394	0.1711	0.1126		0.171	0.1426	0.2745	0.1659	0.1326	0.1803	0.01054	0.10823
004														
005	0.1148	0.1216	0.2738	0.1869	0.1796		0.4086	0.2965	0.1119	0.1685	0.1914	0.2054	0.00808	0.09474
006	0.1891	0.1508	0.1602	0.0583	0.0752		0.1113	0.0575	0.1369	0.0339		0.1081	0.00262	0.05427
007	0.1182	0.146	0.2706	0.1526	0.1937		0.4035	0.1218	0.0868	0.2013		0.1883	0.00844	0.09744
008	0.1452	0.1185	0.0715	0.1469	0.1025		0.0901	0.0402	0.1105		0.0797	0.1006	0.00107	0.03465
009														
010	0.0809	0.1138	0.1227	0.1029	0.0724		0.0274	0.0541	0.1291	0.0504	0.1451	0.0899	0.00135	0.03879
011	0.1517	0.1352	0.0747	0.2819	0.105		0.1684	0.2009	0.0763	0.2087	0.0712	0.1474	0.00433	0.06933
Mean	0.1091	0.1236	0.194	0.176	0.1255		0.2165	0.161	0.1275	0.1301	0.1307			
Variance	0.0026	0.001	0.0139	0.0061	0.0019		0.0197	0.013	0.0035	0.0046	0.0019			
Standard dev	0.0548	0.0339	0.1259	0.0838	0.047		0.15	0.1219	0.0628	0.073	0.0472			

Table 4.20: Muscle VR during treadmill FP at fast walking speed.

On the SP treadmill (Table 4.21), the mean range was of 0.298 and a mean variance of 0.011. The details of the results from individual participants are presented in Table 4.21.

	VR Self Pace Fast speed (over 6 cycles)												
Muscle	L Hams	L Quad	L Gas	L Tib A	L Soleus	R Hams	R Quad	R Gas	R Tib A	R Soleus			
Subject n°											Mean	Variance	Stand dev
001	0.0749	0.1326	0.2278	0.1714	0.1457	0.1635	0.3532	0.1166	0.0872	0.0715	0.154437	0.006497	0.084963
002	0.0345	0.0692	0.1882	0.4805	0.1221	0.1367	0.1286	0.2524	0.0941	0.3067	0.181299	0.016035	0.133478
003	0.0693	0.1262	0.7046	0.2126	0.0813	0.1695	0.2866	0.2844	0.1765	0.4152	0.252619	0.032611	0.190355
004	0.267	0.0535	0.3834	0.2938	0.0657	0.0977	0.1439	0.1817	0.1015	0.1581	0.174631	0.010538	0.10821
005	0.1403	0.3032	0.4201	0.2345	0.1862	0.1308	0.1307	0.0976	0.0959	0.1834	0.192273	0.009462	0.102536
006	0.1558	0.0922	0.1018	0.0563	0.1481	0.0737	0.0548	0.0738	0.0594		0.090662	0.001297	0.038198
007													
008	0.0804	0.1833	0.243	0.1511	0.0995	0.2834	0.0659	0.1214	0.1613	0.1131	0.150239	0.004434	0.070194
009													
010													
011	0.1474	0.0499	0.0773	0.2279	0.166	0.1711	0.0824	0.0779	0.2695	0.2707	0.154013	0.006051	0.081997
Mean	0.1278	0.1254	0.3026	0.2367	0.1241	0.1518	0.1276	0.1556	0.1369	0.2412			
Variance	0.005	0.0072	0.0414	0.0147	0.0017	0.004	0.0052	0.0063	0.0044	0.0103			
Standard dev	0.0765	0.0914	0.2197	0.1312	0.0448	0.0679	0.0782	0.0855	0.0713	0.1114			

Table 4.21: Muscle VR during treadmill SP at fast walking speed.

The mean range of the overground walk being of 0.321 and mean variance 0.017 (Table 4.22). The details of the results from individual participants are presented in Table 4.22.

VR Overground Fast speed (over 6 cycles)														
Muscle	L Hams	L Quad	L Gas	L Tib A	L Soleus		R Hams	R Quad	R Gas	R Tib A	R Soleus			
Subject n°												Mean	Variance	Stand dev
001														
002	0.6217	0.1621	0.1194	0.2481	0.1004		0.4024	0.4974	0.7459	0.2117	0.1886	0.3298	0.04573	0.22541
003	0.1831	0.1789	0.1628	0.112	0.1958		0.3692	0.2953	0.184	0.1213	0.3704	0.2173	0.00801	0.09434
004	0.4812	0.1623	0.1658	0.1757	0.098						0.0669	0.1917	0.01832	0.14829
005	0.4387	0.1457	0.3717	0.4338	0.1052		0.2358	0.3028	0.1977	0.2665	0.1405	0.2638	0.01321	0.12116
006	0.2568	0.2511	0.1643	0.1451	0.1173		0.0928	0.0852	0.1748	0.1372	0.0755	0.15	0.00367	0.06388
007	0.316	0.1038	0.1363	0.2654	0.0709		0.362	0.0949	0.1701	0.0902	0.0548	0.1664	0.01078	0.10943
008														
009	0.2093	0.3171	0.2598	0.136	0.0945						0.109	0.1833	0.00788	0.09924
010	0.1794	0.0789	0.1735	0.1717	0.0896		0.0933	0.0381	0.2138	0.2595	0.1532	0.1451	0.00421	0.06843
011														
Mean	0.3358	0.175	0.1942	0.211	0.109		0.2592	0.219	0.281	0.1811	0.1449			
Variance	0.023	0.0052	0.006	0.0096	0.0012		0.0165	0.0261	0.0434	0.0047	0.0091			
Standard dev	0.1621	0.077	0.0827	0.1046	0.0375		0.1407	0.1768	0.2283	0.075	0.1022			

Table 4.22: Muscle VR during overground walking at fast speed.

4.6.1.4. Slow walking

At the slower walking speed on the FP treadmill walking, the mean VR was 0.322, mean VR range was of 0.756 and mean variance of 0.044 (Table 4.16). The details of the results from individual participants are presented in Table 4.23.

	VR Fixed Pace Slow (over 6 cycles)													
Muscle	L Hams	L Quad	L Gas	L Tib A	L Soleus		R Hams	R Quad	R Gas	R Tib A	R Soleus			
Subject n°												Mean	Variance	Stand dev
001	0.1785	0.178089	0.169	0.2559	0.15389		0.18027	0.83249	0.2316	0.0969	0.18826	0.246	0.03977	0.21022
002	0.29187	0.321343	0.338	0.8647	0.41872		0.12325	0.49881	0.8139	0.16471	0.24268	0.408	0.05751	0.2528
003	0.09152	0.303751	0.3646	0.562	0.27609		0.42623	0.53398	0.5255	0.31252	0.73762	0.413	0.03015	0.18303
004	0.28033	0.057544	0.4232	0.2646	0.04427		0.05852	0.16874	0.3808	0.06105	0.46927	0.221	0.02461	0.16537
005	0.73139	0.256493	0.3785	0.3059	0.14409		0.31999	0.33255	0.4363	0.18927	0.45458	0.355	0.02445	0.16483
006														
007														
008	0.26307	0.147187	0.1926	0.4693	0.14856		0.364	0.213	0.1346	0.22703	0.18253	0.234	0.01027	0.10682
009	0.12467	0.078979	0.2085	0.5883	0.64452		0.30196	0.06796	0.4037	0.1297	0.61666	0.316	0.04809	0.23116
010	0.04522	0.065364	0.0895	0.1637	0.13144		0.07453	0.09863	0.0893		0.23925	0.111	0.00316	0.05965
011	0.36241	0.125594	0.4051	0.8576	0.42397		0.34802	0.26967	0.3586	0.61608	0.83389	0.46	0.05069	0.23733
Mean	0.27381	0.169532	0.3	0.5095	0.27896		0.25206	0.27292	0.3928	0.24291	0.47206			
Variance	0.04068	0.010331	0.0128	0.0599	0.03578		0.01809	0.0262	0.0446	0.02846	0.05166			
Standard dev	0.21562	0.108658	0.1208	0.2616	0.20222		0.1438	0.17303	0.2258	0.18222	0.24299			

Table 4.23: Muscle VR during treadmill FP at slow speed.

On the SP treadmill the mean VR was 0.23, mean range was of 0.458 and a mean variance of 0.022 on the SP treadmill (Table 4.16). The details of the results from individual participants are presented in Table 4.24.

	VR Self Pace Slow (over 6 cycles)												
Muscle	L Hams	L Quad	L Gas	L Tib A	L Soleus	R Hams	R Quad	R Gas	R Tib A	R Soleus			
Subject n°											Mean	Variance	Stand dev
001	0.1744	0.2268	0.137	0.194	0.1667	0.2375	0.5079	0.277	0.1386	0.0862	0.215	0.01232	0.11702
002													
003													
004													
005	0.2767	0.5593	0.451	0.282	0.2435	0.4571	0.2935	0.249	0.2075	0.2291	0.325	0.01287	0.11958
006													
007	0.2044	0.0743	0.219	0.291	0.2119	0.547	0.103	0.252	0.3328	0.3707	0.261	0.01672	0.13629
008	0.046												
009	0.1633	0.0286	0.148	0.156	0.1941	0.054	0.0502	0.111	0.0675	0.08	0.105	0.00293	0.05708
010													
011	0.2001	0.1019	0.12	0.723	0.1854	0.1474	0.1704	0.222	0.5917	0.4429	0.29	0.04246	0.21721
Mean	0.1781	0.1911	0.234	0.363	0.2087	0.3014	0.1543	0.209	0.2999	0.2807			
Variance	0.0057	0.0459	0.017	0.046	0.0005	0.0424	0.0083	0.003	0.0372	0.0193			
Standard dev	0.0845	0.2474	0.15	0.248	0.0257	0.2377	0.1051	0.066	0.2227	0.1606			

Table 4.24: Muscle VR during treadmill SP at slow speed.

The mean VR was 0.25, mean range of the overground walk being of 0.494 and mean variance 0.020 (Table 4.16). The details of the results from individual participants are presented in Table 4.25.

	VR Overground Slow (over 6 cycles)												
Muscle	L Hams	L Quad	L Gas	L Tib A	L Soleus	R Hams	R Quad	R Gas	R Tib A	R Soleus	Mean	Variance	Stand dev
Subject n°													
001													
002	0.3096	0.2282	0.698	0.413	0.1965	0.2746	0.7134	0.6237	0.1496	0.2967	0.39	0.04045	0.212
003	0.1203	0.1687	0.219	0.148	0.1849	0.1984	0.3314	0.2826	0.2299	0.257	0.214	0.00369	0.06404
004	0.1244	0.1452	0.403	0.427	0.1068	0.075	0.2129	0.3572	0.1025	0.0723	0.203	0.01761	0.1399
005	0.2167	0.3579	0.275	0.151	0.207	0.3658	0.4762	0.4184	0.1584	0.3892	0.302	0.01192	0.11511
006	0.5958	0.1239	0.2	0.151	0.1003	0.1742	0.0835	0.1139	0.1284	0.0494	0.172	0.02165	0.15508
007													
008													
009	0.3355	0.1199	0.124	0.17	0.1363	0.1656	0.1005	0.1159	0.0877	0.1843	0.134	0.00097	0.03308
010	0.33	0.2785	0.179	0.287	0.2738	0.37	0.1816	0.3546	0.4361	0.4318	0.312	0.00731	0.09011
011													
Mean	0.2903	0.2032	0.3	0.25	0.1722	0.2319	0.2999	0.3238	0.1847	0.2401			
Variance	0.0227	0.0069	0.033	0.014	0.0033	0.0103	0.0445	0.0271	0.0124	0.0186			
Standard dev	0.1629	0.0894	0.196	0.126	0.0619	0.1098	0.2278	0.1779	0.1201	0.1472			

Table 4.25: Muscle VR during overground at slow speed.

4.6.2. Variance ratio of joint kinematics

The VR was also applied to the sagittal angles of the lower limb joint (hip/knee and ankle) to measure their variability and compare them to the muscle variability. Joint movement is, after all, the final output of the motor system and may be more sensitive to alterations in speed and condition (i.e. overground or treadmill).
When using the PiG as the biomechanics body model, the sagittal plane has been presented in different paper as being more reliable than the frontal and transverse plane [109], [455], [456].

4.6.2.1. Variance Ratio of joint

The results of this analysis are summarized in Table 4.26.

At the self-selected comfortable speed, the ankle presented a mean range in VR of 0.1692, (mean variance of 0.003±0.055) on fixed pace treadmill, this was the highest value in comparison with SP treadmill walking (mean range 0.128, mean variance of 0.003±0.044) or overground (mean range 0.038, mean variance of 0.0002±0.015). The ankle and knee joints displayed lesser variability during FP treadmill walking. The SP walking and FP treadmill walking were closer in their magnitude of variability compared with the OG walking in the hip and knee joints.

The scale of the variation of the VR was smaller for the hip joint, which means that this joint presents an overall more stable behaviour. The ankle presented more variations of the VR.

	Fixed pace treadmill Mean VR			Self-paced treadmill Mean VR			Overground Mean VR		
	Fast	Comfortable	Slow	Fast	Comfortable	Slow	Fast	Comfortable	Slow
Hip Variance (SD)	$1.e^{-5}$ (0.003)	$1e^{-5}$ (0.003)	$1.25e^{-4}$ (0.01)	$6.5.e^{-6}$ (0.002)	$6.5e^{-6}$ (0.002)	$1.1e^{-5}$ (0.003)	0.001 (0.034)	$5.7e^{-5}$ (0.006)	0.001 (0.036)
Range	0.018	**0.01**	0.031	0.01	0.007	0.007	0.076	**0.017**	0.086
Knee Variance (SD)	$8.e^{-5}$ (0.008)	$4.5e^{-5}$ (0.006)	$3.35e^{-5}$ (0.005)	$6.e^{-5}$ (0.008)	$1.45e^{-5}$ (0.003)	$2.5e^{-5}$ (0.005)	0.007 (0.074)	0.002 (0.039)	$1.55e^{-3}$ (0.039)
Range	0.167	**0.021**	0.015	0.022	**0.010**	0.013	0.139	0.104	0.093
Ankle Variance (SD)	0.004 (0.02)	0.003 (0.056)	0.002 (0.021)	0.003 (0.052)	0.003 (0.044)	0.001 (0.035)	0.001 (0.044)	$2.25e^{-4}$ (0.015)	0.002 (0.04)
Range	0.063	**0.169**	0.041	0.15	**0.128**	0.085	0.084	0.038	0.046

Table 4.26: Descriptive Statistics of the joint kinematics VR. In bold, the VR range of closest magnitude during the comfortable walk speed.

When observing the inter-individual data, shared behaviours can be observed on both legs of the participant.

At the comfortable walking speed, the FP treadmill walk generally presents higher VR values (see blue bars in Figure 4.18). As pointed previously, the ankles presented more variability than the other joints (higher VR values).

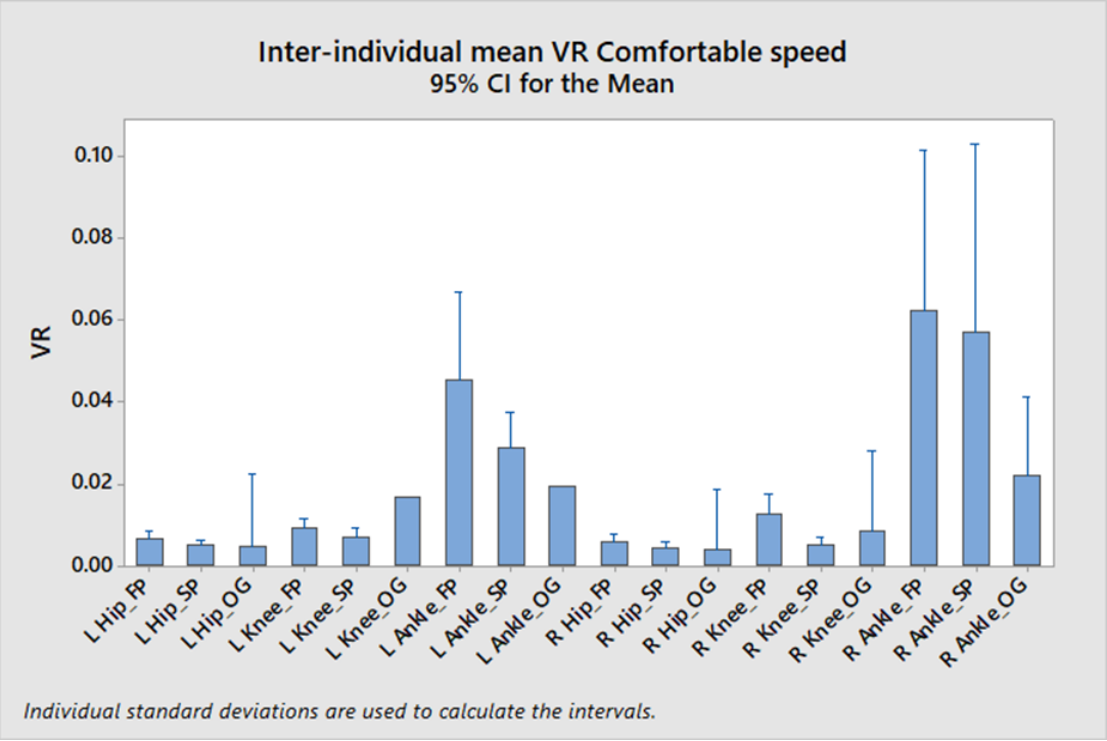


Figure 4.18: Mean Inter-individual bi-lateral VR of sagittal joint angle at comfortable speed (FP: Fix-paced treadmill, SP: self-paced treadmill, OG: overground)

During the fast walks, the variability tended to be higher while walking overground (see green bars in Figure 4.19).

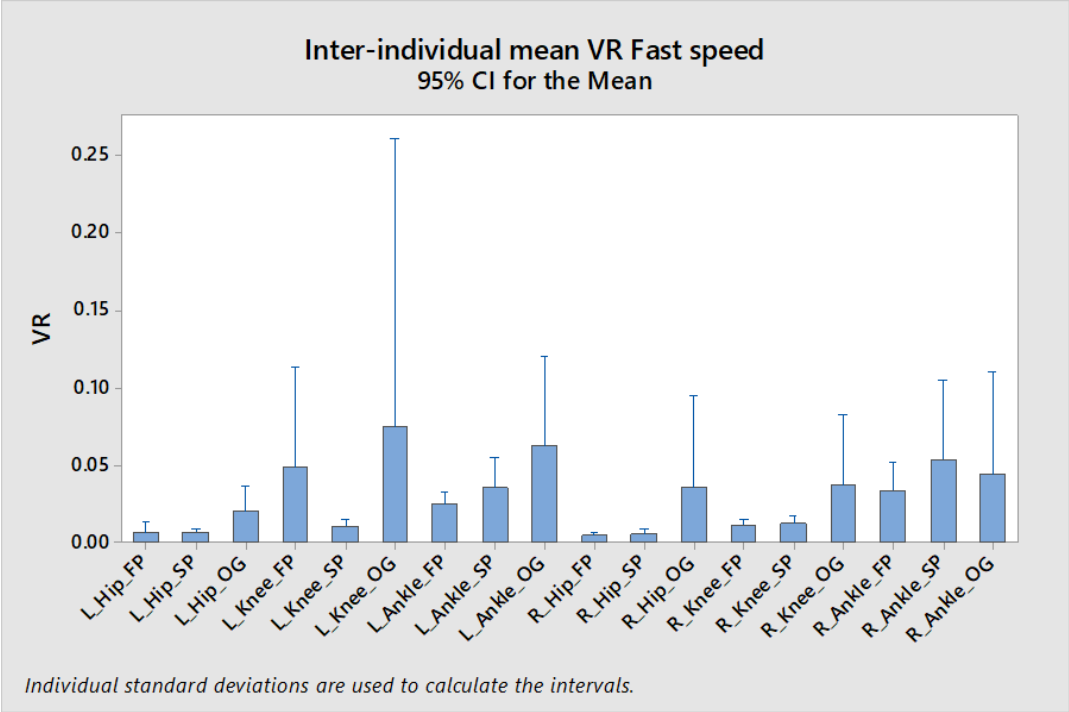


Figure 4.19: Mean Inter-individual bi-lateral VR of sagittal joint angle at fast speed (blue: Fix-paced treadmill, red: self-paced treadmill, green: overground)

During the slower walk, the VR value tended to be higher (more variability) during overground walking (see green bars in Figure 4.20).

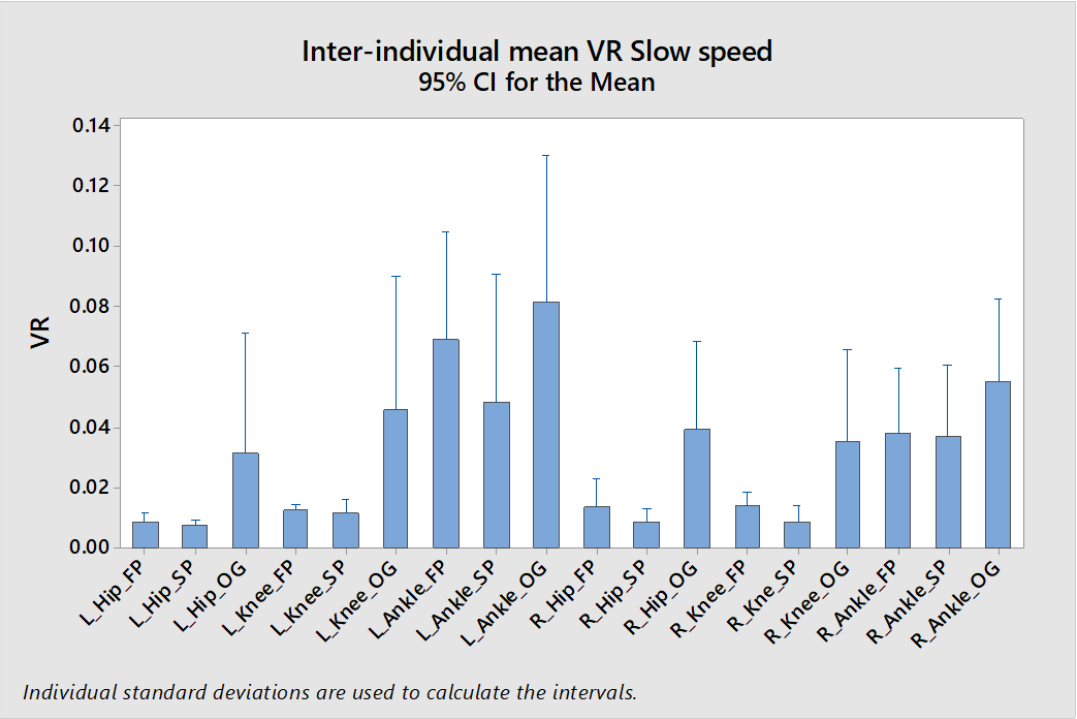


Figure 4.20: Mean Inter-individual bi-lateral VR of sagittal joint angle at slow speed (FP: Fix-paced treadmill, SP: self-paced treadmill, OG: overground)

		FP			SP			OG		
		Fast	Comf	Slow	Fast	Comf	Slow	Fast	Comf	Slow
Hip	mean VR	0.006	0.006	0.01	0.007	0.005	0.001	0.027	0.004	0.035
	(SD)	0.006	0.003	0	0.003	0.002	0.003	0.034	0.003	0.03
	Variance	0.00004	0.00001	0.0001	0.00001	0.000005	0.00001	0.012	0.00001	0.0012
	Range	0.03	0.01	0.05	0.01	0.009	0.01	0.108	0.006	0.09
Knee	mean VR	0.03	0.01	0.013	0.011	0.006	0.01	0.05	0.003	0.012
	(SD)	0.074	0.007	0.006	0.008	0.003	0.005	0.07	0.006	0.037
	Variance	0.0055	0.00005	0.00003	0.00006	0.000012	0.00003	0.0051	0.00003	0.0014
	Range	0.32	0.03	0.021	0.028	0.012	0.014	0.2	0.01	0.1
Ankle	mean VR	0.03	0.054	0.05	0.04	0.04	0.04	0.05	0.02	0.068
	(SD)	0.02	0.06	0.04	0.06	0.05	0.03	0.04	0.003	0.04
	Variance	0.00052	0.003	0.002	0.0032	0.0029	0.0012	0.0018	0.00001	0.0017
	Range	0.09	0.24	0.14	0.23	0.21	0.011	0.1	0.006	0.13
TOTAL	mean VR	0.022	0.02333333	0.02433333	0.01933333	0.017	0.017	0.04233333	0.009	0.03833333
	mean Variance	0.00202	0.00102	0.00071	0.00109	0.00097233	0.00041333	0.0063	1.6667E-05	0.00143333
	mean Range	0.14666667	0.09333333	0.07033333	0.08933333	0.077	0.01166667	0.136	0.00733333	0.10666667

Figure 4.21: Summary of statistical parameter of VR for each joint in the three walking situations at the three self-selected speeds

The repeated ANOVA analysis of the joint VR showed that the hip (p=0.02, f=4.1) presented significantly different VR values according to the walking speeds. The slower walk presented higher VR values than the fast and comfortable one.

The walking situation affected the hip (p=0, f=11.36) and the knee (p=0.03, f=3.65). The hip presented VR values of the same magnitude across the walking speed, making the overall SP walk situation mean VR smaller than the other walk situations. The knee also presented overall smaller VR values.

4.7. Summary of results

- When comparing the results of the different walking speeds, a significantly ($p<0.05$) lower VR value was observed when walking at the participant's self-selected comfortable speed. None of the walking situations presented statistically significant impact on the muscle VR, apart during FP treadmill walking for the soleus muscle (p=0.019, f=4.16) which presented higher VR values. This observation on the soleus muscle agrees with the hypothesis that SP treadmill walking and OG walking are closer walking experience than FP walking and OG walking are.
- When comparing the walking situations at the comfortable walking speed, the mean VR, VR variance and VR range of SP treadmill walking and OG walking had similar magnitude (VR: 0.176, range: 0.458, variance: 0.014 for SP, and VR: 0.196, range: 0.550, variance:0.016, for OG), when FP treadmill walking presented higher values (mean VR: 0.224, mean range: 0.752, mean variance: 0.038). The SP treadmill presented -10.204% of difference with overground walking when the FP presented 14.286%, making SP closer to OG than FP. During the comfortable walking situations only two participants presented significantly (p=0.001 for n°5 and p=0.03 for n°8) higher VR during FP walking. The results for these two participants agree with the hypothesis that SP treadmill walking is a closer analogue to OG walking than FP treadmill walking.
- When comparing the walking situations at fast walking speed a similar trend was displayed, with higher values during FP treadmill training (mean VR: 0.322, mean range: 0.756, mean variance: 0.044) and lower values during SP and OG walking of similar magnitude (VR: 0.23, range: 0.458, variance: 0.022 for SP, and VR: 0.25, range: 0.494, variance: 0.020, for OG). No significant differences were noted ($p>0.05$) between the walking situations. The SP treadmill presented -2% of difference with overground walking when the FP presented 28.8%, making SP closer to OG than FP.
- When comparing the walking situations at slow walking speed, the same trend was observed, presenting higher values during FP treadmill training (mean VR: 0.322,

mean range: 0.756, mean variance: 0.044) and lower values during SP and OG walking of similar magnitude (VR: 0.23, range: 0.458, variance: 0.022 for SP, and VR: 0.25, range: 0.494, variance: 0.020, for OG). No significant differences ($p>0.05$) were noted between the walking situations. The SP treadmill presented -8% of difference with overground walking when the FP presented 28.8%, making SP closer to OG than FP.

- Only the soleus muscle behaviour agreed with the hypothesis as it presented significantly higher VR values during FP walking in comparison to SP and OG walking. This implies that SP and OG walking lead to similar muscle activity outcome. This indicates that SP treadmill walking is a closer analogue to OG walking than FP treadmill walking, which makes SP treadmill walking a better training environment to improve OG walking for patients who had a stroke.

4.8. Discussion

The aim of this study was to observe any differences in the muscular activity and joint kinematics of three different situations of straight walking; overground fixed pace and self-paced treadmill walking at three different self-selected speeds (comfortable, slow, and fast). The aim was to test whether walking on a self-paced treadmill led to similar degrees of variability record for overground walking and then, support the hypothesis that self-paced treadmills are a closer replicant of overground walking than the fixed speed treadmill and therefore a better training modality.

In this study the VR was used to quantify the variability of the EMG envelope's shape and kinematics. When a muscle contracts it is in fact the result of an ensemble of muscle fibres being recruited to produce the movement. A change of the shape of the EMG envelope indicates a change in the muscle fibres recruitment. It was expected for a cyclic movement to observe similar recruitment patterns over the cycles. The surface EMG signal is a reflection of the activity of the muscle that is underneath it (and also the background noise as detailed in section 3.2.1.7). It is possible that changes in the muscle variability were though a manifestation of muscle fatigue [396], [457]. This possibility, however, seems unlikely since the participants were able-bodied and walked at their comfortable self-selected speeds for a relatively short period of time (approximately 30 minutes).

4.8.1. Observations of the variability of the EMG activity and joints movements

This study aimed to test the hypothesis that SP treadmill walking would present greater similarity of variability with OG walking than with FP treadmill walking. Five lower limb muscles were used to observe the variability of muscle activity and three joints were used to observe the variability of the joint kinematic, using the VR as the mathematical tool to measure variability.

The analysis of the kinematic data rejects the hypothesis that the variability of SP treadmill walking is closer to the variability present during OG walking. Only the walking speed presented significant difference with slow speed leading to higher variability than the other walks. These findings do not lead to a clear differentiation between the walking situations.

The small number of participants (n=11) might be the cause of this.

While Hershler and Milner, 1978 [335] found that walking at the participant's most comfortable speed led to less variability, these results agree with Richard et al., 2014 [338] who did not find significant ($p>0.05$) change in the VR when their participants walked faster than their preferred speed. The VR value, nonetheless, was lower during comfortable walking compared to fast and slow walking in each walking situations and in most muscles.

The analysis of the muscle activity did not support the hypothesis that SP treadmill walking leads to a variability that is closer to OG walking than FP walking. However, there was a general trend indicating similar lower VR magnitude between the SP treadmill and the OG walk, and higher VR values during FP walking.

The values of VR observed in this study match the values found in the literature [336], [395], [458]. Hwang et al. (2003) [336] observed the variability of the tibialis anterior and gastrocnemius and found VR values comprised between 0.042 and 0.647. Granata et al. (2005) [337] measured the VR of the rectus femoris, medial hamstrings, tibialis anterior and medial gastrocnemius of children. They found VR values ranging between 0.328 and 0.657. Mickelborough et al. (2004) [458] investigated the variability of the muscle activity of six lower limb muscles at the initiation of the walk of able-bodied older adults. They found values comprised between 0 and 1.

The larger range of variance ratio during FP walking suggests that the muscle activity is more variable during this type of walking compared to SP treadmill and OG.

In a 2003 paper, Goodkin and Thach [459] observed that there were more muscles active than necessary when monkeys performed a constrained task of grabbing a reward were the thumb and/or index fingers were constrained and compared to the unconstrained movement. When the task was performed freely, however, the muscle activity was consistent with what was required to perform the movement. This finding echoes the results of the current study where the constrained nature of FP treadmill walking [460], which may not replicate normal over ground walking, imposes a non-natural recruitment pattern, by using more muscle fibres than necessary during OG walking. FP treadmill walking is a highly repetitive and predictable task, the relatively high variability observed is in agreement with Bernstein's observation on the motor control of precise tasks requiring repetition [268] (c.f. section 2.3.1.1).

During treadmill and OG walking the calculated VR values were different for the same muscle group on the right and the left side. The asymmetrical behaviour noticed between the targeted muscle from the right and the left leg is likely to reflect the dominant side of the participant.
These observations are a first insights on a possibility to retrieve information regarding the motor control strategies used while walking over different mediums (OG, FP and SP treadmill) using the VR. The motor control of walking is influenced by the walking situation and could have clinical implications as the rehabilitation of walking should aim at restoring the patient's walking ability in the community, which is a different walking situation to FP treadmill walking.

The tibialis anterior muscle stood out in comparison to the other muscles as it was not significantly affected by the walking speed. A proposed explanation for this is that the role of the tibialis anterior during walking is to dorsiflex the foot. Foot dorsiflexion allow foot clearance and prevent from tripping and/or falling due to a dragging of the foot. It is possible that the tibialis actuation is a reflexion of the consistency needed to achieve foot clearance regardless of the speed. Byrne et al. (2007) [461] reported in a paper that the contraction duration of the tibialis anterior is consistent across different speeds of walking. Also, the amplitude of the contractions of the tibialis anterior during heel strike increases almost linearly with the increase of walking speed.

The soleus also stands out as it is the only muscle that displayed significantly higher VR during FP in comparison with SP and OG. This behaviour might reflect the role of the soleus during walking. The soleus contributes to plantarflexion with the gastrocnemius. Its activity during stance, through the forward propulsion of the leg, produces breaking of forward velocity and contribute to the vertical support of the leg [462]. The change of variability might reflect a change of strategy in maintaining the ankle's stability in the different walking situations.

On the other hand, the order of magnitude of the kinematics VR were around 100 to 100000 time smaller than the muscles VR which could also be interpreted as negligible variability. Previous papers have assessed the similarity of treadmill walking with OG walking [109], [111] (see Section 2.2.1). They came to the conclusion that the kinematic differences between treadmill and OG walking were negligible [109], [111]. There is, to our knowledge, no paper reporting the measure of kinematics variability relaying on the VR. It could be that the VR is not adapted to measurements of kinematic variability because of their more stable behaviour. Where the EMG signals present much greater changes in amplitude because of its noisy behaviour, the kinematic data, in comparison, present clearly smoother curves. The VR did not prove to be an efficient tool to measure the variability of the kinematic data.

The calculation of the variability of the kinematics presented different behaviour on the ankle joint in comparison with the hip and knee joint. The ankle joint followed the muscle VR behaviour by presenting more stability in the case of OG walking. The hip and knee joint presented opposite results as they present less stability during OG walking. It appears that treadmill walking represents a more challenging task than OG walking for the ankle as one of its roles include the support for the absorption of forces during the walk as well as for progression. It is possible that fixed speed treadmill walking makes the optimal motion more difficult to evaluate or does require less accuracy.

4.8.2. Limitations of the study

The current study was completed with a small able-bodied participant's sample (n=11) while in total, nine different walking conditions were compared, there were three walking speeds over three different walk settings. A small sample size is more likely to lead to statistical error [463], [464]. Consequently, an ANOVA was unlikely to lead to a statistically significant difference and therefore invalidate the hypotheses that SP treadmill walking shares more similarities of muscle activity variability with OG walking than FP treadmill walking.

As the walking speed instructions were not restrictive, the notion of slower or faster walk were the participant's own perceptions which might have led to less clear differentiations between the gait speeds and therefore impact the changes in motor control. The participant's walks OG and on the treadmill were not matched in speed. This choice was supported by the intention of recording natural walk. Literature shows that people tend to walk slower on a treadmill than they would do during OG walking when walking at their comfortable walking speed [109], [231], [232]. In the case of this study, the OG walking speed was not recorded, which does not allow to compare the three walking speeds trend and compare it with the literature.

One limitation coming from using the VR parameter is that there is no clear normalisation method for applying it to EMG signals. Common practice is to apply the EMG to rectified signals that have been smoothed and normalised temporally to separate the strides that are compared to one another [336], [395], [458]. These steps were also present in the treatment of the EMG of this study. However, there is information lacking about the number of strides used to calculate the VR. When Richards et al. (2014) [338] mentions rejecting participant data which did not comprise at least 15 valid cycles, there is no indication of over how many cycles the VR was calculated. Hwang et al. (2003) [336] mentions measuring the EMG of at least 10 consecutive strides but no upper limit gait cycles. Granata et al. (2005) [337] did not provide indication about the number of stride studied. The absence of precision can be an obstacle to the comparability between studies.

This study did not restrict the participation to the study to people who had previous experience with walking on a treadmill. This might affect how the participant adjusted to walking from OG to on the treadmill which might have affect both

muscle recruitment strategy and the joint kinematics. Lee and Hidler (2008) [111] found a diminished range of motion during treadmill walking than OG, looking at the knee joint. Sloot et al. (2014a) [233] also found a reduced range of motion during SP in comparison with FP treadmill walking on the hip and the knee.

4.8.3. Future recommendations

The current method used the knee joint angle data as reference to separate the gait cycles. To improve this aspect of the study, future work should use an IMU-based algorithm, using either the gyroscope or accelerometer data, to detect the gait cycles to have a more accurate method. Methods relying on IMU sensors such as accelerometer or gyroscope data, are supported by more literature validation.
In this study, two treadmill walking situations were compared to one OG walking situation. These are straight walking conditions. The addition of a walking situation matching the community walking experience, for example slope and/or changes in direction should further the investigation on the difference of motor control strategies attached to different walking situations. Ultimately, the best rehabilitation should be the one leading to better community walking.
This study did not reach significant differences between the different walk settings compared. The addition of more participants to the VR analysis might impact the statistical significance of the observed behaviour.
The inclusion of a time of familiarisation to the treadmill walking environment should be implemented in order to insure the collection of data from comfortable walking at a self-selected pace.
As mentioned in section 4.8.1, the ankle joint is the one presenting the most variability. In the next study, the number of muscles observed could be reduced to two muscles participating in ankle movement.

Future work with impaired participants is planned to understand whether these findings occur in populations with stroke. It will include participants with chronic stroke to compare with able-bodied and get a first comparison between the two populations.
An intra-individual, muscle-per-muscle analysis could provide more information on to what the differences are between the different walking situations.

4.9. Summary

In this preliminary study, 11 participants were asked to walk at different self-selected speeds informally called fast, comfortable, and slow speed. The kinematic information was recorded using markers and infrared cameras. Their muscle activity on 5 lower limb muscles from each leg were recorded with wireless surface EMG electrodes. A comparison of the surface EMG collected during the three walking situations (overground, on fixed pace treadmill and self-paced treadmill) revealed a wider range and variance of VR values when the participants walked at a fixed pace on the treadmill, compared to self-paced and overground walking. However, these differences were not statistically significant.

These results refute the hypothesis of significant ($p<0.05$) difference of FP treadmill walking in comparison to SP treadmill walking and OG walking. However, the trends observed in the VR values and the significant difference found in the soleus muscle deserve further exploration.

Chapter 5

5. Observational study comparing walking in four different environments (indoors, outdoors, on a fix-paced and on a self-paced treadmill) with able-bodied and chronic stroke participants

This chapter presents the methods section for the observational study which aimed to compare the muscle activation patterns across eight walking conditions to inform the use of treadmill training in the recovery of walking function following a stroke. The eight walking conditions being: 1) outdoor flat walking, 2) outdoor uphill walking, 3) outdoor downhill walking, 4) indoor flat walking, 5) treadmill fixed pace flat walking, 6) treadmill self-paced flat walking, 7) treadmill self-paced uphill walking and 8) treadmill self-paced downhill walking.

5.1. Hypothesis and Objectives

5.1.1.1. Hypothesis

Hypothesis 1: There will be statistically significant ($p<0.05$) differences in the muscle activation pattern between FP treadmill walking and the three other walking situations (self-paced treadmill, indoor and outdoor flat overground walking).
Self-paced treadmill walking will be closer to overground walking (indoors and outdoors) in comparison to fixed pace treadmill walking in both the able-bodied and chronic stroke participants across the eight walking conditions.

Hypothesis 2: There will be no statistical difference ($p>0.05$) in muscle activation pattern between the SP slope walking and overground outdoor slope walking.

5.1.1.2. Objectives

1. Record the EMG signal from selected lower limb muscle over multiple gait cycles during the eight different walking conditions.
2. Compare the variability of the muscular activity patterns across the walking conditions using parameters of uncomplicated interpretation.
3. Observe if the different walking conditions impact differently the able-bodied participants compared to the chronic stroke participants.

5.2. Ethics and Participants

All participants were adults recruited as two different groups. The first group was composed of 17 able-bodied adults (see *Table 5.1* for details) with no known musculoskeletal, sensory, or neurological impairment. The full exclusion criteria are given in *Table 5.3*.

The second group consisted of seven adult participants with impaired motor function following a stroke at least 12 months previously (see *Table 5.2* for details). The inclusion criteria for theses participants are detailed in *Table 5.4* and included the ability to walk outside independently with or without walking aid.

The study was approved by the university of Strathclyde ethics committee under the title "Comparing outdoor, indoor and treadmill walking for people with and without mobility problems" and the reference number UEC17/15 Kerr/Ibala/Smith.

5.2.1. Baseline measures

Both groups had anthropometric measurements taken, including weight, height, interAsis distance (distance between left and right anterior posterior iliac, illustrated in Figure 4.2, section 4.4.2, Chapter 4), knee width, ankle width and leg length on both sides. These data were necessary for the construction of the biomechanical model (Plug in Gait, Vicon) used during the motion capture. They completed the Montreal Cognitive Assessment (MOCA) [465] to check their cognitive ability (see in Annex H). The MOCA is used to evaluate mild cognitive impairment. A score of below 26/30 (30 being the maximum score) identified an individual as being cognitively impaired. The Rivermead Mobility Index (RMI) [466] was also used to evaluate mobility, this is a well-established clinical test with good reliability [467]–[469] and validity [469]. Lennon and Johnson (2000) [469] reported that the RMI presented stability between tests when used twice (paired t-test = 0.732 ; $p = 0.47$), the RMI is highly reliable between evaluators (ICC = 0.98 ; $p<0.001$). Chen et al. (2007) [468] reported an Interclass Correlation coefficient of 0.96 demonstrating its very good test re-test reliability. In this index, fifteen functional movements (e.g. sit to stand) are rated as either 0

or 1 where 1 means the participant can perform the task and 0 that they can't. All the tasks, apart from one (requesting to stand unsupported for 10 seconds without help), are self-evaluations by the participant. A score of 15 is generally considered to mean the participant has good functional mobility [468]. Schindl et al. (2000) [467] reported a median RMI of 13 for chronic stroke survivors before (50% of the RMI score were comprised between 7, 1st interquartile, and 14, the 3rd interquartile) a three-weeks long physiotherapy intervention. After the physiotherapy intervention a median RMI of 13 was reported (50% of the RMI score were comprised between 9, the 1st interquartile and 15, the 3rd interquartile). It can be noted that when the median MRI remained the same the interquartile value increased by two points, which reflects mobility improvement. Chen et al. (2007) [468] assessed a group of 50 chronic stroke participants with mild to moderate impairments. Their RMI was measured twice and their values were of 9.0±3.8 one the 1st test and 8.9±3.9 on the 2nd test.

5.2.2. Informed consent

All participants read a participant information sheet at least 24 hours before being invited to give consent to participate (see Annex D and E for participant information and consent form details).

Participant identification no.	Gender	Height (m)	Weight (kg)	Age (years)	MOCA	RMI
AB_1	M	1.72	58.7	28	30	15
AB_2	M	1.82	62.3	25	29	15
AB_3	M	1.83	86.0	48	29	15
AB_4	F	1.65	55.0	23	30	15
AB_5	F	1.65	64.5	22	30	15
AB_6	M	1.82	80.3	24	28	15
AB_7	F	1.63	54.5	23	29	15
AB_8	M	1.74	65.1	21	26	15
AB_9	M	1.72	64.3	25	28	15
AB_10	F	1.69	71.9	36	28	15
AB_11	F	1.59	54.2	24	28	15
AB_12	F	1.54	80.8	24	29	15
AB_13	F	1.50	69.3	34	29	15
AB_14	F	1.65	66.1	25	27	15
AB_15	F	1.70	80.4	18	30	15
AB_16	M	1.85	75.0	26	29	15
AB_17	F	1.64	63.7	26	28	15
Mean		1.69	67.8	26.6	28.6	15
Standard deviation		0.10	9.92	7	1.11	0

Table 5.1: Participants information 1st group, able-bodied

Participant no.	Gender	Height (m)	Weight (kg)	Age	MOCA	RMI	Time since stroke (months)	Affected side
S_1	M	1.68	78.5	67	27	12	14	R
S_2	M	1.86	83.2	62	28	13	Missing	L
S_3	F	1.63	45.5	65	28	14	38	L
S_4	F	1.56	88.1	69	24	13	73	L
S_5	F	1.64	52.5	52	27	14	252	L
S_6	F	1.59	58.8	73	25	15	72	R
S_7	F	1.59	64.3	68	28	12	48	L
Mean		1.65	67.3	65.1	26.7	13.3	82.8	
Standard deviation		0.10	16.2	6.7	1.60	1.11	85.8	

Table 5.2: Participants information 2nd group, chronic stroke

Inclusion	Exclusion
• Adult (18+ years old) • Able-bodied • No known musculoskeletal impairment • No known sensory impairment • No known neurological impairment	• Uncorrected hearing-impairment • Uncorrected visual impairment, • Pregnancy • Under the age of 18, • Impaired balance • Currently taking medication that could affect walking ability

Table 5.3: Inclusion and exclusion criteria, able-bodied participants

Inclusion	Exclusion
• Adult (18+ years old) • Impaired motor function as outcome of a stroke at least 12 months previously • Able to walk outside independently with or without walking aid	• Use of medication affecting the performance of mild exercise • Uncorrected hearing-impairment • Uncorrected visual impairment • Severe aphasia • Heart or respiratory conditions • Physical or neurological impairment impacting the walking abilities or balance

Table 5.4: Inclusion and exclusion criteria, stroke participants

5.3. Material and methods

5.3.1. Equipment

5.3.1.1. EMG

Wireless electromyographic (EMG) surface electrodes (Delsys Trigno, Boston, USA) were applied to the skin overlying the following muscles: hamstrings (biceps femori), quadriceps (vastus lateralis), gastrocnemius (lateral gastrocnemius), and tibialis anterior on both sides using hypoallergenic double-sided tape. The sensor's placement followed SENIAM method's recommendations [347]. Prior to the application of the EMG electrodes on the legs, the area was shaved (if there was hair). The skin was then cleansed by rubbing with alcohol wipes. This ensured the removal of hair, dead skins, and oil on the surface in contact with the EMG sensors, thereby minimising signal impedance. The Trigno EMG sensors have 4 bar-shaped silver electrode that are in contact with the skin, designed as two set of parallel of electrodes (see Figure 5.1). These bars are recommended to be placed perpendicular to the orientation of the target muscle fibres as illustrated in Figure *5.2*. The arrow design on top of the sensor's case helps this placement. The sensor case's dimensions are 27x37x15 mm and the contact surface of the silver bar's dimension are 5x1 mm.

The EMG signals were recorded wirelessly, on a radiofrequency (RF) band of 2400 to 2480 MHz, which is within frequencies of the Industrial, Scientific and Medical equipment service (ISM), (which is also within the frequencies of the Bluetooth), at a frequency of 2kHz. Its range of operation is up to 40m away from the sensor base. This range can diminish in the presence of other RF sources. There is an inherent delay in the data transmission between the sensor and the analogue output. These are referred to as group delay and correspond to the sensor filter (1.5 ms), the digitalisation delay (41 ms), the SinX/X correction (2 ms) and the analogue low-pass filtering (3.5 ms) [470].

Figure 5.1: Delsys Trigno EMG sensors have four silver electrodes coming in contact with the skin. Extracted from Delsys Inc (2012) [470]

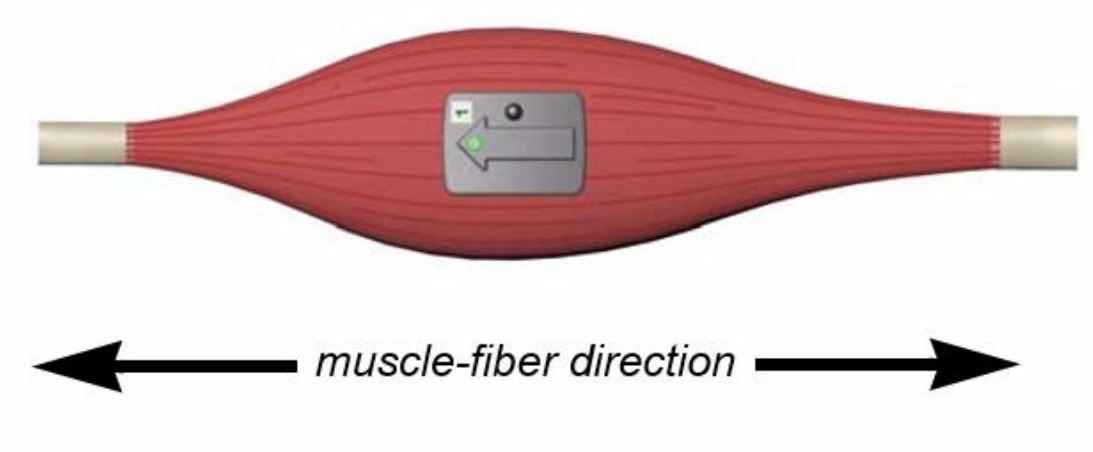


Figure 5.2: Delsys Trigno sensors must be oriented along the muscle fibre's direction, the arrow shape on the sensors is designed to help the placement. Extracted from Delsys Inc (2012) [470].

5.3.1.2. Kinematics measurements

The kinematic data were recorded using 12 Vicon, T-series (Vicon, Oxford Metrics, Oxford, UK) cameras, at a 100Hz frequency, for all overground walking condition excepted the outdoor walking. The trajectory data from the cameras were processed using proprietary software (Nexus, Vicon, Oxford Metrics, Oxford, UK). During the treadmill walking conditions, 12 Bonita (Vicon, Oxford Metrics, Oxford, UK) cameras were used (see *Figure 5.3*), operating at 100Hz, positioned around the treadmill on the 180° screen frame and behind in order to cover the entire exercise environment. The Vicon Bonita cameras are equipped with 68 high powered led emitting in the near infrared wavelength (780 nm). The light emitted by the cameras (Bonita and T-series) is reflected on the reflective markers attached on the body landmarks, according to the Lower-limb Plug-in-Gait model (as presented in chapter 4, section 4.4.2). The overground data were recorded from gait initiation

until a series of approximately 20 steps were performed. Treadmill data were recorded for approximately 20 steps following initiation, which allowed to later extract the data corresponding to ongoing, steady-state walking and cut out what corresponded to the initiation and transition to steady walking state.

Figure 5.3: VICON Bonita Motion Capture camera *[466]*

5.3.1.3. Outdoor data collection

The outdoor data were collected without cameras. Instead, a set of four Force Sensitive Resistors (FSR) (see Annex F for specifications details and technical sheet) (Delsys Trigno, Boston, USA) were placed under the foot of the participants on their socks to act as event detectors (i.e. initial contact and loss of contact). FSR sensors are used to obtain information about the relative pressure exerted between the body part it is attached to and the surface of contact. The output data is a percentage of the sensor's full range of detection. The analogue output range of these FSR sensors is comprised between -4.85 V (0% of the detection range) and 5.00 V (100% of the detection range). No additional signal processing operations were presented in the user's guide document [471]. When placed under the foot, FSR can be used to identify gait events such as the contact of the heel on the ground or the foot off from ground. The FSR membrane used were circular and with the surface of 15 mm^2 as presented in Figure 5.5. Each of Delsys FSR sensors is designed to collect of four channels, which allows the observation of four pressure sensors at the same time (see Figure 5.6). The first channel is sampled at a 1926 samples/sec rate and the three other channels are sampled at a 148 samples/sec rate. The four FSRs were located under the heel, base of the 1^{st} metatarsal, base of the 5^{th} metatarsal and under the base of the hallux (see Figure 5.5). For the stroke participants, the FSRs were placed on the affected side only, whereas they were randomly allocated between sides in the control participants.

Other kinematic parameters were recorded from the dual Delsys Trigno system which combines EMG and an inertial measurement unit (IMU) sensor. The IMU sensors contain gyroscopes (to measure the angular velocity around three axes), accelerometers (to measure

the accelerations along three axes) and magnetometers (to measure the magnetic field along the three axes), see Figure 5.7. With these additional sensors, it is possible to monitor the movements of the participant's limb. The IMU signal is processed from a digital to analogue signal by a Digital to Analogue Converter (DAC) sampling (the DAC filter's bandwidth is 0-500Hz). When collected, the biological signal goes from being an analogue signal (continuous) to a digital signal (ensemble of points) collected at a given sampling rate. By converting the signal from digital to analogue, the signal output is a reconstruction of the original signal. This operation leads to a distortion of the entry signal, because of the quantisation error. The quantisation error corresponds to the vertical distance between two successive samples. Following a DAC operation, the resulting signal is a succession of steps, which take a shape that is similar to the original analogue signal (see Figure 5.4).

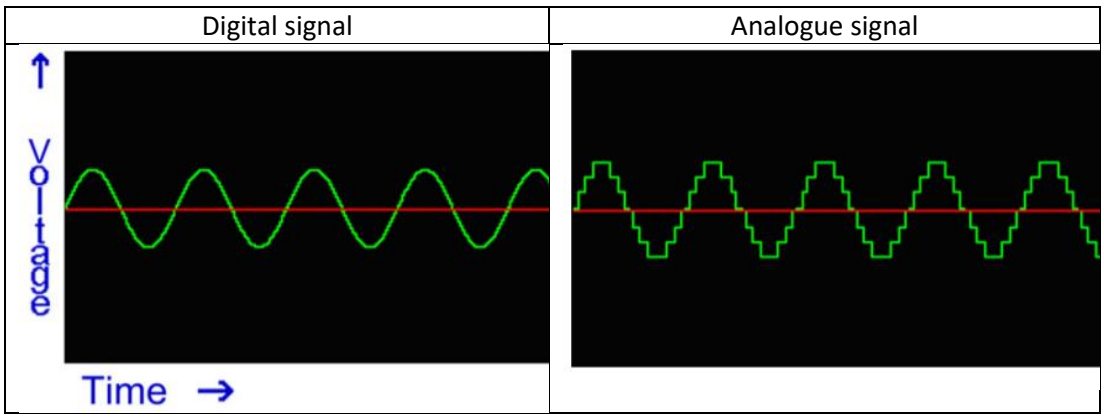


Figure 5.4: Digital to Analogue signal operation on a sine wave. Extracted from Oshana (2012) [472]

To mitigate the effect of this operation the sine(x)/x correction filter is used to preserve the amplitude difference between the analogical points. There is an inherent delay in the data transmission between the sensor and the analogue output. These are referred to as group delay and correspond to the Accelerator filter (2 ms), the digitalisation delay (41 ms), the sine(x)/x correction (27 ms) and the analogue low-pass filtering (26 ms) [470]. They were placed on the lateral surface of each measured segment (foot, shank, thigh) and on the lower back (over the sacrum). Those dual sensors were only used for IMU recording while the EMG only sensors were used for the muscle activity recording.

Figure 5.5: FSR sensor placement and FSR membrane. From Delsys 4-Channel FSR Adapter User's Guide [471]

Figure 5.6: Delsys Trigno, Four-channel FSR sensor. From Delsys 4-Channel FSR Adapter User's Guide [471]

For the outdoor test the data from the sensor (EMG, gyroscope and accelerometer) were streamed, as presented in the EMG section (section 5.3.1.1), through the ISM frequency band and recorded using a LabVIEW (National Instrument, Austin, USA) bespoke programme (c.f. Annex G for more detail on program interfaces and technical developments).

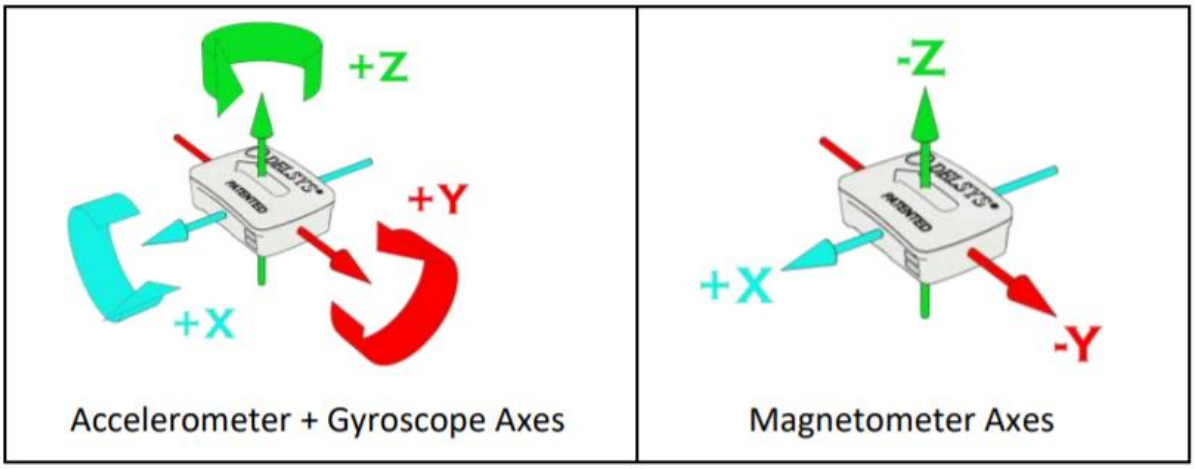


Figure 5.7: Delsys Trigno IMU sensors' axes. From Delsys Inc, (2019) [473]

5.3.1.4. Treadmill system

The treadmill walking trials used the Motek CAREN Extended system. The Motek Extended CAREN system (Motek Medical BV, Amsterdam, Netherlands). The Motek Extended CAREN system combines motion capture with a treadmill equipped of two force plates and embedded on a platform that allows six degrees of freedom. This type of platform has been used for application such as gait analysis [250], [431], [474], gait stability [425], balance [475], and with diverse pathologies or health condition such as multiple sclerosis [427], stroke [476], [477], lower-limb amputation [478], [479], cerebral palsy [480] as well as abled bodied. This system is complemented by an immersive audio and visual experience delivered through the projection of a virtual reality onto a 180° screen facing the treadmill's platform, see figure Figure 4.1 for illustration.

5.3.2. Procedure

Once the anthropometrics measurements were recorded as detailed in section 5.2.1, the EMG electrodes (recording EMG signal only) were attached to the legs of the participants according to the procedure presented in section 5.3.1.1. The EMG sensors were attached to the skin with allergy-free double-sided tape. The EMG sensor's placement was realised using the SENIAM methods [347] (see sensor location in *Figure 5.8*). The FSR sensors were attached using adhesive bandage tape over the socks on the feet of the participant in the locations detailed previously (see *Figure 5.5*) and the shoes were put back on.
Once the EMG only sensors were attached, the dual EMG/IMU sensors (which will be referred as IMU sensors) were attached to the lateral surface of the foot, shank, and thigh and over the participant's sacrum. The sensors' placement is illustrated in Figure *5.8*. These IMU sensors were used for the only purpose of collecting movement information and no EMG data was collected from them. There is support in the literature, detailing on the use of sagittal data of the IMU data for movement analysis [481]–[484].

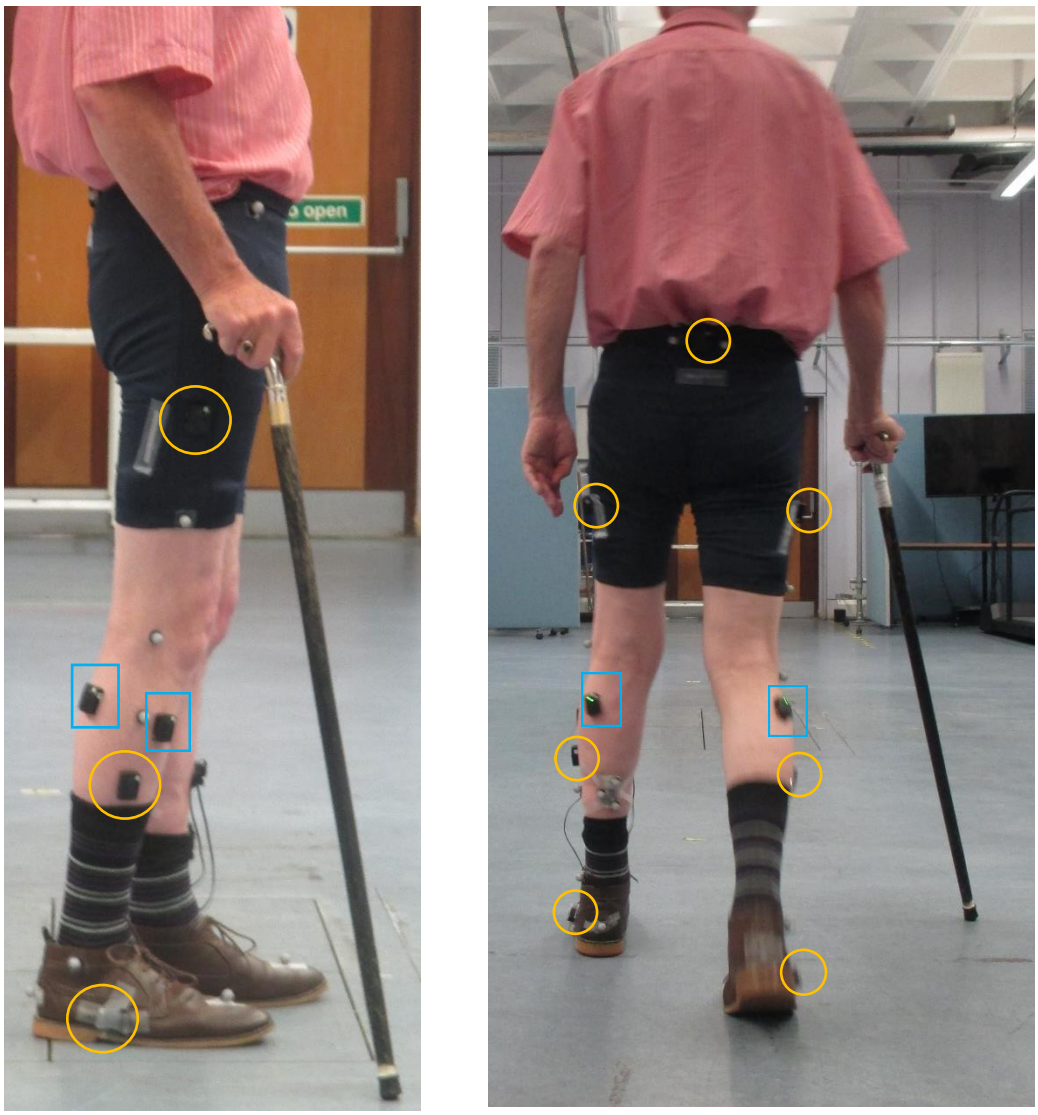


Figure 5.8: IMU sensors (in orange circles) location to collect data for kinematic measurement, EMG sensors location (in blue rectangles) for muscle contraction measurement.

5.3.2.1. Outdoor walking

The first data collection session was the outdoor walking. The reason for outdoor walking being the first walking condition was to minimise the number of sensors attached on the participant when walking outdoors. The outdoor walking was measured with minimal equipment (the reflective markers were added after). Also, starting by outdoor walking was a measure to anticipate the possible changes of weather and ensure the recording of the outdoor data was successful. Before the walking was commenced each participant was asked to stand still while EMG reference data (to measure the background noise) was recorded. Then the straight walking exercise was performed where the participant was asked to walk straight for about 20 meters over the concreted outdoor surface pavements (see Figure 5.9), turn around a cone and walk back to the starting point. Once three repetitions were collected of the straight walk the participant was invited to take a short rest before proceeding to the outdoor slope walk. The outdoor slope walks took place in an area immediately adjacent to the flat outdoor walks. The slope was 20 meters in distance with a gradient that ranged between 3 and 6 degrees (see Figure 5.10).

Figure 5.9: Concrete pavement floor on which participants performed the flat outdoor walking.

Figure 5.10: Participant walking down the outdoor slope.

Between the outdoor and indoor walking trials reflective markers (14mm in diameter) required for the motion capture session (see Figure 4.2 and Figure 4.3 in section 4.4.2 for location details) were applied to each participant in sitting which provided an opportunity for the participant to rest. The testing order following outdoor walking trials (i.e. treadmill or overground) was randomised using a coin toss to reduce the possibility of an order effect. Between the two indoor walking test (indoor overground or treadmill) times, the MOCA test was done with the participants.

5.3.2.2. Indoor overground walking

The indoor overground walking comprised straight walking in a biomechanics lab on a flat surface as can be seen in Figure 5.11.

Figure 5.11: Empty gait laboratory where the indoor walking took place

5.3.2.3. Treadmill walking

The treadmill walking trials consisted of 1) flat fixed pace walking, 2) flat self-paced walking, 3) uphill self-paced and 4) downhill self-paced walking. This was also the order for these conditions which was applied consistently for all participants. The sloped walking had two gradients to reflect the outdoor slope (3 degrees and 6 degrees).

5.4. Data reduction and analysis

5.4.1. Determination of gait cycles

The determination of gait events is important for processing cyclical data allowing multiple cycles to be compared and average values to be calculated. The data from the IMU sensor attached to the lateral border of the shank was used to detect these events. IMUs have been well used for gait event detection [484]–[486] in post-processing but also quasi-real- time [486] including real-time gait analysis [487]. Some of the algorithms used combine the gyroscope data with the accelerometer or other sensors such as FSR [484], [488], [489], which allows the event to be detected by different sensors and confirm the event by information redundancy. Some of these algorithms were designed to identify pathologically constrained gait [487], [490]. The following section will describe these algorithms and justify selection for this study.

Pappas et al. (2004) [484], developed an algorithm able to segment gait into two phases (stance and swing) by detecting two gait events that they referred as "heel strike" and "heel off", in real-time. The sensors used as input to their algorithm were a gyroscope, placed on the lateral side of the foot, measuring the angular velocity of the foot and three FSR sensors attached to the bottom side of an insole, located under the heel, the first metatarsal and the fourth metatarsal [484]. This gait-phase detection system (GPDS), combined data of pressure and angular velocity allowed the detection of the two phases of gait (see *Figure 5.12*). The GPDS was tested on a group of able-bodied participants (group A) and on a group of participants with various gait impairments (group B) including incomplete spinal cord injury and stroke [484], [489]. The reliability of the GPDS was tested on different walking tasks such as walking up and down stairs, walking on uneven ground (walk on and off pavement, overstepping obstacles, walk on grass, snow and earth), walking on levelled ground and walking up and down a slope (50 m long, steep cobblestone road, 15% inclination). The reliability testing of the GPDS during levelled ground, slopes, and irregular terrain walking led to a success rate of 100% for the group A and 99% for the group B [489]. The steps which failed to be identified were explained as hesitant walking from group B members when having to step on an obstacle, irregular walking and very low heel lifting [489]. The reliability testing of the GPDS during stair walking led to a success rate of 99.78% for group A (the missing steps occurred during stairs descent) and 96% for group B [489]. As the participants did not always contact the ground with all the sensors the interpretation of the signal recorded relied more on the gyroscope signal [489].

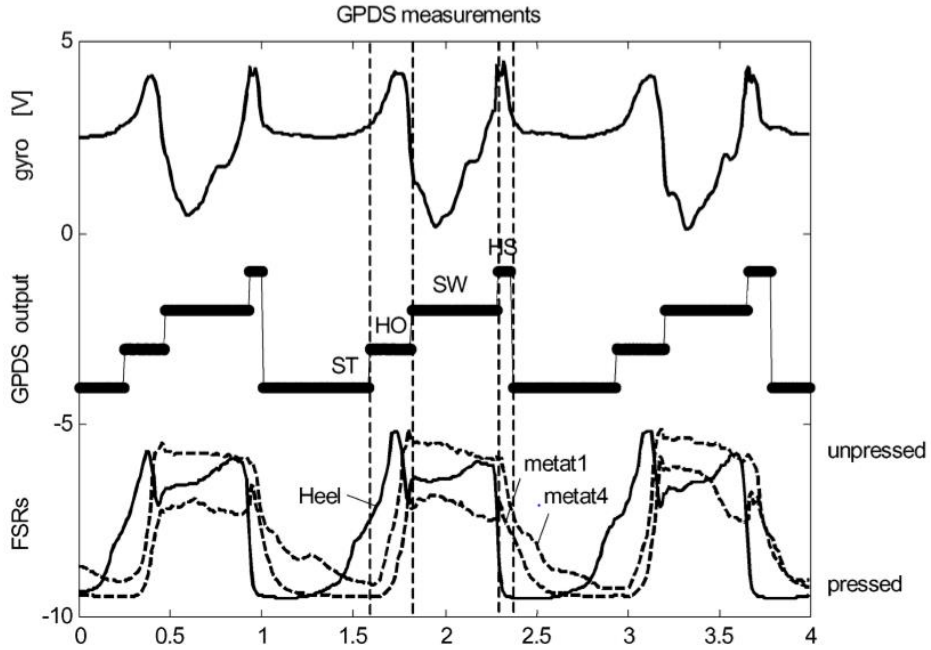


Figure 5.12: Gait-phase detection system (GPDS) output data (middle signal) *[484]* designed from information from FSR data (bottom signals) heel, 1st and 4th metatarsal and gyroscope data (top signal). ST: Stance, HO: Heel Off, SW: Swing, HS: Heel Strike.

Novak et al. (2012) [491] and (2013) [488], focussed on the detection of gait initiation and gait termination events, relying on similar sensors. Nine IMU sensors were placed on the back, on each upper arm, shank, thigh, and feet of the test subjects. They also used a foot insoles instrumented with 64 pressure sensors [488], [491] in order to monitor the distribution of the pressure underneath the user's feet. The success rate of observing gait initiation was of over 97% and over 80% for gait termination [488].

Aminian et al. (2002) [481], used three gyroscope sensors (one attached on each shank and one attached on the right thigh) to measure the angular rate according to the axis perpendicular to the sagittal plane (mediolateral axis). Two FSR sensors were placed under the feet, and two under the big toe, directly on the skin [481]. Relying on the characteristic of the shank's angular rate curve during walking, it is possible to identify the toe-off and heel strike events within the gait cycle (see *Figure 5.13* and *Figure 5.14*). Their algorithm for gait detection relied on the use of the wavelet transformation to enhance the heel-strike and toe-off events of the gait cycle. They reported an error of 7.2% for the stride length estimation (0.07 m) and an error of 6.7% for the estimated speed (0.06m/s).

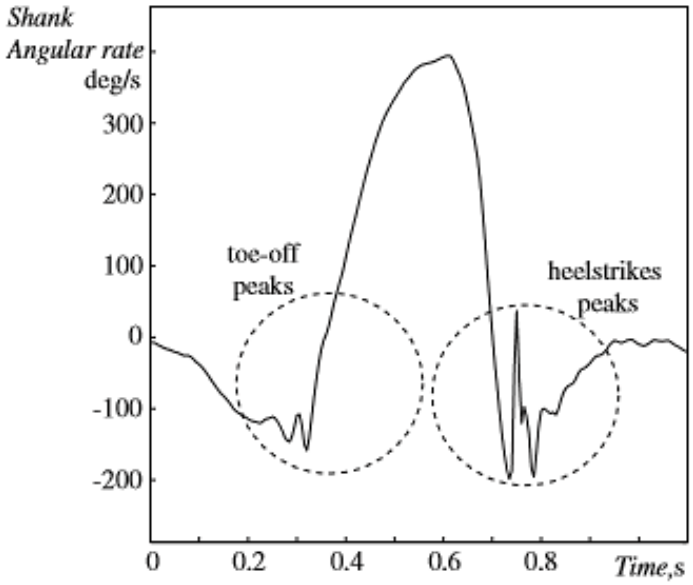


Figure 5.13: The shank's characteristic angular velocity during gait displays the toe-off and heel strike events *[481]*

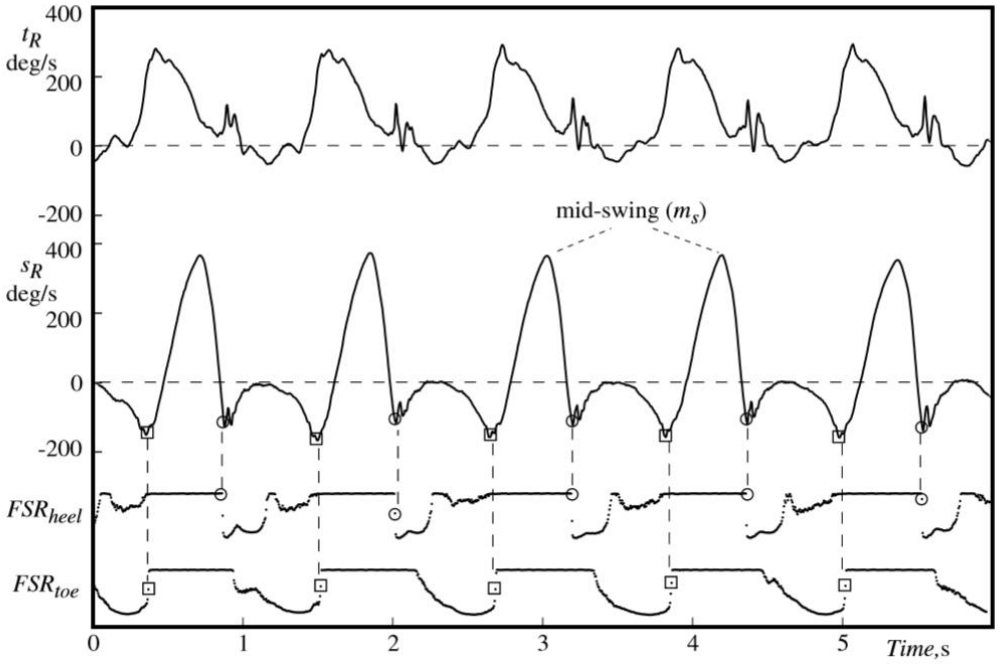


Figure 5.14: Gyroscope from the thigh (t_R), Shank (s_R) and FSR data from the heel (FSR_{heel}) and the toe (FSR_{toe}) with their correspondence during gait events *[481].* Heel strike event are in circles and toe offs in squares.

Lee and Park (2011) [486] developed a quasi-real-time ambulatory method to determine two gait events (initial contact and foot off) using a gyroscope attached to the shank of the participant. Their algorithm is based on the interpretation of the characteristic of the angular velocity from the medio-lateral axis of the gyroscope.

Senanayake and Senanayake (2010) [490] developed a method using a computational regulation method called fuzzy logic. They combined the information extracted from FSR sensors placed under the heel, the big toe, the 1st and 5th metatarsal with IMU data attached on the thigh and shank of the subject [490]. The two IMUs were used to extract the knee angle data. Their algorithm was intended to be used on both able-bodied and pathological gait. Consequently, they recruited able-bodied participants who were asked to perform normal and simulated pathological gaits (toe walking and toe drag). Their method was able to detect abnormalities in gait [490]. Their system identified 100% of the gait phases during normal walking.

The development of methods relying on a single sensor has been explored by Moe-Nilssen and Helbostad (2004) [485], who relied on a single accelerometer sensor attached to the back of the participant. They based their algorithm on the periodicity of the vertical acceleration of the trunk in order to determine the gait events [485].

Catalfamo et al. (2010) [492] used a single gyroscope attached to the shank of the test subjects. Subject also wore insoles instrumented with up to 960 pressure sensing locations as a reference. The subjects walked at their self-selected normal speeds outside on levelled ground (on pavements), and on a slope of about 9° angle inclination. They developed an event-based algorithm able to detect two events of the gait cycle (initial contact and foot off). The detection of event during down slope walking was successful 98.9% of the cases. Up-walking was detected 99.3% of the cases and levelled ground walking events were detected 99.5% of the cases [492].

Gouwanda and Gopalai (2015) [487] also used a single sensor method, relying on a gyroscope attached on each shank, to identity the heel strike and toe-off events of gait in real-time. The following bespoke algorithm is inspired by this single sensor method.

A summary of the paper afore-presented paper's outcome is presented in Table 5.5.

Authors	Sensors	Walking Task	Test on able-bodied (AB) and impaired (I) walkers	Success Rate
Pappas et al. (2004) [484]	1 Gyroscope 3 FSRs	Levelled ground, Uneven ground, Up and down a slope, Up and down stairs	Y	All walk but stairs: 100% (AB) 99% (I) For stair walking: 99.78% (AB) 96% (I)
Novak et al. (2012) [491] and (2013) [488]	9 IMUS 64 Pressure sensors	Gait initiation Gait termination	N	Gait initiation >97% Gait termination >80%
Aminian et al. (2002) [481]	3 Gyroscopes 2 FSRs	Levelled ground	N	
Lee and Park (2011) [486]	1 Gyroscope	Levelled ground	N	100%
Senanayake and Senanayake (2010) [490]	1 Gyroscope 4 FSRs	Levelled ground	N	100%
Moe-Nilssen and Helbostad (2004) [485]	1 Accelerometer	Levelled ground Uneven ground (mat)	N	Intraclass correlation ≥0.79
Catalfamo et al. (2010) [492]	1 Gyroscope (2 Pressure insoles for reference)	Levelled ground, Up and down a slope	N	99.5% (Levelled) 98.9% (Down) 99.3% (Up)
Gouwanda and Gopalai (2015) [487]	1 Gyroscope	Levelled ground w/o ankle brace Treadmill w/o ankle brace	N	100%

Table 5.5: Summary of test method and success rate on gait event algorithms using IMU sensors

While no testing was done with impaired participants, Gouwanda and Gopalai (2015) [493] attempted to mimic walking impairment through the use of ankle braces. Their algorithm had a 100% success rate and was used both overground and, on a treadmill, which are walking scenarios that will be used in this thesis. This level of success, its use both overground and on a treadmill, its potential both able-bodied and impaired walkers added to the fact that it relies on a single sensor made it the most advantageous method to implement to this thesis,

compared to the algorithm of Moe-Nilssen and Helbostad (2004) [485] who while it had a single sensor method, did not test on impaired or constrained walking.

5.4.2. Gait events detection algorithm from single axis gyroscope

The algorithm for gait event detection used in this study used the signal from a single gyroscope to detect both initial contact and toe-off events. The IMU containing the gyroscope was attached to both shanks of the participant on the lateral border side (see *Figure 5.8*). A distinctive [481], [482], [484], [494], repetitive, shank rotation pattern was apparent (see *Figure 5.15*). This was similar to reports in the literature [481], [482], [484], [494], and formed the basis of the gait event detection algorithm (see *Figure 5.15*). Because of the repetition of the pattern and because this work focuses on the analysis on the ongoing walk even if walk does not start with a clear heel strike, it was possible to extract gait event information from this gyroscope signal.

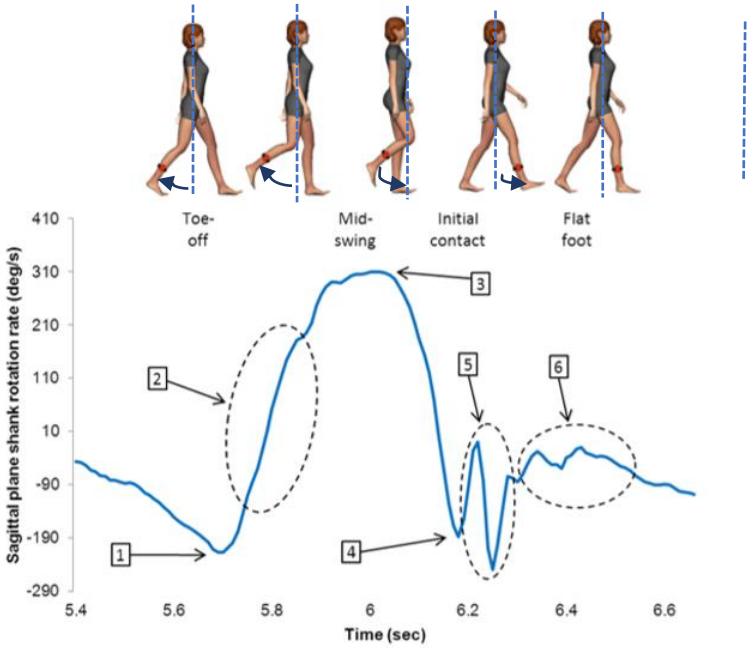


Figure 5.15: The shank gyroscope signal on the sagittal plane of one gait cycle is plotted in blue in the graph in deg/s. The blue dashed line is the vertical axis. 1) The valley corresponds to TO event, 2) Initiation of swing, 3) peak rotation during the swing phase, 4) HS valley, 5) shank perturbations post-HS, 6) shank perturbation on mid-stance. Adapted from Patterson et al. 2014 *[494]*

On *Figure 5.15* The negative values indicate that the shank is rotating in anti-trigonometric (clockwise) direction a positive value indicates the shank is rotating in trigonometric (anti-clockwise) direction in reference to axis (vertical blue dashed lines on the upper half of *Figure 5.15*).

The shank gyroscope signal is composed of characteristic [481], [484], [494] peaks and valleys corresponding to mid-swing, Initial Contact (IC) and Toe off (TO) events. The prominent positive peak corresponds to the mid-swing (see 3) in *Figure 5.15*) [494]. The negative valley following the swing peak corresponds to the IC event (see 4) in *Figure 5.15*) and the negative valley preceding the swing peak corresponds to the toe off event (see 1) in *Figure 5.15*) [494] [481], [486], [487], [495]. It is therefore possible to deduce from the location of the swing peak when the IC and TO occur.

An algorithm was then designed from one signal S(t) (green signal in *Figure 5.16*) from the gyroscope's sagittal plane rotation axis. The steps of the algorithm are illustrated on *Figure 5.16* to *Figure 5.21*.

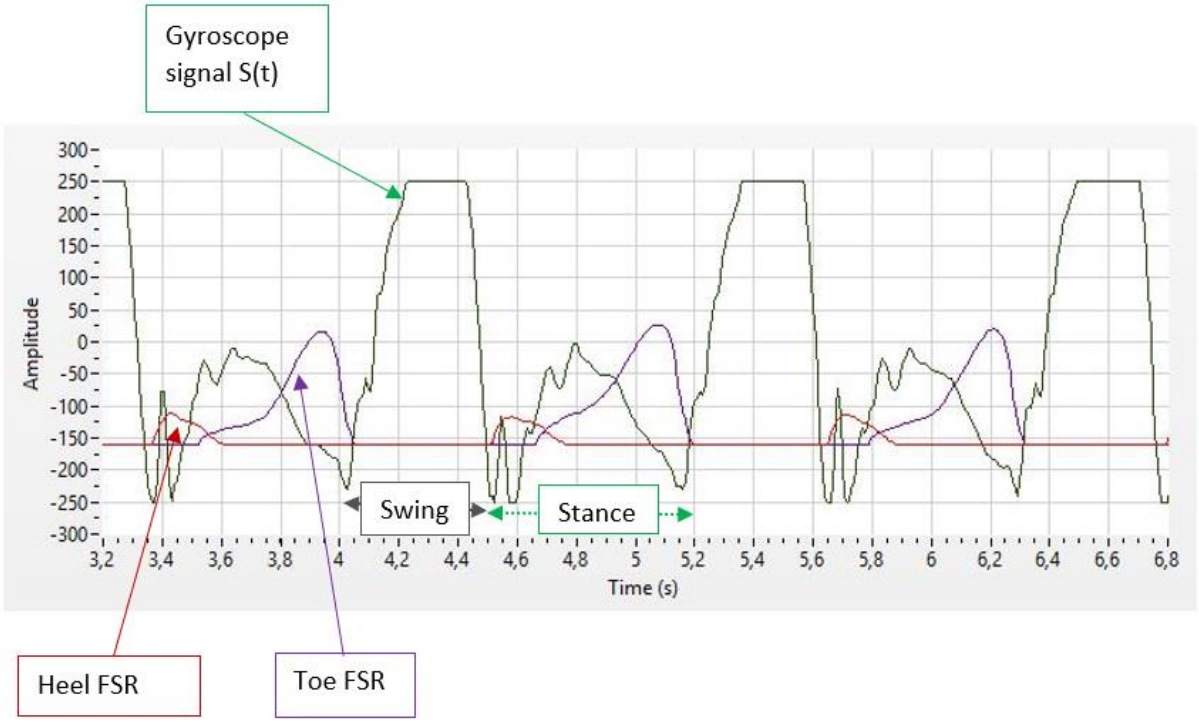


Figure 5.16: Gyroscope signal S(t) (green)and FSR (Heel in red and Toe in purple)

In *Figure 5.16*, the FSR signals from the heel and the big toe are superimposed to the gyroscope signal. In this way, it was possible to confirm which point of the gyroscope signal corresponds to the foot contact events. The first finding is that the foot contacts (IC and TO) occur for negative gyroscope angles.

5.4.2.1. Algorithm's design

The algorithm presented in this thesis is based on the design of two functions $S_1(t)$ and $S_2(t)$ from the signal S(t) of the gyroscope, presented in equation (5.1).

$$S_1(t) = f[S(t)] \; and \; S_2(t) = g[S(t)]$$

(5.1)

The two functions $S_1(t)$ and $S_2(t)$ are built so that they are orthogonal to one another. $S_1(t)$ and $S_2(t)$ are orthogonal to one another if their scalar product is null, $< S_1, S_2 >= 0$. The scalar product of $S_1(t)$ and $S_2(t)$ is expressed in equation (5.2).

$$< S_1, S_2 >= \int_{-\infty}^{+\infty} S_1(t).S_2(t)dt$$

(5.2)

Scalar product of the functions $S_1(t)$ et $S_2(t)$

Since $S_1(t)$ and $S_2(t)$ are orthogonal, they will each contain complementary information which are independent to one another. It is also easier to extract the information contained in the gyroscope signal S(t) when they are affected by distinct functions, which are in this case, $S_1(t)$ and $S_2(t)$.

$S_1(t)$ and $S_2(t)$ will be designed as binary signals to focus on specific events of the gait cycle. The steps of design of the functions $S_1(t)$ and $S_2(t)$ are described in the diagram in *Figure 5.17*.

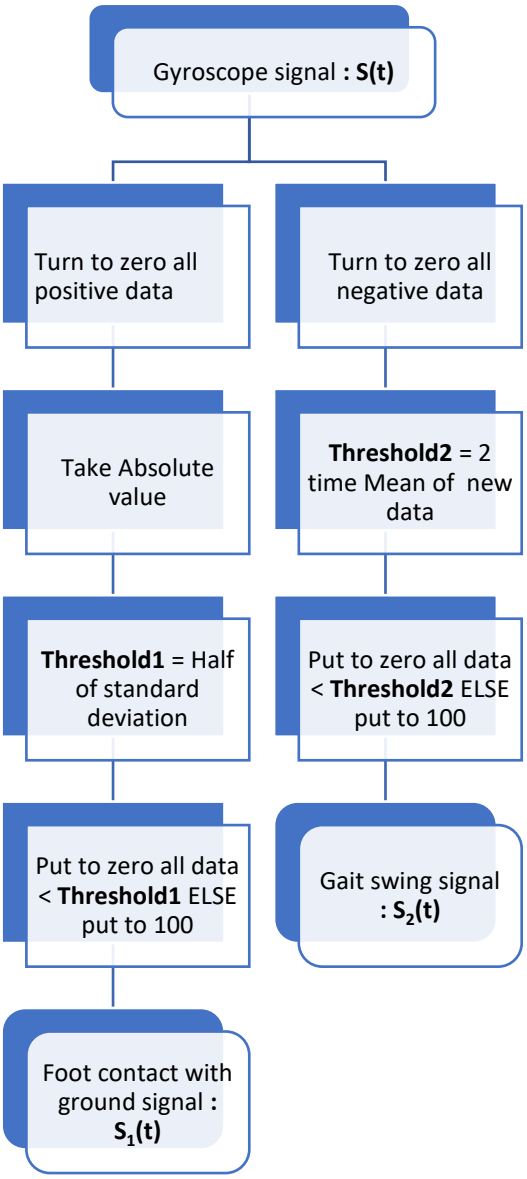


Figure 5.17: Flow chart of design of the orthogonal functions $S_1(t)$ and $S_2(t)$ from S(t) the gyroscope's signal

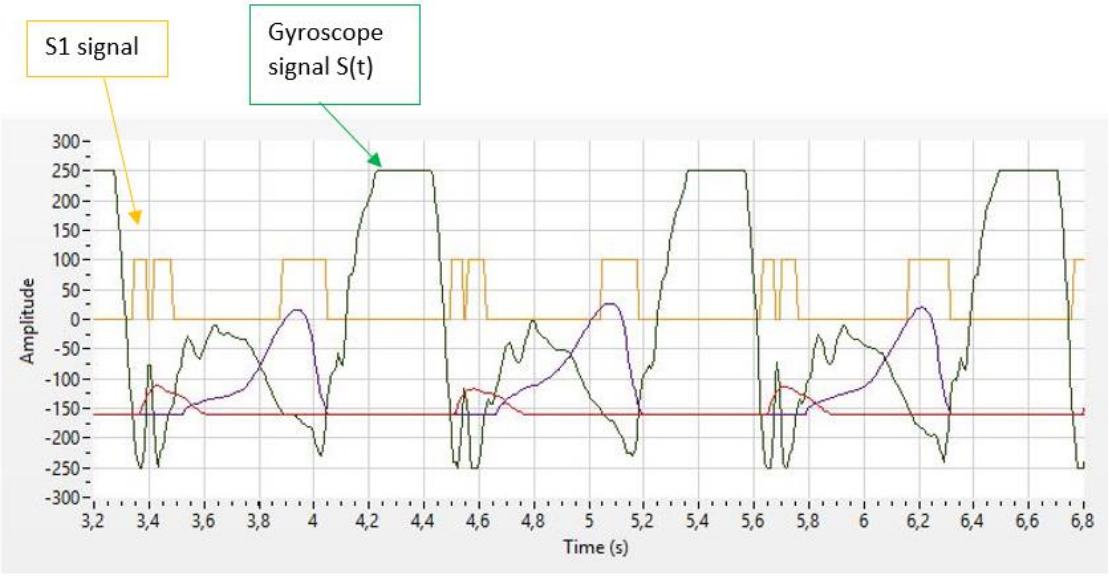


Figure 5.18: Signal S1 from negative S(t) data

In *Figure 5.18* we can observe that S_1 (yellow signal in *Figure 5.18*) matches the occurrences of the contact of the foot on the floor. The function S_1 is only on when the heel FSR and the toe FSR are on.

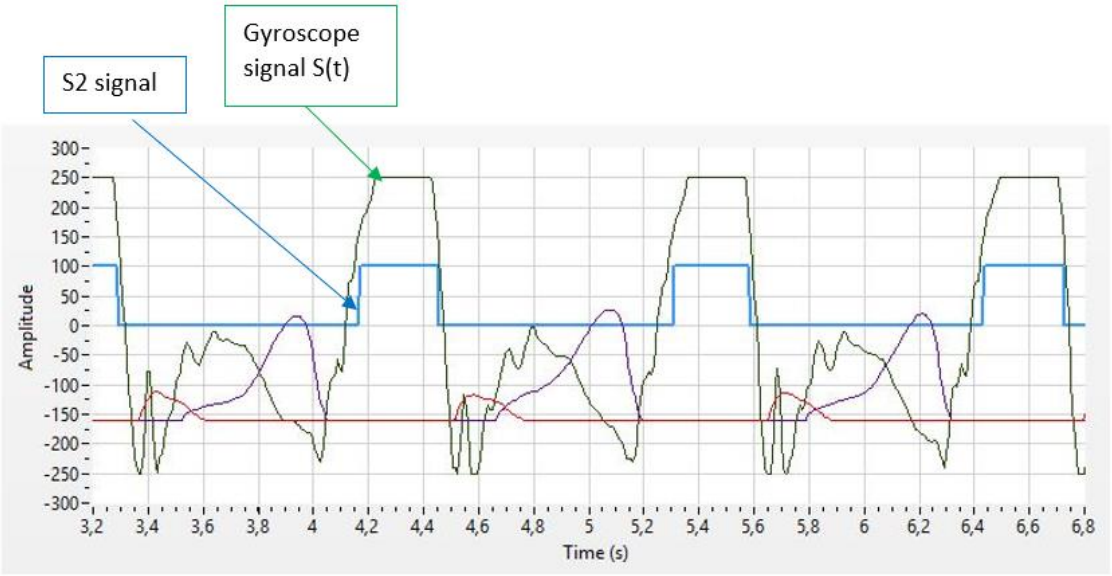


Figure 5.19: Signal S2 from positive S(t) data

In *Figure 5.19* we can observe that S_2 (blue signal in *Figure 5.19*) is on during the swing stage of the gait cycle. S_2 is on when the gyroscope data is positive and the heel FSR and toe FSR are off.

These two signals (S1 and S2) are then used to identify the two critical events of the gait cycle, i.e. IC and TO. The steps of this algorithm are described in the diagram of *Figure 5.20*.

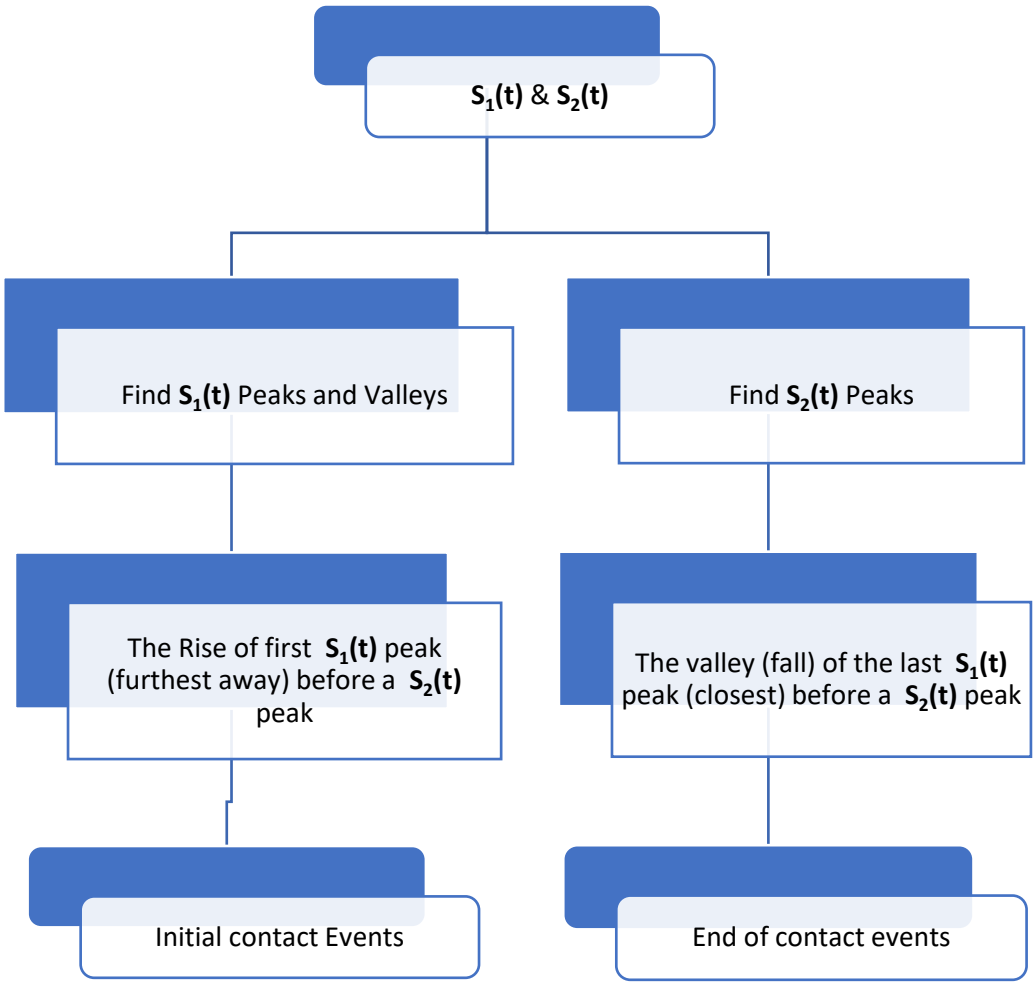


Figure 5.20: Flow chart description of the gait events detection algorithm

Figure 5.21: Initial Contact (IC) and End of Contact (EC) detection

We can observe in *Figure 5.21* that the signal $S_2(t)$ (in blue in *Figure 5.21*) is a succession of square signal corresponding to the stepping duration. The curve $S_1(t)$ presents a first peak after the stance phase (post-EC) and falls to zero before the next step (pre-IC). The IC event is therefore the first S_1 peak following a valley (drop to 0) of the S_2 signal and the EC event is the last valley of S_1 before the peak of S_2.

5.4.3. Calculation of temporal variables

The characterisation of gait typically includes temporal variables [447] including, step and stride duration, swing time, stance time, double support time and gait time. Out of all these, the calculation of the following variable was made possible in the current work.

In this work, **gait initiation** is defined as the initial contact of the foot (IC). IC is identified as the first valley following the positive peak of the gyroscope signal (see Figure 5.22). It is also the first event of the **stance phase**.

Stride time is calculated as the time difference between two consecutive IC events and is equal to the gait cycle time.

The **initiation the swing phase** is defined by the end of contact of the foot (typically the toe) against the ground (EC). It is identified as the point when the gyroscope signal passes from

negative to positive, towards a positive peak (see Figure 5.22). The start of the swing phase was collected for each cycle and converted to a percentage of the gait cycle.

The positive peak of the gyroscope signal was identified as **mid swing** of the gait phase (see Figure 5.22).

Stance time was defined as the time difference between the IC and the consecutive EC.

Swing time was defined as the time difference between the EC and the consecutive IC event.

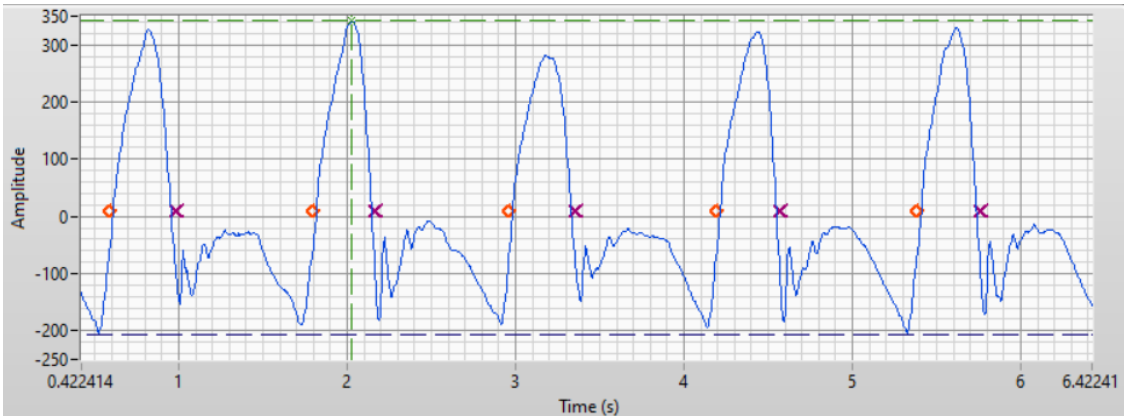


Figure 5.22: Gait event detected from the gyroscope's angular velocity signal (in blue): initial contact (purple x), initiation of swing (orange ◊)

5.4.4. Extraction of the kinematic data

The setup of the study (including multiple IMU) allowed the observation of several kinematic variable. The main variable of interest was the shank angular velocity (see Figure 5.22) as it was used for the gait event algorithm described in this work in Section 5.4.2.

5.4.5. EMG signal processing

The EMG signals were processed using the same procedure presented in the previous chapter (see section 4.4.4). The signal used for the analysis was the RMS of the normalised to the maximal amplitude detected, centred around 0 and rectified EMG signal.

5.4.6. Muscle activation pattern

5.4.6.1. Variance ratio

The VR is presented in detail in section 4.5.2 in the previous chapter, was used as a measure of the variability of the muscle activity. As a brief reminder, the VR compares the EMG envelope over six gait cycles and presents a measure of cycle-to-cycle variability. Its value equals 0 when the cycles are identical and moves closer to 1 as the cycles begin to differ. The mathematical expression of the VR is presented in chapter 4, section 4.5.2, equation (4.1)

5.4.6.2. Muscle contraction ON/OFF pattern using threshold detection

To add to the VR analysis, the muscle contraction duration for the different muscles and participants was calculated using a threshold detection process. This method was applied to the EMG signal to match the visual muscle contraction threshold (see *Figure 5.23*).

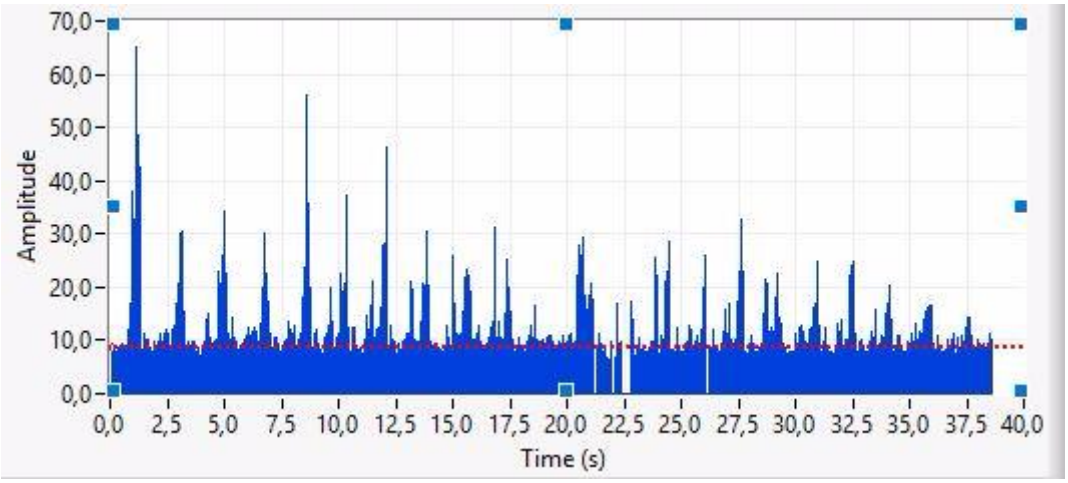


Figure 5.23: Noisy rectified EMG (blue) visual contraction threshold (red dashed line)

The importance of a reliable threshold measure is indispensable for a good interpretation of the muscle phasic activity. Finding an optimal, non-visual, method which is adaptable to every muscle signal is of major importance [496]. While several methods of threshold detection rely on the amplitude of the signal during its baseline reference activity. Some use a threshold corresponding to two standard deviations from the baseline noise[384] or three standard deviations[382], [383] or a percentage of the maximum value of the signal [385]. The visual estimation of the threshold, that we will call visual threshold, was realised using the cumulative distribution function of the signal F(x). The cumulative distribution function

is the probability that X will be less than or equal to x as presented mathematically in equation (5.3):

$$F(x) = P(X \leq x) = \int_{-\infty}^{x} f(u)\, du$$

(5.3)

The cumulative distribution function can also be expressed as the integral of the probability density function.

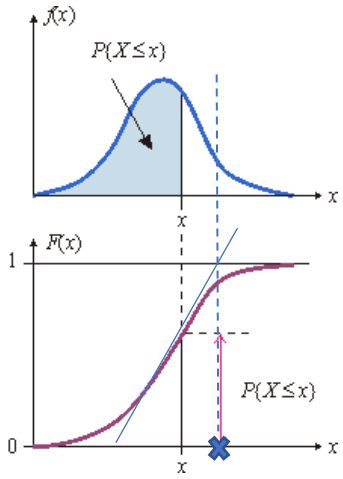


Figure 5.24: Gaussian probability density function (blue) and its cumulative distribution function (pink), the blue cross is the abscissa of the intersection between the slope at the inflection point F(x)=1. Adapted from Hamburg University of Technology (2006-2010) *[497]*

The abscissa of the intersection between the slope at the inflection point and F(x)=1 provides the threshold as illustrated by *Figure 5.24*.

The threshold algorithm used for this study is presented below in a flow chart (*Figure 5.25*): The input data used is the rectified EMG signal as presented in *Figure 5.23* and it is the input signal S(t) of the algorithm. The symbol ← is used to signify that the element at the right of the arrow is inputted into the element at the left of the arrow, and "i" is the increment value.

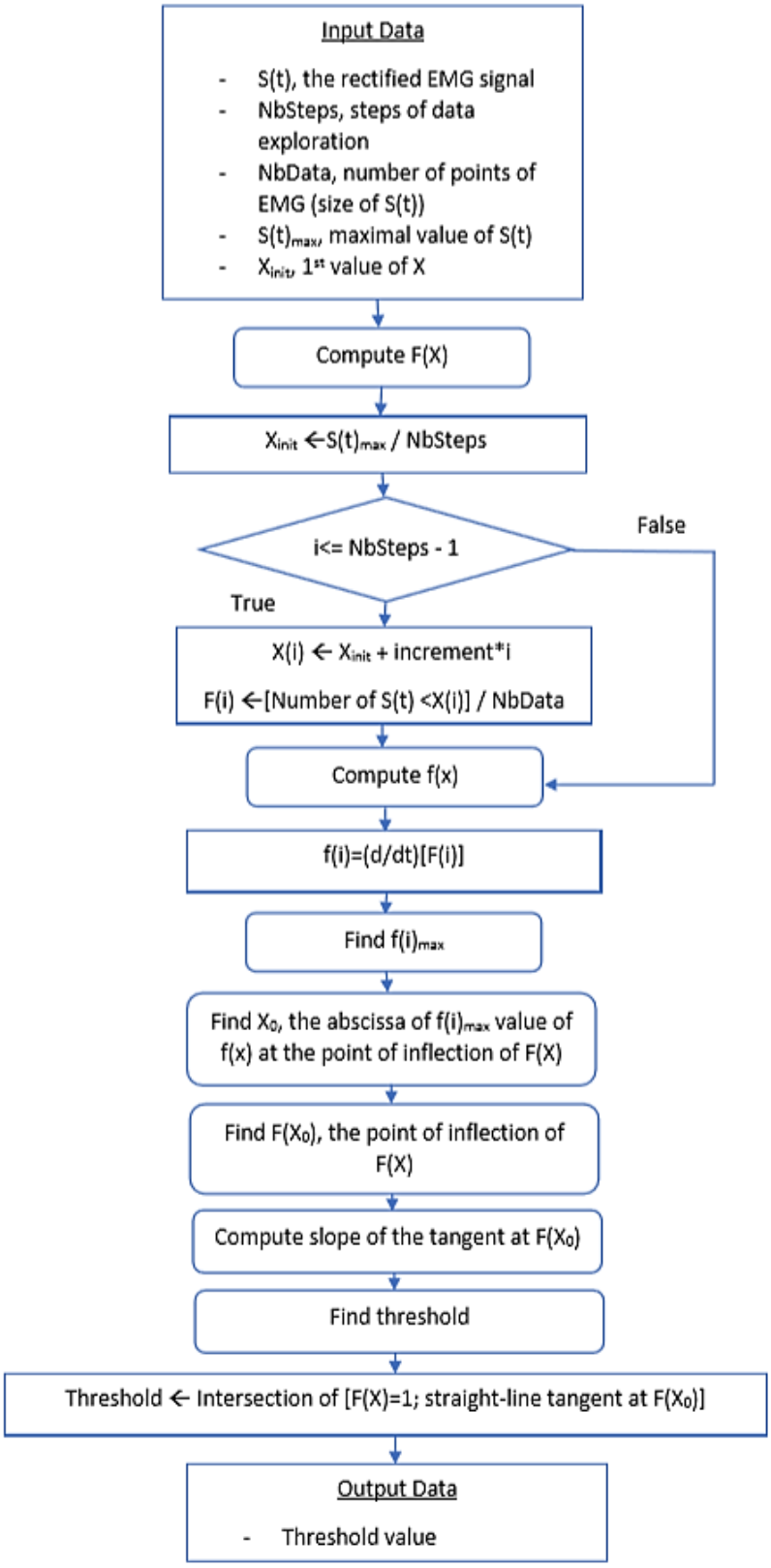


Figure 5.25: Threshold detection Algorithm Flow-chart

The following figure (*Figure 5.26*) represents the results of the algorithm.

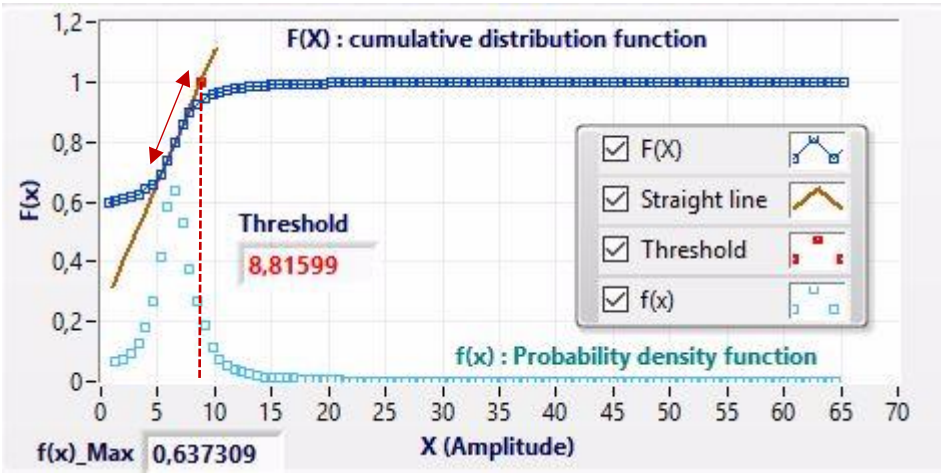


Figure 5.26: Threshold algorithm results. Cumulative Distribution Function (F(X) in dark blue), Probability density function (f(x) in light blue), straight line tangent at the inflection point of F(X)(Orange), Threshold value (red) is the abscise of the intersection between the straight line tangent and F(x)=1.

In *Figure 5.23*, the visual threshold is of a value close to ten while remaining under ten and in *Figure 5.26* the threshold value found is 8.81.

The advantages of this algorithm are that it provides a threshold close to the visual threshold and it has more mathematical articulation than a method base on statistical values such as the standard deviation. It, therefore, removes the uncertainty due to human error done through visual estimation. Moreover, it adapts its value to the signal since it is dependant of the signal.

This new algorithm that works for unfiltered EMG contraction detection was combined with the gait cycle detection program and allows automatic ON/OFF threshold collection by counting the number of contractions per cycles, the duration of each contraction and when they occur during the different cycles.

To this threshold method a temporal condition was added. It operated so that any contraction below the value of 25ms was considered an artefact (noise) [382] and ignored and consecutive contractions separated by less than 25ms were considered to be a single contraction. The 25ms criterion has been used by Bennell et al. (2006) [382] and was applied to this method. After this addition the amount of observed contraction matched better the literature [339], [498], being comprised between one to four (per cycle) in the most cases.

5.4.6.3. Calculation of contraction durations

This parameter was directly derived from the contraction threshold detection algorithm, in which every contraction initiation and termination was recorded. The contraction duration over a cycle was the sum of the duration of each contraction recorded during one gait cycle. This value was then converted into the form of a percentage for each gait cycle.

5.4.6.4. Occurrence frequency

The occurrence frequency is a parameter that takes in account the number of contractions per gait cycles and counts the most frequent pattern of actuation of the muscles (see section 2.3.3 from chapter 2 for further details and justification).

This set of information can be synthesised in a parameter called the occurrence frequency [339]. In their paper Di Nardo et al. (2017) noticed that during a walk, the muscle contraction was not always the same cycle to cycle and could vary independently of the temporal parameter of the EMG signal such as the timings of the contractions and the duration of the contractions as presented in equation (5.4).

The occurrence frequency is defined as follow:

$$Occurence\ Frequency\ (n) = \frac{Number\ of\ gait\ cycles\ with\ n\ activation\ intervals}{Total\ number\ of\ gait\ cycles} \quad (5.4)$$

For a given number n of activation intervals in a cycle, the occurrence frequency determines the most used muscle actuation strategy of the muscle.

In this thesis, rather than using the occurrence frequency, the outcome measure of muscle activity contractions will be the number of contractions for which the occurrence frequency is the biggest. In other words, we will look at the most reoccurring number of muscle contractions within a gait cycle.

5.5. Summary

In this chapter, the methods of data collection and parameters needed to address the hypothesis were presented. The objectives of this chapter were as presented in section 5.1.1.2. Objective 1): Record the EMG activity of selected lower limb muscle over several gait cycles during the eight walking conditions. Objective 1 was achieved using wireless EMG allowing to record multiple gait cycles to be recorded either overground or during treadmill walking. Objective 2): Compare the variability of the muscular activity patterns between the different walking conditions, was achieved using parameters allowing the measure of the variability of the EMG signal such as the VR, the number of contractions per cycles and the mean contraction duration. Objective 3): Observe whether the different walking conditions impact differently the able-bodied participants compared to the chronic stroke participants, is made possible through the bespoke program relying on the afore-presented algorithm, which were described and justified from the published literature.
In particular, the afore-presented method using a single gyroscope to detect gait events (see section 5.4.2) and the EMG threshold detection method (see section 5.4.6.2) developed in this work.

In the following chapter, the different walking conditions performed by able-bodied participants and the chronic stroke participants will be presented and compared. The first hypothesis being that there will be statistically significant ($p<0.05$) differences in the muscle activation pattern between FP treadmill walking and the three other walking situations (self-paced treadmill, indoor and outdoor flat overground walking).
Self-paced treadmill walking will be closer to overground walking (indoors and outdoors) in comparison to fixed pace treadmill walking in both the able-bodied and chronic stroke participants across the eight walking conditions.
The second hypothesis being that there will be no statistical difference ($p>0.05$) in muscle activation pattern between the SP slope walking and overground outdoor slope walking.

Chapter 6

6. Results (able-bodied and stroke survivor participants)

6.1. Introduction

This chapter will present the outcomes of the EMG characterisation analysis. This analysis will allow a comparison between the able-bodied and the chronic stroke participants results. The objective being to gather evidence of pattern similarity between fixed, self-paced treadmill walking, indoor and outdoor overground walking to address the hypothesis that self-paced treadmill walking is a good of analogue to overground outdoor walking.

The chapter will first present the results from the able-bodied participants which will serve as reference data for the second group of participants, as the chapter will present the analysis from the chronic stroke participants. This chapter aims to provide evidence for accepting or rejecting the hypothesis that walking on a self-paced treadmill is a closer analogue to walking overground indoors and outdoors compared to a fixed pace treadmill.

The results have been structured according to the three walking conditions (flat, uphill and, downhill) with comparisons drawn across indoor (flat only), outdoor, fixed pace (flat only) and self- paced treadmill walking. The evidence for accepting or rejecting the hypothesis that walking on a sloped self-paced treadmill is equivalent to walking overground on an outdoors slope will also be provided in this chapter.

The analysis will consider the four characteristics of muscle activity described previously (see chapter 5), these are: variance ratio (VR), number of muscle contraction per walk cycles, muscle contraction duration, and stride duration.

6.2. Results

6.2.1. Participants

Seventeen able-bodied participants took part in this study. The group was composed of 10 females and 7 males of mean age 26.59 ±7 years old, weight 67.78±9.92 kg and height 169.21±10 cm. The details of the participants are presented in table 4.1 (see chapter 4) labelled AB_1 to AB_17 and S_1 to S_7. A full dataset was available from 10 out of the 17 able-bodied participants, consequently the able-bodied participant's numbering will go from AB_8 to AB_17 and two participants who had a stroke: S_5 and S_7.
After checking the normality of the distribution of the data related to muscle activity using the Anderson-Darling normality test, a repeated ANOVA was applied to the data for this analysis of the muscle activity-related data. These results will now be presented beginning with results from flat walking.

The stroke participants are presented separately here since there were only two participants with a full set of comparable data for analysis.

Participant S_5 was a 52 years old female (height 1.64 m, weight 52.5 kg) with left hemiparesis from a stroke that occurred 252 months prior to this study. She scored 27/30 in the Montreal Cognitive Assessment (MOCA) test and 14/15 for the Riverside mobility Index (RI).

Participant S_7 was a 69 years old female (height 1.59 m, weight 64.3 kg) with a left hemiparesis from a stroke that occurred 48 months prior to this study. She scored 25/30 for the MOCA test and 12/15 for the RI.
The results will be presented per participants starting with the flat walking situation and then followed by uphill and downhill walking.

Considering the large amount of remaining data, a qualitative appreciation of the muscle signals and the observations pointing to a greatest variability in the ankle joint (presented in section 4.8.1), the number of muscles observed was reduced to two muscles participating in ankle movement, namely the tibialis anterior (TA) and the gastrocnemius (GA), as proposed in the recommendations section of chapter 4, section 4.8.3.

The summary of the participant's walking speeds are presented in Table 6.1 *f*or the able-bodied group and in Table *6.2* for the participants with stroke.

Participants AB	Speed (m/s)									
n°	FP	SP	IN	OUT	SP UP 03	SP UP 06	SP DOWN 03	SP DOWN 06	UP OUT	DOWN OUT
AB_8	1.3	1.43	1.52	1.56	1.37	1.21	1.22	1.62	0.92	0.93
AB_9	0.95	1.02	1.79	1.84	1.38	1.47	1.42	1.42	1.01	1.27
AB_10	1.1	1.19	1.4	1.47	1.26	1.35	1.34	1.34	0.84	1.26
AB_11	1.1	1.3	1.43	1.7	1.31	1.34	1.45	1.59	0.98	1.07
AB_12	1.01	1.25	1.19	1.92	1.3	1.26	1.35	1.3	0.94	1.36
AB_13	0.9	1.13	1.34	1.3	1.28	1.22	1.03	1.28	1.03	1.49
AB_14	1	1.18	1.47	1.46	1.38	1.26	1.57	1.44	1.09	0.95
AB_15	1.04	1.01	1.4	1.53	1.04	0.95	1.22	1.34	0.97	1.06
AB_16	1.1	1.36	1.6	1.79	1.35	1.18	1.45	1.33	0.97	1.06
AB_17	1	1.05	1.73	1.58	1.1	1.21	1.22	1.28	1.14	1.15
Mean	1.05	1.19	1.49	1.62	1.28	1.25	1.33	1.39	0.99	1.16
Standard Dev	0.11	0.14	0.18	0.19	0.12	0.14	0.16	0.12	0.09	0.18

Table 6.1: Able-bodied participant's speeds

Participants S	Speed (m/s)									
n°	FP	SP	IN	OUT	SP UP 03	SP UP 06	SP DOWN 03	SP DOWN 06	UP OUT	DOWN OUT
S_5	0.9	1.17	1.37	1.28	1		0.79	0.93	0.54	0.96
S_7	0.24	0.32	0.77	0.87	0.35	0.34	0.34	0.28	0.42	0.63
Mean	0.57	0.75	1.07	1.08	0.68	0.34	0.57	0.61	0.48	0.80
Standard Dev	0.47	0.60	0.42	0.29	0.46	NA	0.32	0.46	0.08	0.23

Table 6.2: Waking speeds of the participants with a stroke.

6.2.2. Level walking

6.2.2.1. Variance ratio (VR)

There were clear differences across the four types of level walking. Table 6.3 provides details. Both gastrocnemius and tibialis anterior demonstrated VR values that were similar between self-paced and outdoor overground flat walking.

The able-bodied participants displayed different results for the two observed muscle groups across the walking conditions. The gastrocnemius displayed significantly higher variability (0.38±0.15) during overground outdoor walking ($p=0.015$) compared to SP and FP treadmill and indoor overground walking and significantly lower variability 0.22±0.2 during indoor overground walking ($p=0.019$).
The tibialis anterior presented a significantly higher variability 0.42±0.19 during self-paced EMG walking ($p=0.004$) and a significantly lower variability 0.27±0.13 during indoor overground walking ($p=0.004$).
These data are reported in Table 6.3 and illustrated in Figure 6.1 and Figure 6.2.

The TA of participant S_5, followed the same trend for the able-bodied participants with self-paced and outdoor walking having the highest VR value (lower repeatability) and the fixed-pace and indoor walking with the higher repeatability. The GA did not follow this trend as its lower VR were found during SP treadmill and IN overground walking, the data are presented in Table 6.3.
When looking at both sides together, the participant S_7 presented their lower VR during the overground walks for the GA (IN VR(GA)=0.28±002, OUT VR(GA)=0.36±010) and the TA (IN VR(TA)=0.25±0.06, OUT VR(TA)=0.36). This means that the muscle pattern had a more consistent muscle activation pattern cycle to cycle in comparison with treadmill walking for both the GA (FP VR(GA)=0.92±0.03, SP VR(GA)=0.77±0.15) and the TA (FP VR(TA)=0.59±0.08, SP VR(TA)=0.52±0.04) as presented in Table 6.3).

	VR FP (SD) AB	VR FP (SD) S_5	VR FP (SD) S_7	VR SP (SD) AB	VR SP (SD) S_5	VR SP (SD) S_7	VR IN (SD) AB	VR IN (SD) S_5	VR IN (SD) S_7	VR OUT (SD) AB	VR OUT (SD) S_5	VR OUT (SD) S_7
GA	0.26 (0.13)	0.58 (0.45)	0.92 (0.05)	0.36 (0.03)	0.24 (0.08)	0.77 (0.21)	**0.22 (0.05)**	0.14 (0.06)	0.28 (0.03)	**0.38 (0.03)**	0.51 (0.28)	0.36 (0.15)
TA	0.32 (0.14)	0.25 (0.11)	0.59 (0.11)	**0.42 (0.19)**	0.32 (0.06)	0.52 (0.06)	**0.27 (0.13)**	0.08 (NA)	0.25 (0.08)	0.39 (0.1)	0.59 (NA)	0.29 (NA)

Table 6.3: Mean VR for GA and TA in four flat walking situations (FP= Fixed-pace treadmill, SP= Self-paced treadmill, IN= overground indoors, OUT= Overground outdoors)

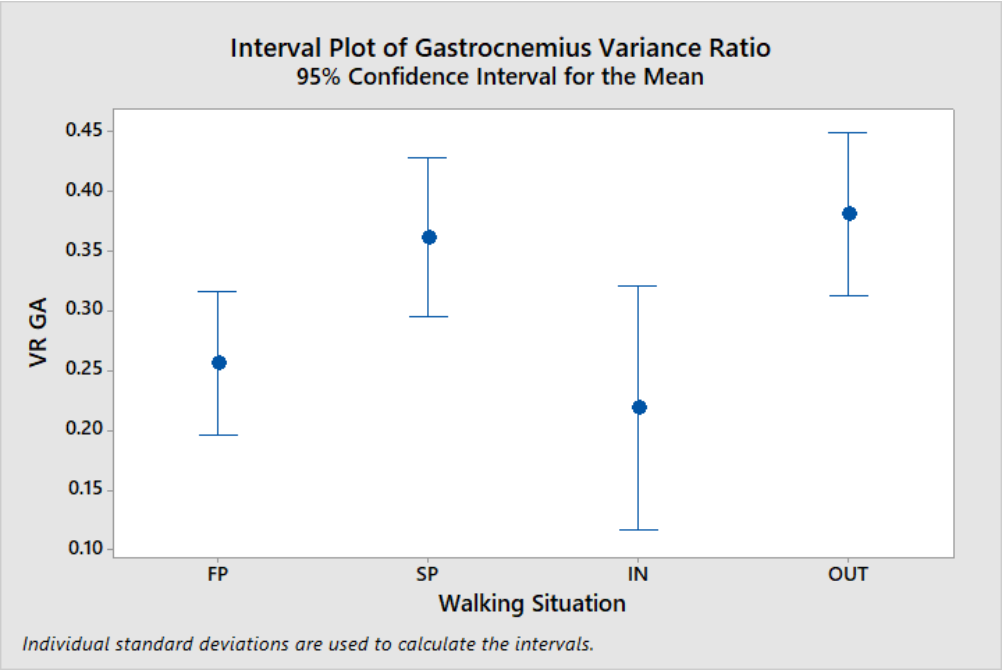


Figure 6.1: 95% Confidence interval plot of the VR of GA muscle during flat walking (FP= Fixed-pace treadmill, SP= Self-paced treadmill, IN= overground indoors, OUT= Ovreground outdoors).

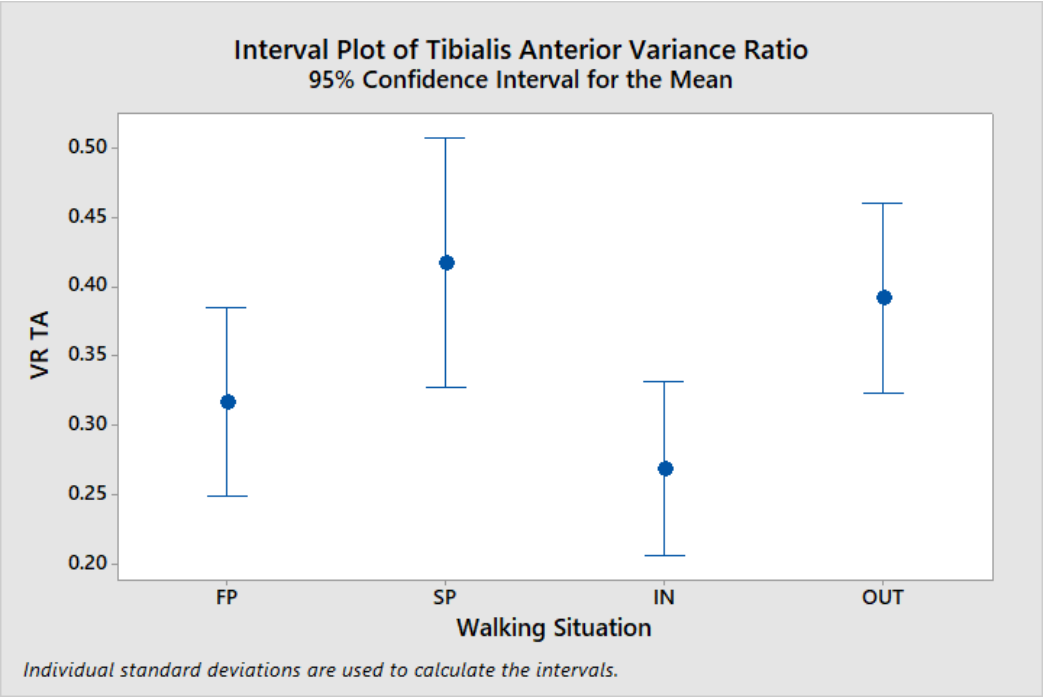


Figure 6.2: 95% confidence interval plot of the VR of TA muscle during flat walking (FP= Fixed-pace treadmill, SP=Self-paced treadmill, IN=Overground, OUT=Overground outdoors).

No statistically significant differences ($p>0.05$) were observed amongst the gastrocnemius of the AB participants.

The Tukey pairwise post-hoc analysis of gastrocnemius identified FP, SP and OUT walking as statistically different from IN walking (see Table 6.4).

VR GA Tukey Pairwise Comparisons of the walking conditions (95% Confidence)			
Walking Condition	Mean VR	Grouping	
SP	0.38	**A**	
OUT	0.36	**A**	
FP	0.26	**A**	B
IN	0.22		**B**

Table 6.4:VR GA Tukey Pairwise Comparison. Means that do not share a letter are significantly different.

The Tukey pairwise comparison of the tibialis anterior identified the SP and OUT statistically different from FP and IN walking (see Table 6.5).

VR TA Tukey Pairwise Comparisons of the walking conditions (95% Confidence)			
Walking Condition	Mean VR	Grouping	
SP	0.40	**A**	
OUT	0.36	**A**	B
FP	0.31		**B**
IN	0.26		**B**

Table 6.5: VR TA Tukey Pairwise Comparison. Means that do not share a letter are significantly different.

In comparison with the able-bodied participants the VR of the gastrocnemius muscle of participant S_5 has a wider range of values across the four walk situations (between 0.14 and 0.58) compared to the able-bodied population which range between 0.22 and 0.38. This can also be observed with the TA's VR values ranging from 0.08 to 0.59 when the able-bodied participant's data ranged from 0.27 to 0.42.

When comparing the hemiplegic (hemi) leg to the opposite leg (op), GA during FP walking presented a high variability on the op side and OUT walking a higher VR on the hemiplegic side (see Table 6.6).

	VR FP		VR SP		VR IN		VR OUT	
	Op	Hemi	Op	Hemi	Op	Hemi	Op	Hemi
GA	0. 9	0.26	0.19	0.3	0.19	0.1	0.32	0.71
TA	0.24	0.27	0.22	0.42	0.08	NA	NA	0.59

Table 6.6: VR for hemiplegic (Hemi) and opposite (Op) side of the participant S_5

In comparison with the able-bodied participants, the VR of participant S_7 had a wider range of values across the four walk situations for this participant. Also, it appears that the values of the VR were for both GA and TA were noticeably higher during the two type of treadmill walks in comparison to the two overground walks. In the case of the able-bodied participants, it appeared that SP and OUT had similar values and FP and IN also seemed to match in terms of magnitude (see Table 6.7).

When comparing the hemiplegic (hemi) leg to the opposite leg (op) of participant S_7, no large differences of VR between the two sides (see Table 6.7).

	VR FP		VR SP		VR IN		VR OUT	
	Op	Hemi	Op	Hemi	Op	Hemi	Op	Hemi
GA	0.89	0.96	0.62	0.92	0.3	0.26	0.47	0.26
TA	0.51	0.67	0.48	0.57	0.31	0.19	NA	0.29

Table 6.7: VR for hemiplegic (Hemi) and opposite (Op) side of the participant S_7 in four flat walking situations

6.2.2.2. Number of contractions per gait cycle

The able-bodied participants showed no statistically significant difference between the different walking situations for the gastrocnemius muscle.

However, there was a significant difference between the left and the right side ($p=0.047$) of the GA (see Table 6.8). Due to a technical issue the outdoor walk data did not record any data from the right TA.

	FP	SP	IN	OUT
N contraction GA Left (SD)	1.15 (0.34)	1.2 (0.42)	1.4 (0.27)	1.65 (1.00)
N contraction GA Right (SD)	1.89 (1.05)	2 (1.47)	1.7 (1.25)	1.4 (0.7)
N contraction TA Left (SD)	2.5 (0.74)	2.3 (1.18)	2 (1.18)	1.45 (0.6)
N contraction TA Right (SD)	2.22 (0.83)	2.06 (0.88)	2.17 (1.22)	NA

Table 6.8: Number of contractions per cycles during flat walking on left and right side for the GA and the TA

The combined left and right EMG data of tibialis anterior displayed a significantly lower number of contractions per cycle outdoors (1.45 ± 0.56) than the other types of walk ($p=0.023$) (see Table 6.9).

For participant S_5, the number of contractions per cycles of the GA remained consistent between the four walking situations. The same was observed from the GA muscle of the able-bodied participants. The results are presented in Table 6.9. Contrarily to the able-bodied participants, the TA of participant S_5 presented, on average, a lower number of contractions across the walking situations compared to the GA.

Participant S_7 presented less contractions during the overground walks for both GA (IN $N=1.5\pm0.71$, OUT $N=1\pm0$) and the TA (IN $N=1.5\pm0.71$, OUT

N=1±NA). The number of contractions was the most important during SP treadmill walking (N(GA)=3.5±0.71, N(TA)=3.2±.47), see in Table 6.9).
In comparison, the mean number of contractions of the able-bodied participants was, for the GA 1.5±0.19 (FP), 1.6±1.13 (SP), 1.55±0.94 (IN), 1.52 ±0.85 (OUT) and for the TA 2.37±0.78 (FP), 2.18.2±1.03 (SP), 2.08±0.71 (IN), 1.45±0.56 (OUT) (see Table 6.9).
It appears that treadmill walking leads to more contractions than the overground walking situations, see Table 6.9.

	FP (SD) AB	FP (SD) S_5	FP (SD) S_7	SP (SD) AB	SP (SD) S_5	SP (SD) S_7	IN (SD) AB	IN (SD) S_5	IN (SD) S_7	OUT (SD) AB	OUT (SD) S_5	OUT (SD) S_7
N contractions GA (SD)	1.5 (0.19)	2 (0)	2.75 (1.06)	1.6 (1.13)	2.5 (0.71)	3.5 (0.71)	1.55 (0.94)	2 (1.41)	1.5 (0.71)	1.52 (0.85)	2.5 (2.12)	1 (0.0)
N contractions TA (SD)	2.37 (0.78)	1.5 (0.71)	2 (0)	2.18 (1.03)	2.25 (0.35)	3.2 (2.47)	2.08 (1.17)	1 (0)	1.5 (0.71)	**1.45 (0.56)**	1 (NA)	1 (NA)

Table 6.9: Mean number of contractions per cycles during flat walking for the GA and the TA

For both stroke participant S_5 and the whole able-bodied group, outdoor flat walking led to a lower number of contractions per cycles in comparison with the SP and FP treadmill and indoor overground walking (see Table 6.9).

6.2.2.3. Contraction duration

Both gastrocnemius and tibialis anterior of the able-bodied participants were not statistically significantly different according to the walking situations. Both muscles contracted for shorter periods during outdoor walking, see Table 6.10, and illustrated in Figure 6.3 and Figure 6.4.

Similarly, to the able-bodied participant's results, the GA of the participant S_5 displayed a shorter contraction duration during outdoor walking in comparison with the other walking situations (see Table 6.10). However, the TA presented a lower contraction duration during FP treadmill walking than outdoor walking (see Table 6.10). This trend (short outdoor walking contractions) doesn't match the able-bodied group, who displayed a similar magnitude of values for the FP treadmill, SP treadmill and IN flat walking (see Table 6.10).

Mean contraction duration (% cycle)	FP (SD) AB	FP (SD) S_5	FP (SD) S_7	SP (SD) AB	SP (SD) S_5	SP (SD) S_7	IN (SD) AB	IN (SD) S_5	IN (SD) S_7	OUT (SD) AB	OUT (SD) S_5	OUT (SD) S_7
GA	23.62 (13.69)	23.11 (0.64)	59.74 (1.34)	23.65 (12.91)	23.53 (5.43)	63.5 (24.8)	23.52 (14.53)	35.23 (9.57)	30.56 (10.3)	14.98 (10.31)	13.36 (10.63)	4.79 (1.22)
TA	26.36 (11.81)	9.83 (6.38)	49.4 (47.3)	30.25 (14.89)	12.67 (5.85)	47.4 (47.9)	27.89 (17.58)	13.48 (2.25)	12.53 (2.53)	10.01 (2.25)	12.14 (NA)	5.63 (NA)

Table 6.10: Mean contraction durations in percentage per cycle during flat walking

Participant S_7's GA and TA displayed longer contractions during the treadmill walking situation (FP(GA)=59.74±1.34, SP(GA)=63.5±24.8, FP(TA)=49.4±47.3, SP(TA)=47.4±47.9) compared to overground walking (IN(GA)=30.56±10.3, OUT(GA)=4.79±1.22, IN(TA)=12.53±2.53, OUT(TA)=5.63), as seen in Table 6.10. Similarly, to able-bodied participants, participant S_7 presented shorter contractions during OUT walking. However, there is also a difference of magnitude of duration values between the treadmill walks (FP and SP having longer contractions), and IN that is about half the value of FP and SP duration in both the cases of GA and TA. In the case of the able-bodied participants, the mean contraction duration of both GA and TA remained in a similar range of value for FP, SP and IN walking (see Table 6.10).

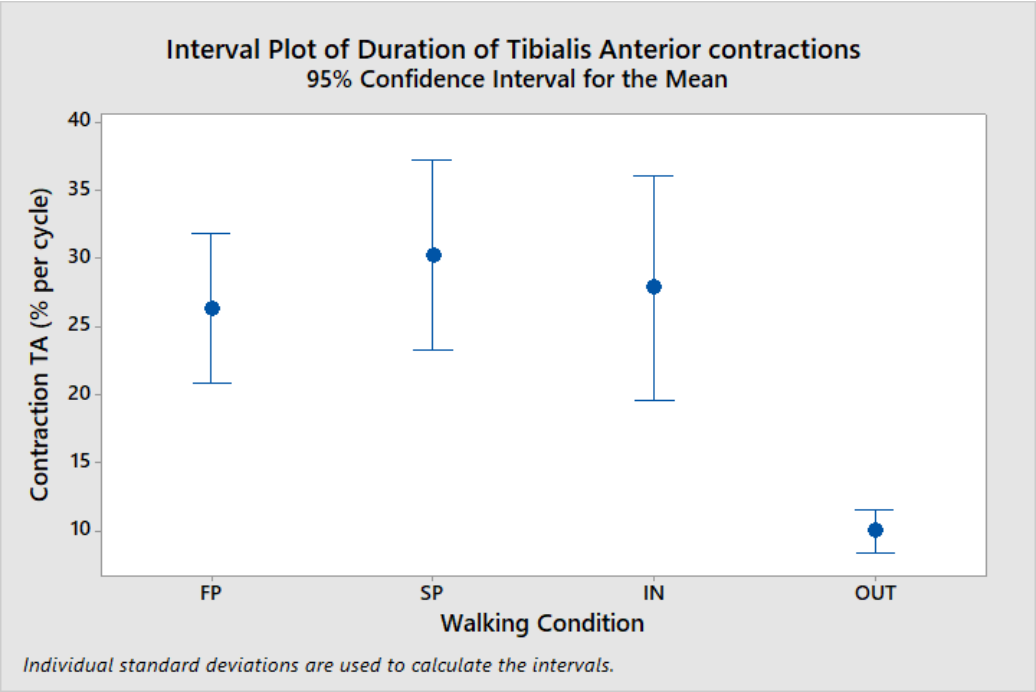


Figure 6.3: Mean TA contraction duration (as % of gait cycle) during level walking situations of able-bodied participants

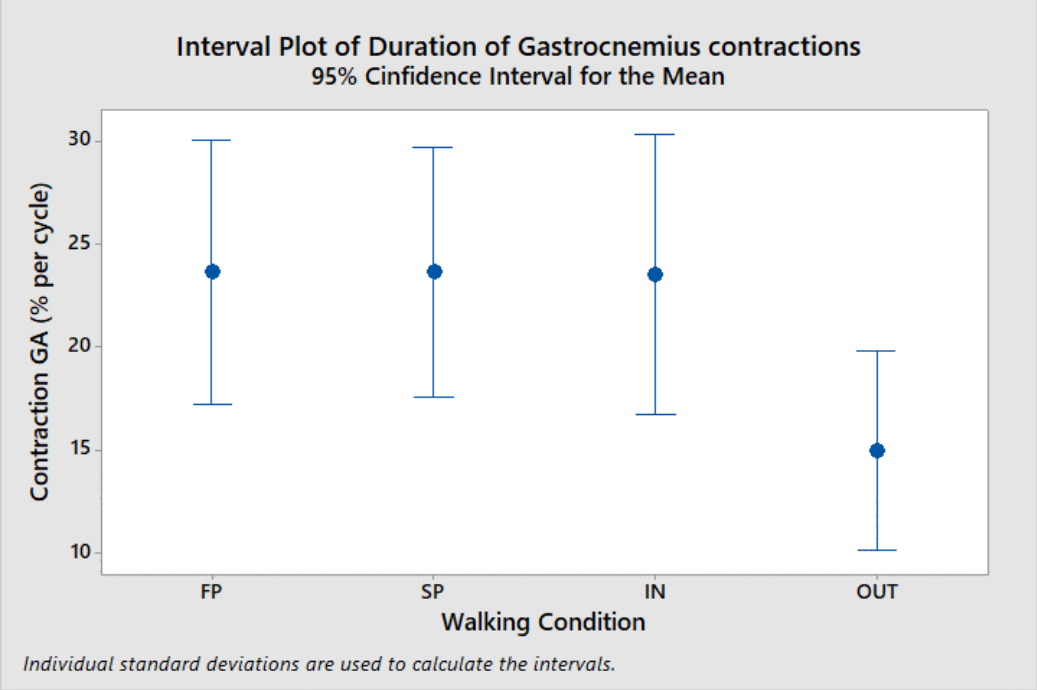


Figure 6.4: Mean GA contraction duration (as % per cycle) during level walking situations of able-bodied participants

The Tukey pairwise comparison of the GA and the TA presented that there was a statistically significant difference from FP, SP, and IN against OUT walking (see Table 6.11 and Table 6.12).

GA Contraction duration Tukey Pairwise Comparisons of the walking conditions (95% Confidence)			
Walking Condition	Mean VR	Grouping	
SP	23.65	**A**	
FP	23.62	**A**	
IN	23.52	**A**	
OUT	14.98		**B**

Table 6.11: GA contraction duration Tukey Pairwise. Means that do not share a letter are significantly different.

TA Contraction duration Tukey Pairwise Comparisons of the walking conditions (95% Confidence)			
Walking Condition	Mean VR	Grouping	
SP	30.25	**A**	
IN	27.89	**A**	
FP	26.36	**A**	
OUT	10.01		**B**

Table 6.12: TA contraction duration Tukey Pairwise. Means that do not share a letter are significantly different.

Some disparity in the duration was observed between the sides of participant S_5. During the treadmill walks, the GA on the hemiplegic side contracted for longer periods compared to the contralateral side, see Table 6.13.

	VR FP		VR SP		VR IN		VR OUT	
	Op	Hemi	Op	Hemi	Op	Hemi	Op	Hemi
Contraction duration GA	22.66 %	23.56 %	27.37 %	19.69 %	41.99 %	28.46 %	5.84 %	20.87 %
Contraction duration TA	5.32 %	14.34 %	16.81 %	8.54 %	11.89 %	15.07 %	NA	12.14 %

Table 6.13: Contraction duration in (% cycle) for GA and TA of participant S_5 on the four walking situations

During the treadmill walks, the hemiplegic side presented more disparity between the side, with longer contractions on the hemi side than on the op side (see Table 6.14).

	VR FP		VR SP		VR IN		VR OUT	
	Op	Hemi	Op	Hemi	Op	Hemi	Op	Hemi
Contraction duration GA	58.79 %	60.69 %	45.89 %	81.02 %	37.84 %	23.28 %	3.93 %	5.66 %
Contraction duration TA	16.00 %	82.85 %	13.48 %	81.28 %	14.32 %	10.74 %	NA	5.63 %

Table 6.14: Contraction duration in (% cycle) for GA and TA of participant S_7 on the four walking situations

6.2.2.4. Stride duration

Participants tended to take shorter steps when walking outdoors. The stride time decreased from fixed-pace treadmill walking (longest with 1.12±0.05 seconds), the self-pace treadmill walking (1.06±0.07), indoor overground walking (1.00±0.10) and to outdoor walking (shortest with 0.92±0.21 seconds) (see Figure 6.5).

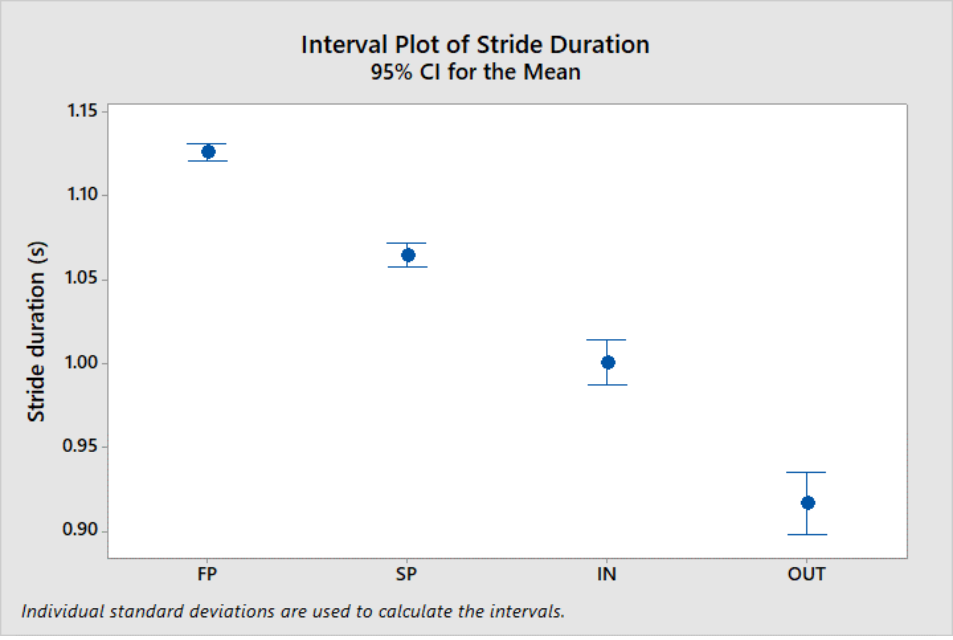


Figure 6.5: Interval plot of stride durations during levelled walking situations

The Tukey post-hoc analysis presented the FP walk as significantly (p=0.000) different from SP, IN and OUT walking. Each walk was significantly different (p=0.000) from the other.

For participant S_5, the strides were longest during FP (1.03±0.00) walking and the shortest during IN walking (0.59±0.01) as presented in Table 6.15.

	FP (SD)	SP (SD)	IN (SD)	OUT (SD)
Stride duration (s)	1.03 (0.00)	0.96 (0.00)	0.59 (0.01)	1.01 (0.00)

Table 6.15: Mean stride duration across the two leg sides in four walking situations (FP= Fixed-pace treadmill, SP= Self-paced treadmill, IN= Overground indoors, OUT= Overground outdoors) participant S_5

This outcome doesn't match the general trend of the able-bodied participants as they presented a decrease in stride duration from FP treadmill walking to OUT walking (see Figure 6.5).

For participant S_7, the strides were longest during FP (1.28±0.00) walking and the shortest during IN walking (0.94±0.01) (result reported in Table 6.16). This behaviour slightly differs from the able-bodied group since it presented the shorter stride duration during OUT walking (see Figure 6.5).

	FP (SD)	SP (SD)	IN (SD)	OUT (SD)
Stride duration (s)	1.28 (0.00)	1.17 (0.01)	0.94 (0.01)	1.05 (0.02)

Table 6.16: Mean stride duration across the two leg sides in four walking situations participant S_7

6.2.2.5. Summary of level walking analysis

The VR analysis presented similarity between SP treadmill and outdoor walking and were significantly different ($p<0.05$) to indoor walking for both GA and TA. The number of contractions per cycles did not display statistical differences across the walking conditions. The duration of contractions of both muscles displayed shorter contractions during OUT walking.

During the flat walking situations, the TA of participant S_5 followed the general behaviour of the able-bodied group displaying relatively high repeatability during FP and IN (respectively VR=0.25 and 0.08) and lower repeatability during SP and OUT (respectively VR=0.32 and 0.59). The GA muscle differed with higher repeatability during SP and IN (respectively VR=0.24 and 0.22). When comparing the sides, the GA presented higher VRs on the side contralateral to the hemiplegia during FP treadmill walking and OUT walking. Like the able-bodied group, the number of contractions per cycle was lesser during outdoor walking. The GA of participant S_5 matched the able-bodied, with shorter contractions during OUT walking. GA presented longer contractions on the hemiplegic side. The TA had shorter contractions during FP

walking. Participant S_5 presented shorted stride durations during IN walking when the able-bodied participants presented shorter strides during OUT walking. The VR of participant S_7 presented higher VR of FP and SP treadmill walking while the IN and Out walks were of smaller VR values (more repeatability). This behaviour differs from the able-bodied population which presented similar (higher VRs) values for FP and IN and similar (lower) values for SP and OUT walk. The number of contractions was lower in both cases of overground walking. This differs with the reference data which presented similar numbers across the walking situations. The duration of contraction was shorter during IN walking and even shorter during OUT walking. The able-bodied group presented the shortest contraction during OUT walking and left the other walking situations with similar values. The hemiplegic side presented longer contraction that its opposite side. The strides of this participant were shorter during IN walking while they were shorter for OUT walking in the case of the able-bodied group. The VR parameter presented similarities between SP treadmill walking and OUT walking as they displayed similar magnitude (higher variability). This trend is in agreement with the hypothesis of greater similarities between SP treadmill and OUT walking.

6.2.3. Uphill walking results

This section will present the analysis of the same motor control parameters (VR, number of contractions per cycles, duration of contractions, and stride duration) for three uphill conditions 1) OUT UP: which is walking uphill outdoors on a gradient that varied between 3 and 6 degrees, 2) SP UP 03: Self-paced on a treadmill set at 3 degrees and 3) SP UP 06: Self-paced on a treadmill set at 6 degrees. (NB participant S_5 was unable to perform the 6 degrees up treadmill walk).

6.2.3.1. Variance ratio (VR)

During uphill walking, the repeatability of the gastrocnemius was significantly lower during outdoor walking (VR=0.36±0.18, p=0.013) and higher during self-paced walking (VR=0.22±0.14, p=0.036) with 3 degrees gradient (see Table 6.17) for the able-bodied group.

For participant S_5, during both uphill walking situations, the VR values of GA and TA were of the same magnitude of values (see Table 6.17). This behaviour is different from the able-bodied participants since it displayed a higher VR value (lower repeatability) for both muscles of interest during OUT UP walking (see Table 6.17).

In the case of participant S_7, for both GA and TA, the VR was lower during OUT UP walking (higher repeatability) and higher during SP UP 03 walking (Table 6.17). These results match the observations on the able-bodied participants and the absence of clear differentiation (statistically significant difference) between self-paced and real uphill walking may underline similarities in muscle recruitment strategy.

Mean VR	OUT UP (SD) AB	OUT UP (SD) S_5	OUT UP (SD) S_7	SP UP 03 (SD) AB	SP UP 03 (SD) S_5	SP UP 03 (SD) S_7	SP UP 06 (SD) AB	SP UP 06 (SD) S_5	SP UP 06 (SD) S_7
GA	0.36 (0.18)	0.33 (0.14)	0.24 (0.10)	0.22 (0.14)	0.28 (0.07)	0.50 (0.08)	0.27 (0.21)	NA (NA)	0.43 (0.32)
TA	0.4 (0.09)	0.37 (NA)	0.29 (NA)	0.28 (0.16)	0.40 (0.03)	0.59 (0.26)	0.29 (0.15)	NA (NA)	0.48 (0.24)

Table 6.17: VR of GA and TA during uphill walking situations

The tibialis anterior of the AB participants did not display significant differences in the muscle pattern repeatability.

The Tukey pairwise post-hoc analysis of the gastrocnemius considered outdoor walking and 6 degrees up treadmill walking in the same group, treadmill walking up 6 degrees and up 3 degrees belonging to the same group (see Table 6.18).

VR GA Tukey Pairwise Comparisons of the walking conditions (95% Confidence)			
Walking Condition	Mean VR	Grouping	
OUT UP	0.36	**A**	
SP UP 06	0.27		**B**
SP UP 03	0.22		**B**

Table 6.18: VR GA Tukey Pairwise comparison. Means that do not share a letter are significantly different.

The comparison of the hemiplegic (hemi) leg to the opposite leg (op) of participant S_5, presented higher variability on the hemiplegic side (higher VR value) (see Table 6.19).

	VR OUT		VR SP UP 03		VR SP UP 06	
	Op	Hemi	Op	Hemi	Op	Hemi
GA	0.23	0.43	0.23	0.33	NA	NA
TA	NA	0.37	0.38	0.42	NA	NA

Table 6.19: VR for hemiplegic (Hemi) and opposite (Op) side of the participant S_5

The comparison of the hemiplegic (hemi) leg to the opposite leg (op) presented higher VRs on the hemiplegic side, which reflects more variability for these muscles (see Table 6.20).

	VR OUT		VR SP UP03		VR SP UP06	
	Op	Hemi	Op	Hemi	Op	Hemi
GA	0.17	0.31	0.45	0.56	0.20	0.66
TA	NA	0.29	0.41	0.78	0.31	0.65

Table 6.20: VR for hemiplegic (Hemi) and opposite (Op) side of the participant S_7

6.2.3.2. Number of contractions per cycle

There were no statistically significant differences observed according to the walking situations for both the gastrocnemius and tibialis anterior on the AB group.

The gastrocnemius muscles of participant AB_8 and AB_15 stood out by their significantly higher number of contractions, respectively N(GA)=2.42±0.8 (p=0.041) and N(GA)=3.1±1.62 (p=0.001).

The tibialis anterior of three participants stood out. Participants AB_8 and AB_15 had a significantly larger number of contractions per cycles (respectively N(TA)=2.8±0.84, p=0.009 and N(TA)=3±1, p=0.002) and participant AB_9 with a significantly lower number of contractions per cycles N(TA)=1±0, p=0.015.

The overall mean number of contractions for each participant during uphill walking is reported in Table 6.21.

Participant n°	Mean number of contractions GA (SD)	Mean number of contraction TA (SD)
AB_8	**2.42 (0.8)**	**2.8 (0.84)**
AB_9	1.5 (0.84)	**1 (0.0)**
AB_10	1.5 (0.55)	1.8 (0.84)
AB_11	1.25 (0.42)	2.4 (0.65)
AB_12	1.42 (0.49)	2.1 (0.89)
AB_13	1 (0.63)	1.3 (0.45)
AB_14	2 (1.55)	1.4 (0.89)
AB_15	**3.1 (1.62)**	**3 (1.0)**
AB_16	1 (0.0)	1 (NA)
AB_17	1.5 (0.71)	2 (NA)

Table 6.21: GA and TA mean number of contractions over all uphill walking situations for each participant.

As presented in Table 6.22, the number of contractions per gait cycle in the stroke survivors seemed close between outdoor and three degrees uphill walking for the GA and the TA. This behaviour is consistent with the overall able-bodied results Table 6.21. For participant S_7, the number of contractions of TA was higher during SP UP 06 treadmill walking.

	OUT UP (SD) S_5	OUT UP (SD) S_7	SP UP 03 (SD) S_5	SP UP 03 (SD) S_7	SP UP 06 (SD) S_5	SP UP 06 (SD) S_7
Number of contractions GA	2.75 (1.06)	1.5 (0.71)	2.5 (0.71)	1 (1.41)	NA (NA)	2 (2.83)
Number of contractions TA	1 (NA)	1 (NA)	1.5 (0.71)	1.5 (2.12)	NA (NA)	3.5 (0.71)

Table 6.22: Mean number of contractions of GA and TA during uphill walking situations for participants S_5 and S_7.

The comparison of the hemiplegic (hemi) leg to the opposite leg (op) presented more contractions on the hemiplegic side (see Table 6.23).

	OUT UP S_5		SP UP 03 S_5		SP UP 06 S_5	
	Op	Hemi	Op	Hemi	Op	Hemi
Number of contractions GA	2	3.5	2	3	NA	NA
Number of contractions TA	NA	1	1	2	NA	NA

Table 6.23: Number of contractions for hemiplegic (Hemi) and opposite (Op) side of the participant S_5 during uphill walking situations.

The comparison of the hemiplegic (hemi) leg to the opposite leg (op) of participant S_7 presented noticeable differences for GA during treadmill walking SP UP 03 and UP 06, where the hemiplegic side contracted more within on cycle (see Table 6.24). The TA presented no contraction on the hemiparetic side during SP UP 03. This does not necessarily reflect an absence of contraction but most probably an intensity of contraction that went below the applied threshold.

	OUT UP n°24		SP UP 03 n°24		SP UP 06 n°24	
	Op	Hemi	Op	Hemi	Op	Hemi
Number of contractions GA	2	1	3	5	2	6
Number of contractions TA	NA	1	3	0	4	3

Table 6.24: Number of contractions of GA and TA for hemiplegic (Hemi) and opposite (Op) side of the participants n°24 during uphill walking situations.

6.2.3.3. Contraction duration

The tibialis anterior displayed no statistically significant difference for contraction duration ($p>0.05$) during the three uphill walking conditions (see Table 6.25).

As observed for able-bodied participants (see Table 6.25), the GA and TA of participant S_5 displayed shorter contraction durations during outdoor uphill walking (see Table 6.25) compared to UP treadmill walking.

For participant S_7, the contraction duration was shorter during OUT UP walking for GA and TA, as reported in Table 6.25. This outcome matches the behaviour of the able-bodied participants (see Table 6.25). This participant also displayed a higher contraction duration during SP UP 06 walking, when the able-bodied participants had similar durations of contractions during the SP walking situations.

Mean contraction duration	OUT UP (SD) AB	OUT UP (SD) S_5	OUT UP (SD) S_7	SP UP 03 (SD) AB	SP UP 03 (SD) S_5	SP UP 03 (SD) S_7	SP UP 06 (SD) AB	SP UP 06 (SD) S_5	SP UP 06 (SD) S_7
GA	13.81 (5.09)	12.57 (4.29)	7.53 (NA)	24.5 (16.57)	19.44 (0.78)	46.4 (33.9)	22.64 (17.94)	NA (NA)	34.3 (21.6)
TA	12.93 (6.3)	4.14 (NA)	5.1 (NA)	24.47 (16.96)	12.35 (4.55)	38.55 (7.4)	22.75 (14.47)	NA (NA)	62.2 (32.8)

Table 6.25: GA and TA mean contraction duration during uphill walking situations.

The gastrocnemius of the AB group presented shorter contractions duration when walking outdoors uphill, however, no significant statistical difference was observed ($p=0.085$, 13.81±5.09 % of gait cycle) (see Figure 6.6).

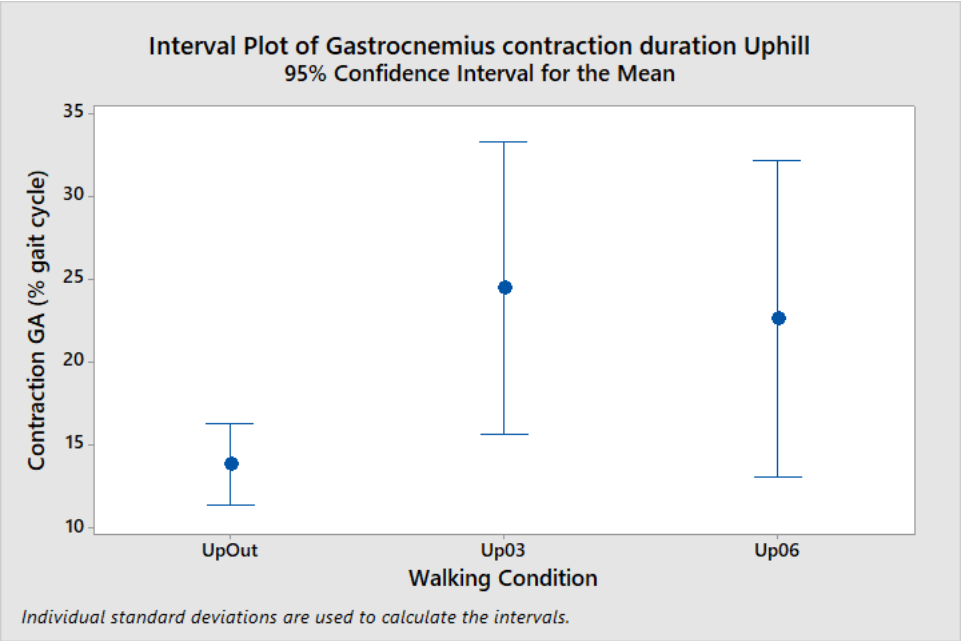


Figure 6.6: Interval plot of GA contraction duration during uphill walking situations

The comparison of the hemiplegic (hemi) leg to the opposite leg (op) of participant S_5, presented longer contraction durations than the opposite side (see Table 6.26). The difference of duration appears to be more obvious during outdoor walking.

	OUT UP S_5		SP UP 03 S_5		SP UP 06 S_5	
	Op	Hemi	Op	Hemi	Op	Hemi
Mean Contraction duration GA	9.54	15.61	18.89	20	NA	NA
Mean contraction duration TA	NA	4.14	9.13	15.56	NA	NA

Table 6.26: Contraction duration for hemiplegic (Hemi) and opposite (Op) side of the participant S_5 during uphill walking situations.

The comparison of the hemiplegic (hemi) leg to the opposite leg (op) of participant S_7 presented, in this case, longer contractions on the non-hemiplegic leg. (see Table 6.27).

	OUT UP S_7		SP UP 03 S_7		SP UP 06 S_7	
	Op	Hemi	Op	Hemi	Op	Hemi
Mean Contraction duration GA	7.53	NA	70.33	22.42	49.56	19
Mean contraction duration TA	5.1	(NA)	43.78	33.32	85.37	39.03

Table 6.27: Contraction duration as a percentage of the gait cycle for hemiplegic (Hemi) and opposite (Op) side of the participant S_7 during uphill walking situations.

6.2.3.4. Stride duration

Outdoor uphill walking presented significantly shorter strides (p=0.005, 1.01±0.09 seconds), compared to the treadmill uphill walking up 3 degrees and up 6 degrees, respectively 1.07±0.07 seconds and 1.09±0.11 seconds (reported in Table 6.28 & Figure 6.7).

For participant S_5, the stride duration was longer during OUT UP walking (1.37±0.02) compared to SP 3° UP walking (1.02±0.01) as reported in Table 6.28. This outcome differs from the observation of stride duration of the able-bodied participants, where the OUT UP walk presented the shorter stride duration.

For participant S_7, the stride duration was similar between OUT UP walking and SP 3° UP walking (1.09±0.00) and longer during SP 6° UP treadmill walking (1.18±0.00), as reported in Table 6.28. This observation is close to the able-bodied group as its shortest stride duration appeared to be during OUT UP walking (see Table 6.28).

Mean Stride duration in seconds	SP OUT UP (SD)	SP UP 03 (SD)	SP UP 06 (SD)
AB	**1.01 (0.01)**	1.07 (0.07)	1.09 (0.11)
S_5	1.37 (0.02)	1.02 (0.01)	NA (NA)
S_7	1.09 (0.00)	1.09 (0.00)	1.18 (0.00)

Table 6.28: Mean stride duration during uphill walking situations.

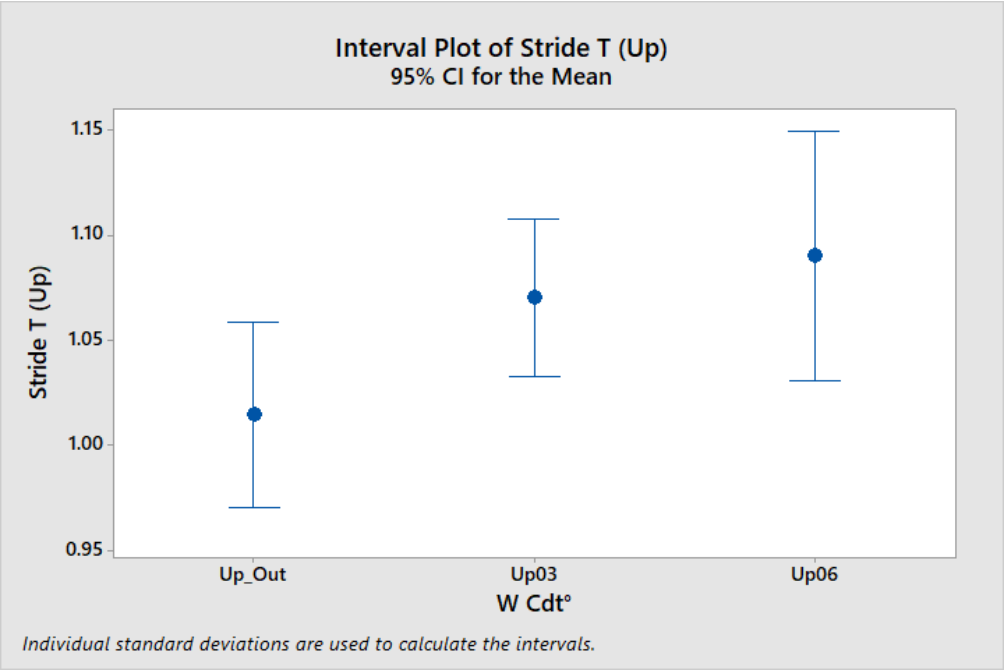


Figure 6.7: Interval plot of stride duration during uphill walking situations

The Tukey pairwise post-hoc analysis of the mean stride duration over the three uphill walks paired together the two treadmill walks and the outdoor uphill walk was paired to the 3 degrees up treadmill walk, making the 6 degree up treadmill walk and outdoor uphill walking significantly different (see Table 6.29).

Stride duration Tukey Pairwise Comparisons of the walking conditions (95% Confidence)			
Walking Condition	Mean VR	Grouping	
SP UP 06	1.09	**A**	
SP UP 03	1.07	**A**	
OUT UP	1.01		**B**

Table 6.29: Stride duration Tukey Pairwise Comparison. Means that do not share a letter are significantly different.

6.2.3.5. Summary of uphill walking parameters analysis

While the VR analysis presented a statistically significant difference between OUT UP and SP UP (3°) on the GA muscle but not the TA. The number of contractions per cycle did not differ between the walking situations. The contraction duration parameter reported shorter contractions during outdoor uphill walking. The stride duration parameter presented a statistically significant ($p=0.005$) difference between SP UP (6°) and UP OUT with shorter UP OUT strides.

The VR of participant S_5 remained of similar magnitude across the walking situations, whereas the able-bodied participants presented higher VR while walking OUT UP. The hemiplegic side presented higher VRs than the opposite. Like the able-bodied group, the number of contractions remained similar across all the uphill walks. More contractions were observed on the hemiplegic side. The duration of participant S_5's muscle contraction followed the able-bodied participant's trend, and the contraction were shorter during OUT walking. This participant had shorter strides during SP UP 03 treadmill walking when the able-bodied group had shorter strides durations during OUT UP walking.

The analysis of the VR of participant S_7 matches the observations from the able-bodied group with lower VR during OUT UP walking and higher VR during SP UP 03 walking. The hemiplegic side displayed a higher VR. The number of contractions per cycles was similar across the different walks for the GA, which matches the reference data (able-bodied participants). The TA displayed a higher number of contractions during SP UP 06 walking. Shorter contractions were observed during OUT UP walking, which matches the reference data. The non-paretic leg presented longer contraction durations. The shorter strides occurred during OUT UP and SP UP walking. This agrees with the able-bodied participants results which presented shorter stride durations during OUT UP.

6.2.4. Downhill results

This section will present the analysis of the same motor control parameters (VR, number of contractions per cycles, duration of contractions, and stride duration) for three uphill conditions 1) OUT DOWN: which is walking downhill outdoors on a gradient that varied between 3 and 6 degrees, 2) SP DOWN (-3°): Self-paced on a treadmill set at minus 3 degrees, 3) SP DOWN (-6°): Self-paced on a treadmill set at minus 6 degrees.

6.2.4.1. Variance ratio (VR)

The gastrocnemius and the tibialis anterior displayed no significant differences between the different walking situations (see Table 6.30).

For participant S_5, the VR of GA was close to the value for outdoors and on the treadmill with treadmill SP DOWN (-3°) being higher than OUT DOWN walking. The TA presented the opposite situation where the VR during OUT DOWN was higher than during treadmill SP DOWN (-3°) (see Table 6.30).

In the case of the able-bodied participants, both the GA and the TA presented a higher VR during OUT DOWN walking (see Table 6.30).

The GA of participant S_7 kept similar VR values across the three DOWN walking situations (see Table 6.30). This outcome matches the observations on the able-bodied participants (see Table 6.30). The VR value of TA during OUT DOWN (VR=0.24) was lower than the one during SP DOWN 06 walking (VR=0.64).

Mean VR	OUT DOWN (SD) AB	OUT DOWN (SD) S_5	OUT DOWN (SD) S_7	SP DOWN 03 (SD) AB	SP DOWN 03 (SD) S_5	SP DOWN 03 (SD) S_7	SP DOWN 06 (SD) AB	SP DOWN 06 (SD) S_5	P DOWN 06 (SD) S_7
GA	0.40 (0.13)	0.41 (0.28)	0.52 (0.11)	0.33 (0.22)	0.46 (0.21)	0.57 (NA)	0.37 (0.22)	NA (NA)	0.55 (NA)
TA	0.36 (0.11)	0.57 (NA)	0.24 (NA)	0.28 (0.15)	0.44 (0.12)	NA (NA)	0.26 (0.13)	NA (NA)	0.64 (NA)

Table 6.30: Mean VR of GA and TA for the different walking situations

The comparison of the hemiplegic (hemi) leg to the opposite leg (op) of participant S_5 presented more variability on the hemiplegic side of the GA. The TA during SP DOWN 03 the hemiplegic side presented less variability than the opposite side (see Table 6.31).

	VR OUT DOWN S_5		VR SP DOWN03 S_5		VR SP DOWN06 S_5	
	Op	Hemi	Op	Hemi	Op	Hemi
GA	0.22	0.61	0.31	0.61	NA	NA
TA	NA	0.57	0.53	0.36	NA	NA

Table 6.31: VR for hemiplegic (Hemi) and opposite (Op) side of the participants S_5 during downhill walking situations

The comparison of the hemiplegic (hemi) leg to the opposite leg (op) of participant S_7 presented a smaller VR value on the hemiplegic side compared to the opposite side. Due to missing data, this observation cannot be observed during the over walking situations (see Table 6.32).

	VR OUT DOWN S_7		VR SP DOWN 03 S_7		VR SP DOWN 06 S_7	
	Op	Hemi	Op	Hemi	Op	Hemi
GA	0.60	0.44	0.57	NA	0.55	NA
TA	NA	0.24	NA	NA	0.64	NA

Table 6.32: VR for hemiplegic (Hemi) and opposite (Op) side of the participants S_7 during downhill walking situations

6.2.4.2. Number of contractions per cycle

The gastrocnemius and the tibialis anterior displayed no significant differences between the three walk situations (see Table 6.33).

For participant S_5, while the TA presented similar number of contractions in the three walk situations, the GA presented a higher number of contractions for the OUT DOWN walk (presented in Table 6.33).

This behaviour differs from the able-bodied participants since their number of contractions remained similar regardless of the walking situation (see Table 6.33).

Mean Number of contractions	OUT DOWN (SD) AB	OUT DOWN (SD) S_5	OUT DOWN (SD) S_7	DOWN 03 (SD) AB	SP DOWN 03 (SD) S_5	SP DOWN 03 (SD) S_7	SP DOWN 06 (SD) AB	SP DOWN 06 (SD) S_5	SP DOWN 06 (SD) S_7
GA	2.12 (1.83)	3.5 (3.54)	0.5 (0.71)	2.1 (1.27)	1 (0)	2 (0)	1.8 (0.7)	1 (0)	2.75 (1.77)
TA	2.23 (0.75)	2.3 (NA)	1 (NA)	2.41 (1.19)	2 (0)	5.5 (2.12)	2.06 (0.7)	2.25 (0.35)	1.5 (0.71)

Table 6.33: Mean number of contractions for GA and TA during downhill walking

The comparison of the hemiplegic (hemi) leg to the opposite leg (op) of participant S_5 presented similar values on both sides apart for the GA OUT

DOWN where the hemiplegic side present a larger number of contractions (see Table 6.34).

	OUT DOWN S_5		SP DOWN 03 S_5		SP DOWN 06 S_5	
	Op	Hemi	Op	Hemi	Op	Hemi
Number of contractions GA	1	6	1	1	1	1
Number of contractions TA	NA	2.3	2	2	2.5	2

Table 6.34: Number of contractions for hemiplegic (Hemi) and opposite (Op) side of the participant S_5 during downhill walking situations

While comparing the hemiplegic (hemi) leg to the opposite leg (op) of participant S_7, it can be noticed that GA presented a high number of contractions on the hemi side, only during the SP DOWN 06 situation as presented in Table 6.35). Also, the TA presented noticeably more contractions on both sides during SP DOWN 03, since the mean number of contractions of the able-bodied participant's TA for this walk situation was of 2.41 (see Table 6.33). In the case of this participant the hemiplegic side of has a noticeably higher number of contractions compared to the opposite leg.

	OUT DOWN S_7		SP DOWN 03 S_7		SP DOWN 06 S_7	
	Op	Hemi	Op	Hemi	Op	Hemi
Number of contractions GA	0	1	2	2	1.5	4
Number of contractions TA	NA	1	4	7	1	2

Table 6.35: Number of contractions per gait cycles of GA and TA for hemiplegic (Hemi) and opposite (Op) side of the participant S_7 during downhill walking situations

6.2.4.3. Contraction duration

The gastrocnemius had statistically significantly shorter contraction durations during outdoor downhill walking (p=0.011, 25.15±26.23) compared to the downhill treadmill walking situations (see Table 6.36).

For participant S_5, both muscles presented shorter contraction duration during OUT DOWN walking and longer from treadmill SP DOWN 06 (see Table 6.36). Shorter contractions were also observed for both muscles, during OUT DOWN walking in the case of the able-bodied participants (reported in Table 6.36).

Mean contraction duration	OUT DOWN (SD) AB	OUT DOWN (SD) S_5	OUT DOWN (SD) S_7	DOWN 03 (SD) AB	SP DOWN 03 (SD) S_5	SP DOWN 03 (SD) S_7	SP DOWN 06 (SD) AB	SP DOWN 06 (SD) S_5	SP DOWN 06 (SD) S_7
GA	**25.15 (26.23)**	14.77 (7.4)	4.33 (3.38)	33.22 (19.92)	14.44 (0.69)	26.55 (4.38)	33.03 (20.48)	19.81 (11.96)	28.5 (23.3)
TA	13.9 (6.67)	15.56 (NA)	5.32 (NA)	30.65 (15.75)	20.75 (12.57)	52.9 (33.7)	29.44 (17.75)	34.5 (26.5)	51 (56.8)

Table 6.36: Mean contraction durations of GA and TA during downhill walking

The Tukey pairwise post-hoc analysis of the contraction duration of the able-bodied participants' TA presented a significant distinction between the two treadmill downhill walks and outdoor downhill walking (see Table 6.37).

TA Contraction duration Tukey Pairwise Comparisons of the walking conditions (95% Confidence)			
Walking Condition	Mean VR	Grouping	
SP UP 03	30.65	**A**	
SP UP 06	29.44	**A**	
OUT UP	13. 90		**B**

Table 6.37: TA contracion duration Tukey pairwise Comparison. Means that do not share a letter are significantly different.

The comparison of the hemiplegic (hemi) leg to the opposite leg (op) of participant S_5 presented different contraction patterns in the different walking situations (see Table 6.38). For the GA, during the OUT DOWN and the SP DOWN, the SP DOWN the hemiplegic side presented longer contractions. The opposite happened during SP DOWN 03 and SP DOWN 06 for the TA, as well as for the GA during SP DOWN treadmill walking.

	OUT DOWN S_5		SP DOWN 03 S_5		SP DOWN 06 S_5	
	Op	Hemi	Op	Hemi	Op	Hemi
Mean Contraction duration GA	9.54	20	13.96	14.93	28.27	11.35
Mean contraction duration TA	NA	15.56	29.64	11.86	53.21	15.8

Table 6.38: Contraction duration for hemiplegic (Hemi) and opposite (Op) side of the participant S_5 during downhill walking situations

The comparison of the hemiplegic (hemi) leg to the opposite leg (op) participant S_7 presented for GA, shorter contractions on the hemiplegic side during OUT DOWN and SP DOWN walking (see Table 6.39). For TA, the shortest contractions were found on the hemiplegic side during SP DOWN 03 and SP DOWN 06.

	OUT DOWN S_7		SP DOWN 03 S_7		SP DOWN 06 S_7	
	Op	Hemi	Op	Hemi	Op	Hemi
Contraction duration GA	6.72	1.94	23.45	29.64	44.98	12.06
Contraction duration TA	5.32	NA	76.73	29.11	91.21	10.82

Table 6.39: Contraction duration of GA and TA for hemiplegic (Hemi) and opposite (Op) side of the participant S_7 downhill walking situations

6.2.4.4. Stride duration

Outdoor downhill walking (p=0.001, t=0.92±0.15) and -3 degrees (p=0.009, t=1.02±0.05) self-paced treadmill walking displayed respectively significantly lower and significantly higher stride durations compared to SP DOWN (06) (see Table 6.40).

For participant S_7, The stride duration was similar between SP DOWN 03 (1.12±0.07) and SP DOWN 06 walking (1.11±0.00) it was shorter during DOWN OUT (1.05±0.10) (see Table 6.40). The able-bodied group also presented the shorter strides during OUT DOWN walking.

Mean Stride duration (s)	OUT DOWN (SD)	SP DOWN 03 (SD)	SP DOWN 06 (SD)
AB	**0.92 (0.15)**	**1.02 (0.05)**	0.98 (0.05)
S_5	1.14 (0.03)	1.03 (0.01)	0.89 (0.01)
S_7	1.05 (0.10)	1.12 (0.07)	1.11 (0.00)

Table 6.40: Mean stride duration per downhill walking situation

The Tukey pairwise comparison presented a clear distinction between the three walking situations (treadmill walks (both down 3 and down 6 degrees) and the outdoor downhill walks, group the DOWN 03 has leading to longest stride durations, followed by DOWN 06 and OUT DOWN which presented the shortest stride durations (see Table 6.41).

Stride duration Tukey Pairwise Comparisons of the walking conditions (95% Confidence)				
Walking Condition	Mean VR	Grouping		
SP UP 03	1.02	**A**		
SP UP 06	0.98		**B**	
OUT UP	0.92			**C**

Table 6.41: Stride duration Tukey Pairwise Comparison. Means that do not share a letter are significantly different.

6.2.4.5. Summary of downhill walking parameters analysis

The VR analysis of both GA and TA presented no statistically significant difference between the different types of downhill walk. The number of contractions also showed no statistically significant differences between the walks. The duration of contraction did however present statistically significant ($p=0.011$) differences with shorter contraction for the GA during OUT DOWN walking in comparison with the two SP treadmill walking slopes. SP DOWN 03 stride duration was significantly ($p=0.009$) longer from SP DOWN 06 and DOWN OUT. The stride duration was significantly shorter during DOWN OUT ($p=0.001$) walking compared to the two SP DOWN walks.

For participant S_5, the behaviour of the TA matched the able-bodied group's behaviour, with a higher VR during OUT DOWN walking. On the GA, the VR was higher on the hemiplegic side. The number of contractions was larger during outdoor walking, which differs with the able-bodied group who add similar values across all walking situations. The GA displayed larger number of contractions during OUT DOWN walking. The duration of the contractions was shorter during OUT DOWN walking, like the reference (able-bodied participants) group. The stride duration was shorter during SP DOWN 06 treadmill walking and not during OUT DOWN walking, as the able-bodied group showed.

The GA of participant S_7 followed the trend of the able-bodied group, keeping similar values across the DOWN walking situations. The TA presented a lower VR for OUT DOWN. Where the able-bodied participants displayed a similar number of contractions per cycles across the walking situations, here the participant's GA presented noticeably less contractions during OUT DOWN walking and its TA presented more contractions during SP DOWN 03. Like the able-bodied group the contraction duration was shorter during OUT DOWN walking. Also, the stride duration was shorter during DOWN OUT which matches the able-bodied participant's results.

6.2.5. Summary of results

- The variance ratio analysis for straight walking grouped together the self-pacing and the outdoor walking situations, with lower variability found during SP treadmill and OUT walking. The downhill walking experiment displayed few significant differences ($p=0.011$) when comparing the contraction duration between the two self-paced walking gradients and outdoor downhill walking, as the outdoor walking situation led to shorter GA contractions. However, during uphill walking the gastrocnemius displayed a significant distinction ($p=0.013$) between outdoor uphill and treadmill walking up 3 degrees.
- The measure of the number of contractions per cycles was not proven to be an effective tool to distinguish the differences between the different walks.
- The duration of the contraction was significantly shorter during outdoor levelled walking. The same observation was made during outdoor walking on the gastrocnemius muscle. The tibialis anterior during outdoor walking grouped outdoor and self-paced 3 degrees downhill walking together. Sloped walking led to shorter contractions during outdoor walking for the stroke participants.
- The measure of stride duration consistently displayed shorter strides during outdoor level walking for the able-bodied participant but was shorter during indoor overground walking for the stroke participants.
- When the stroke participants generally followed the trend of the able-bodied group, they presented a lesser range of VR amplitude which did not lead to statistically significant differences between the walking situations.
- The duration of the contractions during flat walking was not significantly shorter during outdoor walking for the stroke participants.
- The variance ratio analysis presented trends that agree with the hypothesis that SP treadmill walking is a closer analogue to overground outdoor walking.
- Although few differences were found, the hypothesis of similarity between slopped SP treadmill walking and OUT sloped treadmill walking is rejected as significant ($p=0.011$) differences were found during downhill walking.

Chapter 7

7. Discussion

The research presented in this thesis has used computationally undemanding parameters to characterise the muscular activity of selected lower-leg muscles during different walking situations to determine the type of treadmill training that is most similar to overground walking in terms of muscle activation and, therefore, has better training specificity for rehabilitation. The findings have shown that it is possible to use parameters that are not computationally heavy, to analyse the muscle activity and extract indicators of the motor control strategy in different walking situations. Computationally heavy methods require more computer power and can be time consuming and difficult to translate for practitioners, hence unpractical for a routine or clinically based analysis. The intention was to find and use parameters providing an outcome easy to interpret. This chapter will present an interpretation of the results presented in chapter six, explore further meaning and discuss the implications for the future of gait rehabilitation practice and research.

The chapter will consider each parameter in turn (VR, number of contractions per cycles and contraction duration) comparing the results between the two sampled populations: able-bodied (AB) and stroke (S), as well as findings from other published research. Finally, the limitations of the work will be discussed with recommendations for future work.

7.1. Summary and Interpretation of the results

7.1.1. Variance ratio (VR) analysis

Level walking (VR analysis)

During level walking, the able-bodied (AB) and stroke (S) groups presented similar VR values during self-paced (SP) treadmill walking (0.36 and 0.51 respectively for GA; 0.42 and 0.44 respectively for TA) and outdoor (OUT) walking (0.38 and 0.43 respectively for GA 0.39; 0.43 and 0.44 for TA). This suggests that SP treadmill walking, which allows natural speed variability, is a closer analogue to outdoor walking, in terms of muscle activation consistency, than fixed pace (FP) treadmill walking where the VRs showed greater difference (e.g. 0.26 for GA and 0.32 for TA in the able-bodied group) to the control condition of outdoor walking for both the able bodied and stroke groups.

An apparent contradiction to this finding was the similarity between the FP treadmill and indoor (IN) walking for the AB group with both walking situations sharing similarly low VR values (between 0.22±0.05 and 0.32±0.14) indicating a highly repeatable (cycle to cycle) EMG patterns, particularly for GA (FP = 0.26 and IN = 0.22). One possible explanation for the high repeatability (a low VR indicates a high repeatability) of the EMG pattern in both these situations may be the lack of adjustment in speed or gait pattern as both walking conditions could be considered predictable and unchallenging, taking place over flat surfaces, in a straight line in a well-lit obstacle free environment [108], [121].

The lack of statistically significant differences for the VR parameter across the different walking situations for the participants with stroke, may be a function of the very small sample size (n = 2), due to insufficient amount of data collected in the other participants with stroke (see section 6.2. Results), but, may also reflect the impact of stroke on the flexibility of the motor control system [116], [265], [283], [290] with participants more dependent on immutable (stereotypical) gait patterns with limited capacity to alter the motor output in response to changes in environmental conditions. In their paper Vistamehr et al. (2018) [185] observed that while performing tasks of obstacle negotiation AB participants differed from stroke participants in generating significantly ($p < 0.002$) higher soleus muscle EMG amplitude (about 40% more) compared to the stroke participant's non-paretic and paretic legs. This may be a manifestation of the impaired motor control's ability to adapt muscle activity according to the changes in environmental conditions.

Ivanenko et al. (2004) observed different activity patterns from 20 different leg muscles. They observed that for one given muscle (e.g. the Gastrocnemius lateralis), when an individual walked at different fixed treadmill speeds [499]. These observations suggest that walking speed affected the motor strategy of the muscle and not simply the magnitude of the muscle activation. It is therefore not unreasonable to expect a similar variation in muscle pattern when comparing treadmill (SP & FP) and overground (IN & OUT) walking. One possible hypothesis is that, due to the constraining nature of FP treadmill on walking speed, higher values of VR (higher EMG variability) would be expected during FP and lower values (lower signal variability) during the unconstrained nature of both IN and OUT overground walking.

In this thesis, the mean walking speed of the able-bodied participants was found to be slower during FP (1.05±0.11 m/s), then increased for SP (1.19±0.14 m/s), IN (1.49±0.18 m/s) and the fastest during OUT walking (1.62±0.19 m/s), as reported in Table 6.1. It is, therefore expected to observe differences of VR between the four walking situation observed. The speeds of FP and SP situations are closer but do not present the same VR magnitude. Similar observation can be done between the walking speeds of IN and OUT.
The finding from this thesis that the VR values during OUT walking are high compared to the IN walking data, however, suggests that speed alone is not the only factor influencing variability of the muscle activity pattern. Environmental factors including additional perturbations are likely to affect walking and, consequently, muscle activity. This includes perturbations affecting balance [500], [501] destabilising the participant's posture, auditory perturbations [391], [502] and cognitive or attentional perturbations [192], [194]. The experimental protocols used in this thesis were not designed to challenge the balance of the participants. It is therefore unlikely that balance regulation affected the muscle activity pattern of the participants. When it comes to OUT walking the ground was covered by concrete paving stones and tarmac, which created a stable walking surface in comparison with a rocky or beach sand walking surface (see Figure 5.9). There were no scheduled auditory perturbations designed in the protocol. While each participant received automated audio instructions before starting the different tasks with appropriate instructions to slow down at the end of the session the data were only collected once a stable pattern had been established, i.e. about 2 minutes after the instructions had been given and long before the instruction to slow down were given. It is therefore unlikely that these audio announcements would have any impact on the data.

Regarding visual perturbations, during the indoor treadmill walking, a virtual environment was projected in front and on the side of each participant (see Figure 7.1). This environment was consistent for each participant, showing a forest path without obstacle or visual perturbation to surprise or challenge the participant. It is likely that during OUT walking there were auditory and visual perturbations such as pedestrians passing by and talking in the street or vehicles noises as they drove up or down the street. Also, the absence of harness during OUT waking might have contributed to a freer walking experience due to the absence of physical restriction. It should be noted that the use of a safety harness that do not support weight was not found to hinder natural gait dynamics when observing stride time, stride length, and step width [503]. It is, therefore, possible that the data were affected by these audio perturbations, however the extent of such an impact is unknown. Ultimately, there were no perturbations (audio, visual or cognitive) designed in the protocol, although it is important to remember that walking on a SP treadmill with a visual feedback on a large screen was a novel experience for all the participants even though the familiarisation period would have helped minimise this impact. Consequently, the cognitive demand of obstacle anticipation and avoidance [192] or the effect of dual-tasking [194] on cognitive abilities were regarded as trivial and are not considered an influence in the outcome in this thesis.

Figure 7.1: Participant walking on the treadmill with a 180° virtual display

Slope walking (VR analysis)

In the AB group, only the gastrocnemius activity showed similarity in VR values between the uphill walking conditions OUT UP and SP UP (3º).

Franz and Kram (2012) [438], observed that the amplitude of muscle activity of soleus and gastrocnemius increased significantly ($p<0.05$) during uphill walking above 3° to provide the required additional force to lift the body vertically and decreased during downhill walking for the opposite reason. The observations of Franz and Kram (2012) [438] were recorded from young able-bodied adults (aged 25.3±3.9 years old). A similar protocol was applied to a group of older adults (72±4 years old) and a group of young adults (25.3±3.9 years old) by Franz and Kram (2013) [504], the primary measurement was the ground reaction forces (GRFs), they were measured on the perpendicular, parallel, and lateral plane of the treadmill. In comparison with younger adults, when performing uphill walking, older adults presented significantly ($p<0.05$) lower propulsive GRFs (e.g. 24.3±3.2%BW for older vs 30.8±1.5%BW for younger parallel peak propulsive GRFs at +9°). Also, the older participants presented significantly ($p<0.05$) higher mean rates of mechanical work (0.27±0.16 vs 0.12±0.05 W/kg for 0°, 0.86±0.23 vs 0.70±0.10 W/kg for 6° and 1.29±0.25 vs 1.12±0.09 W/kg for 9°) [504]. The comparison of the step time did not provide significant ($p=0.07$) difference between the two groups . Ortega and Farley (2015) [505] measured seven leg muscle's (vastus medialis, vastus lateralis, biceps femoris, lateral gastrocnemius, soleus, tibialis anterior and lateral malleolus) actuation amplitude and the metabolic cost of level and uphill walking on young (22.3±3.6 years) and older adults (74.5±2.9 years) at a set speed for all (1.3 m/s). They observed a higher metabolic cost (a difference of 13-17%) and more muscle coactivation (a difference of 25%) in the older adults group. A significant correlation ($r = 0.233$, ($p = 0.026$) between the coactivation and metabolic cost was found in the older adults group. It is, therefore, worth noting that the differences in muscle activity presented in this thesis, will be influenced by the age of the participants. Macaluso et al. (2002) [314] observed knee flexors and extensors of ten young (22.8±5.7 years) and ten older women (69.5±2.4 years) performing maximum voluntary contractions. They proposed that the lower muscle strength observed in older women resulted from smaller muscle mass during contraction as well as an increase in the coactivation of antagonistic muscles [314]. It is important to note that, in this thesis's study, the young and older adults who participated were able-bodied and active. It is possible and likely that the observations on older stroke participants will be a combination of the effects of age and stroke. This possibility cannot be confirmed with the data from this study as no member of the AB group was of a similar age

to the S participants. All AB participants were substantially younger (26.6 ±7 years old compared to 60.5 ±12 years old).

Phan et al. (2013) [207], compared the spatio-temporal differences between the level, uphill and downhill (4.1° ramp) walking in 15 hemiplegic stroke participants with age and sex-matched references. The experiment was conducted overground on a walkway and a slope. A significant ($p<0.001$) slower walking speed (level: 77.2 ± 35.6 cm/s, uphill: 76.8 ± 35.0 cm/s, downhill: 70.2 ± 32.3 cm/s) was observed in the stroke group (able-bodied group flat: 143.8 ± 17.1 cm/s, uphill: 145.2 ± 17.5 cm/s, downhill: 143.3 ± 19.4 cm/s). Also, similarly to this thesis's study, where the stroke participant walked with longer stride duration, the stroke group of Phan et al. (2013) [207] walked at a significantly ($p<0.001$) slower speed (70.2 ± 32.3 cm/s) when walking downhill, in comparison to uphill (76.8 ± 35.0 cm/s) and level walking (77.2 ± 35.6 cm/s, $p<0.004$). Phan et al. (2013) [207] suggested that the reduced speed was associated to the fear of slipping while walking downhill and the need to compensate for the reduced muscular control abilities.

In their single-blind, randomized, study Carda et al. (2013) [506] looked at whether downhill treadmill downhill training led to better outcomes (improvement of the six minutes and ten minute walk tests (6MWT & 10mWT) than uphill walking. While both groups presented significant improvement ($p<0.01$) after the training, they observed greater improvements in the group of participants who went through a gait training including downhill walking, in comparison to a group in which uphill walking was included to the gait training protocol. Carda et al. (2013) proposed that downhill walking, by forcing the extension of the trunk, works against one of the common deformities affecting people after a stroke, trunk flexion being a cause of gait deviation [506] and, therefore, could be responsible for the better results during this type of walk. While both groups presented significant improvement ($p<0.01$) after the training, they observed greater improvements in the group of participants who went through a gait training including downhill walking, in comparison to a group in which uphill walking was included to the gait training protocol. This study recommended that, to improve independent walking, it is useful to consider adding uphill and downhill walking as part of the training. This study recommended that, to improve independent walking, it is useful to consider adding uphill and downhill walking as part of the training.

While comparing the hemiplegic and non-hemiplegic lower leg muscles of stroke participants and able-bodied participants performing UP, DOWN and level walking, Akoopie et al. (2018) [507], noticed a higher propulsion force on the hemiplegic leg of the stroke survivors during UP walking (11.75±1.04 %BW) compared to level walking (6.14±0.67 %BW) which was a greater difference compared with the able-bodied

participants (UP = 23.10±1.07%BW, level walking = 17.20±1.18 %BW). For stroke participants, however, a higher propulsive force was found during the UP walking (13.81±1.22%BW for non-paretic leg; 23.10±1.07%BW for non-impaired leg) and the peak propulsion force was the lowest during DOWN walking (5.47±1.19%BW for non-paretic leg; 8.43±1.25%BW for non-impaired leg) on both paretic and non-paretic legs, in comparison to level walking (8.66±1.46 %BW for non-paretic leg; 17.20±1.18 %BW for non-impaired leg). For the able-bodied participants, the braking force observed during DOWN walking was higher than during level walking but did not present statistically significant difference ($p=0.192$). The UP walk led to higher propulsion force for the stroke group in comparison to the AB group. This study shows that the motor control of slope walking is different in able-bodied and post-stroke groups in the way the muscle propulsive and braking forces are generated and managed. In this thesis, the hemiplegic leg of both stroke participants displayed higher VR values (more variability in the EMG pattern) than their contralateral side during all UP walking situations. This might be a reflection of the need for higher propulsion force observed by Akoopie et a. (2018) [507]. Since higher muscle activity equates to more muscle unit recruitment, the EMG envelope will be impacted and present a larger amplitude and if the muscle recruitment is variable from one gait cycle to the other, it might be reflected by a higher VR.

Mohammadi et al. 2016 [508] compared the EMG activity of the Medial Gastrocnemius and the Tibialis Anterior muscles during the pre-swing phase of the gait cycle, while 19 stroke participants (6 women) walked on a treadmill at different inclines (+0°, +3° and +6°) and speeds (self-selected speed, self-selected speed +20% and self-selected speed +40%). They observed a significant ($p<0.05$) increase in the activity of the Medial Gastrocnemius on the hemiplegic side while the opposite side did not present significant ($p>0.05$) change in activity. The activity of the Tibialis Anterior was not significantly ($p=0.090$ at +20% of self-selected speed and $p=0.004$ at +40% of self-selected speed) affected by the change of incline during the push-off phase [508]. It appears that, while walking on inclines, the Gastrocnemius muscle on the hemiplegic side uses a different muscle actuation strategy than its opposite side [508]. Due to the small amount of data recorded from the stroke group in this thesis, it is not possible to confirm these observations, but further data collection is recommended. The increased muscular activity presents, nonetheless, similarity with the previously mentioned studies.

7.1.2. Number of contractions per cycle (occurrence frequency)

For the able-bodied group, the number of contractions per cycle (occurrence frequency, OF) was not statistically different ($p>0.05$) across the different walking conditions according to the repeated ANOVA test, suggesting the core motor programme for walking was retained across all the conditions. Since data from only two stroke survivors were available, no statistical comparisons between the two participant groups was possible. It is important to note that in their papers Di Nardo et al. (2017) [339], used the occurrence frequency to differentiate the gender of participants, female participants presenting more contractions per cycle than age-matched male participants. These observations were consistent with the work of Mengarelli et al. (2017) [509] who suggested that women needed more ankle-joint stabilisation, as an explanation for a more complex muscle recruitment strategy (i.e. more contractions of the muscle responsible for ankle movement). They pointed at the observations of Hurd et al. (2004) [510] who suggested a reduced capacity to produce joint stiffness in females, which might relate to the gender differences in muscle properties. In this thesis the impact of the participant's gender was not considered since the objective was to assess whether the number of contractions per cycle was sensitive to the walking situation.

The AB participants presented a consistent OF across all the different walking situations for both recorded muscles with the mean number of contractions per gait cycle ranging between 1.50-1.60 (GAS) and 1.45-2.37 (TA). The stroke participants, on the other hand, presented a wider range of values (1.00 to 3.5. for GAS and 1.00 to 3.20 for TA). This difference between the two groups is perhaps due to an altered contraction pattern that adjusts for each step rather than follows a set pattern for each step. These results may seem counterintuitive since the stroke survivors are expected to have a more limited range of muscle recruitment pattern. It is possible however, that there were a reduced number of muscles available for actuation (due to muscle weakness), creating the need for a greater degree of adjustment in their actuation pattern to fit the intended movement, leading to more phases of muscle activity observed in a smaller number of muscles. Also, the variable involvement of the other leg muscles which were not measured surely played a part in this outcome. It also worth pointing out that since only two muscles were observed in this study (GA an TA), it would be worth repeating similar data collection on more muscles to validate or reject this proposition.

In their study, Cruz and Dhaher (2009) [511], compared the muscle synergies of nine stroke participants and an AB control group during walking (whether they were age-matched control or not is not reported). They found that the stroke participants did not display the

same characteristic muscle synergies nor the same actuation patterns observed in the able-bodied participants. The AB participants displayed four distinct muscle synergies while the stroke participants displayed only two synergies. The stroke participants, while displaying a smaller number of synergies, developed a greater number of activation patterns per muscle synergy [511]. The main reason for this variety is the changes of combination used to achieve the movements, by means of co-contraction between muscles such as hip abductors (gluteus medius or tensor fascia lata) associated with knee extensors (vastus medialis, vastus lateralis or rectus femoris) and hip adductors (adductor longus). The remaining synergies did not display as much consistency in their actuation pattern while completing the walking task, in comparison with the AB controls [511].
This might explain the wider range in the number of contractions observed for the two stroke participants in this study. This behaviour may reflect the necessity to recruit the small number of available synergies in different ways when walking.

7.1.3. Contraction duration

For both the able-bodied group and the two stroke participants, the contraction duration of both muscles was found to be shorter during OUT walking than during any of the other walking situations. During OUT the GA was active for 14.98% (AB) and 9.75% (Stroke) for each cycle while the TA was active for 10.01% (AB) and 8.88% (S). During all other conditions (FP, SP and IN), the durations for TA and GA tended to be longer (range between 23 and 43%) for both groups apart from TA for stroke participants during indoor flat walking (13%).

During uphill sloped walking (OUT UP and Treadmill SP UP), the tibialis anterior and gastrocnemius of the AB group did not show any major differences in contraction duration compared with the flat situations, when higher contraction duration was expected because of the increased mechanical demand of UP walking in comparison to level walking. Instead, shorter contractions were observed during OUT UP (13.81% for GA and 12.93% for TA) in comparison with the SP UP (range between 22.64% and 24.5% for GA; range between 22.75% and 24.47% for TA). However, when compared to the OUT level walking, SP UP presented longer contraction durations than level OUT. Contraction duration were of 14.98% (GA) and 10.01% (TA) for able-bodied participants and 9.75% (GA) and 8.88% (TA) for the participants with stroke.

These findings do not match previous reports, for example Franz and Kram (2012) and (2013) [438], [512], observed longer muscle activity (gluteus maximus, biceps femoris, rectus femoris and vastus medialis [438], medial gastrocnemius and gluteus maximus [512]) during uphill walking in comparison to level walking. While these muscles are not the same as those observed in this thesis, it is interesting to point out the following findings. The contractions were significantly ($p < 0.0063$) longer in the AB group during a +9° uphill walk in comparison to level ($p<0.05$) on the medial gastrocnemius and tibialis anterior [512]. These observations were recorded during standard FP treadmill walking. Nevertheless, it would be expected to have a consistent rise of the muscle activity duration and amplitude, according to the increased effort of UP walking. In fact, during UP walking to lift the centre of mass vertically [438]. Increased muscle activity (especially medial gastrocnemius and vastus medialis) has been associated with a greater need for knee stability during UP walking [438], [512]. Franz and Kram (2012) concluded that UP walking requires an increased use of ankle, knee and hip extensors while DOWN walking only requires an increase in knee extensor muscle [438]. When comparing an older adult group (72 ± 5 years old) with a young adult group (25 ± 4 years old), Franz and Kram (2013) [512] noticed that, during UP walking, the older group recruited much more hip extensor activity (Gluteus Maximus: 73% of maximum voluntary contraction, at +9° gradient) in comparison to the younger group (33% of maximum voluntary contraction). These results present longer muscle recruitment on muscle of the upper leg. These muscles were not monitored in this study. The absence of significant increased muscle activity on the GA and TA during uphill might be an effect of the small data sample. Still longer activity was observed, the results of this study are, therefore, in agreement with the literature.

Contraction duration was found to be shorter during the OUT walking performance in both the flat walking and the UP walking. Significantly ($p=0.011$) shorter contractions were observed for the GA during OUT DOWN walking. No significant ($p=0.085$) differences were found between the OUT and SP walking conditions. The literature suggests that there should be a significant increase of duration of contraction when performing UP walking [512], while the results of this study do not fully support this observation there were increased durations for gastrocnemius at 6 and 3 degrees, in comparison to levelled walking, and the results should be considered in light of the small sample.

7.1.4. Stride duration

During level walking the able-bodied group presented shorter stride duration times during outdoor walking compared to IN, SP and FP walking while the two stroke participants presented their shortest strides during IN walking. There were no statistically significant differences ($p>0.05$) for stride duration during the different walks in the AB group during level walking, which is in accord with previous reports [339], [340]. Since gait speed, step length and stride duration are interrelated, the shorter stride duration observed in this study (OUT mean stride duration< 0.95 s, 0.95<IN and SP<1.05 s, 1.10 s<FP<1.15 s) could simply reflect an overall faster walking speed during outdoor walking (for the able-bodied group) and indoor walking (for the stroke participants), compared to the three other walking conditions. Grazzi et al. (2017) observed slightly faster walking speed outdoors in comparison with treadmill walking (5.73 ± 0.77 km/h vs 5.55 ± 0.84 km/h, $p=0.04$) [513]. This difference was not considered important in comparison to the cardiac rate and peak oxygen uptake that did not present significant difference, suggesting the effort exerted in both situations were similar. Fokkenrood et al. (2015) [514] compared outdoor and treadmill walking in participants with intermittent claudication. They found a significantly faster walking speed outdoor compared to the matching treadmill walking protocol (outdoor walking = 3.8 km/hr, treadmill walking = 2.8 km/hr; $P < 0.001$). The explanation proposed by Fokkenrood et al. (2015) [514] for the faster outdoor walking was the impression of covering a longer distance, since the objective of the test was to estimate the walked distance within a 20 minutes-long walk.

For the AB group in this thesis, outdoor walking resulted in shorter strides durations whether this was flat, UP or DOWN. In the case of participant S_5, the shortest strides were found during SP DOWN 06 AND SP UP 03. Stroke participant S_7 was very similar to the AB participants. Ortega and Farley (2015) [505], observed that older adults (74.5 ± 2.9 years old), regardless of gradient, have a higher stride frequency than the young adults (22.3 ± 3.6 years old).

While not significantly different, the shorter stride durations observed during OUT walking in this study match the literature's observation [339], [340], [513], [515]. Fokkenrood et al. (2015) proposed that the shorter stride as the manifestation of the participant's impression of covering a shorter distance [514].

7.2. Explanatory factors

7.2.1. The influence of age and reduced physical activity on motor control

It possible that some of the differences observed in the motor pattern between the able-bodied group and the two chronic strokes are not only the effect of the stroke but also the direct effect of age on the muscle properties and motor control. The age difference between the able-bodied group (26.59 ±7 years old) and the two chronic stroke participants (aged 52 and 69 years old respectively) means that the effect of ageing should be considered a factor, in addition to the effect of stroke at least for the 69 years old.

Muscle properties are known to change with age [443], [444], [516]. Aging is associated with the loss of motor units, leading to a smaller number of action potentials, which are the brief change of electrical polarisation in the muscle which leads to the nerve impulse responsible for muscle contraction, and consequently a loss of muscle strength [312]. With age, type IIa+b (fast twitch) muscle fibres are subject to a greater level of atrophy, leading to a disproportionally large number of type I (slow twitch) muscle fibre [313], [517]. This could explain some of the differences, for example the slower contractions could have led to the longer contraction duration observed during OUT, SP and FP in comparison to IN walking for participants with stroke, when all participants displayed shorter contraction durations during OUT walking, as observed in this study.

Muscle aging leads to a loss of muscular strength and power. The reduction of muscle strength associated with age might be one of the explanatory factor for the differences of muscle recruitment between the able-bodied participants and the participants with a stroke [518], [519]. Chung and Wang (2010) [520] observed a significant ($p<0.05$) increase in the activity of the rectus femori in older adults (aged above 45 years old) when walking at 140% of the preferred walking speed, compared to young (20 to 30 years old) and middle aged (30 to 45 years) adults. The effect of age on muscle is also observable through the number of muscle units. Piasecki et al. (2016) [444] observed a decrease of 50 to 60% in the number of muscle motor units in older adults (71.4 ± 6.2 years) in comparison with a younger group (25.3 ± 4.8 years). In a paper, Power et al. (2017) [516] compared the number of motor unit in the tibialis anterior of older master athletes (average age of 65 and 80 years) to aged-matched community-dwelling adults. The octogenarian athletes presented more motor unit activity, a higher number of functioning motor units and greater motor unit potential stability than their age-matched healthy controls [516]. While both groups presented muscle

remodelling, aging led to a reduction of the number of motor units and atrophy of type II muscle fibres [517], the older athletes lost less motor units and their neuromuscular transmission was more stable [516]. Exercising appears to be a mechanism for muscle unit retention however, the underlying processes leading to this retention are unclear [516]. Muscle aging is associated to a lowering of type II (fast-twitch) muscle fibres which lead to lower muscle strength [311]–[313], [517].

The participant S_5, who was the youngest (52 years old) presented a different behaviour to the rest of the participants. While both stroke participants were independent walkers, their level of physical activity might not have been. In this study, because participants were not matched for age, the comparison between AB age-matched participants was not possible. It was therefore not possible to compare the muscle activity difference between AB and S participants and see how age and stroke affect the muscle activity.

Macaluso et al. (2002) [314] observed more co-contraction on able-bodied active older women (69.5 ± 2.4 years old) than on able-bodied active younger women (22.8 ± 5.7 years old). This observation points to a difference of muscle recruitment strategy in the older adults. Co-contraction is considered to be a compensatory strategy to the loss of muscle strength and to ensure the stability of the movement [314].

It also important to note that following a stroke, the patients who are able to walk independently are the ones most likely to re-gain a level of walking adaptability that allows them to walk in diverse community settings for example street or shopping centres [52]. This means that beyond the effect of age, the immediate post-stroke ability will influence the walking adaptability of a person with stroke. It might be useful to record the walking ability of the participant following stroke as a supplementary data in future work and see if it has influence on the walking variability during the chronic phase of stroke.

7.2.2. Environmental factors on differences between outdoor and indoor

Walking outside is considered more challenging than indoor due the greater number of environmental demands [521]–[525] but is nevertheless considered very important as it allows individuals to participate in their occupational, domestic and social roles, helping them maintain a good quality of life [93], [526]. Comparing outdoor and indoor walking therefore allows researchers to better understand these differences so that rehabilitation programmes can be tailored accordingly. In particular the suitability of using treadmill simulations of outdoor walking, for example Motek CAREN system [426], [427], [480], [527] as a training modality.

Recording gait data during outdoor walking has its own challenges. For example, the weather will affect the way a person walks outside. A strong wind will undoubtedly affect mobility as the participant adapts muscle recruitment to resist the external perturbation. Consequently, the EMG data should reflect longer contractions, more co-contractions and greater amplitude than in the context of a wind-free weather walk.

The measurement tool used in this study were limited in their range of action. A maximum distance between the sensors and their base unit, which received the transmitted data, was approximately 40m due to the use of the Industrial, Scientific and Medical equipment service (ISM) with a frequency band of 2400 to 2480 MHz (c.f. section 5.3.1.1). However, when used outdoor, this distance was reduced to ensure the integrity of the data collection, despite this precaution some data were still lost due to being out of range of the receiver.
The devices used during this study had environmental limitation as they were not intended for outdoor activity, their use was constrained to days with a dry weather. In this thesis, the participants all walked outdoor in a context of a dry weather at the exception of one AB participant who walked under very mild rain conditions. This participant, however, did not present a statistical outlier.

7.2.3. Possible motor control differences according to the environment

Outdoor walking is likely to affect muscle activation patterns in several ways. According to changes in the surface characteristics, the muscle will need to modulate the magnitude of propulsive power to ensure postural stability [190]. Outdoor walking is also likely to require more attention since it is arguably less predictable than treadmill walking, with the presence of other pedestrians, traffic, and other moving obstacles. In contrast, indoor walking was performed in a lab, free from the distractions associated to community walking, without any challenging task and on a flat surface, making it, similar to FP treadmill walking, a highly predictable walking environment. Patla and Sumway-Cook (1999) [190] proposed a model of eight dimensions of mobility including: walking distance, time constraints, ambient condition, terrain characteristic, external physical load, attentional demands, postural transition, traffic level and minimum walking distance [190]. Designing training protocols based on this model may enhance recovery of mobility impaired patients [525]. In the case of this thesis, there is an estimation of the walking distance thanks to the step counts, no external physical load nor time constraint was imposed to the participant. The ambient condition, terrain characteristic, attentional position and postural transitions were not reported.

In this thesis, the observation of the VR during the different walk situations presented more similarities between SP treadmill walking and outdoor walking. This indicates that, to re-train community walking, the SP treadmill training is the most promising gait training mode. The consistent number of contractions across the different walking situations agrees with the use of SP treadmill to re-train community walking, both on slopes and for flat walking purposes. The parameters of contraction duration and stride duration did not present as much differentiation between the different walk situations. Consequently, those two last parameters, might not be worth reporting in future work.

7.2.4. Possible motor control differences originating from motor redundancy

As presented in chapter 2, walking is the result of combined muscle actuations by which a near infinite possible sequences can lead to the same end position. This was referred to by Bernstein as “motor redundancy” [268]. The muscles functions within modules, also called muscle synergies, allowing motor control flexibility as to how to achieve the intended movement, depending on their biomechanical function to the body or the locomotor function (balance or walking) they are affected to [6], [174], [316], [319]. Muscle synergies simplify the control as they group muscles together. There are five muscle synergies typically used by able-bodied people when they walk [319]. Neptune et al. (2009) [319] identified five modules. Module one is composed of the Gluteus medius, the vasti and the rectus femori, helping to support the body at the beginning of stance. Module two comprises the soleus and gastrocnemius, working to support the body at the end of stance. Module three contains the rectus femoris and tibialis anterior, who help to decelerate the leg at the beginning and the end of swing. Module four is composed of the hamstrings which help decelerating the leg at the end of the swing phase and increase the leg energy at the beginning g of stance. Module five contains the iliopsoas which support the acceleration of the leg’s forward movement before and at the beginning of swing. Stroke survivors tend to present less than the five distinct modules observed on able-bodied adults, when then walking [6], [285]. On the hemiplegic side only two to three muscle synergies may be available. These muscle synergies being a combination of muscles from those observed in healthy controls [285]. This reduction in number of synergies leads to a diminished flexibility in the neural control of the leg [6], [285], which leads to diminished support for the balance and ambulation tasks [174]. Adding to this merging of muscle synergies merging, the effect of muscle’s weakness and spasticity affect the biomechanics of gait and lead to the stereotypical gait pattern observed after a stroke, such as the hemiplegic gait [6]. The typical five muscle synergies are less distinctive in the gait of stroke survivors. This thesis does not contain enough data to support these observations because the data recorded from the participants with stroke were only done from two lower leg muscles only (gastrocnemius and tibialis anterior). Because the muscle synergies are not actuated in the same way as the able-bodied typical pattern, the resulting kinematic patterns are altered. For example the hip, knee, and ankle may be unable to flex appropriately to provide proper foot clearance during swing. Consequently, compensatory mechanisms are developed to ensure forward (and safe) progression, for example elevating the pelvis (hike hip) or swinging the leg out to the side (circumduction) during the swing phase of gait to achieve foot clearance [6]. The use of compensatory

mechanisms relates to the idea of loss of distinctive muscle synergies in that compensatory mechanisms will lead to the recruitment of muscles from other synergies to accomplish the attempted movement but with a loss of movement efficiency and therefore higher energy costs.
This study looked at lower-leg muscles, the observation of stereotypical patterns in hip muscles was, therefore, not available. Further research including at least one muscle from the five typical muscle synergies (c.f. section 2.3.2.4 and Table 2.3) will allow these observations to be corroborated.

An alternative to purely quantitative data analysis, could be found in a more qualitative approach to EMG analysis. Although trends leaning towards a closer motor control strategy between outdoor walking and SP treadmill walking have been observed in the EMG data and parameters, there were no statistically significant differences to note. It is possible that the parameters used to observe variability of muscle activity were not the most sensitive to the intrinsic EMG signal variability. All the previously presented methods were uncomplicated and time-based and may have been too blunt to detect some differences. EMG signals can also be analysed using other methods relying on non-linear analysis. The following section presents the work developed in this thesis to explore non-linear analysis as a method for the analysis of EMG signals.
This technique is based on the intrinsic characteristics of the EMG signal and may offer an alternative approach to the analysis already presented in this thesis. The following section will first briefly define non-linear analysis before presenting several parameters, used for the quantification of the EMG data using example applications. Subsequently, this thesis' investigation relying on non-linear analysis methods and its outcome will be provided.

7.3. Non-linear analysis of the EMG data

To analyse and characterise EMG signal four different methods are principally used. These four methods are either time-based (representation of the amplitude as a function of time), frequency-based (representation of the frequency spectrum in Fourier space, which displays amplitude as a function of the frequency), time-frequency-based (represents the evolution of frequency over time) or non-linear-based [528]. This last method is among the newest and presents promising results [529]–[533].

Non-linear methods facilitate the detection of characteristic magnitudes (also called invariants), in signals which appear to be random. These types of signals, of random appearance, which present invariants, are chaotic signals.

Chaotic signals have a behaviour that is, at first sight, unpredictable but when plotted in a particular space, called phase space, they present an underlying organisation. Their behaviour of a chaotic signal is highly dependent on their initial condition (one example is the heartbeat) [532]. The heartbeat has chaotic behaviour as it is a quasi-periodic signal, while it exhibits periodic pattern, it varies in amplitude and period other time. The heartbeat signal also has auto-similarity properties, which means that its pattern is invariant while observed at different scales [534]. EMG signals have a chaotic behaviour [530], [532], [535]. Although their appearance is random, their change of amplitude is of deterministic origin: the muscle contraction is controlled by the electrical signal induced by the nervous system to produce a movement.

The space in which the dynamic behaviour of a chaotic signal is represented is called the phase space. Phase spaces are used as the time-series that represent the dynamics of the chaotic signal [532]. The axis of the phase space are the position and the successive derivative of the position. Which means that a point in the phase space will have its coordinate designed as (x, $\frac{dx}{dt}, \frac{d^2x}{d^2t}$, ...). For time-series, the delay method is also used $(\boldsymbol{X_i},\ \boldsymbol{X_{i+\tau}},\ \boldsymbol{X_{i+2\tau}}, \dots)$, with $\boldsymbol{\tau}$ the delay**.**

The two most used invariants to analyse chaotic signals are the Lyapunov exponents and the fractal dimensions. The Lyapunov exponent is a measure of the sensitivity of the signal to initial conditions. It is a measure of the dynamical signal's convergence or divergence within the space phase [536]. The fractal dimension is a tool used to measure the disorganization [537] or to quantify the complexity [538] of a system.

More information about these analysis tools is found in the Annex A.

7.3.1. Phase space

7.3.1.1. EMG applications of phase space

Brzozowska & Borowska (2016) [539] analysed electrohysteriograms, which are the electrical signal from the uterus muscle, which are, in effect EMG of the uterus muscles [540]. They found optimal parameters allowing the characterisation of the contraction of the uterus muscles on women during their third trimester of pregnancy and during labour and thus represent these in a space phase [539]. The application of this research was further explored in Borowska et al. (2018) who were able to differentiate between the signals of pregnant women who delivered either more than seven day from the testing day (group A) or within the seven days following the testing day (group B). Their results are illustrated in *Figure 7.2*. This method has great potential as a non-invasive method to predict and analyse the underlying mechanisms leading to premature birth [540] with potential to be applied to skeletal muscles.

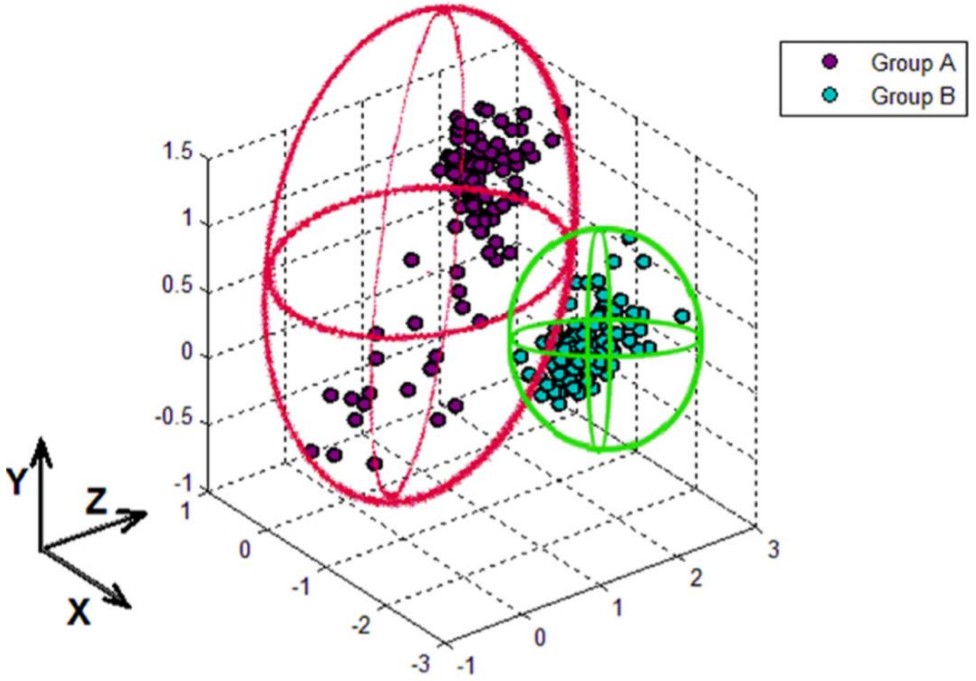


Figure 7.2: 3D Phase space representation of a two group of pregnant women: group A delivered after seven day when group B delivered within seven day post-test *[540]*

7.3.2. Fractal dimension

7.3.2.1. EMG application of fractal dimension

Xiao et al. (2005) showed that the distribution of the fractal dimension of the right flexor muscle was different between pronation (lower values) and supination (higher values) [541] (see *Figure 7.3*). This observation suggested that the fractal dimension can be used as a description of a muscle activation pattern [541].

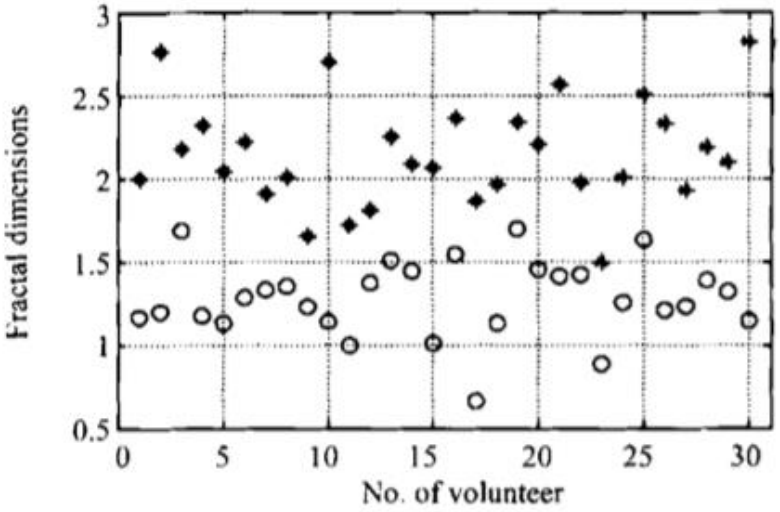


Figure 7.3: The fractal dimension of the filtered EMG signal for forearm supination (*) and forearm pronation (°) signals *[541]*

Ancillao et al. (2014) [538], found a relationship between energy and EMG amplitude for a jumping action [538]. They observed a linear correlation between the fractal dimension of the rectus femori and the height of the jump performed by the test subject [538] (See *Figure 7.4* and *Figure 7.5*). The higher the jump was, the higher the fractal dimension was.

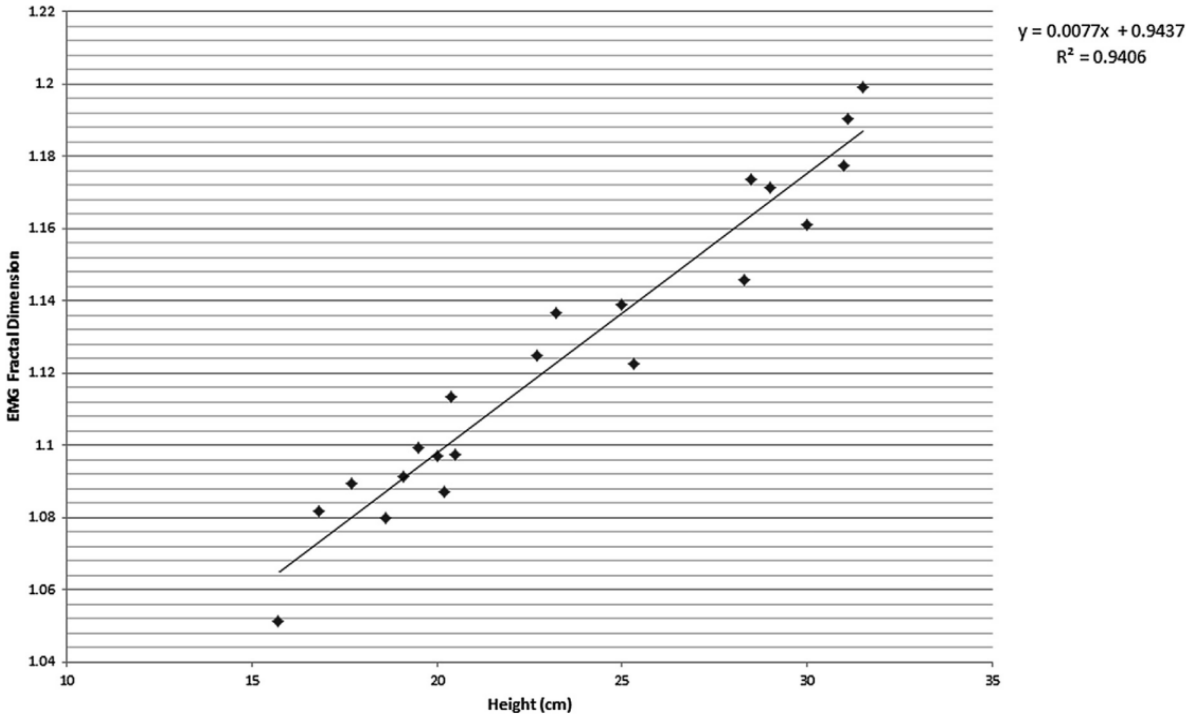


Figure 7.4: Linear correlation (black line) between fractal dimension and height of jumps (*) *[538]*

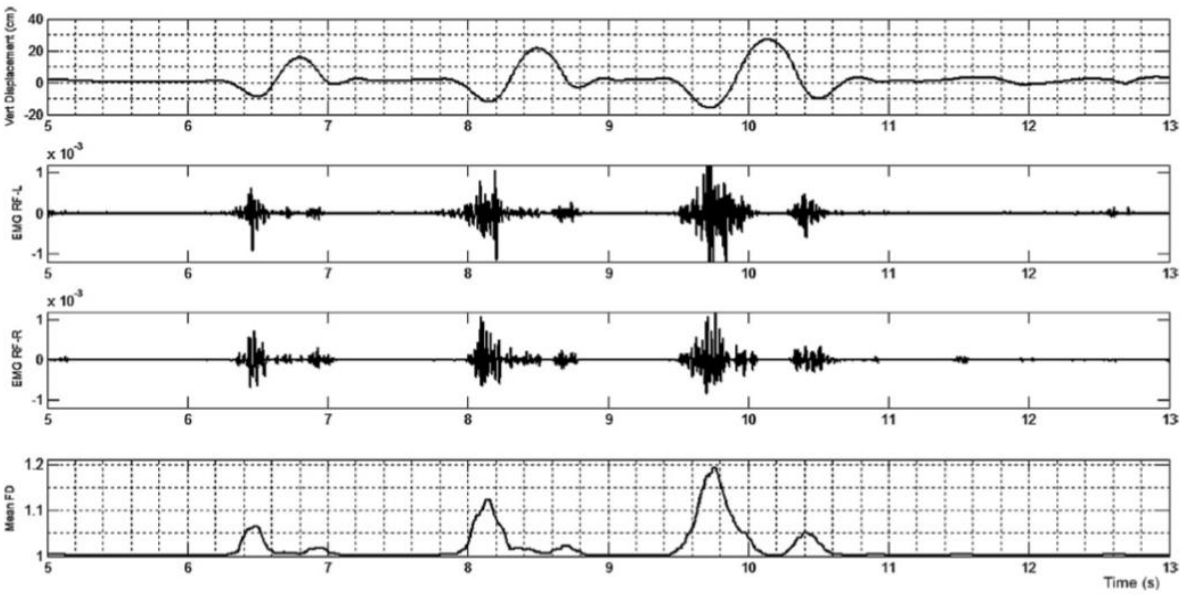


Figure 7.5: Graphs from top to bottom: top: Vertical displacement, top 2nd: left Rectus, top 3rd: Right Rectus, bottom Average fractal dimension of both sEMG *[538]*

7.3.3. Lyapunov exponent

7.3.3.1. EMG application of Lyapunov exponent

Xue & Jue (2019) [529] used a classification algorithm based on the Maximal Lyapunov exponent to differentiate between ten different hand motions from the recordings of surface EMG signals located over five forearm muscles (see *Figure 7.6*). When evaluating the performance of the method, Xue & Jue (2019) found a minimal recognition rate of motion detection of 90.0% at least and of 94.2% at max [529].

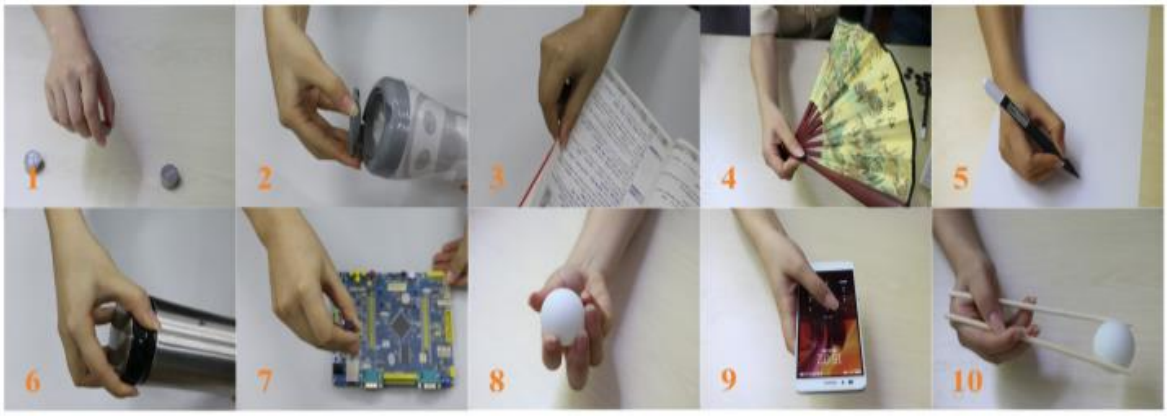


Figure 7.6: The ten hand motions differentiated by Xue & Jue (2019) *[529]*

7.3.4. Exploration of the use of non-linear analysis of EMG

In order to compare a random behaviour in the phase space to a chaotic behaviour, the random function of LabVIEW was compared to the logistical function (see Annex A: Non-linear analysis for description). When plotted against time, the repartition of both function's results seems at first to be random as represented on the left column of Table 7.1. However, when represented in the phase space, it appears clearly that the random function's results are spread over the space when the logistical equation follows a pattern, as can be seen on the right column of Table 7.1.

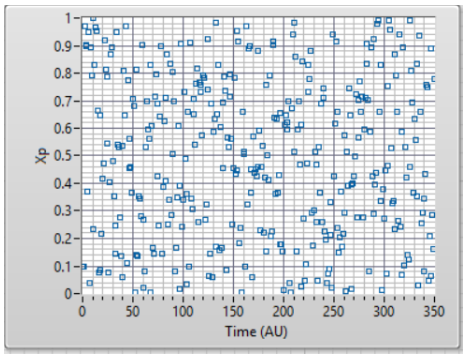
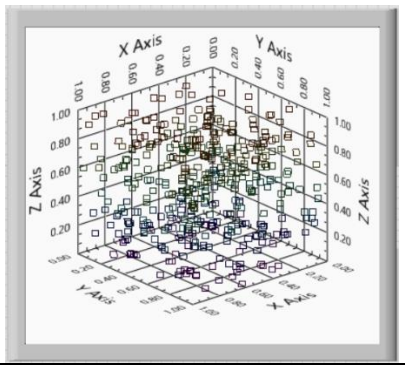
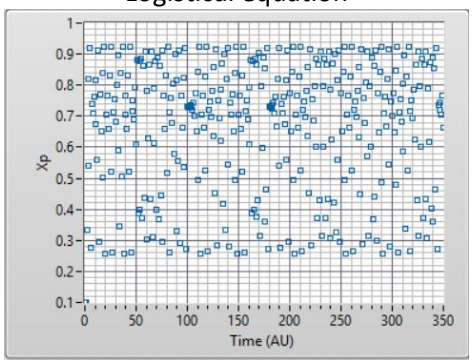
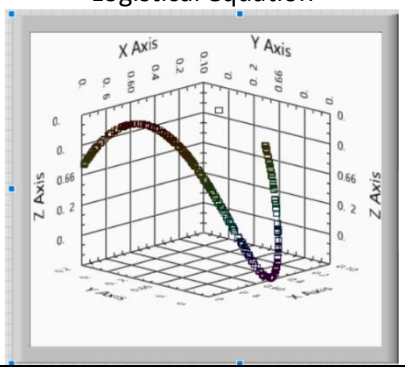
Results as a function of the time	Phase space representation (X_{i+2}, X_{i+1}, X_i)
Random function 	Random function 
Logistical equation 	Logistical equation 

Table 7.1: Comparison of Random function with the logistical equation over time and in the space phase

A preliminary attempt at this type of analysis with this thesis' experimental data is presented in the following figure (Figure 7.7). Simply studying the pattern of the raw EMG signal (in this case gastrocnemius) in the space phase (2D and 3D) during their contraction over several gait cycle could be another means of characterisation of the EMG activity.

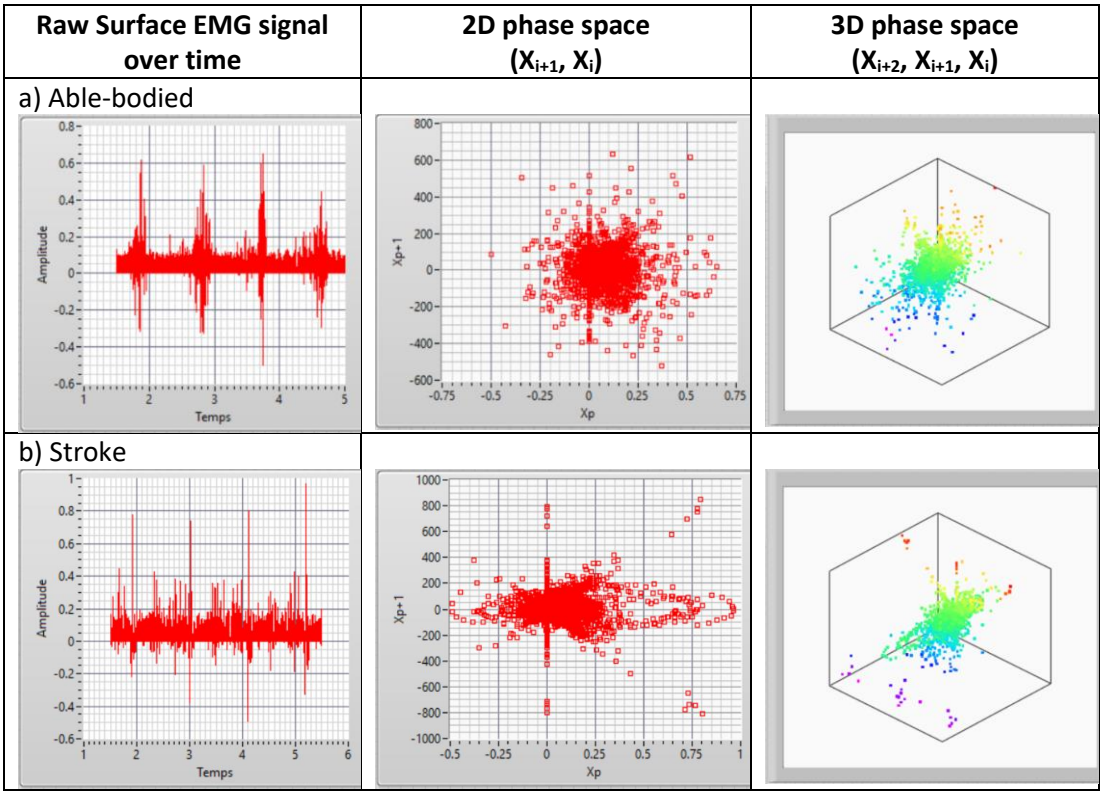


Figure 7.7: Representation of a group of contractions of the gastrocnemius muscle over time (left), in a 2D phase space (middle) and in a 3D phase space (right) a) for an able-bodied participant, b) for a stroke participant on its affected side.

By means of the phase space representation, it can be observed that for the able-bodied participant the phase space repartition of the EMG signal was more sphere like (Figure 7.7 a), when the participant with a stroke presents a repartition with a more dispersed and elongated shape such as an ellipse (Figure 7.7 b).

Due to the challenge of the optimisation of this program presented in regard to the time available to complete this PhD project, this method was left aside to favour the other methods previously mentioned. Non-linear analysis remains, nonetheless, a method worth considering in future studies as it could further improve understanding of the motor control through the EMG signal.

7.4. Limitations

7.4.1. Sample size

Only data from two stroke participants were available for analysis. This prevented statistical comparisons and the observations could not be generalised to the wider stroke population. Stroke is a heterogeneous population with a wide range of physical, cognitive and emotional symptoms [22] so this very small sample can only serve to provide initial clues on the muscle activation differences, inform future researchers on the value of these data analysis techniques and provide reference values for estimating sample size in a future studies designed to definitively test hypotheses. Recruitment to research is a perennial problem in rehabilitation research, recruitment for this study was through the Chest Heart and Stroke Scotland support groups in the West of Scotland, a greater number of groups could have been contacted but the constraint prevented this. Initially, seven stroke survivors participated in the study, however, due to technical faults during the outdoor measurements they could not be included in the analysis. Future research would benefit from having a matching number between the comparison groups as well as age-matched participants to understand the effect of age-related on the data.

7.4.2. Multiple comparisons effect on the statistical analysis

When performing several tests using a pool of data, it is possible to randomly find a statistically significant value ($p<0.05$) when in fact there are none (type one error), especially when the data sample is small [542], [543]. The Bonferroni correction, is a method commonly used to mitigate the effect of multiplicity of testing [542], [543]. It relies on adjusting the p-value to $p<\alpha/k$, with $\alpha=0.05$ and k the number of analyses run. While this method leads to the reduction of type one error, it was criticised for generating type 2 errors, which assert no statistical significance when there is [542], [543].

It is recommended to use the Bonferroni correction if several statistical analysis tests are performed without afore-proposed hypotheses [542], [543]. In the case of exploratory studies, such as the work presented in this thesis, the Bonferroni correction is not needed , as long as the true hypothesis are considered not as definitive findings but rather entry points for further investigation [542].

7.4.3. EMG sample characteristics

The EMG data used were processed with minimal amount of treatment to preserve to the initial shape of the signal (see protocol in section 4.4.4). As the EMG is the representation of the underlying motor control strategy, manifested by a given muscle recruitment pattern, an excess of filtering would smooth away the characteristic of the signal, which would become overly simplified and lose variability. Moreover, the resulting VR data amplitude matched the literature observing EMG during gait. It is, therefore, unlikely that the EMG envelope treatment denatured the original signal to the extent of making it a misleading data set.

7.4.4. Age match

As the effect of age was discussed (section 7.2.1. The influence of age and reduced physical activity on motor control) as a parameter contributing to the properties of the EMG signal, having age-matched participants would have helped understand the effect of age and given more focus on the stroke-related differences in the EMG signal between the two groups, as several paper did to compare people with stroke to their age-matched controls [192]–[194], [544], [545]. In this thesis, the able-bodied participants were much younger than the participants with stroke (26.6 ±7 and 60.5 ±12 years old respectively).

7.4.5. Time since stroke and gender

In this thesis, all the participants with stroke were at the chronic phase of stroke, participant S_5 had a stroke 21 years (252 months) and participant S_7 had a stroke 4 years (48 months) prior of the experiment post-stroke. While the improvement of the aptitudes are usually the more obvious during the first 3 months after stroke [32], [61]–[63], it is common to witness continuous improvement of the abilities of people with stroke through time [32], [64] (see section 1.4). Since S_5 had a stroke much further in the past than S_7, it is possible that the muscle recruitment strategy of S_5 has adapted and displays a pattern that differs from S_7 at the time of the experiment but might match with S_7's when S_7 reach the same time post-stroke. In this context, it could have been interesting to compare the analysis of the two female participants with stroke with able-bodied female results.

Around half of stroke cases occur on women [54], [546], [547]. In this thesis, the two participants with stroke were women, while the able-bodied participants were both male and female. Women who had a stroke have been reported has having worst post-stroke outcomes

[546]–[548]. Due to the small sample of participants with stroke and the disparity in time lived post-stroke, the work of this thesis cannot support this evidence.

7.4.6. Data collection

The number of strides collected were under a hundred in all the walking situations. A parameter that could influence the interpretation of the results is the small number of steps used for the measure of the most recurrent number of EMG actuations. This measure was based on previous work on the occurrence frequency method [339], [340]. Previous authors have advised a minimum of 120 strides for adult participants and more than 400 strides for the adults [340]. Di Nardo et al. (2017) [339] stated that it is possible to use 20 strides to calculate the occurrence frequency while walking at a natural speed. In their paper, however, they recommended at least a hundred strides to have an accurate measure of the occurrence frequency on with a smaller number of strides. A small number of samples can lead to poorer chances to discovering true and significant effect of a study. The restricted number of strides (from 7 IN and up to 70 on treadmill) studied in this experiment might explain the absence of significant differentiation between the different walking situations which might be underestimating the influence of these.

7.4.7. Limited number of muscles observed

In this study, the number of muscles observed was reduced to two as the focus was on the muscles involved in ankle movement. This choice was driven by the observation from the thesis' first study (chapter 4) that the ankle was the joint with the greatest degree of variability (c.f. section 4.6.2.1). The intention was, therefore, to focus on muscles that would act on the muscle synergies relating to the ankle movement (see section 2.3.2.4 and Table 2.3). However, several of the interpretations of the muscle activity observed relies on the muscle synergy model. The muscle synergy model groups muscle that work together in five different groups in the case of able-bodied adults, as reported in the literature [174], [285], [316]–[319]. In the case of impaired gait motor control, these synergies change and, according to the severity of the impairment are reduced in number [6], [174], [283], [285], [307], [322], [511]. There is evidence that the use of muscle synergies combined with other methods of biomechanics analysis methods are complementary for the assessment of gait performances [307].To be able to interpret muscle activity and its specificities during different walking situations, recording and analysing at least one muscle from each of the

five muscle synergies would allow to recreate the muscle synergies patterns and assess whether there are specific strategies according to the walking situation.

7.4.8. Environmental factors

While performing outdoor walking, one of the able-bodied participants talked with pedestrians asking about the experiment. This was a case of unplanned dual tasking while walking outdoors.
Also, on one occasion, the weather was not ideal, as there was a fine drizzly rain. The experiment was carried on, nonetheless. Following data analysis, neither of these participants presented outlier data in comparison with the rest of the able-bodied group, whose data were recorded under optimal experimental setting.

While performing treadmill walking, all participants wore a safety harness. Decker et al. (2012) [549] used the sample entropy and the Lyapunov element (non-linear parameter c.f. section 7.3 and Annex A) to measure the effect of treadmill walking with or without a safety harness, on the lower limb joints angles. The ankle joint presented statistically significant ($p=0.022$) higher values (sample entropy comprised between 0.27 and 0.33) through the sample entropy in comparison to the other joint angles (Sample entropy comprise between 0.2 and 0.25). The ankle also presented significant ($p=0.011$) higher Lyapunov element (Lyapunov element value comprised between 1.1 and 1.2) in comparison to the other joint angles (Lyapunov element comprised between 0.4 and 0.6). These values reflect more variability in the joint angle value while walking. However, Stout et al. (2016) [503] found that the gait dynamics parameters (stride time, stride length, step width) were not altered by wearing the safety harness during a treadmill walk ($p=0.402$ when comparing treadmill walking without harness, with harness, but not attached to the support frame, and with harness and attached to the frame). Non-linear analysis, allows to have a closer look at subtle variations present within a repetitive signal when the common kinematic and dynamic parameter are used to give a general overview of the trend [503].

7.4.9. Non-linear analysis

This thesis presented an attempt to use non-linear analysis to characterise the EMG signal. The program designed to compute and display the fractal dimension was “heavy”, slow to compute the data of just one muscle contraction. While an optimisation of this program was possible, the attempted fractal dimension program was left aside to favour the previously presented analysis methods, which at the time was already ongoing. It was used only on few able-bodied EMG data and has, therefore little material to allow stroke participants data for comparison. This thesis work’s favoured tools with low computational load and which could be readily interpreted.

7.5. Practice Implications

7.5.1. Gait rehabilitation

The findings reported in this thesis have relevance to gait rehabilitation, not just for people with stroke but generally in gait rehabilitation. There is now good evidence that the recovery of motor function (e.g. walking) is improved with task specific repetitive practice [11], [103], [104], [107], [262], [550], [551]. FP treadmills has been found to improve fitness, particularly endurance, allowing an extended amount of stepping repetition [105], [106], [552]. This can have a major impact on the walking capacity of individuals, especially for returning to community walking. A treadmill undoubtedly offers the opportunity for movement repetition but there have been criticisms regarding its specificity, particularly regarding the recovery of community walking in terms of the demanding changes in environment [7], [106], [261], [553], [554]. There is evidence that after a stroke, survivors able to walk can reach a level of independence that allows them to adapt well in different common walking environments such as shopping mall or a street [52].
The findings reported in this thesis offer some preliminary evidence to support the use of self-paced treadmills for recovering outdoor walking based on their similarity in muscle pattern variation with overground walking, particularly VR values, who presented similar magnitudes between self-pacing and outdoor walking. These findings should be considered a first step towards improving the specificity (or tailoring) of treadmill training for restoring community outdoor walking.

It should be said, however, that these findings should not lead to any immediate changes in current practice without further confirmation from studies using larger data samples and

more extensive EMG data collection. The limitations of the study should be addressed in future studies to confirm these findings before intervention trials are considered. Judging from the observed similarity between the motor control of SP treadmill walking and outdoor walking, the possibility of using the SP treadmill to prepare the patient to readapt to community walking is an option worth future exploration.

The re-training of gait is improved by the provision of task-specific training [555]. The principle of task-specificity in training has been demonstrated in balance [556] and muscle strength [557].

To be specific to the task, the addition of SP treadmill training should be tailored to train the patient to the challenges that they will experience during community walking. In this study, the treadmill was equipped with an immersive virtual environment display of a path in a forest, designed to replicate the community walking experience. This can be achieved by designing virtual environments that simulate real experiences such as the presence of obstacles, surrounding noise, adding obstacle avoidance exercises with, if possible, random appearances in the environment. This type of treadmill training would be comparable to a serious gaming environment that would be both engaging and useful. Virtual reality environment are used as engaging training environment especially for children [558]. Cho et al. (2016) [558], used this type of display to train children with cerebral palsy. Fung et al. (2006) [550], designed a feasibility study using together treadmill walking and virtual environment to obtain a training platform allowing to train in obstacle anticipation and avoidance. Timmermans et al. (2016) [191], proposed a protocol for a randomised controlled trial aiming at assessing the effectiveness of obstacle avoidance training, using a treadmill and virtual obstacle display, compared to an overground obstacle course program. Treadmill training with a virtual environment is also useful in improving the gait adaptability and balance during gait as van Dijsseldonk et al. (2018) [559] presented in their 6-week training program with incomplete spinal cord injury patients. A virtual reality environment was used by Aravind et al. (2015) [560], in order to test the obstacle avoidance on people with a stroke with visuospatial neglect.

The addition to this kind of features in a gait rehabilitation training facility would imply setting up a SP treadmill on site but also, to be equipped with large screens (for virtual environment display [550], [558]–[562]), speakers and computers (for software control and data collection) to provide an optimal training experience. Also, it will be necessary to train the staff so that they can operate the different system efficiently [563], [564].

7.5.2. Treadmill technology

As previously stated, self-paced treadmill walking is a training mode with promising application for gait training. There is capacity for optimising and specifying the training. The self-paced treadmill that was used in this thesis was part of a complete training platform called the Extended CAREN (MotekMedical). The Extended CAREN is a costly system (in the range of £500,000). In order to make this type of training available to the greatest number of users, a low-cost version of this training platform needs to be developed. Kim et al. (2013) [565] proposed the use of a depth sensor (ASUS Xtion^{TM}), which cost less than 200 USD [566], in replacement to the motion capture camera and used a low-cost treadmill which they controlled using a position-feedback controller and an observer-based walking speed estimator [565], [567]. When comparing their low-cost SP treadmill alternative to the VICON SP treadmill method, the low-cost alternative presented similar performances apart from the slower transient phase when transitioning from a belt speed to another [565]. No significant difference was observed between the two type of SP treadmills during the steady-state of walking in in regards to: walking speed ($p=0.667$ for fast speed; $p=0.758$ for slow speed), step length ($p=0.281$ for fast speed; $p=0.810$ for slow speed), and cadence ($p=0.251$ for fast speed; $p=0.603$ for slow speed) [566]. The works of Kim et al. (2013) and (2015) show promising results for the development of affordable SP treadmill system which could be implemented in the community, thanks to their affordability.

However, two aspects of this device design need to be addressed to improve this system. The management of the optical flow was not presented in these papers and the possibility to walk up and down a slope on the treadmill. The first can be mitigated relying on the use of a large screen displaying a scenery that will flow in synchronisation with the treadmill's speed. The second aspect should be dependent of the properties of the treadmill used when implementing the low-cost SP control method.

7.6. Novel contribution of work

The techniques employed to analyse surface EMG in this thesis present a starting base for future investigations. It would be beneficial to confirm their value by applying these techniques to a larger group of able-bodied participants to provide a compelling reference database. This reference database would then allow comparisons with mobility impaired populations such as stroke.

In this thesis, the EMG characterisation methods such as the variance ratio, the occurrence frequency and non-linear analysis were used to investigate the differences of muscle activity between the walking indoors overground, outdoors overground, on a fixed pace treadmill, and on a self-paced treadmill.

Because these analysis methods are not widely used, and, to our knowledge, never used for this application, a bespoke LabVIEW program was designed to allow the treatment of these data.

A first study was run, to collect data from able-bodied participants during indoor overground walking and treadmill walking on fixed and self-pace, at different walking speeds (slow, fast, comfortable). Following this first study, an initial version of the program was developed. This version allowed to collect the kinematic and EMG data, display them, process them, and compute the variance ratio over several consecutive cycles by selecting the gait cycles manually (see Annex G, Figure G.5).

Following this first study, the bespoke program was adapted to collect EMG data from outdoor walking, as the current lab material was not designed to be transportable and used outdoors. The bespoke program was enhanced by automating the gait cycles detection, using the IMU data from Delsis Trigno's dual EMG/IMU sensors. The IMU data were used as reference signals to identify different stage of gait cycles. This upgrade allowed, therefore, the computation of the variance ratio and other gait temporal data such as the stride durations, the duration of muscle contractions and the number of muscle contractions per gait cycles.

In order to automatically detect the EMG activity, without having to rely on eye checking and threshold adjustments, a novel threshold detection method was designed to ensure consistency in the treatment of the EMG data (see section 5.4.2). The method proposed to detect EMG activity onset and offset is a custom-made self-adapting double threshold method. The methods used in the software were designed to be available to use for any muscle without having to change threshold parameters nor need to use manual readjustments. The possibility of using manual means to study the signal is still available for

use. The gait event detection algorithm was custom-made, based on the principles presented by other algorithm found in the literature. The objective was, there again to be able to automatically identify and select the gait cycles using a simple method that would work both on able-bodied participants and participants with an impaired gait.
A second study was conducted. This time, able-bodied participants, and people with stroke at the chronic stage were recruited. They walked indoors overground, outdoors overground on a flat surface and on a slope (up and down). They also performed treadmill walks on a fixed pace and on self-pace mode (flat, up, and down slope).
While not fully exploited in this thesis, the design of an initial version of an EMG non-linear analysis was designed for future further investigations.

In summary, this thesis developed a bespoke software allowing the collection of EMG and IMU data from Delsys Trigno sensor, their processing, and the calculation of several EMG characterisation parameters in order to investigate the differences of motor control strategies between outdoor walking, indoor walking, fixed pace treadmill walking and self-pace treadmill walking and, thus evaluate whether SP treadmill walking is a better training mode to improve community walking performances in comparison to indoors walking and fixed pace treadmill walking.

7.7. Recommendations for future work

Measuring how EMG profiles alter over time, particularly during a period of rehabilitation would be valuable in understanding their influence on gait function. Ideally, this should be done with sub-acute stroke patients, in the process of going through their gait rehabilitation training. The protocol could, initially, consist of an observational study before being used in a controlled trial. During the observational study, the EMG data collection would take place at several points of the gait rehabilitation training, before, during and after the intervention. The changes in the EMG signal could then be observed to better understand how they correlate with changes in an individual's mobility. The data collection on acute stroke patients would also benefit from adding to the EMG signal collection, the addition of standard walking ability predictive measure such as the walking speed [92], [215], [216] or the 6 minutes walking test [568], in order to make a correlation with walking change in capacity.
Furthermore, it would be interesting to use the same protocol for a comparative study. The aim would be to compare the outcome of a traditional rehabilitation training regime, with FP

treadmill walking, and another one that includes the use of SP treadmill walking. This could allow a better understanding of the effect of one method and the other over the course of gait rehabilitation. This research project could take the shape of a comparative single-blinded study, involving stroke patients at the start of the course of their rehabilitation training. One group of patients would undergo a usual FP treadmill training treatment, while the other one will follow a SP treadmill training involving the use of an immersive environment adapted to train walk variability that can be found in the community (see section 7.5 Practice Implications). For both groups, the muscle activity data would be collected at different points of time during the time of training, to monitor the evolution of muscle activity pattern. At the beginning and the end of the training program, each participant will undergo selected test to assess the evolution of their walking ability.

Chapter 8

8. Conclusion

8.1. Support or reject the research hypothesis

The hypothesis was that the walking on a self-pacing treadmill would generate statistically significantly similar patterns of muscle activity to overground outdoor (i.e., community) and indoor walking in able-bodied participants when compared with walking on a standard fixed pace treadmill. Secondly that these similarities would persist when tested with people with hemiplegia following a stroke.
The results from both studies demonstrated that it is possible to observe the muscle activity in different walking situations including outdoors and analyses the EMG signals to characterise the motor outputs from different types of walks. Despite trends in the data showing a similarity between SP and outdoor walking there was insufficient evidence to accept this hypothesis.

The second study of this thesis provided a method realised via bespoke software. With this software, it was possible to collect the EMG and IMU data both indoors while walking overground and, on a treadmill, but also outdoors, where the Vicon motion capture cameras could not be transported. Once the EMG and IMU data were collected, it was possible to then apply different treatments on the different signals in post-processing to interpret the results.
The output data, computed via the software, allowed the user to obtain parameters, independent for the EMG amplitude and contributing to the characterisation of the variability of the EMG signal. These parameters were the variance ratio over a set number of consecutive gait cycles, the number of contractions per gait cycles and their duration in percentage of the gait cycle, the total duration of the contraction during each gait cycles. These parameters are intended to constitute a baseline for the investigation of the effects of different type of walking situations on the motor control strategy.
Upon the examination of these parameters on the EMG signal of the able-bodied participants, the variance ratio result during levelled walking agreed with the primary hypotheses. The occurrence frequency values presented a trend of value in favour of part of the hypotheses. The variance ratio values of the muscle during outdoor walking were the closest to the variance ratio values observed during self-paced treadmill walking. The indoor

walking variance ratio value were closer to the values observed during fixed pace treadmill walking. Consequently, the hypotheses of FP treadmill walking being significantly different from the other walks (SP, indoors and outdoors is rejected. The participants with stroke presented did not present trends as clearly as the able-bodied participants but seemed similar across the walking situations. The secondary hypothesis is rejected since significant differences were found between outdoors slope walking and self-paced slope walking.
Future work should include more participants with stroke to confirm whether post-stroke muscle recruitment varies according to the walking situation. There should also include age-matched able-bodied participant to eliminate the hypothesis of the effect of age on the change of muscle recruitment strategy. To insure the self-paced walking experience is the closest to community walking, the treadmill training should be task-specific and mimic real-life challenges. This could be achieved using the virtual environment and sound effects.
To be used by healthcare specialists, the software used to collect, process, and compute the EMG data will benefit from being redesigned to be more user friendly, with simpler interfaces. Moreover, the non-linear analysis tool should be added to the complete program to allow further investigation of this promising method.
Ultimately, to reach as many people as possible, an affordable alternative to the Motek CAREN platform, that could be installed in rehabilitation centres to be available to more people and become a common gait training practice to improve community walking.

8.2. Summary of thesis outcomes

The key outcomes of this thesis are:

- Development of a software allowing simultaneous collection of outdoor surface EMG and IMU data from the Delsys Trigno devices.
    - Collection of raw EMG data from individuals with and without movement impairment under a range of different walking conditions including overground walking indoors and outdoors and treadmill walking on fixed pace and self-pace mode.
    - The IMU data were used as reference data for the interpretation of the kinematics, allowing to identify the gait events and count their number.
    - The post-processing EMG parameters collected and computed were the variance ration (VR), the number of contractions per gait cycles, the occurrence of the muscle contractions during the gait cycle, the total duration of contraction per cycles as a percentage of gait cycle.

    - The user interface allows the collection of data spreadsheets and graphs to illustrate the data and treatments applied to the signals.
- Development of a custom-made gait phases detection algorithm, using a single IMU sensor.
- Development of a custom-made self-adapting EMG contraction detection double threshold method.
- A method to collect data outdoors and indoors, independently from the Vicon 3D motion capture system.
- Identifying the similarities of muscle activity behaviour between the four different type of walks observed, namely, outdoor overground walking, indoor overground walking, Fixed pace treadmill walking and self-paced treadmill walking.
- Identifying the similarities between sloped outdoor overground and self-paced treadmill walking.
- Analysis of the repeatability and the temporal parameters of the muscle activity during the two treadmill and the two overground walks.
- Comparison of the parameters of a reference able-bodied group with two chronic stroke individuals.

In conclusion, the main outcome of this thesis was the creation of a protocol and software for collecting and comparing muscle activity and kinematic data indoors (overground and treadmill) and outdoors on flat and sloped surfaces. These comparisons are necessary to evaluate the potential of the self-paced treadmill training for the recovery of community walking among stroke patients. Regrettably, there was insufficient statistical evidence to support this possibility although the statistical trends showing similarity between outdoor and self-paced treadmill walking should be tested further with larger samples.

8.3. Summary of thesis conclusions

The key conclusions of this thesis are:

- The VR is dependent of walking speed and presents lower values (lower variability) when walking at self-selected comfortable speed.
- The muscular activity during SP treadmill walking is a closer analogue to outdoor overground walking.
- The muscular activity during slopped walking on a self-paced treadmill is different to outdoors slopped walking.

Annex A

A. Non-linear analysis

Dynamical systems are systems of which the characteristic parameters evolve over time. These dynamical systems have either linear or non-linear behaviours. Linear systems can be described by linear equations (with the f(x)=(ax+b) format, with *a* and *b* being constant values). Non-linear systems are described by non-linear equations. The non-linearity comes from feedback, the interaction with the environment or cross-dependencies between the characteristic parameters of the system [569]. A number of biological systems such as the EMG signal [540], [570], heart beat [532], [536] and electroencephalograms [571], [572] are dynamic systems with a non-linear behaviour. Chaotic systems are a sub-category of non-linear system (see Figure A.1). Chaotic systems can follow simple rules and have few components interrelating but are very sensitive to the initial condition applied to them and their behaviour depend on it [569].

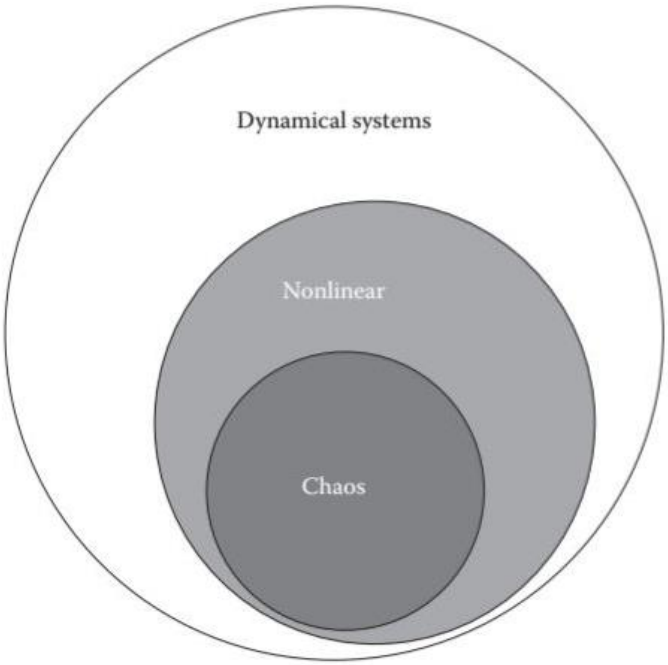


Figure A.1: Chaotic systems are a type of non-linear systems and non-linear systems are a type of dynamical system. From Stergiou (2016) [573]

To study a non-linear phenomenon from its signals, we rely on characteristic magnitudes called invariants. The different signals are usually interpreted through two approaches, one being the signal is random, the other being that the signal is made of a sum of periodic

signals. There is a third behaviour classification called the chaotic behaviour. While chaotic signals look random, they are not random. However, chaotic signals are not as predictable as periodic signals (see Figure *A.2*), which make them more complex than these two other types of signal [573].

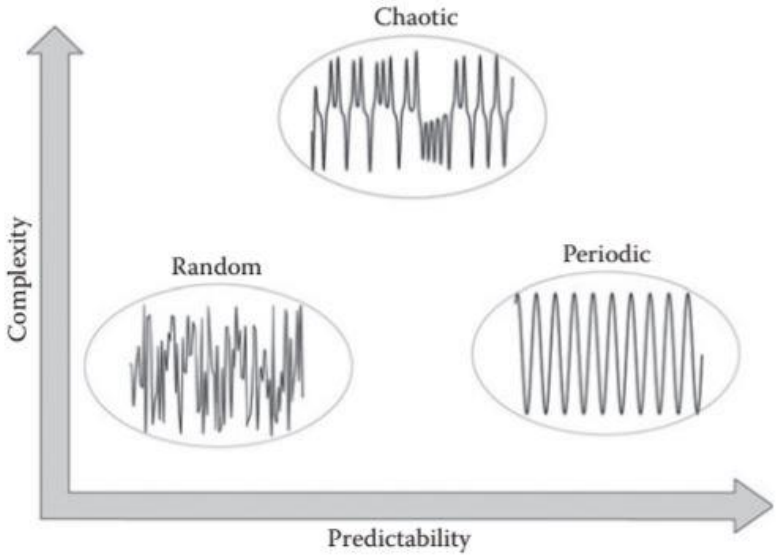


Figure A.2: Chaotic systems are more predictable than random signal but more complex than both random and periodic signals. From Stergiou (2016) [573]

In order to present the principle of non-linear analysis explored in this thesis's discussion, we will illustrate the concepts through the study of a model called the logistic map.

1. The logistic map

   In order to illustrate a signal with a chaotic behaviour as opposed to a random signal, we will present here the logistic map (A.1) [569]. The logistic map represents the evolution of a population of a specie in an environment with a finite amount of resources.

$$x_{t+1} = a x_t (1 - x_t) \quad (A.1)$$

With x_t : population at a time t,

a : growth rate

   Consequently, at any time, the population is a function of the growth rate a, and the last population level. A low growth rate will lead to the extinction of the population. A higher growth rate may settle toward a given value or alternate between times of population growth and decrease [569] (see Figure *A.3*).

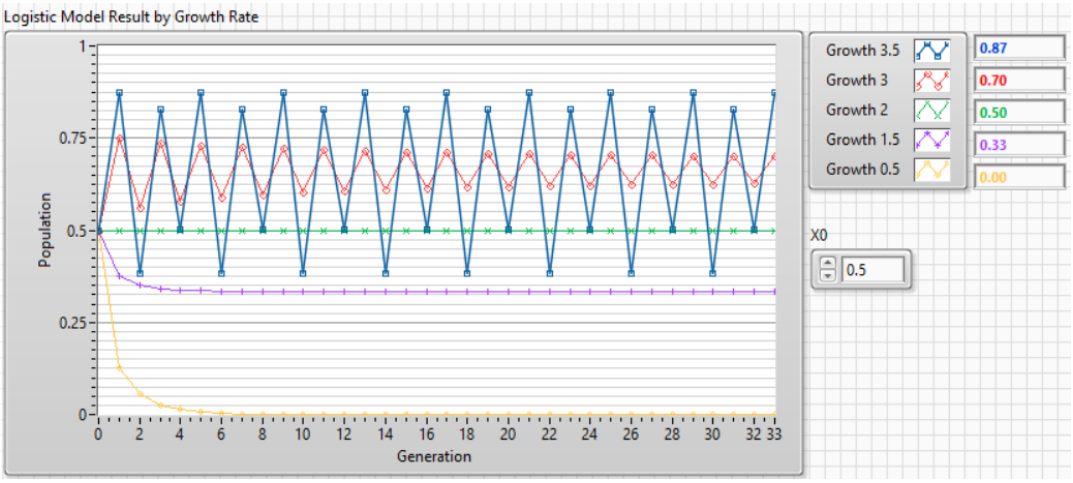


Figure A.3: Time series graph of the logistic map according to the growth rate value for 33 generations

In Figure *A.3*, the population starts at 0.5 (the initial condition X_0), which is 50% of the maximum population. For a growth rate of 2 the population is constant. In the case of a growth rate of 0.5 the population goes extinct after 5 generations. For a higher growth rate such as 3.0, the population oscillates between two values and in the case of a 3.5 growth rate, the population oscillates between four different values (see Figure *A.3*).

When plotted as a function of *a*, the logistical map's result is as presented in the bifurcation diagram in Figure A.4.

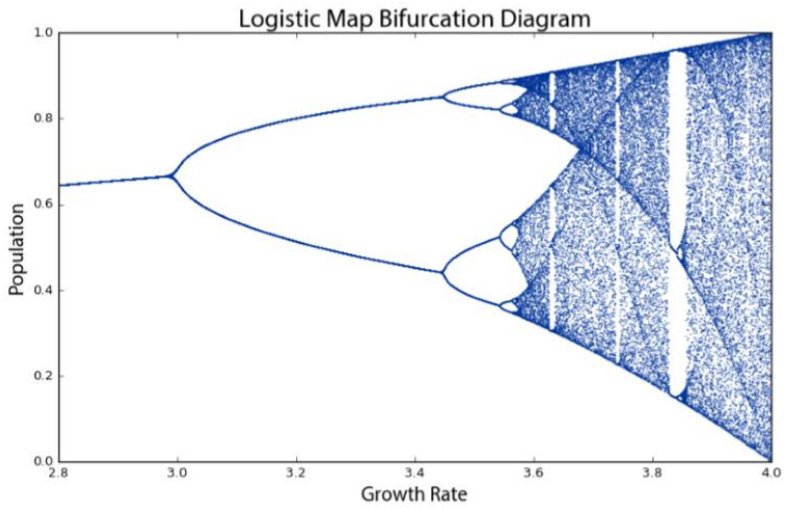


Figure A.4: Bifurcation diagram of the Logistic map as a function of a extracted from Boeing (2016) [569]

The solution of the equation of the logistic map (the value towards which the equation will converge) will change according to the value of *a*, going from one

value when *a* is inferior to 3. When *a* is superior to 3 the solution of the equation is oscillating between two values. When the parameter *a* has a value above 3.6 the system reaches a space where there is a wide range of possible results for this equation, which appear, at first sight, to be of random distribution.

1.1. Phase diagram

In a phase diagram, every point represents a state of the system. The coordinates of this diagram are the space coordinates and their temporal derivations. In the case of a signal with one variable x(t), its space phase would be constructed using x(t) its derivatives (x(t), x'(t), x"(t), …).

Another way to construct phase diagrams is the delay method. The delay method constructs the coordinates of the points in the phase space of dimension *n* as expressed in equation (A.2):

$$X(t) = \big(x(t), x(t+\tau), x(t+2\tau), \dots, x(t+(n)\tau)\big)$$

(A.2)

$$\tau \textit{ represents an arbitrary time called a delay}$$

$$X(t) \textit{ is the position of the point in space at the instant } t$$

When this delay method is used for the construction of the logistical map's space diagram, taking $\boldsymbol{\tau}$=1, we obtain the diagrams presented in Figure A.5. A three-dimension phase diagram will plot the value of the system at *t+2* against its value at *t+1* against its value at *t*, as showed in Figure A.5 (B) [574]. In case of a two-dimension phase diagram, the plot will be the value of the system at *t+1* on the y-axis against its value at *t* on the x-axis, as showed in Figure A.5 (A). With a phase diagram, it is possible to represent a one-dimension time-series in a two or even a three-dimensional state-space. It is an imaginary space that is built on the variables of a system to build its dimension [569].

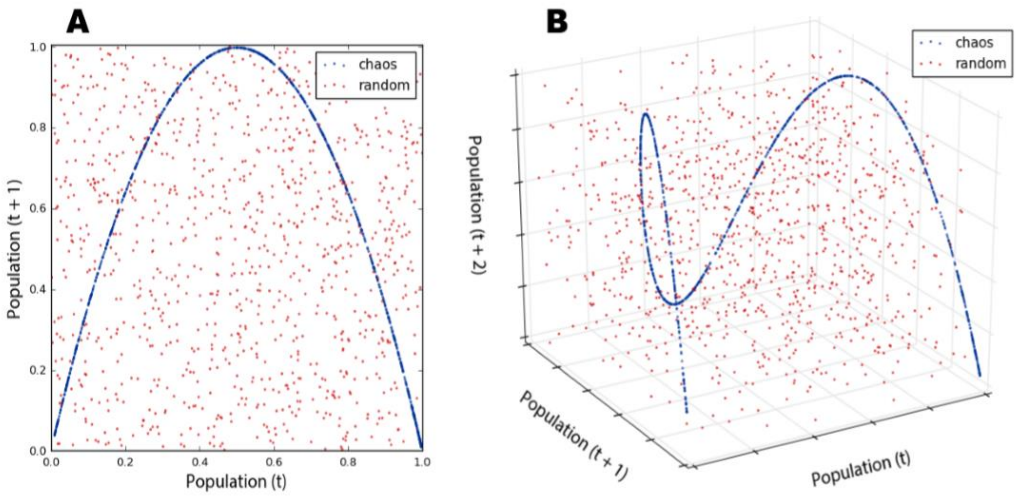


Figure A.5: Phase diagrams of the logistic map's time series. (A) two-dimensional state space representation, (B) three-dimensional representation Boeing (2016) [569]

When the logistical equation, in the case of the parameter r is equal to 3.7, is compared to the random function of a computer software such as LabVIEW, the repartition of both function's results seems random see Table 1. However, when represented in the phase space, it appears clearly that the random function's results are spread over the space when the logistical equation follows a pattern.

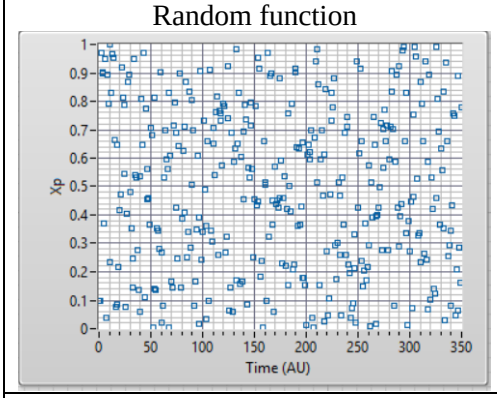
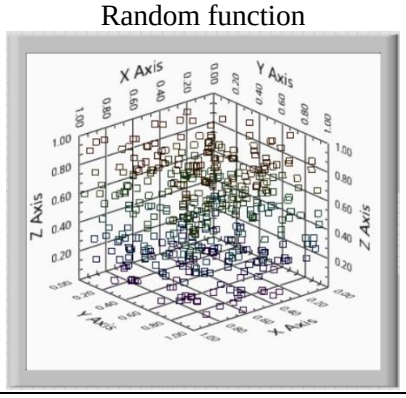
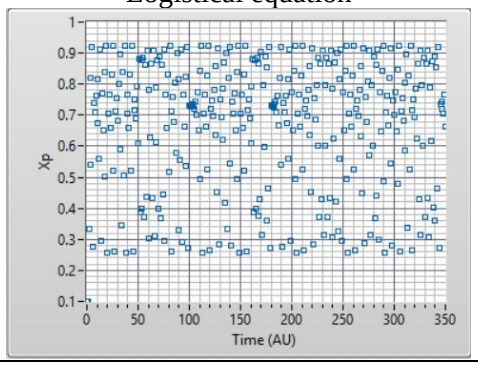
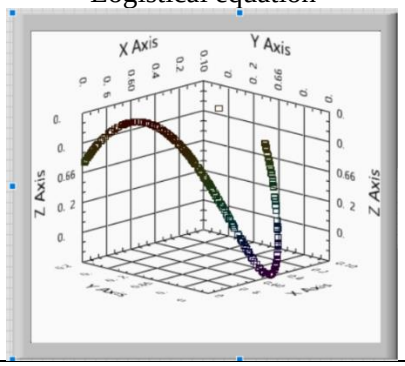
Results as a function of the time	**Phase space representation (Xi+2, Xi+1, Xi)**
Random function 	Random function 
Logistical equation 	Logistical equation 

Table A.1: Comparison of Random function with the logistical equation over time and in the space phase

1.2. The attractor

The attractor represents one or a set of values that the system is going to converge, regardless of the initial condition value. This is illustrated in *Figure A.6* were different initial values (X0) are used when the growth rate is set to 1.5, all the solutions converge toward 0.33. In the case of the logistic equation, represented graphically in Figure A.4, for the growth parameter a set between 2.8 and 3.0 the equation reaches one given value. We can see that the system oscillates between four different values when the growth parameter is set to 3.5 (see *Figure A.7*). When the growth parameter value goes beyond 3.5, we can observe the chaotic behaviour of the system. It is a case of strange attractor, where the system oscillates endlessly without taking the same value twice [569], [575], as represented on the left graph of *Figure A.8*. Also, its structure is fractal, which means, it has a pattern that repeats itself at every scale of the system, it is self-similar [575].

Strange attractors are noticeable in the phase diagram as the repartition of the chaotic system's value is constrained into a specific pattern shape, the basin of attraction (blue points in Figure A.5 and on the phase space graph on the right of *Figure A.8*) [569].

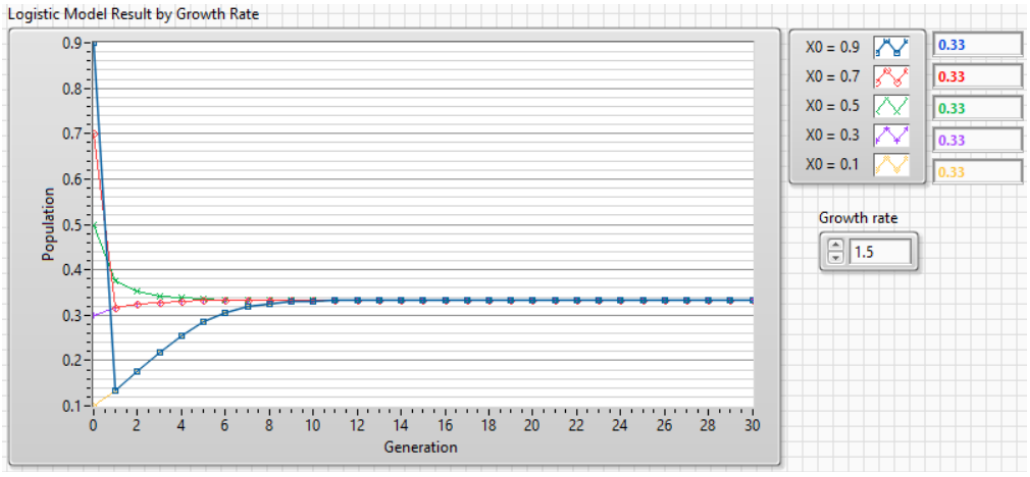


Figure A.6: Logistic model converging to an attractor value of 0.33 for a growth rate of 1.5 and different initial values

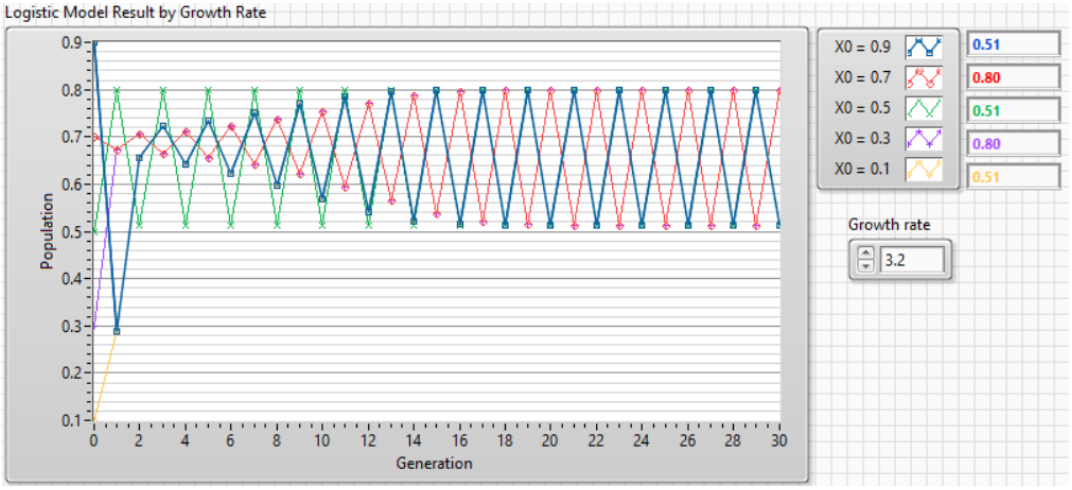


Figure A.7: Logistic model converging to two attractors of respective values 0.51 and 0.80 for a growth rate of 3.2 and different initial values

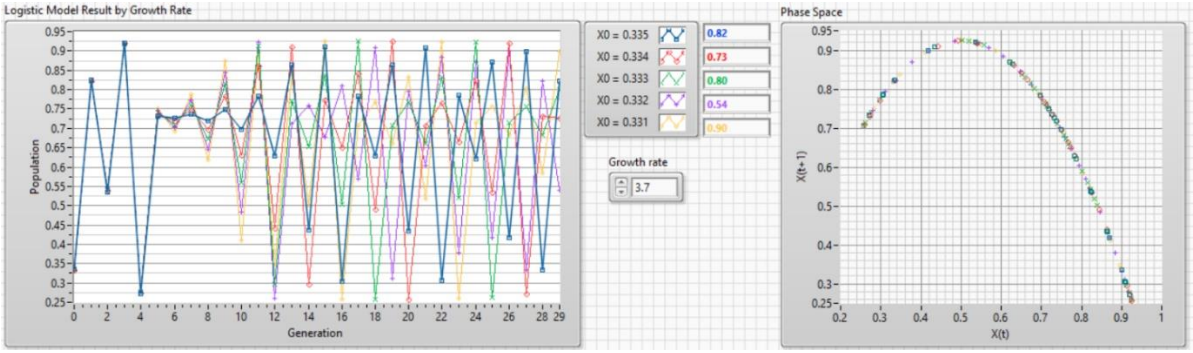


Figure A.8: In the chaotic zone (here growth rate = 3.7), the system is highly sensitive to the initial conditions (here on a thousandth difference), on the right graph, the phase space of the system presents the same basin of attraction regardless for each initial condition

1.3. Fractal dimension

Fractal don't have a whole numbered dimension, but rather a fractional value to quantify their dimension [576]. The fractal dimension, represents the space filled by the fractal pattern which is more than one dimensional but still less than two dimensional [569]. It is a measure of the degree of freedom of the system [576]. The fractal dimension is a parameter used to quantify the disorganisation of, for example, cells or tissues as a non-whole number [537]. It is also used for pattern recognition and feature extractions of EMG signals and other biomedical waveforms [528], [538], [571].

Examples of fractal structures are presented in Table A.2. In Table A.2, the fractal dimension of the Sierpinski triangle is superior to 1 as a curve should be but inferior to 2 (as is expected from a surface) because it does not use all the 2D space.

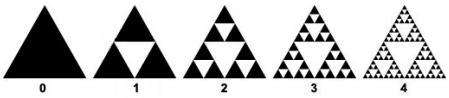
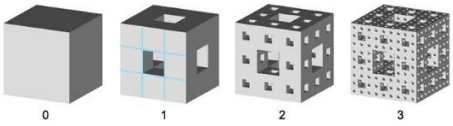
Antor ensemble D=0.63 < 1 [577]	Sierpinski triangles D=1.58 < 2 Modified from [578]	Sierpinski cube D= 2.73 < 3 [578]
		

Table A.2: Example of fractal structures. D is the fractal dimension

Fractal dimension can be used to characterise a system with chaotic behaviour [528], [571], [572].

1.4. Lyapunov Exponent

Chaotic systems are sensitive to their initial condition. While their basin of attraction is stable on the large scale, the attractors are locally unstable. Within the strange attractor phase of a system, there are infinitesimally close points that are diverging over time while remaining within the attractors boundaries [569].

The Lyapunov exponent is the parameter used to quantify this divergence [536], [569], [579]. It is a parameter of the measure of the "sensitive dependence on initial condition" [580]. When the Lyapunov exponent's value is positive, it means that two points are moving apart exponentially. When the Lyapunov exponent's value is negative, it means that two points are converging exponentially. When the Lyapunov exponent's value is zero, it means that there is a bifurcation [569], [580].

Taking again the example of the logistical map, when the growth rate is set at 3, the Lyapunov exponent equal to zero, the logistical equation reaches a bifurcation point (see bifurcation diagram Figure A.4). The Lyapunov exponent below 3 will be negative because there is one value, one fixed point for each value of growth rate. The Lyapunov exponent value will be positive for the values of growth rate that correspond to the chaotic behaviour phase (see bifurcation diagram Figure A.4). A positive Lyapunov exponent indicates that the system is very sensitive to initial conditions [569].

Annex B

B. Description of the Functional Ambulatory Categories (FAC)

FAC	Ambulation Description	Definition
0	Nonfunctional ambulation	Subject cannot ambulate, ambulates in parallel bars only, or requires supervision or physical assistance from more than one person to ambulate safely outside of parallel bars
1	Ambulator-Dependent for Physical Assistance Level II	Subject requires manual contacts of no more than one person during ambulation on level surfaces to prevent falling. Manual contacts are continuous and necessary to support body weight as well as maintain balance and/or assist coordination
2	Ambulator-Dependent for Physical Assistance Level I	Subject requires manual contact of no more than one person during ambulation on level surfaces to prevent falling. Manual contact consists of continuous or intermittent light touch to assist balance or coordination
3	Ambulator-Dependent for Supervision	Subject can physically ambulate on level surfaces without manual contact of another person but for safety requires standby guarding on no more than one person because of poor judgment, questionable cardiac status, or the need for verbal cuing to complete the task.
4	Ambulator-Independent Level Surfaces only	Subject can ambulate independently on level surfaces but requires supervision or physical assistance to negotiate any of the following: stairs, inclines, or non-level surfaces.
5	Ambulator-Independent	Subject can ambulate independently on nonlevel and level surfaces, stairs, and inclines.

Annex C

C. Participant information sheet and consent form of the preliminary study

Participant Information Sheet

Name of department: Department of Biomedical Engineering
Title of the study: Characterisation of the variability of walking parameters during self-paced, fixed-pace treadmill and overground walking.

Introduction
What is the purpose of this investigation?
Treadmills are used to help people with different medical conditions recover the ability to walk, for example they are used in the rehabilitation of stroke survivors and people with spinal cord injury. Although this kind of training improves walking speed it doesn't help as much with walking around the home environment or outside where individuals encounter a greater number of challenges, varying conditions and obstacles.
A new type of treadmill which adapts its speed to the person's own speed ('self-paced' walking) may allow more variety in walking practice that is closer to the normal walking experience.
We would like to investigate this possibility by measuring different aspects of walking (joint movement, step lengths, muscle activity) and comparing them across different walking conditions: overground, fixed-pace (traditional treadmill walking) and self-paced walking.

This study aims to determine similarities and differences between walking over the ground, on a fixed-pace treadmill and self-paced treadmill.

This study is being undertaken as part of a PhD thesis.

Do you have to take part?
You are not required to take part in this investigation. It is up to you whether or not you takes part in the investigation. Participants reserve the right to refuse to participate in the study or withdraw from the study at any time without having to provide a reason. For Strathclyde students and staff: participation (or declining to take part) in this study will not affect your standing in the university in any way. However, should you wish to withdraw from this study after data collection has been completed, your pseudo-anonymised data will still be included in the analysis, unless you explicitly state it should be removed.

Can anyone take part?
We are looking for someone over 18 year of age who :

- Is able bodied
- Weight under 135 kg / 300 Lbs
- Has normal lower limb function

- Is able to walk at a self-determined pace for approximately 500m
- 20/20 vision (with or without visual aid)

If any of the following apply to you, you will be unable to participate. However, we would like to thank you for considering participation.

- Known musculoskeletal, neurological or sensory deficit
- Pregnant
- An irritable skin condition
- History of motion sickness

What will you do in the project?

In order to track walking patterns using 3D motion analysis, investigators need to locate certain bony landmarks over the body. Up to 30 markers (little shiny balls) will be placed at these locations.

The activity of different muscles can be measured as electrical signals using a technique known as electromyography (EMG). EMG activity of key muscles used during walking can be recorded using electrodes placed on the skin surface.

By recording human motion parameters and lower limb muscle activity at the same time, we expect to have a better understanding of those characteristics and how they are impacted by different walking speeds.

The investigation will take place in the Biomechanics Laboratories in the Department of Biomedical Engineering, university of Strathclyde.

The study itself will be structured as follows:

- A week day and time (morning or afternoon) will be arranged with the participant, according to his/her availability.
- Participant preparation (EMG positioning), calibration (anatomical landmark positioning) and assessment (3 walking speeds in 3 different contexts) should take no longer than 3 hour, including set-up time. The participant will therefore be required to be available for 3 hours of a day.

The timeline of activities is as follows:

On the day of the experiment:

1. On arrival to the laboratory any questions or concerns will be discussed, and you will have the opportunity to familiarise yourself with the equipment.
2. You will then be asked to change into tight fitting clothing. We recommend that you bring your own, however this clothing can be provided if required. Please come along with a pair of trainers or comfortable shoes.

3. The skin on your legs and thighs may need to be shaved to provide a smooth surface. You might want to shave yourself prior to the experiment day. Your legs will be wiped with alcohol and wireless EMG electrodes, used to record your muscle activity, will be attached at 5 different places on each leg, using double-sided tape.
4. Reflective markers (16) for the Plug-in-Gait model will then be placed on your clothing and skin (hips, legs and feet). To locate these landmarks, the rater will be required to palpate the landmarks (Figure 1).
5. Anthropometric measurements (e.g. height, leg length, knee and ankle width) will also be taken.
6. Following calibration, you will be asked to stand for a moment to enable the rater to record your joint angles during quiet standing. You will then be asked to perform a number of short (approximately 10m) walking trials at a comfortable speed until three good trials are recorded.
7. Once this first trial at comfortable speed is complete, you will be asked to perform another number of short walking at a faster speed. Then again a three good trials will be recorded.
8. Once this second trial at a faster speed is complete, you will be asked to perform another number of short walking at a slower speed. Then again a three good trials will be recorded.
9. You will then be directed in a second room, with a treadmill and then the same things will be asked of you

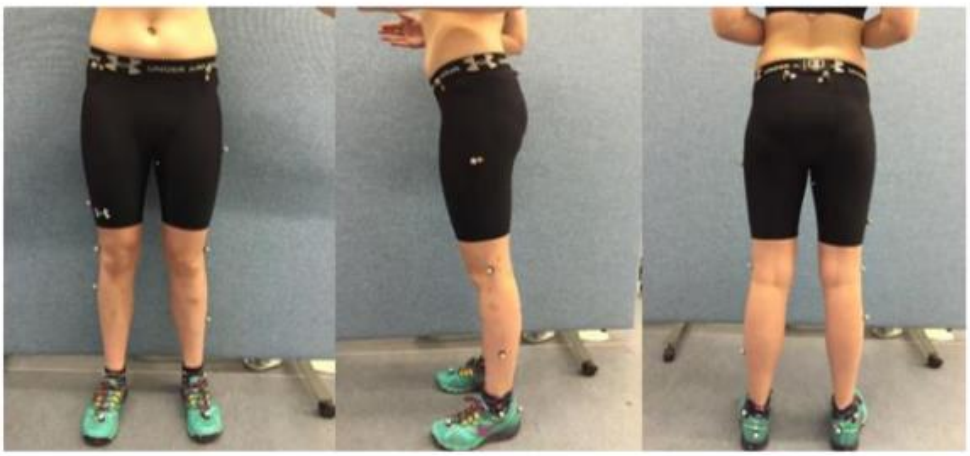


Figure 1: Example of the reflective markers set-up

Once the data has been collected no further participation will be required. You will not receive any payment or reimbursement for your participation. This study involves no invasive procedures and participants will not be asked to do any high intensity exercise.

Why have you been invited to take part?

You have been invited to participate because you are a healthy able-bodied adult. This investigation is aiming to recruit a minimum of 10 participants.

What are the potential risks to you in taking part?

This is a very low risk investigation and providing you can complete the tasks outlined in the previous section there should be no risk. All small risks such as slipping and tripping will be mitigated and minimised by the researchers carrying out the study. There is also a risk of skin irritation due to the shaving and/or attachment electrodes and reflective markers using tape.

What happens to the information in the project?

All data collected from this investigation will be treated confidentially and will be handled in accordance with the departmental Data Management Plan (December 2015). The stored data will not include your personal details. Data will be stored on a password locked computer hard-drive and access will be restricted to the investigators only. The anonymised results of this study may be submitted for presentation at scientific and clinical conferences and may be submitted for scientific and clinical peer-reviewed publication. Moreover, the results from this study will be included in the research student's PhD thesis.

The University of Strathclyde is registered with the Information Commissioner's Office who implements the Data Protection Act 1998. All personal data on participants will be processed in accordance with the provisions of the Data Protection Act 1998.

Thank you for reading this information – please ask any questions if you are unsure about what is written here.

What happens next?

If you are happy to voluntarily participate in this study please complete and sign the consent form on the next page. Please send an e-mail to eunice.ibala@strath.ac.uk to say you are willing to consent and bring the consent form along with you for your first session.

If you do not wish to participate then please accept our thanks for taking the time to read this information.

Researcher Contact Details:

Researcher: Eunice Ibala
Status: PhD Candidate
Department: Biomedical Engineering
Contact: eunice.ibala@strath.ac.uk

Chief Investigator Details:

The chief investigator: Andrew Kerr
Status: Lecturer
Department: Biomedical Engineering
Contact: andrew.kerr@strath.ac.uk, +44 (0)141 548 2855

Investigator: Sylvie Coupaud
Status: Lecturer
Department: Biomedical Engineering
Contact: sylvie.coupaud@strath.ac.uk, +44 (0)141 548 3930

This investigation was granted ethical approval by the University of Strathclyde BME Departmental Ethics Committee.

If you have any questions/concerns, during or after the investigation, or wish to contact an independent person to whom any questions may be directed or further information may be sought from, please contact:

Linda Gilmour
Secretary to the Departmental Ethics Committee
Department of Biomedical Engineering
Wolfson Centre, 106 Rottenrow
Glasgow G4 0NW
Tel: 0141 548 3298 E-mail: linda.gilmour@strath.ac.uk

Consent Form

Name of department: Department of Biomedical Engineering
Title of the study: Characterisation of the variability of walking parameters during self-paced, fixed-pace treadmill and overground walking.

- I confirm that I have read and understood the information sheet for the above project and the researcher has answered any queries to my satisfaction.
- I understand that my participation is voluntary and that I am free to withdraw from the project at any time, without having to give a reason and without any consequences.
- I understand that I can withdraw my data from the study up until 2 weeks after the participation day. After which point the pseudo-anonymised data will be included in the analysis unless I explicitly request they are removed.
- I understand that any information recorded in the investigation will remain confidential and no information that identifies me will be made publicly available.
- I confirm I satisfy the inclusion and exclusion criteria of the study
- For Strathclyde staff and students: I understand that participation (or withdrawing from the study) in this study will not affect my standing in the University in any way.
- I consent to being a participant in the project
- I consent to being photographed as part of the project knowing that it will be blurred and might be used for publications. (Yes/No)

(PRINT NAME)	Hereby agree to take part in the above project
Signature of Participant:	Date

Annex D

D. Participant information sheet and consent form of the second study – Unimpaired participants

Participant Information Sheet

Name of department: Department of Biomedical engineering
Title of the study: Comparison of biomechanical and muscle activation variables between mobility impaired and unimpaired individuals walking outdoors, indoors and on a treadmill.

Introduction
Treadmills are used to help people with different medical conditions recover the ability to walk. They are used, for example, in the rehabilitation of stroke survivors. This type of training improves the fitness and the walking speed of the user. However, it doesn't help as much when it comes to walking around the home environment or outside where individuals face several challenges, such as turns, slopes or obstacles avoidance. A new type of treadmill which adapts its speed to the person's own speed, also called 'self-paced' walking can lead to more variety in walking practice that is closer to a real-life walking experience.

This study will be led by two doctoral students, one focussing on leg movement observation and the second focussing on muscle activity information. They will be supported by a KTP associate and a lecturer member of staff of the Biomedical Engineering Department of the University of Strathclyde, who is also a qualified physiotherapist and HCPC (Health Care Professions Council) registered physiotherapist.

What is the purpose of this investigation?
This study aims to determine similarities and differences between walking over the ground while inside and outside, and on a self-paced treadmill.

Do you have to take part?
It is up to you whether or not you take part in the investigation. You have the right to refuse to participate in the study or withdraw from the study at any time, without having to provide a reason. This will not have any consequence on the you, nor on any of the health or social services you may be receiving.

For Strathclyde students and staff, participation (or declining to take part) in this study will not affect your standing in the university in any way.

If you wish to retract your participation from the study after you have already taken part, all non-anonymous data will be removed, and where possible, pseudo-anonymised data will also be removed at your request.

Why have you been invited to take part?
You have been invited to participate because you are an unimpaired able-bodied adult. This investigation is aiming to recruit a minimum of 5 participants.

The inclusion criteria are:

- you are 18 years old or older
- you are currently well
- you are able to follow simple instructions and communicate in English
- you have good vision (with or without corrective aids)
- you are able to provide informed consent
- you are able to come to the University of Strathclyde during working hours (9-5) Monday to Friday

The exclusion criteria are:

- you are pregnant
- you have a severe speech disorder preventing you from communicating promptly that would affect your communication with the researches
- you have a hearing problem that is not corrected by a hearing aid
- you have balance issues or have a medical condition that reduces your ability to walk
- you are unwell during the investigation period or are taking medication that may compromise your ability to participate in mild physical activity.
- your height is above 195cm, your waist and leg are respectively above 125cm and 75cm round.
- you have a skin irritation on one or both legs

What will you do in the project?

If you decide to take part in this study, you will need to come to the University of Strathclyde for an appointed time that will be arranged with you. Here you will be asked a few questions about your health state, your memory (cognitive abilities) and your mobility. The questions about your mobility will encompass the distances, frequency, and conditions at which you usually walk outside of your home. We will give you an overview of the outdoor exercises you will be asked to perform. If you are happy to proceed, you will then be asked to change into provided shorts and a tight-fitting top, within a private changing room. One of the doctoral students will then ask your age and take some measurements such as your height, weight, and width of your joints. This same doctoral student will then, with your consent, stick small sensing devices to certain points of your legs that will record your movements throughout the experiment.

The second doctoral student will then stick another set of sensors to your legs that will record the activity of your muscles. If required, this student may ask to shave small areas of leg hair to allow good sensor placement. The way you step on the ground will be recorded thanks to little round patches that will be stuck under your socks.

All the recorded tasks you will be asked to do will be performed at your own pace. You will need to perform walks without interruption for a duration varying between 2 to 20 minutes.

Once this is done you will be led out of the building and asked to follow an indicated path on a flat area. Then you will be asked to walk up a slope for around 30 steps and then go back down the slope. If you feel cold, we will provide a pair of large trousers that you will be able to wear over your shorts. In case of mild rain, the physiotherapist will walk beside you holding an umbrella to keep you as dry as possible. In the event of poor weather we may need to cancel your appointment. We will inform you of any cancellation at least an hour before your scheduled appointment.

Then you will be asked to come back into the lab and we will stick some light marble size markers on your feet, legs and hips. These are visible to special infra-red cameras, which will capture information about the way you move when you walk. After this, you will be asked to follow an indicated path on the ground.

You will then be shown to the treadmill room. There you will be introduced to the system which is composed of a treadmill on a platform facing a big curved screen. On the screen, you will see an outside road and will have to follow different instructions as you walk on. You will be given a time to walk freely on the treadmill to get used to

the system. Once you are ready the walk exercise will begin. During this walk on the treadmill several challenges will be proposed to you, such as avoiding objects on the road or walking up and down gentle slopes.

During the walks, you will be free to use whatever walking aid you need and are comfortable with. During the walk on the treadmill, if you feel that the harness is no enough to provide stability for your walk, a trained physiotherapist will be besides you to hold your hand if needed.

Between each walk situation you will be given the opportunity to rest and will be asked to answer a list of questions about your experience.

If you have given consent in the attached form, we will take photographs as you perform the exercises. These will be pseudo-anonymised by facial blurring.

When the three types of walking experience and final questionnaire are completed, all the markers and sensors will be removed, and you will be free to change back into your clothes.

You are very welcome to give your thoughts about the experiment and whether you enjoyed particular aspects, or what could be improved.

We are unfortunately not able to provide payments for your time or provide any reimbursement for your transport expenses. If you would like, we can arrange free transport to and from the university by a university car.

What are the potential risks to you in taking part?
This is a very low risk investigation and providing you can complete the tasks outlined in the previous section there should be no risks. All small risks such as slipping and tripping will be mitigated and minimised by the researchers carrying out the study. The risk of slipping or tripping on the treadmill will be prevented by having you wearing a harness.
There is a possibility that you will experience motion sickness from walking on the treadmill. This is the reason why you will be given some time to get used to walking on the treadmill. Moreover, we will keep checking how you feel so that if you feel bad we can stop the experiment.

There is also a risk of skin irritation due to the shaving and/or attachment electrodes and reflective markers using tape.

What happens to the information in the project?
All data collected from this investigation will be treated confidentially. Your personal details will not be included in the stored data. In the short term, data will be stored on an encrypted and password secured hard-drive. This data will then be transferred to encrypted servers within the University. At all times only the named investigators will have access to this data

The anonymised results of this study may be submitted for presentation at scientific and clinical conferences and may be submitted for scientific and clinical peer-reviewed publication. Moreover, the results from this study will be included in the research students' PhD theses. Any research publications or presentations resulting from this work will only discuss group results and will not report on individual. At no time will any personal or identifiable information be released.

If you would like to hear about any outcomes of this research, you are invited to contact the researchers at any time using their details below.

The University of Strathclyde is registered with the Information Commissioner's Office who implements the Data Protection Act 1998. All personal data on participants will be processed in accordance with the provisions of the Data Protection Act 1998.

Thank you for reading this information – please ask any questions if you are unsure about what is written here.

What happens next?
If you are happy to voluntarily participate in this study please complete and sign the consent form on the next page. Please send an e-mail to **eunice.ibala@strath.ac.uk** to say you are willing to consent and bring the consent form along with you for your session.

If you do not wish to participate then please accept our thanks for taking the time to read this information.

Researcher(s)contact details:

Researcher: Eunice Ibala

Status: PhD Candidate

Department: Biomedical Engineering

Contact: eunice.ibala@strath.ac.uk

Researcher: Karen Chase

Status: PhD Candidate

Department: Biomedical Engineering

Contact: karen.chase@strath.ac.uk

Researcher: Nicholas Smith

Status: KTP associate

Department: Biomedical Engineering

Contact: nicholas.l.smith@strath.ac.uk

Chief Investigator details:

The chief investigator: Andrew Kerr

Status: Lecturer

Department: Biomedical Engineering

Contact: andrew.kerr@strath.ac.uk, +44 (0)141 548 2855

This investigation was granted ethical approval by the University of Strathclyde Ethics Committee.

If you have any questions/concerns, during or after the investigation, or wish to contact an independent person to whom any questions may be directed or further information may be sought from, please contact:

Secretary to the University Ethics Committee
Research & Knowledge Exchange Services
University of Strathclyde
Graham Hills Building
50 George Street
Glasgow
G1 1QE

Telephone: 0141 548 3707
Email: ethics@strath.ac.uk

Consent Form

Name of department: Biomedical Engineering
Title of the study: Comparison of biomechanical and muscle activation variables between mobility impaired and unimpaired individuals walking outdoors, indoors and on a treadmill.

- I confirm that I have read and understood the information sheet for the above project and the researcher has answered any queries to my satisfaction.
- I understand that my participation is voluntary and that I am free to withdraw from the project at any time, up to the point of completion, without having to give a reason and without any consequences. If I exercise my right to withdraw and I don't want my data to be used, any data which have been collected from me will be destroyed.
- I understand that I can withdraw from the study any personal data (i.e. data which identify me personally such as name, e-mail, telephone number,...) at any time.
- I understand that anonymised data (i.e. data which do not identify me personally, measures taken and other numerical data collected during the experiment) cannot be withdrawn once they have been included in the study.
- I understand that any information recorded in the investigation will remain confidential and no information that identifies me will be made publicly available.
- I consent to being a participant in the project
- I consent to being photographed as part of the project knowing that it will be blurred and might be used for publications. (Yes/No)

(PRINT NAME)	
Signature of Participant:	Date:

Annex E

E. Participant information sheet and consent form of the second study – Participants with stroke

Participant Information Sheet

Name of department: Department of Biomedical engineering
Title of the study: Comparison of biomechanical and muscle activation variables between mobility impaired and unimpaired individuals walking outdoors, indoors and on a treadmill.

Introduction
Treadmills are used to help people with different medical conditions recover the ability to walk. They are used, for example, in the rehabilitation of stroke survivors. This type of training improves the fitness and the walking speed of the user. However, it doesn't help as much when it comes to walking around the home environment or outside where individuals face several challenges, such as turns, slopes or obstacles avoidance. A new type of treadmill which adapts its speed to the person's own speed, also called 'self-paced' walking can lead to more variety in walking practice that is closer to a real-life walking experience.

This study will be led by two doctoral students, one focussing on leg movement observation and the second focussing on muscle activity information. They will be supported by a KTP associate and a lecturer member of staff of the Biomedical Engineering Department of the University of Strathclyde, who is also a qualified physiotherapist and HCPC (Health Care Professions Council) registered physiotherapist.

What is the purpose of this investigation?
This study aims to determine similarities and differences between walking over the ground while inside and outside, and on a self-paced treadmill.

Do you have to take part?
It is up to you whether or not you take part in the investigation. You have the right to refuse to participate in the study or withdraw from the study at any time, without having to provide a reason. This will not have any consequence on the you, nor on any of the health or social services you may be receiving.

For Strathclyde students and staff, participation (or declining to take part) in this study will not affect your standing in the university in any way.

If you wish to retract your participation from the study after you have already taken part, all non-anonymous data will be removed, and where possible, pseudo-anonymised data will also be removed at your request.

Why have you been invited to take part?
You have been invited to participate because you are an adult stroke survivor. This investigation is aiming to recruit a minimum of 3 participants.

The inclusion criteria are:

- you are over 18
- you have had a stroke at least 12 months ago, which affected your ability to walk
- you walk outside of your residence using whatever walking aids needed
- you have good vision (with or without corrective aids)
- you are able to provide informed consent
- you are able to follow simple instructions and communicate in English

- you are able to come to the University of Strathclyde during working hours (9-5) Monday to Friday

The exclusion criteria are:

- you have a hearing and/or visual problem that is not corrected by a hearing or visual aid
- you are unwell during the investigation period or are taking medication that may compromise your ability to participate in mild physical activity.
- You have speech problems significant enough to prevent safe communication with staff during the walking sessions (e.g. informing staff they are feeling dizzy or breathless) and which would present a barrier to the interview process.
- you have a heart or respiratory condition that reduces your ability to walk or any other neurological or orthopaedic condition (e.g. lower limb amputation) that limits their ability to walk.
- you have a vestibular impairment significant enough to be affected by treadmill walking.
- your height is above 195cm, your waist and leg are respectively above 125cm and 75cm round.
- you are pregnant
- you have a skin irritation on one or both legs

What will you do in the project?
If you decide to take part in this study, you will need to come to the University of Strathclyde for an appointed time that will be arranged with you. Here you will be asked a few questions about your health state, your memory (cognitive abilities) and your mobility. The questions about your mobility will encompass the distances, frequency, and conditions at which you usually walk outside of your home. We will give you an overview of the outdoor exercises you will be asked to perform. If you are happy to proceed, you will then be asked to change into provided shorts and a tight-fitting top, within a private changing room. One of the doctoral students will then ask your age and take some measurements such as your height, weight, and width of your joints. This same doctoral student will then, with your consent, stick small sensing devices to certain points of your legs that will record your movements throughout the experiment.

The second doctoral student will then stick another set of sensors to your legs that will record the activity of your muscles. If required, this student may ask to shave small areas of leg hair to allow good sensor placement. The way you step on the ground will be recorded thanks to little round patches that will be stuck under your socks.

All the recorded tasks you will be asked to do will be performed at your own pace. You will need to perform walks without interruption for a duration varying between 2 to 20 minutes.

Once this is done you will be led out of the building and asked to follow an indicated path on a flat area. Then you will be asked to walk up a slope for around 30 steps and then go back down the slope. If you feel cold, we will provide a pair of large trousers that you will be able to wear over your shorts. In case of mild rain, the physiotherapist will walk beside you holding an umbrella to keep you as dry as possible. In the event of poor weather we may need to cancel your appointment. We will inform you of any cancellation at least an hour before your scheduled appointment.

Then you will be asked to come back into the lab and we will stick some light marble size markers on your feet, legs and hips. These are visible to special infra-red cameras, which will capture information about the way you move when you walk. After this, you will be asked to follow an indicated path on the ground.

You will then be shown to the treadmill room. There you will be introduced to the system which is composed of a treadmill on a platform facing a big curved screen. On the screen, you will see an outside road and will have to follow different instructions as you walk on. You will be given a time to walk freely on the treadmill to get used to the system. Once you are ready the walk exercise will begin. During this walk on the treadmill several challenges will be proposed to you, such as avoiding objects on the road or walking up and down gentle slopes.

During the walks, you will be free to use whatever walking aid you need and are comfortable with. During the walk on the treadmill, if you feel that the harness is no enough to provide stability for your walk, a trained physiotherapist will be besides you to hold your hand if needed.

Between each walk situation you will be given the opportunity to rest and will be asked to answer a list of questions about your experience.

If you have given consent in the attached form, we will take photographs as you perform the exercises. These will be pseudo-anonymised by facial blurring.

When the three types of walking experience and final questionnaire are completed, all the markers and sensors will be removed, and you will be free to change back into your clothes.

You are very welcome to give your thoughts about the experiment and whether you enjoyed particular aspects, or what could be improved.

We are unfortunately not able to provide payments for your time or provide any reimbursement for your transport expenses. If you would like, we can arrange free transport to and from the university by a university car.

What are the potential risks to you in taking part?
This is a very low risk investigation and providing you can complete the tasks outlined in the previous section there should be no risks. All small risks such as slipping and tripping will be mitigated and minimised by the researchers carrying out the study. The risk of slipping or tripping on the treadmill will be prevented by having you wearing a harness.

There is a possibility that you will experience motion sickness from walking on the treadmill. That is the reason why you will be given some time to get used to walking on the treadmill. Moreover, we will keep checking how you feel so that if you feel bad we can stop the experiment.

There is also a risk of skin irritation due to the shaving and/or attachment electrodes and reflective markers using tape.

What happens to the information in the project?
All data collected from this investigation will be treated confidentially. Your personal details will not be included in the stored data. In the short term, data will be stored on an encrypted and password secured hard-drive. This data will then be transferred to encrypted servers within the University. At all times only the name investigators will have access to this data

The anonymised results of this study may be submitted for presentation at scientific and clinical conferences and may be submitted for scientific and clinical peer-reviewed publication. Moreover, the results from this study will be included in the research students' PhD theses. Any research publications or presentations resulting from this

work will only discuss group results and will not report on individual. At no time will any personal or identifiable information be release.

If you would like to hear about any outcomes of this research, you are invited to contact the researchers at any time using their details below.

The University of Strathclyde is registered with the Information Commissioner's Office who implements the Data Protection Act 1998. All personal data on participants will be processed in accordance with the provisions of the Data Protection Act 1998.

Thank you for reading this information – please ask any questions if you are unsure about what is written here.

What happens next?
If you are happy to voluntarily participate in this study please complete and sign the consent form on the next page. Please send an e-mail to **eunice.ibala@strath.ac.uk** to say you are willing to consent and bring the consent form along with you for your session.

If you do not wish to participate then please accept our thanks for taking the time to read this information.

The researchers contact detail will be available to you. You can contact us if you want to know about the outcomes of the study you participated in.

Researcher(s)contact details:

Researcher: Eunice Ibala

Status: PhD Candidate

Department: Biomedical Engineering

Contact: eunice.ibala@strath.ac.uk

Researcher: Karen Chase

Status: PhD Candidate

Department: Biomedical Engineering

Contact: karen.chase@strath.ac.uk

Researcher: Nicholas Smith

Status: KTP associate

Department: Biomedical Engineering

Contact: nicholas.l.smith@strath.ac.uk

Chief Investigator details:

The chief investigator: Andrew Kerr

Status: Lecturer

Department: Biomedical Engineering

Contact: andrew.kerr@strath.ac.uk, +44 (0)141 548 2855

This investigation was granted ethical approval by the University of Strathclyde Ethics Committee.

If you have any questions/concerns, during or after the investigation, or wish to contact an independent person to whom any questions may be directed or further information may be sought from, please contact:

Secretary to the University Ethics Committee
Research & Knowledge Exchange Services
University of Strathclyde
Graham Hills Building
50 George Street
Glasgow
G1 1QE

Telephone: 0141 548 3707
Email: ethics@strath.ac.uk

Consent Form

Name of department: Biomedical Engineering
Title of the study: Comparison of biomechanical and muscle activation variables between mobility impaired and unimpaired individuals walking outdoors, indoors and on a treadmill.

- I confirm that I have read and understood the information sheet for the above project and the researcher has answered any queries to my satisfaction.
- I understand that my participation is voluntary and that I am free to withdraw from the project at any time, up to the point of completion, without having to give a reason and without any consequences. If I exercise my right to withdraw and I don't want my data to be used, any data which have been collected from me will be destroyed.
- I understand that I can withdraw from the study any personal data (i.e. data which identify me personally such as name, e-mail, and telephone number) at any time.
- I understand that anonymised data (i.e. data which do not identify me personally, measures taken and other numerical data collected during the experiment) cannot be withdrawn once they have been included in the study.
- I understand that any information recorded in the investigation will remain confidential and no information that identifies me will be made publicly available.
- I consent to being a participant in the project
- I consent to being photographed as part of the project knowing that it will be blurred and might be used for publications. (Yes/No)

(PRINT NAME)	
Signature of Participant:	Date:

Annex F

F. Delsys FSR sensor specifications

Typical Operating Range(1)	20 m
RF Frequency Band	2400-2483 MHz (ISM band)
Power Consumption	<65 mW
Effective Radiated Power	9 mW
RF Protocol	Proprietary
Case Dimension (main sensor)	27 x 37 x 15 mm
Full-charge Operation Time(2)	8 hours (typical)
Recharge Time(3)	<2.5 hours
Auto Shut-down timer	300 seconds
Temperature Range(4)	5 - 50 degrees Celsius
FSR resistance range(5)	180 - 30000 ohms
Bandwidth	DC-50 Hz ± 5 Hz, 20 dB/dec
Channel 1 Sampling Rate	1926 samples/sec
Channels 2-4 Sampling Rate	148 samples/sec
Channel 1 Resolution Depth	16 bits
Channels 2-4 Resolution Depth	10 bits
Analog Output Range (6)	-4.85 V to 5.00 V

(1) Range is characterized in open office environments. Interfering RF sources in the 2.4 GHz spectrum, as well as absorptive objects occluding the RF communication path may degrade transmission distance. Stated range can be exceeded under favorable RF conditions.

(2) Battery duration is a function of charge and discharge conditions. Optimal battery performance is obtained when the device is operated at room temperature. Note that the stated Operation Time reflects the expected performance of a fully charged new battery used in a sensor that is transmitting data. Operation Time is expected to decrease as a function of charge cycles, and when the sensor is searching for a network.

(3) 80% of original battery capacity is maintained after 300 discharge/recharge cycles or after 2 years if recharge cycles are less than 300. These values represent typical expectations under normal conditions. Actual performance will vary depending on usage conditions.

(4) Operation beyond these temperature limits may damage the rechargeable battery.

(5) The resistance range is characterized by the full scale ability of the sensor output the minimum signal above 50 mV and the maximum at 3.30V. FSR membranes operated within these bounds, but not necessarily at the full range limits.

(6) The analog output signal is scaled to full range of the FSR sensor, where an output of 0% in EMGworks corresponds to the most negative output of -4.85V and a full scale output of 100% corresponds to +5.00V. Refer to the Trigno EMG System User's Guide for additional details on the analog output specifications.

Annex G

G. Technical developments of a bespoke LabVIEW program to collect and analyse EMG data

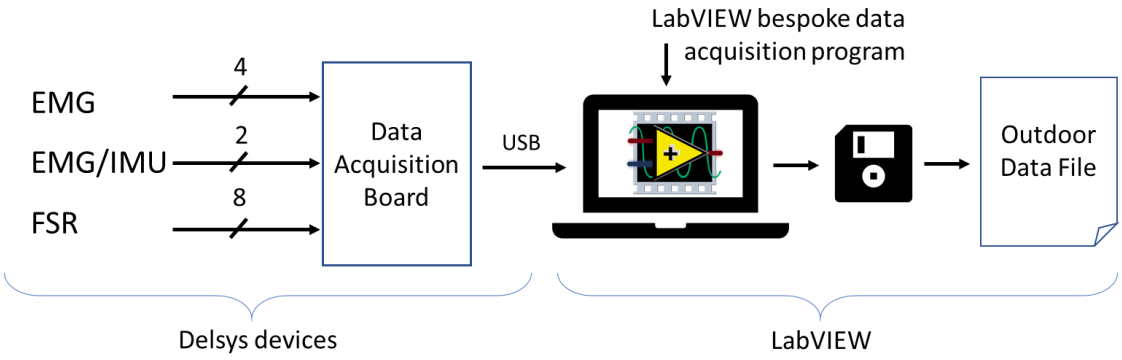
G.0. Why use LabVIEW for this research project, for data collection & processing?

The LabVIEW programs designed in this thesis answer for two requirements:

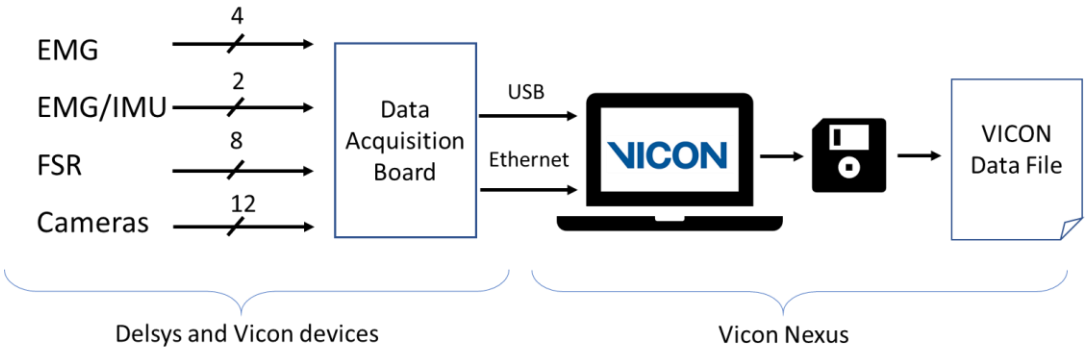
- Insure the collection of EMG and IMU data outdoor,
- Process the data to compute specific parameters, that were not available via the software available in the Biomedical Engineering department of the University of Strathclyde. These parameters as presented in this thesis (see sections 2.3.3 and 5.4.2 to 5.4.6).

G.1. Hardware architecture of the data collection system

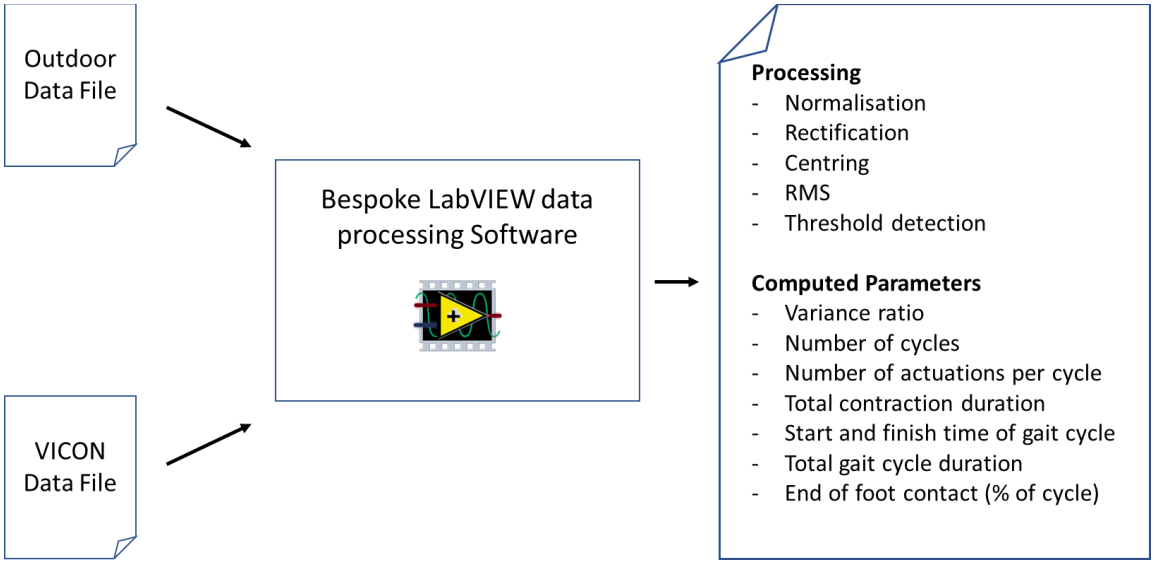
G.1.1. Outdoors Data collection



G.1.2. Indoors Data collection



G.2. Software architecture of the data processing program



G.2.1. Computing of the test data files into the bespoke LabVIEW data processing program

After having selected the files containing the joint angle, the EMG and the gyroscope data of interest the user is directed to the "GUI Data processing" front panel (Figure G.1). This interface allows a display of the data collected over time. The different operation on the signal are calculated in the background (see bloc diagram Figure G.2) and available to display individually or with the other data. In this figure, the curve in red is the knee joint angle, in blue the gyroscope data, in purple the rectified EMG data.

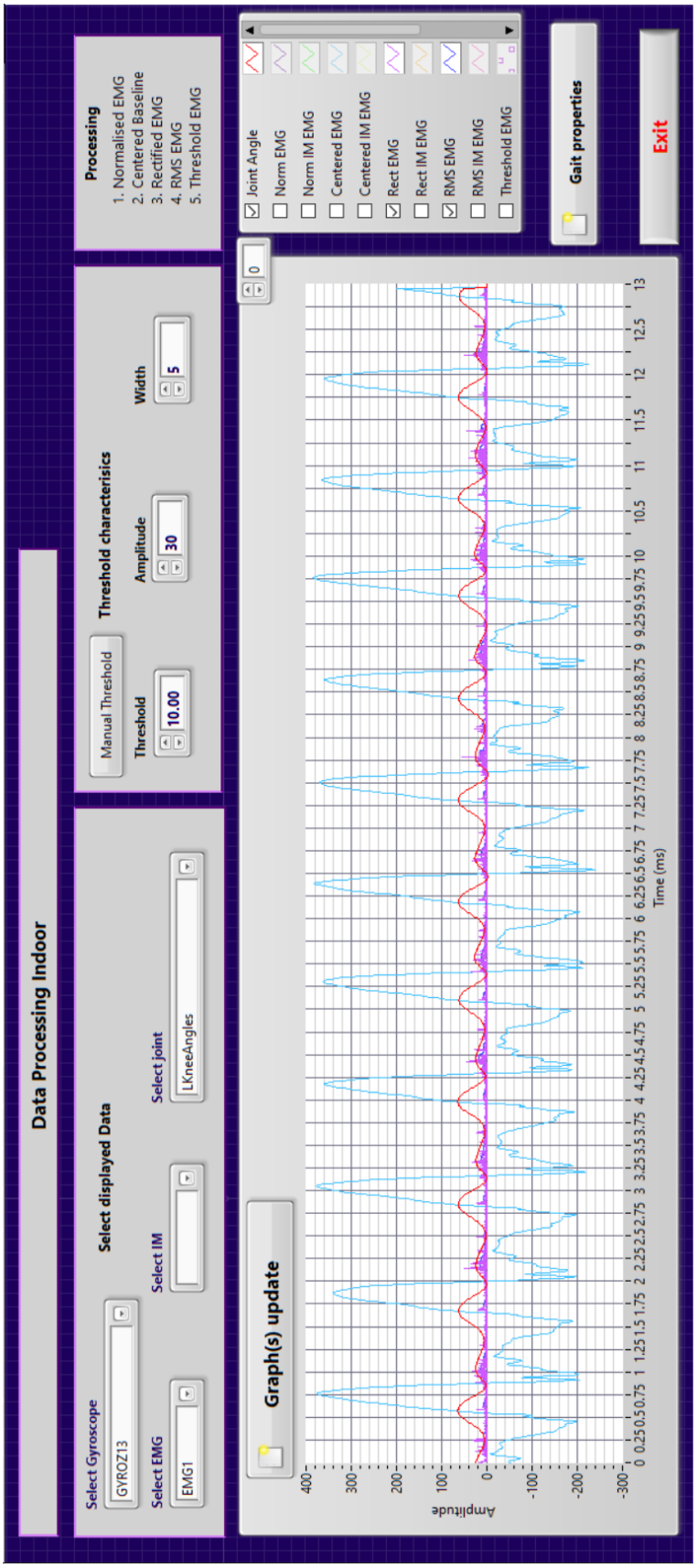


Figure G.1: Front panel GUI Data processing

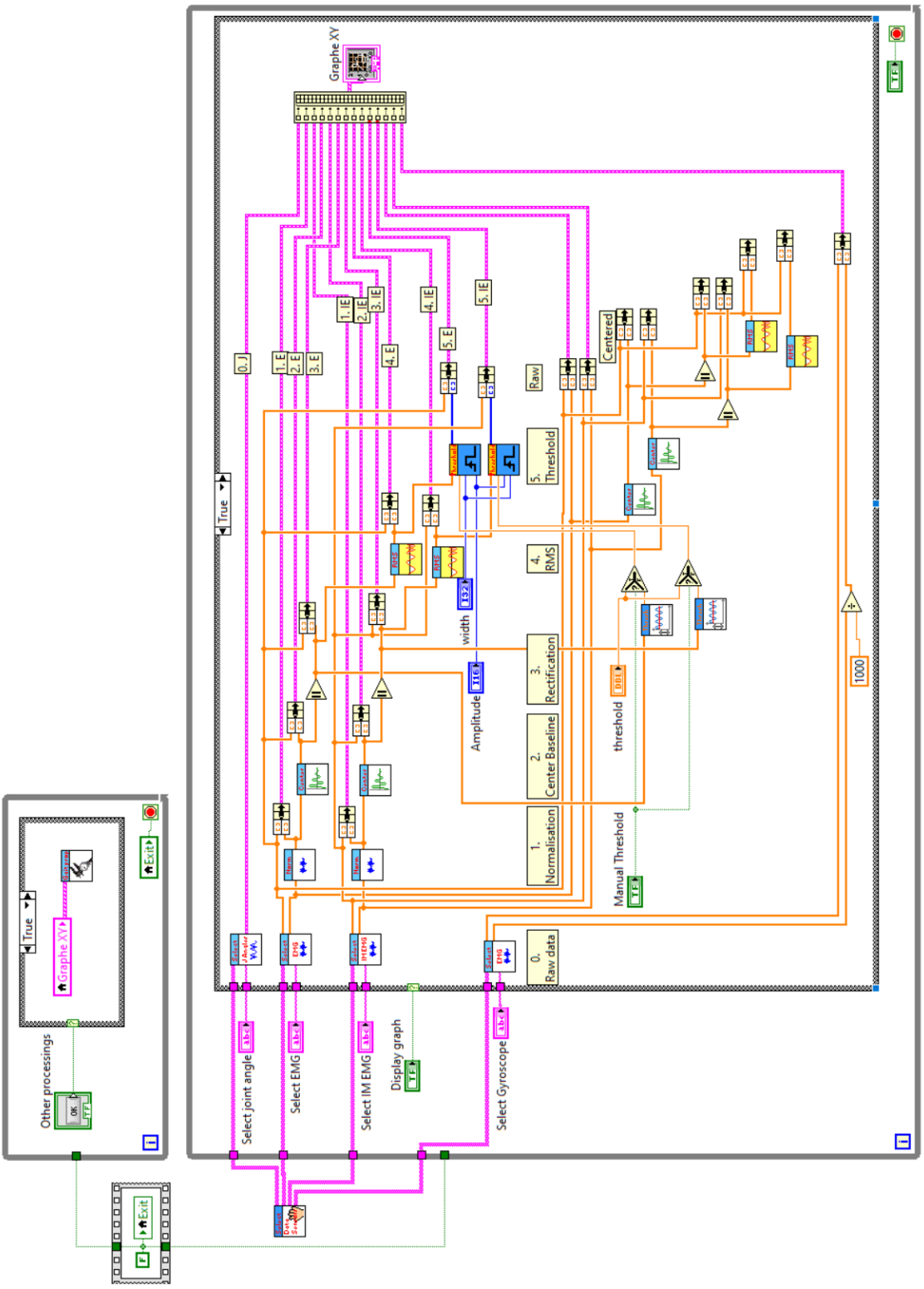


Figure G.2: Bloc diagram of the GUI Data processing VI. The different operation on the EMG are indicated by numbered labels. 0: reading of the raw data, 1: Normalisation, 2: centring of the data, 3: Rectification, 4: RMS, 5: threshold calculation.

Upon clicking on the gait properties button, on the bottom left of the interface, the user reaches another interface (GUI Gait properties, Figure G.3). Upon clicking on the “variance ratio” button, on the top right of the interface, the user reaches the interface where the variance ratio and other parameter are calculated. The button “Gait cycle” was originally designed to open an interface to where the computation of spatio-temporal data, however, it was neither used nor completed in this thesis.

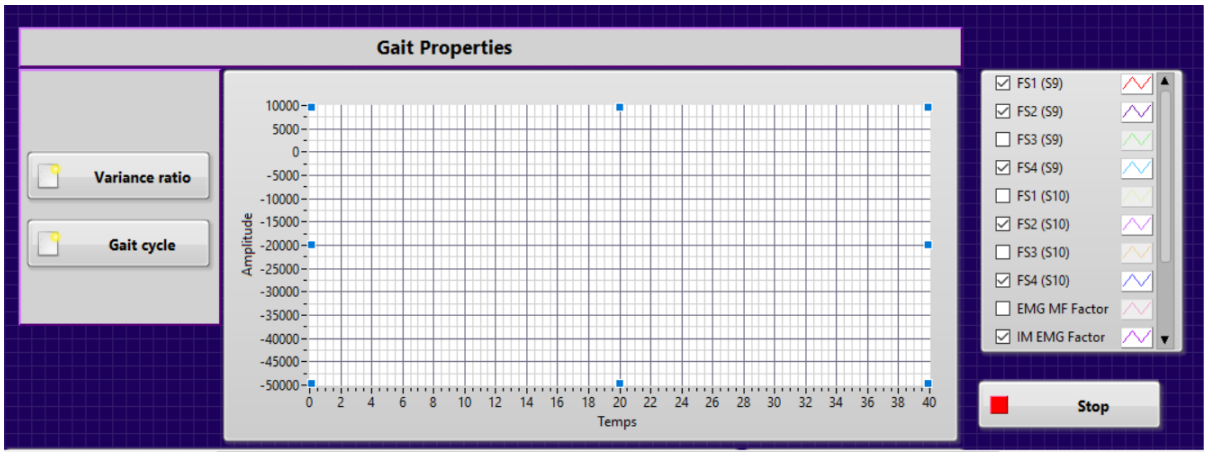


Figure G.3: GUI Gait properties panel, allow to choose between the computations associated to the variance ratio of the EMG envelope data and the gait cycle button was designed to lead to spatio-temporal computations (unachieved).

The interface “GUI Gait properties variance ratio” (Figure G.4) is the interface were the data relating to analysis of the EMG envelop signal.

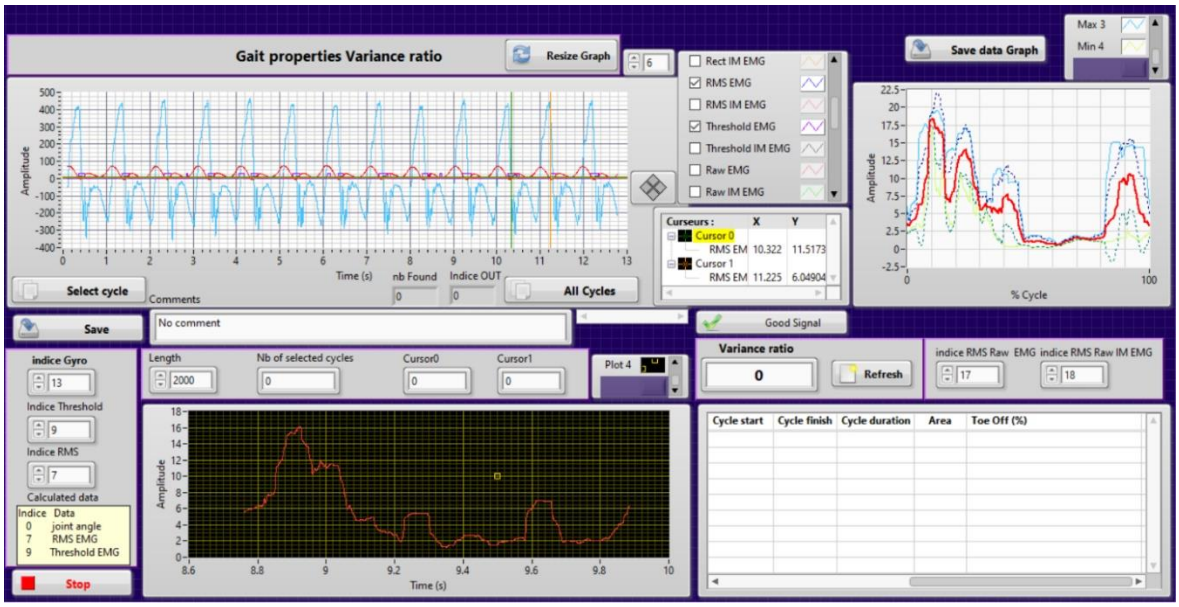


Figure G.4: GUI Gait properties Variance ratio front panel.

The top left graph (see Figure G.5) contains all the data from the “GUI Data processing” panel. It is equipped with cursors (that allow the manual selection of each gait cycle portions one by one. Once one cycle is selected the user clicks on the “Select cycle” and repeat the operation, as necessary. By clicking on the “All Cycles” button, the program will automatically select the sections of EMG envelope cycle per cycle and complete the variance ratio operations.

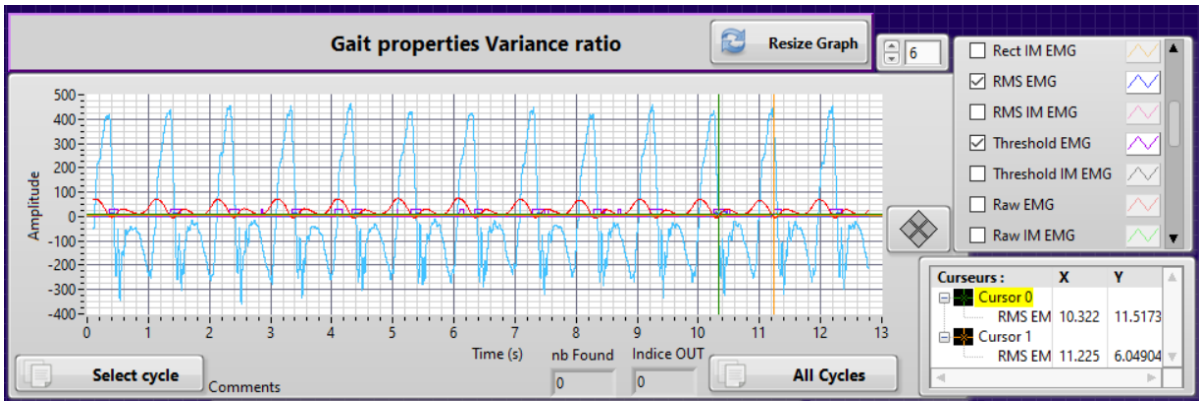


Figure G.5: Top left graph: contains EMG data for variance ratio computation. Allows both automatic (All cycles button) and manual, using the cursors (select cycle button) cycle selection.

The bottom right table (see Figure G.6) contains the results of several operations: the number of cycles, the variance ratio, the number of actuations per cycles, the action time (total duration of the contraction over one cycle), the timing of the star and of the finish of a gait cycle, the total duration of the cycle, and at which point of the cycle the foot contact stops (in % of cycle).

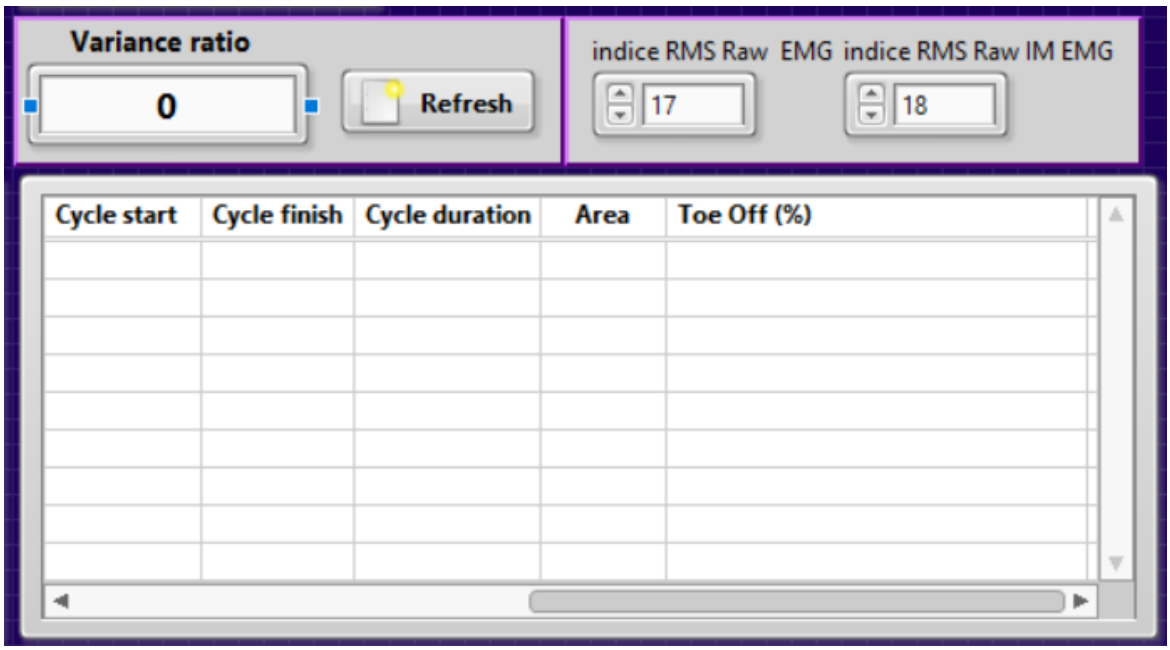


Figure G.6: Variance ratio computation table. Computes the number of cycles, the variance ratio, the number of actuations per cycles, the action time (total duration of the contraction over one cycle), the timing of the star and of the finish of a gait cycle, the total duration of the cycle, and at which point of the cycle the foot contact stops (in % of cycle).

The bottom left graph (see Figure G.7) represents for each cycle selected, the EMG envelope's shape (red curve) and the time of end of foot contact (yellow square).

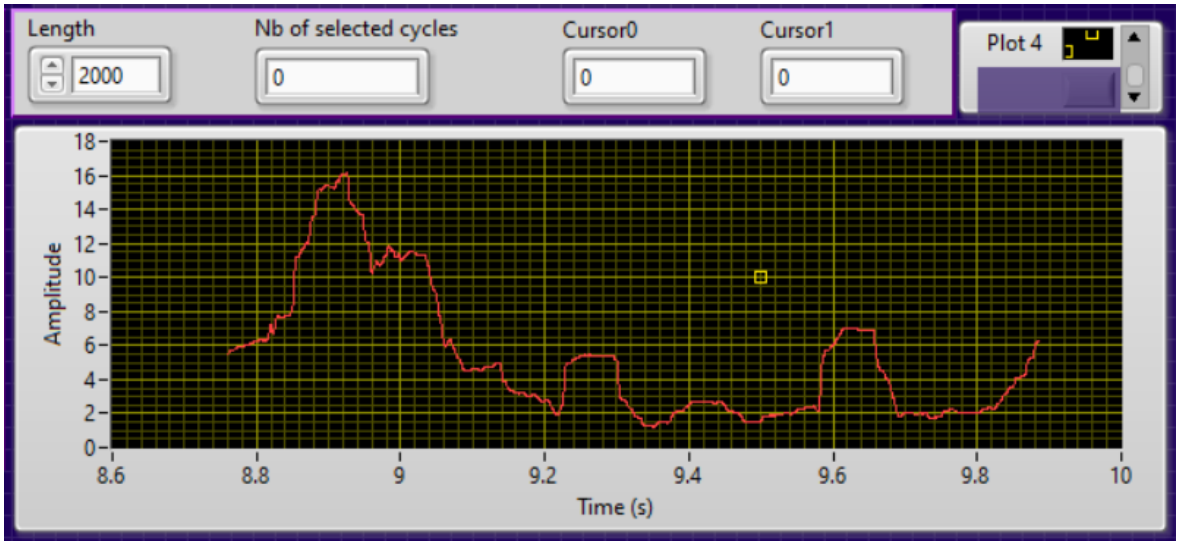


Figure G.7: Cycle per cycle representation of the EMG envelope (red curve) and the end of foot contact (yellow square).

The top right graph (see Figure G.8) represents the Mean envelope (in red), plus one standard deviation (dark blue short dashed line), minus one standard deviation (dark green dashed line), maximum (light blue) and minimum (light green) for all the cycles observed.

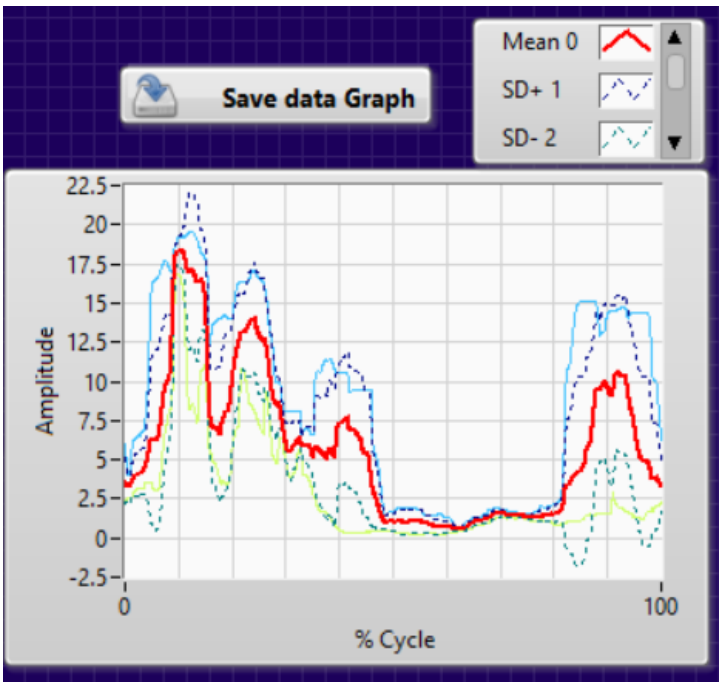
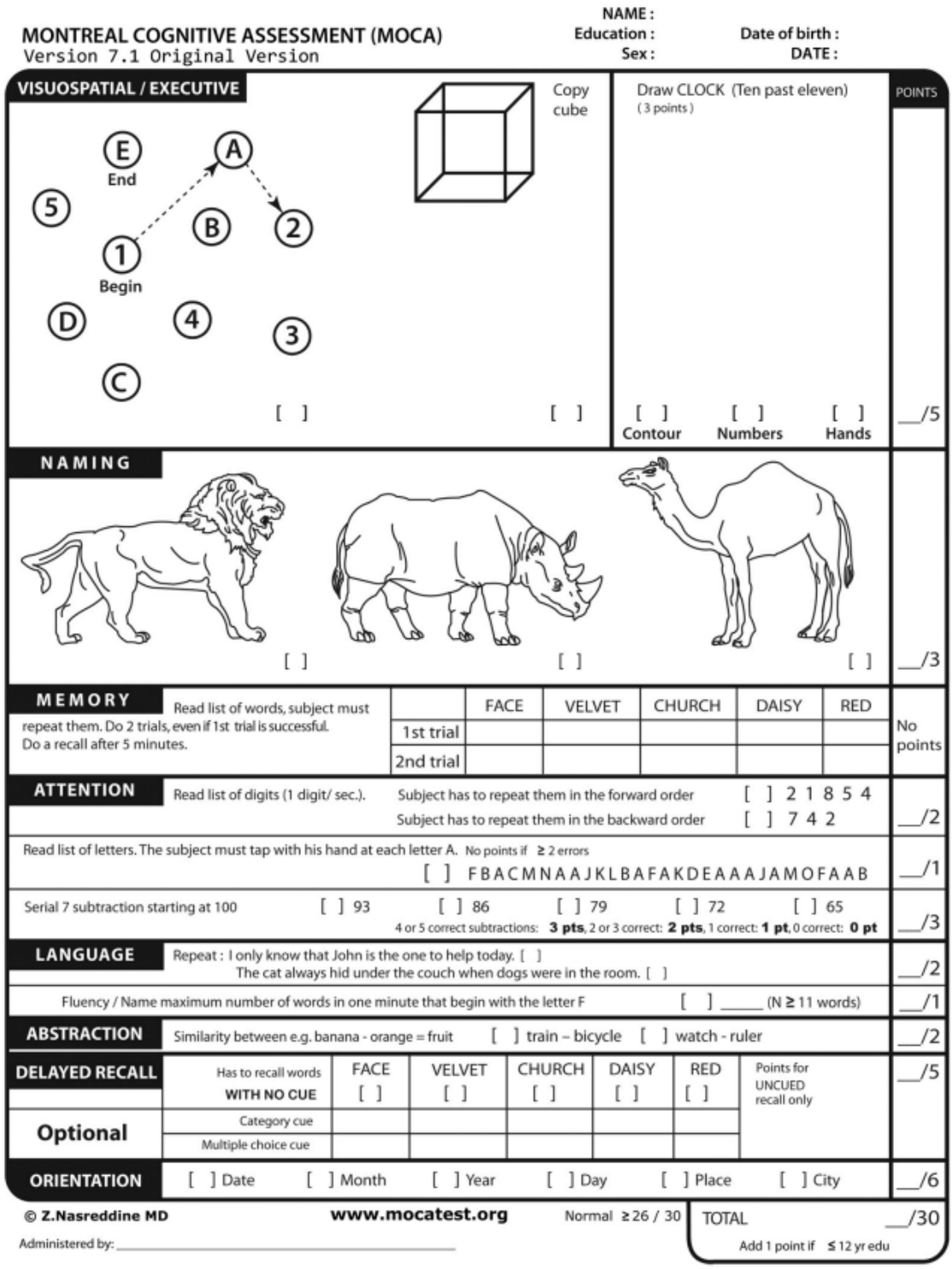


Figure G.8: Mean envelope (in red), plus one standard deviation (dark blue short dashed line), minus one standard deviation (dark green dashed line), maximum (light blue) and minimum (light green)

Annex H

H. Montreal Cognitive Assessment (MOCA)



MONTREAL COGNITIVE ASSESSMENT (MOCA)
Version 7.1 Original Version

NAME :
Education : Date of birth :
Sex : DATE :

VISUOSPATIAL / EXECUTIVE — POINTS

Copy cube [ ] [ ]

Draw CLOCK (Ten past eleven) (3 points) [ ] Contour [ ] Numbers [ ] Hands ___/5

NAMING [ ] [ ] [ ] ___/3

MEMORY Read list of words, subject must repeat them. Do 2 trials, even if 1st trial is successful. Do a recall after 5 minutes.

	FACE	VELVET	CHURCH	DAISY	RED
1st trial					
2nd trial					

No points

ATTENTION Read list of digits (1 digit/ sec.). Subject has to repeat them in the forward order [ ] 2 1 8 5 4
Subject has to repeat them in the backward order [ ] 7 4 2 ___/2

Read list of letters. The subject must tap with his hand at each letter A. No points if ≥ 2 errors
[ ] F B A C M N A A J K L B A F A K D E A A A J A M O F A A B ___/1

Serial 7 subtraction starting at 100 [ ] 93 [ ] 86 [ ] 79 [ ] 72 [ ] 65
4 or 5 correct subtractions: **3 pts**, 2 or 3 correct: **2 pts**, 1 correct: **1 pt**, 0 correct: **0 pt** ___/3

LANGUAGE Repeat : I only know that John is the one to help today. [ ]
The cat always hid under the couch when dogs were in the room. [ ] ___/2

Fluency / Name maximum number of words in one minute that begin with the letter F [ ] _____ (N ≥ 11 words) ___/1

ABSTRACTION Similarity between e.g. banana - orange = fruit [ ] train – bicycle [ ] watch - ruler ___/2

DELAYED RECALL — **Optional**

	Has to recall words WITH NO CUE	FACE	VELVET	CHURCH	DAISY	RED	Points for UNCUED recall only
		[ ]	[ ]	[ ]	[ ]	[ ]	
Optional	Category cue						
	Multiple choice cue						

___/5

ORIENTATION [ ] Date [ ] Month [ ] Year [ ] Day [ ] Place [ ] City ___/6

© Z.Nasreddine MD www.mocatest.org Normal ≥ 26 / 30

TOTAL ___/30
Add 1 point if ≤ 12 yr edu

Administered by: _____

Annex I

I. Stroke severity scales

The level of impairment following a stroke varies from case to case. There are several methods to measure the severity of a stroke, which help predict the level of physical autonomy a patient can have and therefore determine an appropriate rehabilitation program. These methods also contribute to the setting of physical goals for future evaluation in a patient's mobility post-rehabilitation.

The modified Rankin Scale [581]–[584] (mRS) rates is used to rate the global outcome of the stroke. This assessment tool assigns a rank, ranging from 0 to 5, with 0 describing no symptom and 5 describing severe disability. A mRS score of 0 to 2 equates to independent to mild disability and a score of 3 to 5 equates to moderate to severe disability.

The Barthel Index [585]–[587] (BI) is used to evaluate the independence of a patient in their self-care related activities of daily life. The total score of BI is out of 100. A high score indicates a high level of functional independence. A BI score of 75 or higher equates to a level of mild functional dependence to functional independence. A score below 75 equate to a levels of moderate to severe dependence [34].

The National Institutes of Health Stroke Scale (NIHSS) [588] is used to assess the neurological state of stroke patients. The NIHSS is composed of 11 items assessing the patient's level deficiencies in sensory capability, motor skills, language, consciousness, facial symmetry, and vision. The maximum potential score of the NIHSS is 42, with a high score being an indicator of a high level of stroke severity. A score of 1 to 4 equates to a mild stroke, 5 to 14 equate to mild to moderate stroke, 15 to 24 equates to a severe stroke and any score superior or equal to 25 equates to a very severe stroke.

The functional independence measure (FIM) [73], [74] is a scale composed of 18 items, 13 physical and 5 social-cognitive. The FIM ranges from 18 which corresponds to a total need of assistance, to 126 which corresponds to complete independence in all assessed items [74].

Cioncoloni et al. (2012) [589] compared the BI and the mRS at different stages post stroke. They concluded that after 3 months post stroke, the mRS describes the patient's functional status globally, at six months post stroke it is able to differentiate between various function levels. When used before three months after the incident of stroke, the mRS doesn't provide enough differentiation between the patients that are functionally dependent and the patients who are functionally autonomous [589].

Annex J

J. Paper

OCIMUM

Ibala E et al. J Ann Bioeng 2019(1): 47-55.
https://doi.org/10.33513/BIOE/1901-04

Journal of Annals of Bioengineering

Research Article

Comparison of the Muscle Pattern Variability During Treadmill Walking (Fixed and Self-Pace) and Over Ground Walking of Able-Bodied Adults

Eunice Ibala*, Sylvie Coupaud and Andrew Kerr

Department of Biomedical Engineering, University of Strathclyde, 40 George St, Glasgow G1 1XP, Lanarkshire, United Kingdom

Received: 25 March 2019
Accepted: 09 May 2019
Version of Record Online: 20 May 2019

Citation

Ibala E, Coupaud S, Kerr A (2019) Comparison of the Muscle Pattern Variability during Treadmill Walking (Fixed and Self-Pace) and Over Ground Walking of Able-Bodied Adults. J Ann Bioeng 2019(1): 47-55.

Correspondence should be addressed to
Eunice Ibala, United Kingdom
E-mail: eunice.ibala@strath.ac.uk

Abstract

Study purpose: The purpose of the study was to understand whether treadmill walking (fixed and self-paced) exhibits sufficiently similar motor patterns to overground walking to justify its use as a rehabilitation modality in the recovery of normal walking function. The study compared the activity patterns of five lower-limb muscle groups (Hamstrings, Quadriceps, Tibialis Anterior, Gastrocnemius and Soleus) while walking on a Traditional Treadmill (FPT), a Self-Paced Treadmill (SPT) and during Overground Walking (OG). The Variance Ratio (VR), which quantifies cycle-to-cycle repeatability, was used as the primary comparator with a higher VR indicating greater variability across cycles. Eleven able-bodied adults participated (mean age 27.8 years, weight 72.3 kg, 5 female).

Major findings: The VR observed during FPT walking (0.22) was higher than both the SPT (0.18) and OG (0.20) walking but these differences were not statistically significant (F=1.23, P=0.3).

Interpretation: Counter intuitively, FPT walking created a more variable pattern of muscle activity than SPT, possibly by constraining the natural tendency to vary speed. The similarity between SPT and OG suggests this form of treadmill walking may have better training specificity than FPT walking for functional gait recovery. This possibility should be tested in future statistically powered trials including clinical populations.

Conclusion: Differences in muscle activity variability, while not statistically significant, suggests that SPT walking may offer a more specific training experience than fixed pace for gait rehabilitation.

Keywords

Fixed-Pace; Gait Rehabilitation; Self-Paced Treadmill; Variance Ratio; EMG

Abbreviations

EMG	:	Electromyogram
FPT	:	Fixed-Pace Treadmill
OG	:	Overground
SPT	:	Self-Paced Treadmill
VR	:	Variance Ratio

Introduction

Treadmill training is used for the gait rehabilitation of several neurological conditions such as uncomplete spinal cord injury [1-3], stroke [4-7] and cerebral palsy [8,9]. The kinematics of treadmill walking are considered similar enough to over ground walking [10-12] to recommend it as an appropriate tool for gait training. While reduced range of motion at the hip and knee have been reported during treadmill walking, compared with Overground (OG), [11], the magnitude of the differences (-2°) is small enough to consider treadmill walking kinematically equivalent to OG walking. During treadmill walking, the maximums of the ground reaction force were found significantly lower than during OG [11]. Riley et al., [11] also reported significant smaller moments at the hip knee joints as well as lower power maximums. In children with cerebral palsy, treadmill walking requires less ankle power but greater hip moments [13]. Watt et al., [14] observed the situation of healthy older adults during treadmill and OG walking. Treadmill walking induced lower power and lower moments compared with OG walking [14]. In terms of kinematics, the elderly participants presented shorter stride time, stride length and greater cadence [14].

The measurement of biomechanical variables has generated substantial insight into the mechanics of both normal [10,11,15] and impaired gait [7,8,16]. It can, however, only provide indirect evidence of the underlying control of the movement which is produced by the muscle activity. Rehabilitation, whether through manual techniques [17-19] or electrical stimulation [20,21] seeks to influence this muscle activity to attain better control of the movement. Understanding the effectiveness of these therapies can only be gained through direct measurement of muscle or motor cortex excitation, since the motor cortex is a principal actor in the changes in gait as its controls the muscle activity of the muscle groups at different stages of the gait cycle in order to achieve the target position [22,23]. The observation of muscle activity is therefore important information to observe when studying movement.

Martin and Li quantified muscle activity and measured the energy consumption during treadmill and OG walking [15]. Walking on a treadmill led to greater muscle activity defined by the root-mean-square and higher peak muscle activity [15], indicating higher energy expenditure. Lee and Hidler [10] also compared the muscle activity between treadmill and OG walking. They observed that, during treadmill walking the activity of the tibialis anterior and gastrocnemius was lower during the stance phase but higher during terminal swing compared to OG. The selected thigh muscles (adductor longus, vastus medialis, hamstrings) presented a higher activity OG from early to mid-swing and at the end of the swing phase and the muscle activity was lower than during treadmill walking [10].

Clinical trials have found that treadmill training can improve endurance and functional mobility of stroke patients [4-6]. However, the level of mobility achieved is typically not sufficient to regain independent community ambulation [5,24]. Ada et al., [24] and Globas et al., [5] both reported that while most stroke patients (60-80%) were capable of walking independently at discharge, they were still limited in their walking abilities due to reduced walking speed [24] and the decrease of cardiovascular fitness linked to reduced mobility [5]. The predictable nature of standard treadmill walking, with unvarying speeds, can be useful for training symmetrical gait [7,16,25] but does not reflect community walking which is inherently variable and less predictable [26-28]. Rehabilitation outcomes are improved when the training modality matches the intended outcome [29], if independent community walking is the desired outcome, training should incorporate speed variation within a multi-sensorial experience that attempts to simulate the complexity and challenging nature of community walking, for example through the use of a virtual environment [30].

Self-Paced Treadmill (SPT) training differs from standard FPT training in that the treadmill can adapt its belt speed to the user's own speed, using position detection systems (e.g. motion analysis technology), making it possible to naturally vary walking speed. When combined with a virtual reality environment, this treadmill walking experience has been considered to be more similar to over ground walking than a traditional fixed pace treadmill [31,32].

The aim of this study was to test which type of treadmill walking (fixed or self-paced) was a better analogue for OG walking in terms of the muscle activity. This knowledge could help to optimise rehabilitation approaches for the recovery of functional walking, including community walking, by providing clear guidance on which type of treadmill training is most similar to everyday walking. To gain this understanding, the repeatability of the muscle pattern of five lower-limb muscle groups, selected for their primary role in walking, were compared between FPT, SPT and OG walking in healthy able-bodied participants.

The hypothesis tested in this study is that SPT walking will show more similarities with OG walking than FPT walking in terms of muscle pattern repeatability.

Materials and Methods

Study design: This was an observational study comparing the

repeatability of lower-limb muscle activity patterns (measured with EMG) during three walking scenarios: FPT, SPT and indoor OG walking. For each participant, EMG recordings were made for each walking scenario, during which 20 to 30 steps were recorded. Each scenario was recorded at least three times.

Participants: Participants were unimpaired adults (6 male and 5 females) with a mean age of 27.8 years, (range 19 to 56), mean weight 72.3 kg (range 59.5 to 118 kg). Participants were recruited from the student body of a University using the following criteria; able to walk unassisted for a minimum of 500 m and communicate in English. Participants with a history of motion sickness, known to be pregnant or with a musculoskeletal injury that impaired their ability to walk were excluded. Wireless EMG electrodes (Delsys Trigno, Boston, USA) were then attached to the skin overlying five muscles of interest on both legs (hamstrings (biceps femoris), quadriceps (vastus lateralis), gastrocnemius, tibialis anterior and soleus) following the SENIAM recommendations [33].

All participants read an information sheet and signed a consent form that had been approved by the local ethics committee (reference KR/LG DEC.BioMed.2016.79).

Equipment: 3D kinematic data (joint angles and lower limb displacements) were collected using a 12-camera motion capture system (VICON, Oxford Metrics, Oxford, UK), at a sampling frequency of 100Hz. The cameras tracked reflective markers placed on body landmarks (Figure 1) according to the manufacturer's Plug-In-Gait model (VICON, Oxford Metrics, Oxford, UK). The kinematic data were only used as a means of identifying the different gait cycles. The treadmill data were recorded over 20 to 30 steps using a CAREN (Computer Assisted Rehabilitation Environment, Motek Medical, Amsterdam) N-mill treadmill system (Figure 2). Wireless EMG surface electrode (Delsys Trigno, Boston, USA) were used to record muscle activity (Figure 1), at a sampling frequency of 2kHz. The skin was prepared prior to EMG sensor attachment (including shaving if necessary and rubbing with alcohol) and the electrodes were attached to the skin using double sided sticking tape at anatomical locations.

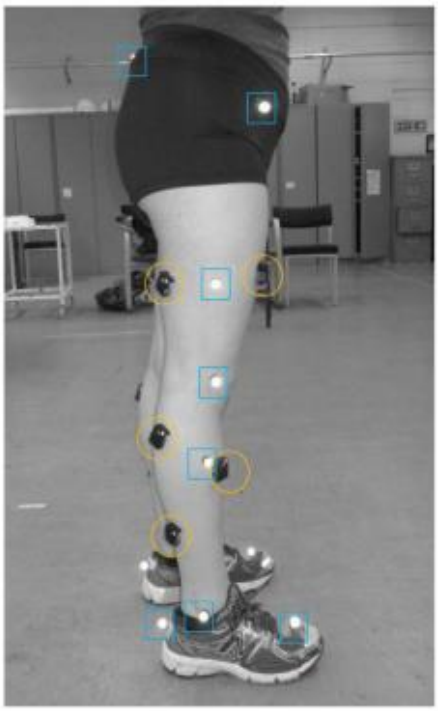


Figure 1: Wireless EMG electrodes (in circles) and reflective markers (in rectangles) placement.

Figure 2: Participant walking on the Motek CAREN treadmill platform facing a 180° virtual environment screen.

Movement tasks: Participants were first asked to walk in a straight line in a flat, well-lit gait lab. This OG walk was repeated four times at three speeds (comfortable, slow and fast). The recordings at the three different speeds allowed referring to them as everyday life walking situations such as fast walk as when running late to catch a bus, slow walk as during a stroll in the park on a warm sunny day. Also, the analysis of the data at different speeds and how they influence the EMG data outcome might be the object of further investigations. The participant then walked on the treadmill at a fixed pace. The data were collected during continuous walking, after a period of adaptation to the treadmill of around three to five minutes. The FPT walk was performed at three self-selected walk paces (comfortable, slow and fast). To determine the participant's preferred self-selected speed, the treadmill speed was initially set at a speed of 0.8 m/s. Then the speed was increased or decreased according to the request of the user until the comfortable speed was reached.

Only the comfortable self-selected speed's results will be presented here. The same procedure was repeated for the collection of self-paced walking data. Participants wore comfortable shoes (trainers) throughout.

Variance Ratio (VR) calculations: The variability of the EMG signal was calculated for each muscle during each of the three walking conditions (SPT, FPT, OG) at the self-selected comfortable walking speed of each participant, using a mathematical parameter known as the Variance Ratio (VR). The VR was used to compare the envelopes of the EMG signals. The EMG signal was first normalised to the maximal amplitude of the muscle signal. The signal was then centred around 0 by subtracting its median value to the signal, leaving as many values over zero than below zero. The signal was then rectified. The envelope was designed as the Root Mean Square (RMS) of the signal which also leads to a smoother signal.

The VR is defined as the sum of the square of the deviation from the mean envelope of the EMG, over one gait cycle divided by the sum of the square of the deviation from the mean EMG envelope of all recorded cycles. When the consecutive cycles have very different shapes the VR value is close to 1, whereas, when the shapes are similar the VR is closer to 0. The VR was calculated over six consecutive gait cycles for each condition.

$$VR = \frac{\sum_{i=1}^{k}\sum_{j=1}^{n}(X_{ij}-\overline{X_i})^2/k(n-1)}{\sum_{i=1}^{k}\sum_{j=1}^{n}(X_{ij}-\overline{X})^2/(kn-1)} \quad (1)$$

Where X_{ij} is the value of the j^{th} EMG envelope element at time i, $\overline{X}$ is the mean of the average EMG envelope signal, $\overline{X_i}$ is the average of the EMG envelope values over j cycles at time i, k is the number of points in a cycle and n is the number of cycles.

To analyse the variability of the muscle activity, the VR was used [34,35]. For each participant, the VR data of muscles from both sides were averaged to produce one value per muscle.

Statistical analysis

The VR were compared statistically across the three walking conditions at the comfortable walking speed using a repeated ANOVA. A level of statistical significance was set at $p<0.05$. The participant's speed and step length were also statistically compared using a one way ANOVA, with a level of statistical significance set at $p<0.05$.

Results

Variance Ratio: The results of the inter-individual analyses are shown in table 1. When all muscles were combined the FPT walking had the largest mean VR value and wider range of VR values (Mean VR = 0.22, mean Range = 0.75) compared to SPT (Mean VR = 0.18, mean Range = 0.46) and OG walking (Mean VR = 0.20, mean Range = 0.55).

The repeated ANOVA analysis did not reveal any significant differences between the three walking scenarios, apart for the soleus muscle ($p=0.019$) which presented higher VR values during FPT walking. There was, however, a trend for the VR values, to be lower for SPT and OG walking for all muscle groups, except for the hamstrings which had its highest VR during OG walking (Figure 3).

The following table shows the superimposition of the muscle signals (envelope and rectified signal) over six gait cycles. The duration of each gait cycle was normalised in order to observe the variability of the signal. The upper leg muscles (hamstrings and quadriceps) appear to present more repeatability across the different walking scenarios in comparison to the Tibialis anterior and the soleus. In this case the Hamstrings show more variability during OG than in the other cases. While the soleus appeared to act during the swing phase only during SPT, it appears to be activated also during stance during SPT and OG.

		FP	SP	OG
Hams	mean VR	0.16	0.16	0.21
	(SD)	0.11	0.12	0.15
	Variance	0.01	0.01	0.02
	Range	0.4	0.42	0.48
Quad	mean VR	0.19	0.13	0.19
	(SD)	0.18	0.12	0.12
	Variance	0.03	0.01	0.01
	Range	0.74	0.48	0.48
Gas	mean VR	0.26	0.2	0.21
	(SD)	0.24	0.12	0.15
	Variance	0.06	0.01	0.02
	Range	0.86	0.44	0.62
TibA	mean VR	0.29	0.24	0.19
	(SD)	0.24	0.19	0.15
	Variance	0.06	0.03	0.02
	Range	0.89	0.58	0.68
Sol *	mean VR	0.22	0.15	0.18
	(SD)	0.18	0.09	0.12
	Variance	0.03	0.01	0.01
	Range	0.87	0.39	0.49
TOTAL	**Mean VR**	**0.224**	**0.176**	**0.196**
	Mean Variance	0.038	0.014	0.016
	Mean Range	**0.752**	**0.462**	**0.55**

Table 1: Descriptive statistics of the VR for each muscle group Hamstrings (Hams) Quadriceps (Quad), Gastrocnemius (Gas), Tibialis Anterior (TibA) and Soleus (Sol) in Fixed Pace (FP), Self-Pace (SP) and Overground (OG) walking, at a comfortable (Comf) self-selected walking speed; *$p<0.05$.

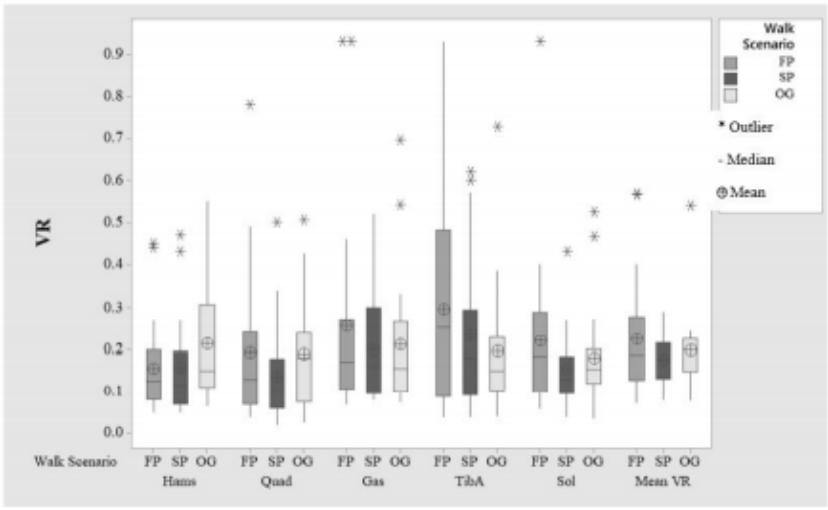


Figure 3: Mean VR value for each muscle group at the self-selected comfortable speed for the three walking scenarios.

Muscle	FP	SP	OG
Hams			
Quad			
Gas			
TibA			
Soleus			

Table 2: Superimposed muscle Activity pattern over six gait cycles for one participant. For each muscle, on top the EMG envelopes, at the bottom the rectified EMG signals.

Walking speed and step length: The average walking speed across the participants was slower during FPT walking (1.25±0.16 m/s) in comparison with SPT and OG walking. The slower walk during FPT at a self-selected speed in comparison to OG as been previously reported in the literature previously [36,37]. The speed was the fastest during SPT walking s presented in table 3. The step length was the shortest during OG walking (0.60±0.04 m) and longest during SPT walking (0.70±0.09 m).

The results of the ANOVA analysis showed no significant differences between the speeds of the different walking situations (p=0.194). The outcome of the ANOVA analysis of the step length show significant differences between the walking situations (p=0.013), in this case, the step length during SPT were found significantly different from OG's step length.

Participant	Speed (m/s)			Step length (m)		
n°	FP	SP	OG	FP	SP	OG
1	1.15	1.37	1.32	0.63	0.72	0.65
2	1.2	1.32	1.3	0.63	NA	0.53
3	1.35	1.32	1.43	0.68	0.68	0.61
4	1.15	1.28	1.12	0.6	0.67	0.56
5	1.25	1.6	1.21	0.67	0.78	0.57
6	1.3	1.28	1.43	0.63	0.64	0.61
7	1.55	1.83	1.49	0.77	0.84	0.64
8	0.9	1	1.35	0.52	0.52	0.57
9	1.3	1.4	1.37	0.66	0.71	0.64
10	1.3	1.3	1.47	0.65	0.65	0.66
11	1.35	1.5	1.34	0.73	0.77	0.61
Mean	1.25	1.38	1.35	0.65	0.70	0.60
SD	0.16	0.21	0.11	0.07	0.09	0.04

Table 3: Walking speed and step length per participants.

Discussion

The hypothesis tested in this study was that SPT walking would show more similarities with OG walking than FPT walking. While the individual VR values support this hypothesis with a small sample, no statistical significances were observed.

Observation of muscle variability

Range of the VR: The larger range of VR during FPT walking suggests that the muscle activity is more variable cycle to cycle during this type of walking compared to SPT and OG. In their study on monkeys, Goodkin and Thach [38] found that more muscles than necessary were activated when the primate was performing a constrained task. In contrast, when the task was performed freely the muscle activity was consistent with the minimum required to perform the movement. Similarly, the result of our study could be explained by the restrictive nature of FPT walking which may not replicate normal OG walking. Indeed, FPT walking may impose a non-natural recruitment pattern that activates more muscle groups than necessary for normal gait.

It appears, therefore that the use of SPT should be integrated to the treadmill training instead of FPT as it may better prepare the patient for natural overground walking.

Interpretation of the higher variability: FPT walking has been described as an unnatural walk that is simplified due to the reduction of the normal comfortable speed and stepping variations, leading to a predictable and repetitive pattern of walk [12,39]. Treadmill walking is described by Hollman et al., [40] as the imposition of mechanical constraints that affect the gait dynamic. The higher variability (high VR values) of the FP agrees with Berstein's statement regarding the motor control associated with the repetition of precise tasks. To perform successfully a task that require precision several times, it is necessary to possess a large range of motor control variability [41].

Limitations of this Study

Number of participants and its influence on statistical significance: This study only included 11 unimpaired

participants and so lack of statistical significance when comparing VRs between the different walking situations could be due partly to the small sample size. Despite this, there was a trend for the VR to be smaller during SPT walking than in the other two types of walking (OG and FPT). EMG is a notoriously a noisy signal so a larger sample might clarify the differences.

Familiarity with treadmill walking: Another factor that might have affected the results was each participant's level of familiarity with treadmill walking. The recruitment criteria did not define or restrict prior experience of walking on a treadmill. This potential risk was moderated by the fact that participants were given time for familiarisation with the treadmill before data recording was initiated. However, this familiarisation time was not fixed, and may have been insufficient for some individuals, introducing an unquantified influence. Papegaaiji and Steenbrink [12] recommended a treadmill familiarisation of at least six minutes. This could be used to improve the data collection for future work on treadmill data collection.

Clinical implication: Taking into account the ultimate goal of recovery and the afore mentioned utility to make the training match the end goal [29], the practice of speed variation is necessary in order to perform efficiently everyday walking. While the amount of training and the administration of the training have still to be measured and adjusted, the integration of SPT walking in the gait rehabilitation could provide further insurance of the walking independence of the rehabilitation patients.

It appears that FPT training is preferable when the end goal of the rehabilitation training is to improve fitness as it has been proven effective and important. SPT might be preferable when the end goal is to prepare to everyday indoor and outdoor community walking. The combination of SPT with a virtual environment can make SPT treadmill walking a tool of choice to practice overground walking, speed changes and/or practice obstacle avoidance or negotiation.

Conclusion

While no statistically significant difference was observed between FPT, SPT and indoor OG walking, the VR values during SPT and OG walking were the closest compared to FPT which had the highest VR values. These observations suggest that SPT might be a more relevant training practice than fixed pace for gait rehabilitation.

Conflict of Interests

All authors declare no conflicts of interest in this article.

References

1. Dobkin B, Apple D, Barbeau H, Basso M, Behrman A, et al. (2006) Weight-supported treadmill vs over-ground training for walking after acute incomplete SCI. Neurology 66: 484-493.
2. Wernig A (2006) Weight-supported treadmill vs over-ground training for walking after acute incomplete SCI. Neurology 67: 1900.
3. van Dijsseldonk RB, de Jong LAF, Groen BE, Vos-van der Hulst M, Geurts ACH, et al. (2018) Gait Stability Training in a Virtual Environment Improves Gait and Dynamic Balance Capacity in Incomplete Spinal Cord Injury Patients. Front Neurol 9: 963.
4. Mackay-Lyons M, McDonald A, Matheson J, Eskes G, Klus MA (2013) Dual Effects of Body-Weight Supported Treadmill Training on Cardiovascular Fitness and Walking Ability Early After Stroke A Randomized Controlled Trial. Neurorehabil Neural Repair 27: 644-653.
5. Globas C, Becker C, Cerny J, Lam JM, Lindemann U, et al. (2012) Chronic Stroke Survivors Benefit from High-Intensity Aerobic Treadmill Exercise A Randomized Control Trial. Neurorehabil Neural Repair 26: 85-95.
6. Macko RF, Ivey FM, Forrester LW, Hanley D, Sorkin JD, et al. (2005) Treadmill Exercise Rehabilitation Improves Ambulatory Function and Cardiovascular Fitness in Patients with Chronic Stroke: A Randomized, Controlled Trial. Stroke 36: 2206-2211.
7. Chen G, Patten C, Kothari DH, Zajac FE (2005) Gait deviations associated with post-stroke hemiparesis: improvement during treadmill walking using weight support, speed, support stiffness, and handrail hold. Gait Posture 22: 57-62.
8. Cho C, Hwang W, Hwang S, Chung Y (2016) Treadmill Training with Virtual Reality Improves Gait, Balance, and Muscle Strength in Children with Cerebral Palsy. Tohoku J Exp Med 238: 213-218.
9. Wu M, Kim J, Gaebler-Spira DJ, Schmit BD, Arora P (2017) Robotic Resistance Treadmill Training Improves Locomotor Function in Children with Cerebral Palsy: A Randomized Controlled Pilot Study. Arch Phys Med Rehabil 98: 2126-2133.
10. Lee SJ, Hidler J (2008) Biomechanics of overground vs. treadmill walking in healthy individuals. J Appl Physiol 104: 747-755.
11. Riley PO, Paolini G, Della Croce U, Paylo KW, Kerrigan DC (2007) A kinematic and kinetic comparison of overground and treadmill walking in healthy subjects. Gait Posture 26: 17-24.
12. Papegaaij S, Steenbrink F (2017) Clinical gait analysis: Treadmill-based vs overground. Motek, Amsterdam, The Netherlands.
13. van der Krogt MM, Sloot LH, Buizer AI, Harlaar J (2015) Kinetic comparison of walking on a treadmill versus over ground in children with cerebral palsy. J Biomech 48: 3577-3583.
14. Watt JR, Franz JR, Jackson K, Dicharry J, Riley PO, et al.,

(2010) A three-dimensional kinematic and kinetic comparison of overground and treadmill walking in healthy elderly subjects. Clin Biomech 25: 444-449.

15. Martin JP, Li Q (2017) Overground vs. treadmill walking on biomechanical energy harvesting: An energetics and EMG study. Gait Posture 52: 124-128.
16. Harris-Love ML, Forrester LW, Macko RF, Silver KH, Smith GV (2001) Hemiparetic Gait Parameters in Overground Versus Treadmill Walking. Neurorehabil Neural Repair 15: 105-112.
17. Langhorne P, Bernhardt J, Kwakkel G (2011) Stroke rehabilitation. Lancet 377: 1693-1702.
18. Richards CL, Malouin F, Nadeau S (2015) Stroke rehabilitation: clinical picture, assessment, and therapeutic challenge. Prog Brain Res 218: 253-280.
19. Dobkin B (2005) Rehabilitation after Stroke. N Engl J Med 352: 1677-1684.
20. Micera S, Keller T, Lawrence M, Morari M, Popovic DB (2010) Wearable Neural Prostheses. IEEE Eng Med Biol Mag 29: 64-69.
21. Laufer Y, Elboim-Gabyzon M (2011) Does Sensory Transcutaneous Electrical Stimulation Enhance Motor Recovery Following a Stroke? A Systematic Review. Neurorehabil Neural Repair 25: 799-809.
22. Drew T, Marigold DS (2015) Taking the next step: cortical contributions to the control of locomotion. Curr Opin Neurobiol 33: 25-33.
23. Turvey MT, Fonseca S (2009) Nature of Motor Control: Perspectives and Issues. In: Sternad D (ed.). Progress in Motor Control. Advances in Experimental Medicine and Biology. Springer, Boston, MA, USA. Pg no: 93-123.
24. Ada L, Dean CM, Hall JM, Bampton J, Crompton S (2003) A treadmill and overground walking program improves walking in persons residing in the community after stroke: a placebo-controlled, randomized trial. Arch Phys Med Rehabil 84: 1486-1491.
25. Feasel J, Whitton MC, Kassler L, Brooks FP, Lewek MD (2011) The Integrated Virtual Environment Rehabilitation Treadmill System. IEEE Trans Neural Syst Rehabil Eng 19: 290-297.
26. Lord S, Rochester L (2008) Gait Velocity and Community Ambulation: The Limits of Assessment. Stroke 39: e75.
27. Lord SE, Rochester L, Weatherall M, McPherson KM, McNaughton HK (2006) The Effect of Environment and Task on Gait Parameters After Stroke: A Randomized Comparison of Measurement Conditions. Arch Phys Med Rehabil 87: 967-973.
28. Patla AE, Shumway-Cook A (1999) Dimensions of Mobility: Defining the Complexity and Difficulty Associated with Community Mobility. J Aging Phys Act 7: 7-19.
29. Hornby TG, Straube DS, Kinnaird CR, Holleran CL, Echauz AJ, et al. (2011) Importance of Specificity, Amount, and Intensity of Locomotor Training to Improve Ambulatory Function in Patients Poststroke. Top Stroke Rehabil 18: 293-307.
30. Mirelman A, Patritti BL, Bonato P, Deutsch JE (2010) Effects of virtual reality training on gait biomechanics of individuals post-stroke. Gait Posture 31: 433-437.
31. Plotnik M, Azrad T, Bondi M, Bahat Y, Gimmon Y, et al. (2015) Self-selected gait speed - over ground versus self-paced treadmill walking, a solution for a paradox. J Neuro Engineering Rehabil 12: 20.
32. Sloot LH, van der Krogt MM, Harlaar J (2014) Self-paced versus fixed speed treadmill walking. Gait Posture 39: 478-484.
33. http://seniam.org/sensor_location.htm [Accessed: 13-Feb-2019].
34. Hershler C, Milner M (1978) An Optimality Criterion for Processing Electromyographic (EMG) Signals Relating to Human Locomotion. IEEE Trans Biomed Eng 25: 413-420.
35. Richards RE, Thornton MT, Delaney RMR (2014) EMG variance ratio- A useful clinical outcome measure? Gait Posture 39: 80-81.
36. Row Lazzarini BS, Kataras TJ (2016) Treadmill walking is not equivalent to overground walking for the study of walking smoothness and rhythmicity in older adults. Gait Posture 46: 42-46.
37. Dal U, Erdogan T, Resitoglu B, Beydagi H (2010) Determination of preferred walking speed on treadmill may lead to high oxygen cost on treadmill walking. Gait Posture 31: 366-369.
38. Goodkin HP, Thach WT (2003) Cerebellar Control of Constrained and Unconstrained Movements. II. EMG and Nuclear Activity. J Neurophysiol 89: 896-908.
39. Hollman JH, Watkins MK, Imhoff AC, Braun CE, Akervik KA, et al. (2016) A comparison of variability in spatiotemporal gait parameters between treadmill and overground walking conditions. Gait Posture 43: 204-209.
40. Hollman JH, Watkins MK, Imhoff AC, Braun CE, Akervik KA, et al. (2016) Complexity, fractal dynamics and determinism in treadmill ambulation: Implications for clinical biomechanists. Clin Biomech 37: 91-97.
41. Latash ML (1998) Progress in motor control: Bernstein's traditions in movement studies. Human Kinetics, Champaign, IL, USA.

Bibliography

[1] M. Nichols, N. Townsend, P. Scarborough, and M. Rayner, 'Cardiovascular disease in Europe: epidemiological update', *Eur. Heart J.*, vol. 34, no. 39, pp. 3028–3034, Oct. 2013, doi: 10.1093/eurheartj/eht356.

[2] Ö. Saka, A. McGuire, and C. Wolfe, 'Cost of stroke in the United Kingdom', *Age Ageing*, vol. 38, no. 1, pp. 27–32, Jan. 2009, doi: 10.1093/ageing/afn281.

[3] 'WHO | The top 10 causes of death', *WHO*. http://www.who.int/mediacentre/factsheets/fs310/en/ (accessed Jun. 29, 2017).

[4] The European Registers of Stroke (EROS) Investigators, 'Incidence of Stroke in Europe at the Beginning of the 21st Century', *Stroke*, vol. 40, no. 5, pp. 1557–1563, May 2009, doi: 10.1161/STROKEAHA.108.535088.

[5] 'Scottish Stroke Statistics', p. 44, Jan. 2019.

[6] S. Li, G. E. Francisco, and P. Zhou, 'Post-stroke Hemiplegic Gait: New Perspective and Insights', *Front. Physiol.*, vol. 9, 2018, doi: 10.3389/fphys.2018.01021.

[7] J. Jonsdottir and M. Ferrarin, 'Gait Disorders in Persons After Stroke', in *Handbook of Human Motion*, B. Müller, S. I. Wolf, G.-P. Brueggemann, Z. Deng, A. McIntosh, F. Miller, and W. S. Selbie, Eds. Cham: Springer International Publishing, 2017, pp. 1–11.

[8] A. Pollock, B. S. George, M. Fenton, and L. Firkins, 'Top ten research priorities relating to life after stroke', *Lancet Neurol.*, vol. 11, no. 3, p. 209, Mar. 2012, doi: 10.1016/S1474-4422(12)70029-7.

[9] R. Dickstein, 'Rehabilitation of Gait Speed After Stroke: A Critical Review of Intervention Approaches', *Neurorehabil. Neural Repair*, vol. 22, no. 6, pp. 649–660, Nov. 2008, doi: 10.1177/1545968308315997.

[10] P. S. Jones *et al.*, 'Does stroke location predict walk speed response to gait rehabilitation?', *Hum. Brain Mapp.*, vol. 37, no. 2, pp. 689–703, 2016, doi: 10.1002/hbm.23059.

[11] P. Langhorne, F. Coupar, and A. Pollock, 'Motor recovery after stroke: a systematic review', *Lancet Neurol.*, vol. 8, no. 8, pp. 741–754, Aug. 2009, doi: 10.1016/S1474-4422(09)70150-4.

[12] J. A. Edlow, *Stroke*. Westport, Conn: Greenwood Press, 2008.

[13] 'Global Stroke Fact Sheet', *World Stroke Organization (WSO)*, 2019. https://www.world-stroke.org/assets/downloads/WSO_Global_Stroke_Fact_Sheet.pdf (accessed Jun. 04, 2020).

[14] P. B. Gorelick, 'The global burden of stroke: persistent and disabling', *Lancet Neurol.*, vol. 18, no. 5, pp. 417–418, May 2019, doi: 10.1016/S1474-4422(19)30030-4.

[15] A. Bowen *et al.*, 'Effectiveness of enhanced communication therapy in the first four months after stroke for aphasia and dysarthria: a randomised controlled trial', *BMJ*, vol. 345, no. jul13 1, pp. e4407–e4407, Jul. 2012, doi: 10.1136/bmj.e4407.

[16] M. Ali, C. Hazelton, P. Lyden, A. Pollock, and M. Brady, 'Recovery From Poststroke Visual Impairment: Evidence From a Clinical Trials Resource', *Neurorehabil. Neural Repair*, vol. 27, no. 2, pp. 133–141, Feb. 2013, doi: 10.1177/1545968312454683.

[17] K. M. Sand, A. Midelfart, L. Thomassen, A. Melms, H. Wilhelm, and J. M. Hoff, 'Visual impairment in stroke patients – a review', *Acta Neurol. Scand.*, vol. 127, no. s196, pp. 52–56, 2013, doi: 10.1111/ane.12050.

[18] H. Jokinen *et al.*, 'Post-stroke cognitive impairment is common even after successful clinical recovery', *Eur. J. Neurol.*, vol. 22, no. 9, pp. 1288–1294, 2015, doi: 10.1111/ene.12743.
[19] M. E. Klinke, T. B. Hafsteinsdóttir, B. Thorsteinsson, and H. Jónsdóttir, 'Living at home with eating difficulties following stroke: a phenomenological study of younger people's experiences', *J. Clin. Nurs.*, vol. 23, no. 1–2, pp. 250–260, 2014, doi: 10.1111/jocn.12401.
[20] M. Schimmel, T. Ono, O. L. T. Lam, and F. Müller, 'Oro-facial impairment in stroke patients', *J. Oral Rehabil.*, vol. 44, no. 4, pp. 313–326, 2017, doi: 10.1111/joor.12486.
[21] M. L. Hackett, S. Köhler, J. T. O'Brien, and G. E. Mead, 'Neuropsychiatric outcomes of stroke', *Lancet Neurol.*, vol. 13, no. 5, pp. 525–534, May 2014, doi: 10.1016/S1474-4422(14)70016-X.
[22] P. Langhorne, J. Bernhardt, and G. Kwakkel, 'Stroke rehabilitation', *The Lancet*, vol. 377, no. 9778, pp. 1693–1702, May 2011, doi: 10.1016/S0140-6736(11)60325-5.
[23] E. Ghaziani, C. Couppé, V. Siersma, M. Søndergaard, H. Christensen, and S. P. Magnusson, 'Electrical Somatosensory Stimulation in Early Rehabilitation of Arm Paresis After Stroke: A Randomized Controlled Trial', *Neurorehabil. Neural Repair*, vol. 32, no. 10, pp. 899–912, Oct. 2018, doi: 10.1177/1545968318799496.
[24] T. Balchin, *The successful stroke survivor: the new guide to functional recovery from stroke*. Surrey: Bagwyn Books, 2011.
[25] A. N. Aliansyah, A. Arifin, D. Purwanto, and M. H. Fatoni, 'Extraction of Brain Signal during Motor Imagery Task for Wheelchair Control Command', presented at the Jan. 31-Feb. 1, 2017 Bali (Indonesia), Jan. 2017, doi: 10.17758/EIRAI.F0217118.
[26] K. Kiruba, B. Kamalini, C. Anu, B. Arunkumar, and J. Sathyaraj, 'Auto Assist Physio Arm', *Asian J. Appl. Sci. Technol.*, vol. 2, no. 2, pp. 537–542, Jun. 2018.
[27] V. K. Mansourian, 'Chapter 160 - Stroke in Young Adults', in *Essentials of Physical Medicine and Rehabilitation (Fourth Edition)*, W. R. Frontera, J. K. Silver, and T. D. Rizzo, Eds. Philadelphia: Content Repository Only!, 2020, pp. 937–944.
[28] L. Chuang, C. Wu, and K. Lin, 'Reliability, Validity, and Responsiveness of Myotonometric Measurement of Muscle Tone, Elasticity, and Stiffness in Patients With Stroke', *Arch. Phys. Med. Rehabil.*, vol. 93, no. 3, pp. 532–540, Mar. 2012, doi: 10.1016/j.apmr.2011.09.014.
[29] S. Li and G. E. Francisco, 'New insights into the pathophysiology of post-stroke spasticity', *Front. Hum. Neurosci.*, vol. 9, 2015, doi: 10.3389/fnhum.2015.00192.
[30] X. Zhu and J. Hou, 'Clinical observation on electroacupuncture for post-stroke flaccid paralysis', *J. Acupunct. Tuina Sci.*, vol. 11, no. 4, pp. 240–243, Aug. 2013, doi: 10.1007/s11726-013-0699-9.
[31] L. C. Rutten-Jacobs *et al.*, 'Genetic risk, incident stroke, and the benefits of adhering to a healthy lifestyle: cohort study of 306 473 UK Biobank participants', *BMJ*, vol. 363, p. k4168, Oct. 2018, doi: 10.1136/bmj.k4168.
[32] P. Enderby *et al.*, 'Accessing rehabilitation after stroke – a guessing game?', *Disabil. Rehabil.*, vol. 39, no. 7, pp. 709–713, Mar. 2017, doi: 10.3109/09638288.2016.1160448.
[33] G. Corso *et al.*, 'Outcome Predictors in First-Ever Ischemic Stroke Patients: A Population-Based Study', *International Scholarly Research Notices*, 2014. https://www.hindawi.com/journals/isrn/2014/904647/ (accessed Mar. 12, 2020).
[34] M. Franceschini *et al.*, 'Acute Phase Predictors of 6-Month Functional Outcome in Italian Stroke Patients Eligible for In-Hospital Rehabilitation', *Am. J. Phys. Med. Rehabil.*, vol. 97, no. 7, pp. 467–475, Jul. 2018, doi: 10.1097/PHM.0000000000000897.

[35] I. J. Marshall, Y. Wang, S. Crichton, C. McKevitt, A. G. Rudd, and C. D. A. Wolfe, 'The effects of socioeconomic status on stroke risk and outcomes', *Lancet Neurol.*, vol. 14, no. 12, pp. 1206–1218, Dec. 2015, doi: 10.1016/S1474-4422(15)00200-8.

[36] Stinear Cathy M., Byblow Winston D., Ackerley Suzanne J., Barber P. Alan, and Smith Marie-Claire, 'Predicting Recovery Potential for Individual Stroke Patients Increases Rehabilitation Efficiency', *Stroke*, vol. 48, no. 4, pp. 1011–1019, Apr. 2017, doi: 10.1161/STROKEAHA.116.015790.

[37] D. Haselbach, A. Renggli, S. Carda, and A. Croquelois, 'Determinants of Neurological Functional Recovery Potential after Stroke in Young Adults', *Cerebrovasc. Dis. Extra*, vol. 4, no. 1, pp. 77–83, 2014, doi: 10.1159/000360218.

[38] A. Ragoschke-Schumm *et al.*, 'Translation of the "time is brain" concept into clinical practice: focus on prehospital stroke management', *Int. J. Stroke*, vol. 9, no. 3, pp. 333–340, 2014, doi: 10.1111/ijs.12252.

[39] R. F. Yu, Ma. C. Z. San Jose, B. M. Manzanilla, M. Y. Oris, and R. Gan, 'Sources and reasons for delays in the care of acute stroke patients', *J. Neurol. Sci.*, vol. 199, no. 1–2, pp. 49–54, Jul. 2002, doi: 10.1016/S0022-510X(02)00103-X.

[40] L. K. Casaubon *et al.*, 'Canadian Stroke Best Practice Recommendations: Hyperacute Stroke Care Guidelines, Update 2015', *Int. J. Stroke*, vol. 10, no. 6, pp. 924–940, Aug. 2015, doi: 10.1111/ijs.12551.

[41] S. D. Liu, A. Rudd, and C. Davie, 'Hyper acute stroke unit services', *Clin. Med.*, vol. 11, no. 3, pp. 213–214, Jun. 2011, doi: 10.7861/clinmedicine.11-3-213.

[42] J. Aoki, K. Kimura, and Y. Sakamoto, 'Early administration of tissue-plasminogen activator improves the long-term clinical outcome at 5 years after onset', *J. Neurol. Sci.*, vol. 362, pp. 33–39, Mar. 2016, doi: 10.1016/j.jns.2016.01.018.

[43] B. H. Dobkin, '58 - Rehabilitation and Recovery of the Patient with Stroke', in *Stroke (Sixth Edition)*, J. C. Grotta, G. W. Albers, J. P. Broderick, S. E. Kasner, E. H. Lo, A. D. Mendelow, R. L. Sacco, and L. K. S. Wong, Eds. London: Elsevier, 2016, pp. 963–971.

[44] S. Abbasian and M. Rastegar MM, 'Is the Intensity or Duration of Treadmill Training Important for Stroke Patients? A Meta-Analysis', *J. Stroke Cerebrovasc. Dis.*, vol. 27, no. 1, pp. 32–43, Jan. 2018, doi: 10.1016/j.jstrokecerebrovasdis.2017.09.061.

[45] N. Takeuchi and S.-I. Izumi, 'Rehabilitation with Poststroke Motor Recovery: A Review with a Focus on Neural Plasticity', *Stroke Research and Treatment*, 2013. https://www.hindawi.com/journals/srt/2013/128641/ (accessed Feb. 27, 2020).

[46] L. Ekstam, U. Johansson, S. Guidetti, G. Eriksson, and C. Ytterberg, 'The combined perceptions of people with stroke and their carers regarding rehabilitation needs 1 year after stroke: a mixed methods study', *BMJ Open*, vol. 5, no. 2, p. e006784, Feb. 2015, doi: 10.1136/bmjopen-2014-006784.

[47] B. E. Bates *et al.*, 'Factors Influencing Receipt of Early Rehabilitation After Stroke', *Arch. Phys. Med. Rehabil.*, vol. 94, no. 12, pp. 2349–2356, Dec. 2013, doi: 10.1016/j.apmr.2013.07.021.

[48] R. M. San Segundo, J. J. Aguilar, F. Santos, and T. Usabiaga, 'A model for predicting delay in discharge of stroke patients', *Ann. Réadapt. Médecine Phys.*, vol. 50, no. 1, pp. 14–19, Jan. 2007, doi: 10.1016/j.annrmp.2006.06.005.

[49] S. Hesse and C. Werner, 'Connecting research to the needs of patients and clinicians', *Brain Res. Bull.*, vol. 78, no. 1, pp. 26–34, Jan. 2009, doi: 10.1016/j.brainresbull.2008.06.004.

[50] Winstein Carolee J. *et al.*, 'Guidelines for Adult Stroke Rehabilitation and Recovery', *Stroke*, vol. 47, no. 6, pp. e98–e169, Jun. 2016, doi: 10.1161/STR.0000000000000098.

[51] L. Turner-Stokes, 'Cost-efficiency of longer-stay rehabilitation programmes: Can they provide value for money?', *Brain Inj.*, vol. 21, no. 10, pp. 1015–1021, Jan. 2007, doi: 10.1080/02699050701591445.
[52] S. E. Lord, L. Rochester, M. Weatherall, K. M. McPherson, and H. K. McNaughton, 'The Effect of Environment and Task on Gait Parameters After Stroke: A Randomized Comparison of Measurement Conditions', *Arch. Phys. Med. Rehabil.*, vol. 87, no. 7, pp. 967–973, Jul. 2006, doi: 10.1016/j.apmr.2006.03.003.
[53] F. Coupar, A. Pollock, P. Rowe, C. Weir, and P. Langhorne, 'Predictors of upper limb recovery after stroke: a systematic review and meta-analysis', *Clin. Rehabil.*, vol. 26, no. 4, pp. 291–313, Apr. 2012, doi: 10.1177/0269215511420305.
[54] C. S. Kwok *et al.*, 'Association Between Prestroke Disability and Inpatient Mortality and Length of Acute Hospital Stay After Acute Stroke', *J. Am. Geriatr. Soc.*, vol. 60, no. 4, pp. 726–732, 2012, doi: 10.1111/j.1532-5415.2011.03889.x.
[55] J. Wagle *et al.*, 'Early Post-Stroke Cognition in Stroke Rehabilitation Patients Predicts Functional Outcome at 13 Months', *Dement. Geriatr. Cogn. Disord.*, vol. 31, no. 5, pp. 379–387, 2011, doi: 10.1159/000328970.
[56] C. Stinear, 'Prediction of recovery of motor function after stroke', *Lancet Neurol.*, vol. 9, no. 12, pp. 1228–1232, Dec. 2010, doi: 10.1016/S1474-4422(10)70247-7.
[57] DeVetten Giselle *et al.*, 'Acute Corticospinal Tract Wallerian Degeneration Is Associated With Stroke Outcome', *Stroke*, vol. 41, no. 4, pp. 751–756, Apr. 2010, doi: 10.1161/STROKEAHA.109.573287.
[58] R. S. Marshall, E. Zarahn, L. Alon, B. Minzer, R. M. Lazar, and J. W. Krakauer, 'Early Imaging Correlates of Subsequent Motor Recovery After Stroke', *Ann. Neurol.*, vol. 65, no. 5, pp. 596–602, May 2009, doi: 10.1002/ana.21636.
[59] V. Di Lazzaro *et al.*, 'Motor Cortex Plasticity Predicts Recovery in Acute Stroke', *Cereb. Cortex*, vol. 20, no. 7, pp. 1523–1528, Jul. 2010, doi: 10.1093/cercor/bhp216.
[60] S. Prabhakaran *et al.*, 'Inter-individual Variability in the Capacity for Motor Recovery After Ischemic Stroke', *Neurorehabil. Neural Repair*, vol. 22, no. 1, pp. 64–71, Jan. 2008, doi: 10.1177/1545968307305302.
[61] H. Nakayama, H. Stig Jørgensen, H. Otto Raaschou, and T. Skyhøj Olsen, 'Recovery of upper extremity function in stroke patients: The Copenhagen stroke study', *Arch. Phys. Med. Rehabil.*, vol. 75, no. 4, pp. 394–398, Apr. 1994, doi: 10.1016/0003-9993(94)90161-9.
[62] Nijland Rinske H.M., van Wegen Erwin E.H., Harmeling-van der Wel Barbara C., and Kwakkel Gert, 'Presence of Finger Extension and Shoulder Abduction Within 72 Hours After Stroke Predicts Functional Recovery', *Stroke*, vol. 41, no. 4, pp. 745–750, Apr. 2010, doi: 10.1161/STROKEAHA.109.572065.
[63] G. Kwakkel and B. J. Kollen, 'Predicting Activities after Stroke: What is Clinically Relevant?', *Int. J. Stroke*, vol. 8, no. 1, pp. 25–32, Jan. 2013, doi: 10.1111/j.1747-4949.2012.00967.x.
[64] R. W. Teasell, M. Murie Fernandez, A. McIntyre, and S. Mehta, 'Rethinking the Continuum of Stroke Rehabilitation', *Arch. Phys. Med. Rehabil.*, vol. 95, no. 4, pp. 595–596, Apr. 2014, doi: 10.1016/j.apmr.2013.11.014.
[65] C. L. Richards, F. Malouin, and S. Nadeau, 'Chapter 13 - Stroke rehabilitation: clinical picture, assessment, and therapeutic challenge', in *Progress in Brain Research*, vol. 218, S. N. and S. R. Numa Dancause, Ed. Elsevier, 2015, pp. 253–280.
[66] J. Bernhardt, B. Indredavik, and P. Langhorne, 'When should rehabilitation begin after stroke?', *Int. J. Stroke*, vol. 8, no. 1, pp. 5–7, 2013, doi: 10.1111/ijs.12020.
[67] J. Bernhardt *et al.*, 'Efficacy and safety of very early mobilisation within 24 h of stroke onset (AVERT): a randomised controlled trial', *Lancet*, vol. 386, no. 9988, Art.

no. 9988, Jul. 2015, doi: Bernhardt, J., Langhorne, P. <http://eprints.gla.ac.uk/view/author/10193.html> <http://orcid.org/0000-0001-8185-2659>, Lindley, R. I., Thrift, A. G., Ellery, F., Collier, J., Churilov, L., Moodie, M., Dewey, H. and Donnan, G. (2015) Efficacy and safety of very early mobilisation within 24 h of stroke onset (AVERT): a randomised controlled trial. Lancet <http://eprints.gla.ac.uk/view/journal_volume/Lancet.html>, 386(9988), pp. 46-55. (doi:10.1016/S0140-6736(15)60690-0 <http://dx.doi.org/10.1016/S0140-6736(15)60690-0>) (PMID:25892679).

[68] S. A. Maulden, J. Gassaway, S. D. Horn, R. J. Smout, and G. DeJong, 'Timing of Initiation of Rehabilitation After Stroke', *Arch. Phys. Med. Rehabil.*, vol. 86, no. 12, Supplement, pp. 34–40, Dec. 2005, doi: 10.1016/j.apmr.2005.08.119.

[69] M. Sawabe *et al.*, 'Rehabilitation Characteristics in High-Performance Hospitals after Acute Stroke', *J. Stroke Cerebrovasc. Dis.*, vol. 27, no. 9, pp. 2431–2435, Sep. 2018, doi: 10.1016/j.jstrokecerebrovasdis.2018.04.037.

[70] A. Chen and L. Xiao, 'An early rehabilitation clinical pathway promoted functional recovery and improved quality of life in patients with ischemic stroke', *Int J Clin Exp Med*, p. 8, 2019.

[71] P. Langhorne, O. Wu, H. Rodgers, A. Ashburn, and J. Bernhardt, 'A Very Early Rehabilitation Trial after stroke (AVERT): a Phase III, multicentre, randomised controlled trial', *Health Technol. Assess.*, vol. 21, no. 54, pp. 1–120, Sep. 2017, doi: 10.3310/hta21540.

[72] P. Chippala and R. Sharma, 'Effect of very early mobilisation on functional status in patients with acute stroke: a single-blind, randomized controlled trail', *Clin. Rehabil.*, vol. 30, no. 7, pp. 669–675, Jul. 2016, doi: 10.1177/0269215515596054.

[73] W. J. Oczkowski and S. Barreca, 'The functional independence measure: Its use to identify rehabilitation needs in stroke survivors', *Arch. Phys. Med. Rehabil.*, vol. 74, no. 12, pp. 1291–1294, Dec. 1993, doi: 10.1016/0003-9993(93)90081-K.

[74] I.-P. Hsueh, J.-H. Lin, J.-S. Jeng, and C.-L. Hsieh, 'Comparison of the psychometric characteristics of the functional independence measure, 5 item Barthel index, and 10 item Barthel index in patients with stroke', *J. Neurol. Neurosurg. Psychiatry*, vol. 73, no. 2, pp. 188–190, Aug. 2002, doi: 10.1136/jnnp.73.2.188.

[75] A. Lo, N. Tahair, S. Sharp, and M. T. Bayley, 'Clinical Utility of the AlphaFIM® Instrument in Stroke Rehabilitation', *Int. J. Stroke*, vol. 7, no. 2, pp. 118–124, Feb. 2012, doi: 10.1111/j.1747-4949.2011.00694.x.

[76] H. Rodgers and C. Price, 'Stroke unit care, inpatient rehabilitation and early supported discharge', *Clin. Med.*, vol. 17, no. 2, pp. 173–177, Jan. 2017, doi: 10.7861/clinmedicine.17-2-173.

[77] B. Dobkin, 'Rehabilitation after Stroke', *N. Engl. J. Med.*, vol. 352, no. 16, p. 8, 2005.

[78] K. Salter *et al.*, 'Impact of Early vs Delayed Admission to Rehabilitation on Functional Outcomes in Persons with Stroke', *J. Rehabil. Med.*, vol. 38, no. 2, pp. 113–117, Mar. 2006, doi: 10.1080/16501970500314350.

[79] N. E. Mayo, S. Wood-Dauphinee, R. Côté, L. Durcan, and J. Carlton, 'Activity, participation, and quality of life 6 months poststroke', *Arch. Phys. Med. Rehabil.*, vol. 83, no. 8, pp. 1035–1042, Aug. 2002, doi: 10.1053/apmr.2002.33984.

[80] S. Hebblethwaite and L. Curley, 'Exploring the Role of Community Recreation in Stroke Recovery Using Participatory Action Research and Photovoice', *Ther. Recreation J.*, vol. 49, no. 1, Art. no. 1, Jan. 2015, Accessed: Mar. 12, 2020. [Online]. Available: https://js.sagamorepub.com/trj/article/view/5433.

[81] S. Anderson and K. Whitfield, 'An Ecological Approach to Activity After Stroke: It Takes a Community', *Top. Stroke Rehabil.*, vol. 18, no. 5, pp. 509–524, Sep. 2011, doi: 10.1310/tsr1805-509.

[82] M. E. Walsh, R. Galvin, C. Loughnane, C. Macey, and N. F. Horgan, 'Factors associated with community reintegration in the first year after stroke: a qualitative meta-synthesis', *Disabil. Rehabil.*, vol. 37, no. 18, pp. 1599–1608, Aug. 2015, doi: 10.3109/09638288.2014.974834.

[83] J. H. Morris, T. Oliver, T. Kroll, S. Joice, and B. Williams, 'From physical and functional to continuity with pre-stroke self and participation in valued activities: A qualitative exploration of stroke survivors', carers' and physiotherapists' perceptions of physical activity after stroke', *Disabil. Rehabil.*, vol. 37, no. 1, pp. 64–77, Jan. 2015, doi: 10.3109/09638288.2014.907828.

[84] L. Scobbie, E. A. Duncan, M. C. Brady, and S. Wyke, 'Goal setting practice in services delivering community-based stroke rehabilitation: a United Kingdom (UK) wide survey', *Disabil. Rehabil.*, vol. 37, no. 14, pp. 1291–1298, Jul. 2015, doi: 10.3109/09638288.2014.961652.

[85] Cumming Toby B. *et al.*, 'Very Early Mobilization After Stroke Fast-Tracks Return to Walking', *Stroke*, vol. 42, no. 1, pp. 153–158, Jan. 2011, doi: 10.1161/STROKEAHA.110.594598.

[86] J. Perry, M. Garrett, J. K. Gronley, and S. J. Mulroy, 'Classification of Walking Handicap in the Stroke Population', *Stroke*, vol. 26, no. 6, pp. 982–989, Jun. 1995, doi: 10.1161/01.STR.26.6.982.

[87] Fulk George D., He Ying, Boyne Pierce, and Dunning Kari, 'Predicting Home and Community Walking Activity Poststroke', *Stroke*, vol. 48, no. 2, pp. 406–411, Feb. 2017, doi: 10.1161/STROKEAHA.116.015309.

[88] S. E. Lord, K. McPherson, H. K. McNaughton, L. Rochester, and M. Weatherall, 'Community ambulation after stroke: how important and obtainable is it and what measures appear predictive?', *Arch. Phys. Med. Rehabil.*, vol. 85, no. 2, pp. 234–239, Feb. 2004, doi: 10.1016/j.apmr.2003.05.002.

[89] L. Asher, M. Aresu, E. Falaschetti, and J. Mindell, 'Most older pedestrians are unable to cross the road in time: a cross-sectional study', *Age Ageing*, vol. 41, no. 5, pp. 690–694, Sep. 2012, doi: 10.1093/ageing/afs076.

[90] P. C. Fletcher, 'Restriction in activity associated with fear of falling among community-based seniors using home care services', *Age Ageing*, vol. 33, no. 3, pp. 273–279, May 2004, doi: 10.1093/ageing/afh077.

[91] A. Schinkel-Ivy, E. L. Inness, and A. Mansfield, 'Relationships between fear of falling, balance confidence, and control of balance, gait, and reactive stepping in individuals with sub-acute stroke', *Gait Posture*, vol. 43, pp. 154–159, Jan. 2016, doi: 10.1016/j.gaitpost.2015.09.015.

[92] M. Bijleveld-Uitman, I. Port, and G. Kwakkel, 'Is gait speed or walking distance a better predictor for community walking after stroke?', *J. Rehabil. Med.*, vol. 45, no. 6, pp. 535–540, 2013, doi: 10.2340/16501977-1147.

[93] E. Hong, 'Comparison of quality of life according to community walking in stroke patients', *J. Phys. Ther. Sci.*, vol. 27, no. 7, pp. 2391–2393, 2015, doi: 10.1589/jpts.27.2391.

[94] M. A. Alzahrani, C. M. Dean, L. Ada, S. Dorsch, and C. G. Canning, 'Mood and Balance are Associated with Free-Living Physical Activity of People after Stroke Residing in the community', *Stroke Research and Treatment*, 2012. https://www.hindawi.com/journals/srt/2012/470648/abs/ (accessed Mar. 18, 2019).

[95] J. P. Chau, D. R. Thompson, S. Twinn, A. M. Chang, and J. Woo, 'Determinants of participation restriction among community dwelling stroke survivors: A path analysis', *BMC Neurol.*, vol. 9, no. 1, Dec. 2009, doi: 10.1186/1471-2377-9-49.
[96] J. Z. Goldfinger *et al.*, 'Correlates of Post-traumatic Stress Disorder in Stroke Survivors', *J. Stroke Cerebrovasc. Dis.*, vol. 23, no. 5, pp. 1099–1105, May 2014, doi: 10.1016/j.jstrokecerebrovasdis.2013.09.019.
[97] M. Lindsay, G. Gubitz, M. Bayley, and S. Phillips, 'CHAPTER 5 Stroke Rehabilitation', in *CANADIAN BEST PRACTICE RECOMMENDATIONS FOR STROKE CARE*, Fourth., 2013, p. 97.
[98] A. Dawson, J. Knox, A. McClure, N. Foley, and R. Teasell, 'On behalf of the stroke rehabilitation writing group stroke erhabilitation', in *Canadian Best Practice Recommendations for Stroke Care*, Heart and Stroke Foundation and the Canadian Stroke Network, 2013.
[99] Scottish Intercollegiate Guidelines Network, *Management of patients with stroke: rehabilitation, prevention and management of complications, and discharge planning. A national clinical guideline.* Edinburgh: SIGN, 2010.
[100] Scottish Intercollegiate Guidelines Network, *Management of patients with stroke: rehabilitation, prevention and management of complications, and discharge planning. Quick reference guide.* Edinburgh: SIGN, 2010.
[101] T. J. Quinn *et al.*, 'Evidence-Based Stroke Rehabilitation: An Expanded Guidance Document from the European Stroke Organisation (ESO) Guidelines for Management of Ischaemic Stroke and Transient Ischaemic Attack 2008', Jan. 2009. https://www.ingentaconnect.com/content/mjl/sreh/2009/00000041/00000002/art00002 (accessed Feb. 27, 2020).
[102] Lohse Keith R., Lang Catherine E., and Boyd Lara A., 'Is More Better? Using Metadata to Explore Dose–Response Relationships in Stroke Rehabilitation', *Stroke*, vol. 45, no. 7, pp. 2053–2058, Jul. 2014, doi: 10.1161/STROKEAHA.114.004695.
[103] B. French *et al.*, 'Does Repetitive Task Training Improve Functional Activity After Stroke? A Cochrane Systematic Review and Meta-Analysis', Jan. 2010. https://www.ingentaconnect.com/content/mjl/sreh/2010/00000042/00000001/art00003 (accessed Mar. 20, 2019).
[104] M. MacKay-Lyons, A. McDonald, J. Matheson, G. Eskes, and M.-A. Klus, 'Dual Effects of Body-Weight Supported Treadmill Training on Cardiovascular Fitness and Walking Ability Early After Stroke A Randomized Controlled Trial', *Neurorehabil. Neural Repair*, vol. 27, no. 7, pp. 644–653, Sep. 2013, doi: 10.1177/1545968313484809.
[105] R. F. Macko *et al.*, 'Treadmill Exercise Rehabilitation Improves Ambulatory Function and Cardiovascular Fitness in Patients With Chronic Stroke: A Randomized, Controlled Trial', *Stroke*, vol. 36, no. 10, pp. 2206–2211, Oct. 2005, doi: 10.1161/01.STR.0000181076.91805.89.
[106] C. Globas *et al.*, 'Chronic Stroke Survivors Benefit From High-Intensity Aerobic Treadmill Exercise A Randomized Control Trial', *Neurorehabil. Neural Repair*, vol. 26, no. 1, pp. 85–95, Jan. 2012, doi: 10.1177/1545968311418675.
[107] J. C. Outermans, R. P. van Peppen, H. Wittink, T. Takken, and G. Kwakkel, 'Effects of a high-intensity task-oriented training on gait performance early after stroke: a pilot study', *Clin. Rehabil.*, vol. 24, no. 11, pp. 979–987, Jan. 2010, doi: 10.1177/0269215509360647.
[108] S. Papegaaij and F. Steenbrink, 'Clinical gait analysis: Treadmill-based vs overground', *Motek*, p. 6, May 2017.
[109] P. O. Riley, G. Paolini, U. Della Croce, K. W. Paylo, and D. C. Kerrigan, 'A kinematic and kinetic comparison of overground and treadmill walking in healthy subjects',

Gait Posture, vol. 26, no. 1, pp. 17–24, Jun. 2007, doi: 10.1016/j.gaitpost.2006.07.003.
[110] S. C. Wearing, L. F. Reed, and S. R. Urry, 'Agreement between temporal and spatial gait parameters from an instrumented walkway and treadmill system at matched walking speed', *Gait Posture*, vol. 38, no. 3, pp. 380–384, Jul. 2013, doi: 10.1016/j.gaitpost.2012.12.017.
[111] S. J. Lee and J. Hidler, 'Biomechanics of overground vs. treadmill walking in healthy individuals', *J. Appl. Physiol.*, vol. 104, no. 3, pp. 747–755, Mar. 2008, doi: 10.1152/japplphysiol.01380.2006.
[112] J. R. Watt, J. R. Franz, K. Jackson, J. Dicharry, P. O. Riley, and D. C. Kerrigan, 'A three-dimensional kinematic and kinetic comparison of overground and treadmill walking in healthy elderly subjects', *Clin. Biomech.*, vol. 25, no. 5, pp. 444–449, Jun. 2010, doi: 10.1016/j.clinbiomech.2009.09.002.
[113] J.-P. Martin and Q. Li, 'Overground vs. treadmill walking on biomechanical energy harvesting: An energetics and EMG study', *Gait Posture*, vol. 52, no. Supplement C, pp. 124–128, Feb. 2017, doi: 10.1016/j.gaitpost.2016.11.027.
[114] W. A. Sparrow, R. K. Begg, and S. Parker, 'Variability in the foot-ground clearance and step timing of young and older men during single-task and dual-task treadmill walking', *Gait Posture*, vol. 28, no. 4, pp. 563–567, Nov. 2008, doi: 10.1016/j.gaitpost.2008.03.013.
[115] M. M. Morrow, E. A. Pohlmeyer, and L. E. Miller, 'Control of Muscle Synergies by Cortical Ensembles', in *Progress in Motor Control*, Springer, Boston, MA, 2009, pp. 179–199.
[116] N. Lodha *et al.*, 'EMG synchrony to assess impaired corticomotor control of locomotion after stroke', *J. Electromyogr. Kinesiol.*, vol. 37, pp. 35–40, Dec. 2017, doi: 10.1016/j.jelekin.2017.08.007.
[117] D. Farina, R. Merletti, and R. M. Enoka, 'The extraction of neural strategies from the surface EMG', *J. Appl. Physiol.*, vol. 96, no. 4, pp. 1486–1495, Apr. 2004, doi: 10.1152/japplphysiol.01070.2003.
[118] K. M. Steele, A. Rozumalski, and M. H. Schwartz, 'Muscle synergies and complexity of neuromuscular control during gait in cerebral palsy', *Dev. Med. Child Neurol.*, vol. 57, no. 12, pp. 1176–1182, Dec. 2015, doi: 10.1111/dmcn.12826.
[119] J. Laczko and M. L. Latash, Eds., *Progress in Motor Control*, vol. 957. Cham: Springer International Publishing, 2016.
[120] F. Lacquaniti, Y. P. Ivanenko, and M. Zago, 'Patterned control of human locomotion', *J. Physiol.*, vol. 590, no. 10, pp. 2189–2199, May 2012, doi: 10.1113/jphysiol.2011.215137.
[121] M. Plotnik *et al.*, 'Self-selected gait speed - over ground versus self-paced treadmill walking, a solution for a paradox', *J. NeuroEngineering Rehabil.*, vol. 12, p. 20, 2015, doi: 10.1186/s12984-015-0002-z.
[122] B. B. Johansson, 'Current trends in stroke rehabilitation. A review with focus on brain plasticity', *Acta Neurol. Scand.*, vol. 123, no. 3, pp. 147–159, 2011, doi: 10.1111/j.1600-0404.2010.01417.x.
[123] S. H. Jang *et al.*, 'Cortical Reorganization and Associated Functional Motor Recovery After Virtual Reality in Patients With Chronic Stroke: An Experimenter-Blind Preliminary Study', *Arch. Phys. Med. Rehabil.*, vol. 86, no. 11, pp. 2218–2223, Nov. 2005, doi: 10.1016/j.apmr.2005.04.015.
[124] You Sung H. *et al.*, 'Virtual Reality–Induced Cortical Reorganization and Associated Locomotor Recovery in Chronic Stroke', *Stroke*, vol. 36, no. 6, pp. 1166–1171, Jun. 2005, doi: 10.1161/01.STR.0000162715.43417.91.

[125] K. E. Laver, B. Lange, S. George, J. E. Deutsch, G. Saposnik, and M. Crotty, 'Virtual reality for stroke rehabilitation', *Cochrane Database Syst. Rev.*, no. 11, 2017, doi: 10.1002/14651858.CD008349.pub4.
[126] I. C. Rosbergen *et al.*, 'Embedding an enriched environment in an acute stroke unit increases activity in people with stroke: a controlled before–after pilot study', *Clin. Rehabil.*, vol. 31, no. 11, pp. 1516–1528, Nov. 2017, doi: 10.1177/0269215517705181.
[127] I. C. Rosbergen, R. S. Grimley, K. S. Hayward, and S. G. Brauer, 'The impact of environmental enrichment in an acute stroke unit on how and when patients undertake activities', *Clin. Rehabil.*, vol. 33, no. 4, pp. 784–795, Apr. 2019, doi: 10.1177/0269215518820087.
[128] Krueger Hans, Lindsay Patrice, Cote Robert, Kapral Moira K., Kaczorowski Janusz, and Hill Michael D., 'Cost Avoidance Associated With Optimal Stroke Care in Canada', *Stroke*, vol. 43, no. 8, pp. 2198–2206, Aug. 2012, doi: 10.1161/STROKEAHA.111.646091.
[129] D. Hebert *et al.*, 'Canadian stroke best practice recommendations: Stroke rehabilitation practice guidelines, update 2015', *Int. J. Stroke*, vol. 11, no. 4, pp. 459–484, Jun. 2016, doi: 10.1177/1747493016643553.
[130] P. Langhorne, S. Baylan, and E. S. D. Trialists, 'Early supported discharge services for people with acute stroke', *Cochrane Database Syst. Rev.*, no. 7, 2017, doi: 10.1002/14651858.CD000443.pub4.
[131] Fisher Rebecca J. *et al.*, 'A Consensus on Stroke', *Stroke*, vol. 42, no. 5, pp. 1392–1397, May 2011, doi: 10.1161/STROKEAHA.110.606285.
[132] A. Mansfield, E. L. Inness, and W. E. Mcilroy, 'Chapter 13 - Stroke', in *Handbook of Clinical Neurology*, vol. 159, B. L. Day and S. R. Lord, Eds. Elsevier, 2018, pp. 205–228.
[133] P. M. van Vliet, N. B. Lincoln, and A. Foxall, 'Comparison of Bobath based and movement science based treatment for stroke: a randomised controlled trial', *J. Neurol. Neurosurg. Psychiatry*, vol. 76, no. 4, pp. 503–508, Apr. 2005, doi: 10.1136/jnnp.2004.040436.
[134] B. Langhammer and J. K. Stanghelle, 'Bobath or Motor Relearning Programme? A comparison of two different approaches of physiotherapy in stroke rehabilitation: a randomized controlled study', *Clin. Rehabil.*, vol. 14, no. 4, pp. 361–369, Aug. 2000, doi: 10.1191/0269215500cr338oa.
[135] N. M. Salbach, N. E. Mayo, S. Wood-Dauphinee, J. A. Hanley, C. L. Richards, and R. Côté, 'A task-orientated intervention enhances walking distance and speed in the first year post stroke: a randomized controlled trial', *Clin. Rehabil.*, vol. 18, no. 5, pp. 509–519, Aug. 2004, doi: 10.1191/0269215504cr763oa.
[136] J. Blennerhassett and W. Dite, 'Additional task-related practice improves mobility and upper limb function early after stroke: A randomised controlled trial', *Aust. J. Physiother.*, vol. 50, no. 4, pp. 219–224, 2004, doi: 10.1016/S0004-9514(14)60111-2.
[137] C. M. Dean, C. L. Richards, and F. Malouin, 'Task-related circuit training improves performance of locomotor tasks in chronic stroke: A randomized, controlled pilot trial', *Arch. Phys. Med. Rehabil.*, vol. 81, no. 4, pp. 409–417, Apr. 2000, doi: 10.1053/mr.2000.3839.
[138] D. Rose *et al.*, 'Feasibility and Effectiveness of Circuit Training in Acute Stroke Rehabilitation', *Neurorehabil. Neural Repair*, vol. 25, no. 2, pp. 140–148, Feb. 2011, doi: 10.1177/1545968310384270.
[139] S. Barreca, C. S. Sigouin, C. Lambert, and B. Ansley, 'Effects of Extra Training on the Ability of Stroke Survivors to Perform an Independent Sit-to-Stand: A Randomized Controlled Trial', *J. Geriatr. Phys. Ther.*, vol. 27, no. 2, pp. 59-64,68, 2004.

[140] R. Cabanas-Valdés, C. Bagur-Calafat, M. Girabent-Farrés, F. M. Caballero-Gómez, M. Hernández-Valiño, and G. Urrútia Cuchí, 'The effect of additional core stability exercises on improving dynamic sitting balance and trunk control for subacute stroke patients: a randomized controlled trial', *Clin. Rehabil.*, vol. 30, no. 10, pp. 1024–1033, Oct. 2016, doi: 10.1177/0269215515609414.
[141] G. Verheyden *et al.*, 'Additional Exercises Improve Trunk Performance After Stroke: A Pilot Randomized Controlled Trial', *Neurorehabil. Neural Repair*, vol. 23, no. 3, pp. 281–286, Mar. 2009, doi: 10.1177/1545968308321776.
[142] J. Park, D. Seo, W. Choi, and S. Lee, 'The Effects of Exercise with TENS on Spasticity, Balance, and Gait in Patients with Chronic Stroke: A Randomized Controlled Trial', *Med. Sci. Monit. Int. Med. J. Exp. Clin. Res.*, vol. 20, pp. 1890–1896, Oct. 2014, doi: 10.12659/MSM.890926.
[143] S. Lin, Q. Sun, H. Wang, and G. Xie, 'Influence of transcutaneous electrical nerve stimulation on spasticity, balance, and walking speed in stroke patients: A systematic review and meta-analysis', *J. Rehabil. Med.*, vol. 50, no. 1, pp. 3–7, 2018, doi: 10.2340/16501977-2266.
[144] A. Mahmood, S. K. Veluswamy, A. Hombali, A. Mullick, M. N, and J. M. Solomon, 'Effect of Transcutaneous Electrical Nerve Stimulation on Spasticity in Adults With Stroke: A Systematic Review and Meta-analysis', *Arch. Phys. Med. Rehabil.*, vol. 100, no. 4, pp. 751–768, Apr. 2019, doi: 10.1016/j.apmr.2018.10.016.
[145] R. L. Harvey, 'Improving poststroke recovery: Neuroplasticity and task-oriented training', *Curr. Treat. Options Cardiovasc. Med.*, vol. 11, no. 3, pp. 251–259, Jun. 2009, doi: 10.1007/s11936-009-0026-4.
[146] E. Dolatabadi *et al.*, 'The toronto rehab stroke pose dataset to detect compensation during stroke rehabilitation therapy', in *Proceedings of the 11th EAI International Conference on Pervasive Computing Technologies for Healthcare*, Barcelona, Spain, May 2017, pp. 375–381, doi: 10.1145/3154862.3154925.
[147] R. Ranganathan, R. Wang, R. Gebara, and S. Biswas, 'Detecting Compensatory Trunk Movements in Stroke Survivors using a Wearable System', in *Proceedings of the 2017 Workshop on Wearable Systems and Applications*, Niagara Falls, New York, USA, Jun. 2017, pp. 29–32, doi: 10.1145/3089351.3089353.
[148] C. M. Borges *et al.*, 'Compensatory Movement Detection Through Inertial Sensor Positioning fro Post-Stroke Rehabilitation', in *Proceedings of the International Conference on Bio-inspired Systems and Signal Processing*, Vilamoura, Algarve, Portugal, 2012, pp. 297–302, doi: 10.5220/0003798102970302.
[149] T. Krabben *et al.*, 'Influence of gravity compensation training on synergistic movement patterns of the upper extremity after stroke, a pilot study', *J. NeuroEngineering Rehabil.*, vol. 9, no. 1, p. 44, Jul. 2012, doi: 10.1186/1743-0003-9-44.
[150] S. F. Tyson and R. M. Kent, 'Effects of an Ankle-Foot Orthosis on Balance and Walking After Stroke: A Systematic Review and Pooled Meta-Analysis', *Arch. Phys. Med. Rehabil.*, vol. 94, no. 7, pp. 1377–1385, Jul. 2013, doi: 10.1016/j.apmr.2012.12.025.
[151] T. IJmker *et al.*, 'Effect of Balance Support on the Energy Cost of Walking After Stroke', *Arch. Phys. Med. Rehabil.*, vol. 94, no. 11, pp. 2255–2261, Nov. 2013, doi: 10.1016/j.apmr.2013.04.022.
[152] S. Prenton, K. Hollands, L. Kenney, and P. Onmanee, 'Functional electrical stimulation and ankle foot orthoses provide equivalent therapeutic effects on foot drop: A meta-analysis providing direction for future research', *J. Rehabil. Med.*, vol. 50, no. 2, pp. 129–139, 2018, doi: 10.2340/16501977-2289.

[153] D. Rand, J. J. Eng, P.-F. Tang, J.-S. Jeng, and C. Hung, 'How Active Are People With Stroke?: Use of Accelerometers to Assess Physical Activity', *Stroke*, vol. 40, no. 1, pp. 163–168, Jan. 2009, doi: 10.1161/STROKEAHA.108.523621.
[154] N. A. Fini, A. E. Holland, J. Keating, J. Simek, and J. Bernhardt, 'How Physically Active Are People Following Stroke? Systematic Review and Quantitative Synthesis', *Phys. Ther.*, vol. 97, no. 7, pp. 707–717, Jul. 2017, doi: 10.1093/ptj/pzx038.
[155] C. English, P. J. Manns, C. Tucak, and J. Bernhardt, 'Physical Activity and Sedentary Behaviors in People With Stroke Living in the Community: A Systematic Review', *Phys. Ther.*, vol. 94, no. 2, pp. 185–196, Feb. 2014, doi: 10.2522/ptj.20130175.
[156] D. H. Saunders *et al.*, 'Physical fitness training for stroke patients', *Cochrane Database Syst. Rev.*, no. 3, 2016, doi: 10.1002/14651858.CD003316.pub6.
[157] O. Stoller, E. D. de Bruin, R. H. Knols, and K. J. Hunt, 'Effects of cardiovascular exercise early after stroke: systematic review and meta-analysis', *BMC Neurol.*, vol. 12, no. 1, p. 45, Jun. 2012, doi: 10.1186/1471-2377-12-45.
[158] D. L. Marsden, A. Dunn, R. Callister, C. R. Levi, and N. J. Spratt, 'Characteristics of Exercise Training Interventions to Improve Cardiorespiratory Fitness After Stroke: A Systematic Review With Meta-analysis', *Neurorehabil. Neural Repair*, vol. 27, no. 9, pp. 775–788, Nov. 2013, doi: 10.1177/1545968313496329.
[159] E. V. Cooke, R. C. Tallis, A. Clark, and V. M. Pomeroy, 'Efficacy of Functional Strength Training on Restoration of Lower-Limb Motor Function Early After Stroke: Phase I Randomized Controlled Trial', *Neurorehabil. Neural Repair*, vol. 24, no. 1, pp. 88–96, Jan. 2010, doi: 10.1177/1545968309343216.
[160] A. Tang and J. J. Eng, 'Physical Fitness Training After Stroke', *Phys. Ther.*, vol. 94, no. 1, pp. 9–13, Jan. 2014, doi: 10.2522/ptj.20120331.
[161] D. Barbosa, C. P. Santos, and M. Martins, 'The Application of Cycling and Cycling Combined with Feedback in the Rehabilitation of Stroke Patients: A Review', *J. Stroke Cerebrovasc. Dis.*, vol. 24, no. 2, pp. 253–273, Feb. 2015, doi: 10.1016/j.jstrokecerebrovasdis.2014.09.006.
[162] F. M. Ivey, A. D. Stookey, C. E. Hafer-Macko, A. S. Ryan, and R. F. Macko, 'Higher Treadmill Training Intensity to Address Functional Aerobic Impairment after Stroke', *J. Stroke Cerebrovasc. Dis.*, vol. 24, no. 11, pp. 2539–2546, Nov. 2015, doi: 10.1016/j.jstrokecerebrovasdis.2015.07.002.
[163] A. Kerr, A. Clark, E. V. Cooke, P. Rowe, and V. M. Pomeroy, 'Functional strength training and movement performance therapy produce analogous improvement in sit-to-stand early after stroke: early-phase randomised controlled trial', *Physiotherapy*, vol. 103, no. 3, pp. 259–265, Sep. 2017, doi: 10.1016/j.physio.2015.12.006.
[164] Kollen Boudewijn J. *et al.*, 'The Effectiveness of the Bobath Concept in Stroke Rehabilitation', *Stroke*, vol. 40, no. 4, pp. e89–e97, Apr. 2009, doi: 10.1161/STROKEAHA.108.533828.
[165] G. V. Bhalerao, V. Kulkarni, and D. Kapoor, 'Comparison Of Two Physiotherapy Approaches In Acute Stroke Rehabilitation: Motor Relearning Program Versus Bobath Approach.', vol. 1, no. 1, p. 11, 2011.
[166] G. Bhalerao, V. Kulkarni, C. Doshi, S. Rairikar, A. Shyam, and P. Sancheti, 'Comparison of motor relearning program versus Bobath approach at every two weeks interval for improving activities of daily living and ambulation in acute stroke rehabilitation', vol. 3, p. 9, 2013.
[167] V. Rethnam *et al.*, 'Early mobilisation post-stroke: a systematic review and meta-analysis of individual participant data', *Disabil. Rehabil.*, vol. 0, no. 0, pp. 1–8, Jul. 2020, doi: 10.1080/09638288.2020.1789229.

[168] H. Sankaranarayan, A. Gupta, M. Khanna, A. B. Taly, and K. Thennarasu, 'Role of ankle foot orthosis in improving locomotion and functional recovery in patients with stroke: A prospective rehabilitation study', *J. Neurosci. Rural Pract.*, vol. 7, no. 4, pp. 544–549, Apr. 2016, doi: 10.4103/0976-3147.185507.
[169] Y.-I. Hwang, 'Effects of an Elastic AFO on the Walking Patterns of Foot-drop Patients with Stroke', *Korean Soc. Phys. Med.*, vol. 15, no. 1, pp. 1–9, Feb. 2020, doi: 10.13066/kspm.2020.15.1.1.
[170] C. D. Nikamp, J. H. Buurke, J. van der Palen, H. J. Hermens, and J. S. Rietman, 'Six-month effects of early or delayed provision of an ankle-foot orthosis in patients with (sub)acute stroke: a randomized controlled trial', Apr. 14, 2017. file:///C:/Users/Eunice/Downloads/six%20month%20effct%20of%20early%20or%20late%20AFO%20provision.pdf (accessed May 23, 2017).
[171] J. H. Kim and B. H. Won, 'Kinematic on Ankle and Knee Joint of Post-Stroke Elderly Patients by Wearing Newly Elastic Band-Type Ankle–Foot Orthosis in Gait', *Clin. Interv. Aging*, vol. 14, pp. 2097–2104, Dec. 2019, doi: 10.2147/CIA.S222087.
[172] A. M. Malagoni, C. Zambon, and F. Manfredini, 'Effects of low-intensity endurance and resistance training on mobility in chronic stroke survivors: a pilot randomized controlled study', *Eur. J. Phys. Rehabil. Med.*, vol. 53, no. 2, p. 12, 2017.
[173] F. Bethoux *et al.*, 'Long-Term Follow-up to a Randomized Controlled Trial Comparing Peroneal Nerve Functional Electrical Stimulation to an Ankle Foot Orthosis for Patients With Chronic Stroke', *Neurorehabil. Neural Repair*, vol. 29, no. 10, pp. 911–922, Nov. 2015, doi: 10.1177/1545968315570325.
[174] C. Beyaert, R. Vasa, and G. E. Frykberg, 'Gait post-stroke: Pathophysiology and rehabilitation strategies', *Neurophysiol. Clin. Neurophysiol.*, vol. 45, no. 4, pp. 335–355, Nov. 2015, doi: 10.1016/j.neucli.2015.09.005.
[175] H. S. Jørgensen, H. Nakayama, H. O. Raaschou, and T. S. Olsen, 'Recovery of walking function in stroke patients: The copenhagen stroke study', *Arch. Phys. Med. Rehabil.*, vol. 76, no. 1, pp. 27–32, Jan. 1995, doi: 10.1016/S0003-9993(95)80038-7.
[176] X.-M. Xu *et al.*, 'The economic burden of stroke care in England, Wales and Northern Ireland: Using a national stroke register to estimate and report patient-level health economic outcomes in stroke', *Eur. Stroke J.*, vol. 3, no. 1, pp. 82–91, Mar. 2018, doi: 10.1177/2396987317746516.
[177] T. G. Hornby *et al.*, 'Importance of Specificity, Amount, and Intensity of Locomotor Training to Improve Ambulatory Function in Patients Poststroke', *Top. Stroke Rehabil.*, vol. 18, no. 4, pp. 293–307, Jul. 2011, doi: 10.1310/tsr1804-293.
[178] A. L. Leddy *et al.*, 'Alterations in aerobic exercise performance and gait economy following high intensity dynamic stepping training in persons with subacute stroke', *J. Neurol. Phys. Ther. JNPT*, vol. 40, no. 4, pp. 239–248, Oct. 2016, doi: 10.1097/NPT.0000000000000147.
[179] P. W. Duncan *et al.*, 'Body-Weight–Supported Treadmill Rehabilitation after Stroke', *N. Engl. J. Med.*, vol. 364, no. 21, pp. 2026–2036, May 2011, doi: 10.1056/NEJMoa1010790.
[180] M. Lloyd, D. A. Skelton, G. E. Mead, B. Williams, and F. van Wijck, 'Physical fitness interventions for nonambulatory stroke survivors: A mixed-methods systematic review and meta-analysis', *Brain Behav.*, vol. 8, no. 7, p. e01000, 2018, doi: 10.1002/brb3.1000.
[181] S. S. Kuys, L. Ada, J. Paratz, and S. G. Brauer, 'Steps, duration and intensity of usual walking practice during subacute rehabilitation after stroke: an observational study', *Braz. J. Phys. Ther.*, vol. 23, no. 1, pp. 56–61, Jan. 2019, doi: 10.1016/j.bjpt.2018.06.001.

[182] A. Pollock, G. Baer, P. Langhorne, and V. Pomeroy, 'Physiotherapy treatment approaches for the recovery of postural control and lower limb function following stroke: a systematic review', *Clin. Rehabil.*, vol. 21, no. 5, pp. 395–410, May 2007, doi: 10.1177/0269215507073438.
[183] L. S. Yoward, P. Doherty, and C. Boyes, 'A survey of outcome measurement of balance, walking and gait amongst physiotherapists working in neurology in the UK', *Physiotherapy*, vol. 94, no. 2, pp. 125–132, Jun. 2008, doi: 10.1016/j.physio.2007.08.005.
[184] F. A. Batchelor, S. B. Williams, T. Wijeratne, C. M. Said, and S. Petty, 'Balance and Gait Impairment in Transient Ischemic Attack and Minor Stroke', *J. Stroke Cerebrovasc. Dis.*, vol. 24, no. 10, pp. 2291–2297, Oct. 2015, doi: 10.1016/j.jstrokecerebrovasdis.2015.06.014.
[185] A. Vistamehr, C. K. Balasubramanian, D. J. Clark, R. R. Neptune, and E. J. Fox, 'Dynamic balance during walking adaptability tasks in individuals post-stroke', *J. Biomech.*, vol. 74, pp. 106–115, Jun. 2018, doi: 10.1016/j.jbiomech.2018.04.029.
[186] K.-T. Park and H.-J. Kim, 'Effect of the a circuit training program using obstacles on the walking and balance abilities of stroke patients', *J. Phys. Ther. Sci.*, vol. 28, no. 4, pp. 1194–1198, 2016, doi: 10.1589/jpts.28.1194.
[187] C. K. Balasubramanian, D. J. Clark, and E. J. Fox, 'Walking Adaptability after a Stroke and Its Assessment in Clinical Settings', *Stroke Res. Treat.*, vol. 2014, pp. 1–21, 2014, doi: 10.1155/2014/591013.
[188] M. W. van Ooijen, M. Roerdink, M. Trekop, T. W. J. Janssen, and P. J. Beek, 'The efficacy of treadmill training with and without projected visual context for improving walking ability and reducing fall incidence and fear of falling in older adults with fall-related hip fracture: a randomized controlled trial', *BMC Geriatr.*, vol. 16, no. 1, Art. no. 1, Dec. 2016, doi: 10.1186/s12877-016-0388-x.
[189] P. Terrier and F. Reynard, 'Effect of age on the variability and stability of gait: A cross-sectional treadmill study in healthy individuals between 20 and 69 years of age', *Gait Posture*, vol. 41, no. 1, pp. 170–174, Jan. 2015, doi: 10.1016/j.gaitpost.2014.09.024.
[190] A. E. Patla and A. Shumway-Cook, 'Dimensions of Mobility: Defining the Complexity and Difficulty Associated with Community Mobility', *J. Aging Phys. Act.*, vol. 7, no. 1, pp. 7–19, Jan. 1999, doi: 10.1123/japa.7.1.7.
[191] C. Timmermans, M. Roerdink, M. W. van Ooijen, C. G. Meskers, T. W. Janssen, and P. J. Beek, 'Walking adaptability therapy after stroke: study protocol for a randomized controlled trial', *Trials*, vol. 17, no. 1, p. 425, Aug. 2016, doi: 10.1186/s13063-016-1527-6.
[192] K. Smulders, R. van Swigchem, B. J. M. de Swart, A. C. H. Geurts, and V. Weerdesteyn, 'Community-dwelling people with chronic stroke need disproportionate attention while walking and negotiating obstacles', *Gait Posture*, vol. 36, no. 1, pp. 127–132, May 2012, doi: 10.1016/j.gaitpost.2012.02.002.
[193] A. Darekar, A. Lamontagne, and J. Fung, 'Locomotor circumvention strategies are altered by stroke: I. Obstacle clearance', *J. NeuroEngineering Rehabil.*, vol. 14, no. 1, p. 56, Jun. 2017, doi: 10.1186/s12984-017-0264-8.
[194] K. L. Hollands, D. Agnihotri, and S. F. Tyson, 'Effects of dual task on turning ability in stroke survivors and older adults', *Gait Posture*, vol. 40, no. 4, pp. 564–569, Sep. 2014, doi: 10.1016/j.gaitpost.2014.06.019.
[195] K. L. Hollands *et al.*, 'Visual cue training to improve walking and turning after stroke: a study protocol for a multi-centre, single blind randomised pilot trial', *Trials*, vol. 14, p. 276, 2013, doi: 10.1186/1745-6215-14-276.

[196] M. Punt, S. M. Bruijn, H. Wittink, I. G. van de Port, G. Wubbels, and J. H. van Dieën, 'Virtual obstacle crossing: Reliability and differences in stroke survivors who prospectively experienced falls or no falls', *Gait Posture*, vol. 58, pp. 533–538, Oct. 2017, doi: 10.1016/j.gaitpost.2017.09.013.
[197] Y.-R. Yang, M.-P. Tsai, T.-Y. Chuang, W.-H. Sung, and R.-Y. Wang, 'Virtual reality-based training improves community ambulation in individuals with stroke: A randomized controlled trial', *Gait Posture*, vol. 28, no. 2, pp. 201–206, Aug. 2008, doi: 10.1016/j.gaitpost.2007.11.007.
[198] J. H. Buurke, A. V. Nene, G. Kwakkel, V. Erren-Wolters, M. J. IJzerman, and H. J. Hermens, 'Recovery of Gait After Stroke: What Changes?', *Neurorehabil. Neural Repair*, vol. 22, no. 6, pp. 676–683, Nov. 2008, doi: 10.1177/1545968308317972.
[199] Y. Hashiguchi *et al.*, 'Merging and Fractionation of Muscle Synergy Indicate the Recovery Process in Patients with Hemiplegia: The First Study of Patients after Subacute Stroke', *Neural Plast.*, vol. 2016, 2016, doi: 10.1155/2016/5282957.
[200] A. Bowen, R. Wenman, J. Mickelborough, J. Foster, E. Hill, and R. Tallis, 'Dual-task effects of talking while walking on velocity and balance following a stroke', *Age Ageing*, vol. 30, no. 4, pp. 319–323, Jul. 2001, doi: 10.1093/ageing/30.4.319.
[201] J.-H. Shin *et al.*, 'Dual task interference while walking in chronic stroke survivors', *Phys. Ther. Rehabil. Sci.*, vol. 6, no. 3, pp. 134–139, Sep. 2017, doi: 10.14474/ptrs.2017.6.3.134.
[202] P. Haggard, J. Cockburn, J. Cock, C. Fordham, and D. Wade, 'Interference between gait and cognitive tasks in a rehabilitating neurological population', *J. Neurol. Neurosurg. Psychiatry*, vol. 69, no. 4, pp. 479–486, Oct. 2000, doi: 10.1136/jnnp.69.4.479.
[203] J. Cockburn, P. Haggard, J. Cock, and C. Fordham, 'Changing patterns of cognitive-motor interference (CMI) over time during recovery from stroke', *Clin. Rehabil.*, vol. 17, no. 2, pp. 167–173, Mar. 2003, doi: 10.1191/0269215503cr597oa.
[204] P. Plummer-D'Amato, L. J. P. Altmann, D. Saracino, E. Fox, A. L. Behrman, and M. Marsiske, 'Interactions between cognitive tasks and gait after stroke: A dual task study', *Gait Posture*, vol. 27, no. 4, pp. 683–688, May 2008, doi: 10.1016/j.gaitpost.2007.09.001.
[205] N. A. Gomeñuka, R. L. Bona, R. G. da Rosa, and L. A. Peyré-Tartaruga, 'Adaptations to changing speed, load, and gradient in human walking: Cost of transport, optimal speed, and pendulum', *Scand. J. Med. Sci. Sports*, vol. 24, no. 3, pp. e165–e173, 2014, doi: 10.1111/sms.12129.
[206] P. L. Entin, C. Gest, S. Trancik, and J. Richard Coast, 'Fuel oxidation in relation to walking speed: influence of gradient and external load', *Eur. J. Appl. Physiol.*, vol. 110, no. 3, pp. 515–521, Oct. 2010, doi: 10.1007/s00421-010-1523-6.
[207] P. L. Phan, J. M. Blennerhassett, N. Lythgo, W. Dite, and M. E. Morris, 'Over-ground walking on level and sloped surfaces in people with stroke compared to healthy matched adults', *Disabil. Rehabil.*, vol. 35, no. 15, pp. 1302–1307, Jul. 2013, doi: 10.3109/09638288.2012.729646.
[208] C. Bonnyaud, R. Zory, D. Pradon, N. Vuillerme, and N. Roche, 'Clinical and biomechanical factors which predict Timed Up and Down Stairs test performance in hemiparetic patients', *Gait Posture*, vol. 38, no. 3, pp. 466–470, Jul. 2013, doi: 10.1016/j.gaitpost.2013.01.015.
[209] A. C. Novak and B. Brouwer, 'Kinematic and Kinetic Evaluation of the Stance Phase of Stair Ambulation in Persons with Stroke and Healthy Adults: A Pilot Study', *J. Appl. Biomech.*, vol. 29, no. 4, pp. 443–452, Aug. 2013, doi: 10.1123/jab.29.4.443.

[210] S. Ng, H. Ng, K. Chan, J. Lai, A. To, and C. Yeung, 'Reliability of the 12-step ascend and descend test and its correlation with motor function in people with chronic stroke', *J. Rehabil. Med.*, vol. 45, no. 2, pp. 123–129, 2013, doi: 10.2340/16501977-1086.
[211] C. Carvalho, K. S. Sunnerhagen, and C. Willén, 'Walking speed and distance in different environments of subjects in the later stage post-stroke', *Physiother. Theory Pract.*, vol. 26, no. 8, pp. 519–527, Nov. 2010, doi: 10.3109/09593980903585042.
[212] K. Donovan, S. E. Lord, H. K. McNaughton, and M. Weatherall, 'Mobility beyond the clinic: the effect of environment on gait and its measurement in community-ambulant stroke survivors', *Clin. Rehabil.*, vol. 22, no. 6, pp. 556–563, Jun. 2008, doi: 10.1177/0269215507085378.
[213] D. Taylor, C. M. Stretton, S. Mudge, and N. Garrett, 'Does clinic-measured gait speed differ from gait speed measured in the community in people with stroke?', *Clin. Rehabil.*, vol. 20, no. 5, pp. 438–444, May 2006, doi: 10.1191/0269215506cr945oa.
[214] J. C. E. Kempen, V. de Groot, D. L. Knol, C. H. Polman, G. J. Lankhorst, and H. Beckerman, 'Community walking can be assessed using a 10-metre timed walk test', *Mult. Scler. J.*, vol. 17, no. 8, pp. 980–990, Aug. 2011, doi: 10.1177/1352458511403641.
[215] S. An, Y. Lee, H. Shin, and G. Lee, 'Gait velocity and walking distance to predict community walking after stroke', *Nurs. Health Sci.*, vol. 17, no. 4, pp. 533–538, Dec. 2015, doi: 10.1111/nhs.12234.
[216] S. Lord and L. Rochester, 'Gait Velocity and Community Ambulation: the Limits of Assessment', *Stroke*, vol. 39, no. 4, pp. e75–e75, Apr. 2008, doi: 10.1161/STROKEAHA.107.502203.
[217] K. M. Means, 'The Obstacle Course: A Tool for the Assessment of Functiona lBalance and Mobility In the Elderly', p. 17, 1996.
[218] A. Shumway-Cook, M. Baldwin, N. L. Polissar, and W. Gruber, 'Predicting the Probability for Falls in Community-Dwelling Older Adults', *Phys. Ther.*, vol. 77, no. 8, pp. 812–819, Aug. 1997, doi: 10.1093/ptj/77.8.812.
[219] D. M. Wrisley, G. F. Marchetti, D. K. Kuharsky, and S. L. Whitney, 'Reliability, Internal Consistency, and Validity of Data Obtained With the Functional Gait Assessment', *Phys. Ther.*, vol. 84, no. 10, pp. 906–918, Oct. 2004, doi: 10.1093/ptj/84.10.906.
[220] Baer Heather R. and Wolf Steven L., 'Modified Emory Functional Ambulation Profile', *Stroke*, vol. 32, no. 4, pp. 973–979, Apr. 2001, doi: 10.1161/01.STR.32.4.973.
[221] J. A. Howe, E. L. Inness, A. Venturini, J. I. Williams, and M. C. Verrier, 'The Community Balance and Mobility Scale-a balance measure for individuals with traumatic brain injury', *Clin. Rehabil.*, vol. 20, no. 10, pp. 885–895, Oct. 2006, doi: 10.1177/0269215506072183.
[222] G. Williams, V. Robertson, K. Greenwood, P. Goldie, and M. E. Morris, 'The Concurrent Validity and Responsiveness of the High-Level Mobility Assessment Tool for Measuring the Mobility Limitations of People With Traumatic Brain Injury', *Arch. Phys. Med. Rehabil.*, vol. 87, no. 3, pp. 437–442, Mar. 2006, doi: 10.1016/j.apmr.2005.10.028.
[223] G. P. Williams, K. M. Greenwood, V. J. Robertson, P. A. Goldie, and M. E. Morris, 'High-Level Mobility Assessment Tool (HiMAT): Interrater Reliability, Retest Reliability, and Internal Consistency', *Phys. Ther.*, vol. 86, no. 3, pp. 395–400, Mar. 2006, doi: 10.1093/ptj/86.3.395.
[224] P.-F. Tang, S. Moore, and M. H. Woollacott, 'Correlation Between Two Clinical Balance Measures in Older Adults: Functional Mobility and Sensory Organization Test', *J. Gerontol. Ser. A*, vol. 53A, no. 2, pp. M140–M146, Mar. 1998, doi: 10.1093/gerona/53A.2.M140.

[225] S. Bandinelli *et al.*, 'Adding Challenge to Performance-Based Tests of Walking: The Walking InCHIANTI Toolkit (WIT)', *Am. J. Phys. Med. Rehabil. Assoc. Acad. Physiatr.*, vol. 85, no. 12, pp. 986–991, Dec. 2006, doi: 10.1097/01.phm.0000233210.69400.d4.
[226] L. Z. Rubenstein, K. R. Josephson, P. R. Trueblood, K. Yeung, J. O. Harker, and A. S. Robbins, 'The reliability and validity of an obstacle course as a measure of gait and balance in older adults', *Aging Clin. Exp. Res.*, vol. 9, no. 1, pp. 127–135, Feb. 1997, doi: 10.1007/BF03340138.
[227] B. R. Bloem, V. V. Valkenburg, M. Slabbekoorn, and M. D. Willemsen, 'The Multiple Tasks Test: Development and normal strategies', *Gait Posture*, vol. 14, no. 3, pp. 191–202, Dec. 2001, doi: 10.1016/S0966-6362(01)00141-2.
[228] S. Madhavan, J. W. Stinear, and N. Kanekar, 'Effects of a Single Session of High Intensity Interval Treadmill Training on Corticomotor Excitability following Stroke: Implications for Therapy', *Neural Plasticity*, 2016. https://www.hindawi.com/journals/np/2016/1686414/abs/ (accessed Mar. 07, 2019).
[229] J. Mehrholz, S. Thomas, and B. Elsner, 'Treadmill training and body weight support for walking after stroke', in *Cochrane Database of Systematic Reviews*, John Wiley & Sons, Ltd, 2017.
[230] B. H. Dobkin and P. W. Duncan, 'Should Body Weight–Supported Treadmill Training and Robotic-Assistive Steppers for Locomotor Training Trot Back to the Starting Gate?', *Neurorehabil. Neural Repair*, vol. 26, no. 4, pp. 308–317, May 2012, doi: 10.1177/1545968312439687.
[231] S. S. Kuys, S. G. Brauer, L. Ada, and T. G. Russell, 'Immediate effect of treadmill walking practice versus overground walking practice on overground walking pattern in ambulatory stroke patients: an experimental study', *Clin. Rehabil.*, vol. 22, no. 10–11, pp. 931–939, Oct. 2008, doi: 10.1177/0269215508094245.
[232] H. Nagano, R. K. Begg, W. A. Sparrow, and S. Taylor, 'Ageing and limb dominance effects on foot-ground clearance during treadmill and overground walking', *Clin. Biomech.*, vol. 26, no. 9, pp. 962–968, Nov. 2011, doi: 10.1016/j.clinbiomech.2011.05.013.
[233] L. H. Sloot, M. M. van der Krogt, and J. Harlaar, 'Self-paced versus fixed speed treadmill walking', *Gait Posture*, vol. 39, no. 1, pp. 478–484, Jan. 2014, doi: 10.1016/j.gaitpost.2013.08.022.
[234] A. E. Minetti, L. Boldrini, L. Brusamolin, P. Zamparo, and T. McKee, 'A feedback-controlled treadmill (treadmill-on-demand) and the spontaneous speed of walking and running in humans', *J. Appl. Physiol.*, vol. 95, no. 2, pp. 838–843, Aug. 2003, doi: 10.1152/japplphysiol.00128.2003.
[235] L. Lichtenstein, J. Barabas, R. L. Woods, and E. Peli, 'A feedback-controlled interface for treadmill locomotion in virtual environments', *ACM Trans. Appl. Percept.*, vol. 4, no. 1, pp. 7-es, Jan. 2007, doi: 10.1145/1227134.1227141.
[236] Motek, 'Self-paced: How to use and tweak self-paced in D-Flow'. Motek Medical BV, Apr. 15, 2014.
[237] J. Yoon, H.-S. Park, and D. L. Damiano, 'A novel walking speed estimation scheme and its application to treadmill control for gait rehabilitation', *J. NeuroEngineering Rehabil.*, vol. 9, p. 62, 2012, doi: 10.1186/1743-0003-9-62.
[238] F. Prochaczek *et al.*, 'The Six-Minute Walk Test on the Treadmill', in *Chronic Obstructive Pulmonary Disease - Current Concepts and Practice*, K.-C. Ong, Ed. InTech, 2012.

[239] F. A. Salem and A. Aly, 'PD Controller Structures: Comparison and Selection for an Electromechanical System', *Int. J. Intell. Syst. Appl.*, vol. 7, pp. 1–12, Jan. 2015, doi: 10.5815/ijisa.2015.02.01.
[240] J. L. Souman *et al.*, 'CyberWalk: Enabling unconstrained omnidirectional walking through virtual environments', *ACM Trans. Appl. Percept.*, vol. 8, no. 4, p. 25:1-25:22, Dec. 2008, doi: 10.1145/2043603.2043607.
[241] A. D. Luca, R. Mattone, and P. R. Giordano, 'Feedback/feedforward schemes for motion control of the CyberCarpet', *IFAC Proc. Vol.*, vol. 39, no. 15, pp. 400–406, Jan. 2006, doi: 10.3182/20060906-3-IT-2910.00068.
[242] S. Kim, J. Roh, J. Hyeong, G. Yang, and Y. Kim, 'Dynamic stability on nonmotorized curved treadmill: Self-paced speed versus fixed speed', *Int. J. Precis. Eng. Manuf.*, vol. 18, no. 6, pp. 887–893, Jun. 2017, doi: 10.1007/s12541-017-0105-5.
[243] A. L. Hof, M. G. J. Gazendam, and W. E. Sinke, 'The condition for dynamic stability', *J. Biomech.*, vol. 38, no. 1, pp. 1–8, Jan. 2005, doi: 10.1016/j.jbiomech.2004.03.025.
[244] R. B. Edwards, P. J. Tofari, S. J. Cormack, and D. G. Whyte, 'Non-motorized Treadmill Running Is Associated with Higher Cardiometabolic Demands Compared with Overground and Motorized Treadmill Running', *Front. Physiol.*, vol. 8, Nov. 2017, doi: 10.3389/fphys.2017.00914.
[245] S. A. Combs, E. L. Dugan, E. N. Ozimek, and A. B. Curtis, 'Effects of body-weight supported treadmill training on kinetic symmetry in persons with chronic stroke', *Clin. Biomech.*, vol. 27, no. 9, pp. 887–892, Nov. 2012, doi: 10.1016/j.clinbiomech.2012.06.011.
[246] B. Kollen, G. Kwakkel, and E. Lindeman, 'Longitudinal robustness of variables predicting independent gait following severe middle cerebral artery stroke: a prospective cohort study', *Clin. Rehabil.*, vol. 20, no. 3, pp. 262–268, Mar. 2006, doi: 10.1191/0269215506cr910oa.
[247] J. Mehrholz, K. Wagner, K. Rutte, D. Meiβner, and M. Pohl, 'Predictive Validity and Responsiveness of the Functional Ambulation Category in Hemiparetic Patients After Stroke', *Arch. Phys. Med. Rehabil.*, vol. 88, no. 10, pp. 1314–1319, Oct. 2007, doi: 10.1016/j.apmr.2007.06.764.
[248] F. M. Ivey, C. E. Hafer-Macko, and R. F. Macko, 'Task-oriented treadmill exercise training in chronic hemiparetic stroke', *J. Rehabil. Res. Dev.*, vol. 45, no. 2, pp. 249–259, 2008, doi: 10.1682/JRRD.2007.02.0035.
[249] B. H. Dobkin, P. Plummer-D'Amato, R. Elashoff, and J. Lee, 'International Randomized Clinical Trial, Stroke Inpatient Rehabilitation With Reinforcement of Walking Speed (SIRROWS), Improves Outcomes', *Neurorehabil. Neural Repair*, vol. 24, no. 3, pp. 235–242, Mar. 2010, doi: 10.1177/1545968309357558.
[250] E. Ibala, S. Coupaud, and A. Kerr, 'Comparison of The Muscle Pattern Variability During Treadmill Walking (Fixed and Self-Pace) And Overground Walking of Able-Bodied Adults', *J. Ann. Bioeng.*, vol. 2019, no. 01, May 2019, doi: 10.33513/BIOE/1901-04.
[251] Y. Wang, G. Zhai, S. Chen, X. Min, Z. Gao, and X. Song, 'Assessment of eye fatigue caused by head-mounted displays using eye-tracking', *Biomed. Eng. OnLine*, vol. 18, no. 1, p. 111, Nov. 2019, doi: 10.1186/s12938-019-0731-5.
[252] O. Merhi, E. Faugloire, M. Flanagan, and T. A. Stoffregen, 'Motion Sickness, Console Video Games, and Head-Mounted Displays', *Hum. Factors*, vol. 49, no. 5, pp. 920–934, Oct. 2007, doi: 10.1518/001872007X230262.
[253] J. Munafo, M. Diedrick, and T. A. Stoffregen, 'The virtual reality head-mounted display Oculus Rift induces motion sickness and is sexist in its effects', *Exp. Brain Res.*, vol. 235, no. 3, pp. 889–901, Mar. 2017, doi: 10.1007/s00221-016-4846-7.

[254] S. Park and G. Lee, 'Full-immersion virtual reality: Adverse effects related to static balance', *Neurosci. Lett.*, vol. 733, p. 134974, Aug. 2020, doi: 10.1016/j.neulet.2020.134974.
[255] S. Sharples, S. Cobb, A. Moody, and J. R. Wilson, 'Virtual reality induced symptoms and effects (VRISE): Comparison of head mounted display (HMD), desktop and projection display systems', *Displays*, vol. 29, no. 2, pp. 58–69, Mar. 2008, doi: 10.1016/j.displa.2007.09.005.
[256] G. Cheok, D. Tan, A. Low, and J. Hewitt, 'Is Nintendo Wii an Effective Intervention for Individuals With Stroke? A Systematic Review and Meta-Analysis', *J. Am. Med. Dir. Assoc.*, vol. 16, no. 11, pp. 923–932, Nov. 2015, doi: 10.1016/j.jamda.2015.06.010.
[257] Saposnik Gustavo *et al.*, 'Effectiveness of Virtual Reality Using Wii Gaming Technology in Stroke Rehabilitation', *Stroke*, vol. 41, no. 7, pp. 1477–1484, Jul. 2010, doi: 10.1161/STROKEAHA.110.584979.
[258] M. S. Cameirão, S. B. i. Badia, E. D. Oller, and P. F. Verschure, 'Neurorehabilitation using the virtual reality based Rehabilitation Gaming System: methodology, design, psychometrics, usability and validation', *J. NeuroEngineering Rehabil.*, vol. 7, no. 1, p. 48, Sep. 2010, doi: 10.1186/1743-0003-7-48.
[259] M. da Silva Cameirão, S. Bermúdez i Badia, E. Duarte, and P. F. M. J. Verschure, 'Virtual reality based rehabilitation speeds up functional recovery of the upper extremities after stroke: A randomized controlled pilot study in the acute phase of stroke using the Rehabilitation Gaming System', *Restor. Neurol. Neurosci.*, vol. 29, no. 5, pp. 287–298, Jan. 2011, doi: 10.3233/RNN-2011-0599.
[260] H. J. R. van Duijnhoven, D. De Kam, W. Hellebrand, E. Smulders, A. C. H. Geurts, and V. Weerdesteyn, 'Development and Process Evaluation of a 5-Week Exercise Program to Prevent Falls in People after Stroke: The FALLS Program', *Stroke Research and Treatment*, 2012. https://www.hindawi.com/journals/srt/2012/407693/ (accessed Mar. 17, 2020).
[261] C. M. Stretton, S. Mudge, N. M. Kayes, and K. M. McPherson, 'Interventions to improve real-world walking after stroke: a systematic review and meta-analysis', *Clin. Rehabil.*, vol. 31, no. 3, pp. 310–318, Mar. 2017, doi: 10.1177/0269215516640863.
[262] C. E. Lang *et al.*, 'Observation of Amounts of Movement Practice Provided During Stroke Rehabilitation', *Arch. Phys. Med. Rehabil.*, vol. 90, no. 10, pp. 1692–1698, Oct. 2009, doi: 10.1016/j.apmr.2009.04.005.
[263] C. Timmermans, M. Roerdink, T. W. J. Janssen, P. J. Beek, and C. G. M. Meskers, 'Automatized, Standardized, and Patient-Tailored Progressive Walking-Adaptability Training: A Proof-of-Concept Study', *Phys. Ther.*, vol. 99, no. 7, pp. 882–892, Jul. 2019, doi: 10.1093/ptj/pzz013.
[264] E. Lederman, '2 - Motor control', in *Neuromuscular Rehabilitation in Manual and Physical Therapy*, E. Lederman, Ed. Edinburgh: Churchill Livingstone, 2010, pp. 5–18.
[265] C. Grefkes and N. S. Ward, 'Cortical Reorganization After Stroke: How Much and How Functional?', *The Neuroscientist*, vol. 20, no. 1, pp. 56–70, Feb. 2014, doi: 10.1177/1073858413491147.
[266] D. S. Reisman, R. Wityk, K. Silver, and A. J. Bastian, 'Locomotor adaptation on a split-belt treadmill can improve walking symmetry post-stroke', *Brain*, vol. 130, no. 7, pp. 1861–1872, Jul. 2007, doi: 10.1093/brain/awm035.
[267] M. L. Latash, '1 - A philosophical introduction', in *Fundamentals of Motor Control*, M. L. Latash, Ed. San Diego: Academic Press, 2012, pp. 1–4.
[268] M. L. Latash, Ed., *Progress in motor control: Bernstein's traditions in movement studies*. Champaign, IL: Human Kinetics, 1998.

[269] V. S. Gurfinkel and P. J. Cordo, 'The scientific legacy of Nikolai Bernstein', *Prog. Mot. Control*, vol. 1, pp. 1–19, 1998.
[270] O. Sporns and G. M. Edelman, 'Bernstein's Dynamic View of the Brain: The Current Problems of Modern Neurophysiology (1945)', *Motor Control*, vol. 2, no. 4, pp. 283–305, Oct. 1998, doi: 10.1123/mcj.2.4.283.
[271] L. P. Latash, 'Automation of movement: challenges to the notions of the orienting reaction and memory', *Prog. Mot. Control*, vol. 1, pp. 51–88, 1998.
[272] M. L. Latash and V. M. Zatsiorsky, '10 - Redundancy and Abundance', in *Biomechanics and Motor Control*, M. L. Latash and V. M. Zatsiorsky, Eds. San Diego: Academic Press, 2016, pp. 177–204.
[273] D. J. Cech and S. "Tink" Martin, 'Chapter 4 - Motor Control and Motor Learning', in *Functional Movement Development Across the Life Span (Third Edition)*, D. J. Cech and S. "Tink" Martin, Eds. Saint Louis: W.B. Saunders, 2012, pp. 68–87.
[274] N. A. Bernstein, 'On the construction of movements', 1947.
[275] N. A. Bernstein, 'New direction in the development of contemporary physiology', *Proc. Conf. Methods Physiol. Hum. Stud.*, no. Moscow, USSR Academy of Sciences, pp. 15–21, 1962.
[276] I. E. Sirotkina and E. V. Biryukova, 'Futurism in Physiology: Nikolai Bernstein, Anticipation, and Kinaesthetic Imagination', in *Anticipation: Learning from the Past: The Russian/Soviet Contributions to the Science of Anticipation*, M. Nadin, Ed. Cham: Springer International Publishing, 2015, pp. 269–285.
[277] J. Munzert, B. Lorey, and K. Zentgraf, 'Cognitive motor processes: The role of motor imagery in the study of motor representations', *Brain Res. Rev.*, vol. 60, no. 2, pp. 306–326, May 2009, doi: 10.1016/j.brainresrev.2008.12.024.
[278] R. E. Burke, 'Sir Charles Sherrington's The integrative action of the nervous system: a centenary appreciation', *Brain*, vol. 130, no. 4, pp. 887–894, Apr. 2007, doi: 10.1093/brain/awm022.
[279] D. G. Stuart, 'Integration of posture and movement: Contributions of Sherrington, Hess, and Bernstein', *Hum. Mov. Sci.*, vol. 24, no. 5, pp. 621–643, Oct. 2005, doi: 10.1016/j.humov.2005.09.011.
[280] S. Gielen, B. van Bolhuis, and E. Vrijenhoek, 'On the number of degrees of freedom in biological limbs', *Prog. Mot. Control*, vol. 1, pp. 173–190, 1998.
[281] M. Casadio, I. Tamagnone, S. Summa, and V. Sanguineti, 'Neuromotor recovery from stroke: computational models at central, functional, and muscle synergy level', *Front. Comput. Neurosci.*, vol. 7, 2013, doi: 10.3389/fncom.2013.00097.
[282] E. Bizzi and V. C. Cheung, 'The neural origin of muscle synergies', *Front. Comput. Neurosci.*, vol. 7, 2013, doi: 10.3389/fncom.2013.00051.
[283] V. C. K. Cheung *et al.*, 'Muscle synergy patterns as physiological markers of motor cortical damage', *Proc. Natl. Acad. Sci.*, vol. 109, no. 36, pp. 14652–14656, Sep. 2012, doi: 10.1073/pnas.1212056109.
[284] A. B. Ajiboye and R. F. Weir, 'Muscle synergies as a predictive framework for the EMG patterns of new hand postures', *J. Neural Eng.*, vol. 6, no. 3, p. 036004, May 2009, doi: 10.1088/1741-2560/6/3/036004.
[285] D. J. Clark, L. H. Ting, F. E. Zajac, R. R. Neptune, and S. A. Kautz, 'Merging of Healthy Motor Modules Predicts Reduced Locomotor Performance and Muscle Coordination Complexity Post-Stroke', *J. Neurophysiol.*, vol. 103, no. 2, pp. 844–857, Feb. 2010, doi: 10.1152/jn.00825.2009.
[286] W. Z. Rymer, J. Dewald, J. Given, and R. Beer, 'Abnormal muscle synergies in hemiparetic stroke: origins and implications for movement control', *Prog. Mot. Control*, vol. 1, pp. 191–202, 1998.

[287] J. C. Rothwell, M. Vidailhet, P. D. Thompson, A. J. Lees, and C. D. Marsden, 'The auditory startle response in progressive supranuclear palsy', in *Progressive Supranuclear Palsy: Diagnosis, Pathology, and Therapy*, 1994, pp. 43–50.
[288] P. H. J. A. Nieuwenhuijzen, M. W. Horstink, B. R. Bloem, and J. Duysens, 'Startle responses in Parkinson patients during human gait', *Exp. Brain Res.*, vol. 171, no. 2, p. 215, Nov. 2005, doi: 10.1007/s00221-005-0270-0.
[289] C. F. Honeycutt and E. J. Perreault, 'Planning of Ballistic Movement following Stroke: Insights from the Startle Reflex', *PLOS ONE*, vol. 7, no. 8, p. e43097, août 2012, doi: 10.1371/journal.pone.0043097.
[290] N. Ward, 'Assessment of cortical reorganisation for hand function after stroke', *J. Physiol.*, vol. 589, no. 23, pp. 5625–5632, 2011, doi: 10.1113/jphysiol.2011.220939.
[291] N. Neckel, M. Pelliccio, D. Nichols, and J. Hidler, 'Quantification of functional weakness and abnormal synergy patterns in the lower limb of individuals with chronic stroke', *J. NeuroEngineering Rehabil.*, vol. 3, no. 1, p. 17, Jul. 2006, doi: 10.1186/1743-0003-3-17.
[292] E. M. Arnold, S. R. Hamner, A. Seth, M. Millard, and S. L. Delp, 'How muscle fiber lengths and velocities affect muscle force generation as humans walk and run at different speeds', *J. Exp. Biol.*, vol. 216, no. 11, pp. 2150–2160, Jun. 2013, doi: 10.1242/jeb.075697.
[293] M. Cadova, M. Vilimek, and M. Daniel, 'A comparative study of muscle force estimates using Huxley's and Hill's muscle model', *Comput. Methods Biomech. Biomed. Engin.*, vol. 17, no. 4, pp. 311–317, Mar. 2014, doi: 10.1080/10255842.2012.683426.
[294] K. Jovanovic, J. Vranic, and N. Miljkovic, 'Hill's and Huxley's muscle models - tools for simulations in biomechanics', *Serbian J. Electr. Eng.*, vol. 12, no. 1, pp. 53–67, 2015, doi: 10.2298/SJEE1501053J.
[295] G. J. van Ingen Schenau, 'How Are Explosive Movements Controlled?', *Prog. Mot. Control Bernsteins Tradit. Mov. Stud.*, p. 361, 1998.
[296] N. Bernstein, 'Essay 6: on exercises and motor skill', *Dexterity Its Dev. Lawrence Erlbaum N. J.*, pp. 171–205, 1996.
[297] K. Naito, Y. Fukui, and T. Maruyama, 'Multijoint kinetic chain analysis of knee extension during the soccer instep kick', *Hum. Mov. Sci.*, vol. 29, no. 2, pp. 259–276, Apr. 2010, doi: 10.1016/j.humov.2009.04.008.
[298] J. F. Kalaska, 'From Intention to Action: Motor Cortex and the Control of Reaching Movements', in *Progress in Motor Control*, Springer, Boston, MA, 2009, pp. 139–178.
[299] B. R. Townsend, L. Paninski, and R. N. Lemon, 'Linear Encoding of Muscle Activity in Primary Motor Cortex and Cerebellum', *J. Neurophysiol.*, vol. 96, no. 5, pp. 2578–2592, Nov. 2006, doi: 10.1152/jn.01086.2005.
[300] D. M. Santucci, J. D. Kralik, M. A. Lebedev, and M. A. L. Nicolelis, 'Frontal and parietal cortical ensembles predict single-trial muscle activity during reaching movements in primates: Cortical ensembles predict muscle activity', *Eur. J. Neurosci.*, vol. 22, no. 6, pp. 1529–1540, Sep. 2005, doi: 10.1111/j.1460-9568.2005.04320.x.
[301] M. M. Morrow and L. E. Miller, 'Prediction of Muscle Activity by Populations of Sequentially Recorded Primary Motor Cortex Neurons', *J. Neurophysiol.*, vol. 89, no. 4, pp. 2279–2288, Apr. 2003, doi: 10.1152/jn.00632.2002.
[302] M. T. Turvey and S. Fonseca, 'Nature of Motor Control: Perspectives and Issues', in *Progress in Motor Control*, Springer, Boston, MA, 2009, pp. 93–123.
[303] R. D. Beer, 'Beyond Control: The Dynamics of Brain-Body-Environment Interaction in Motor Systems', in *Progress in Motor Control*, Springer, Boston, MA, 2009, pp. 7–24.

[304] M. L. Latash, M. F. Levin, J. P. Scholz, and G. Schöner, 'Motor Control Theories and Their Applications', *Med. Kaunas Lith.*, vol. 46, no. 6, pp. 382–392, 2010.
[305] Y. P. Ivanenko, A. D'avella, and F. Lacquaniti, 'Muscle Coordination, Motor Synergies, and Primitives from Surface EMG', in *Surface Electromyography : Physiology, Engineering, and Applications*, R. Merletti and D. Farina, Eds. John Wiley & Sons, Inc., 2016, pp. 158–179.
[306] Y. Yang, 'A Signal Theoretic Approach for Envelope Analysis of Real-Valued Signals', *IEEE Access*, vol. 5, pp. 5623–5630, 2017, doi: 10.1109/ACCESS.2017.2688467.
[307] F. O. Barroso *et al.*, 'Combining muscle synergies and biomechanical analysis to assess gait in stroke patients', *J. Biomech.*, vol. 63, pp. 98–103, Oct. 2017, doi: 10.1016/j.jbiomech.2017.08.006.
[308] A. d'Avella, A. Portone, L. Fernandez, and F. Lacquaniti, 'Control of Fast-Reaching Movements by Muscle Synergy Combinations', *J. Neurosci.*, vol. 26, no. 30, pp. 7791–7810, Jul. 2006, doi: 10.1523/JNEUROSCI.0830-06.2006.
[309] M. D. Klein Breteler, K. J. Simura, and M. Flanders, 'Timing of Muscle Activation in a Hand Movement Sequence', *Cereb. Cortex*, vol. 17, no. 4, pp. 803–815, Apr. 2007, doi: 10.1093/cercor/bhk033.
[310] A. d'Avella and E. Bizzi, 'Shared and specific muscle synergies in natural motor behaviors', *Proc. Natl. Acad. Sci.*, vol. 102, no. 8, pp. 3076–3081, Feb. 2005, doi: 10.1073/pnas.0500199102.
[311] F. M. Purves-Smith, N. Sgarioto, and R. T. Hepple, 'Fiber Typing in Aging Muscle', *Exerc. Sport Sci. Rev.*, vol. 42, no. 2, p. 45, Apr. 2014, doi: 10.1249/JES.0000000000000012.
[312] N. Miljkovic, J.-Y. Lim, I. Miljkovic, and W. R. Frontera, 'Aging of Skeletal Muscle Fibers', *Ann. Rehabil. Med.*, vol. 39, no. 2, pp. 155–162, Apr. 2015, doi: 10.5535/arm.2015.39.2.155.
[313] R. Nilwik *et al.*, 'The decline in skeletal muscle mass with aging is mainly attributed to a reduction in type II muscle fiber size', *Exp. Gerontol.*, vol. 48, no. 5, pp. 492–498, May 2013, doi: 10.1016/j.exger.2013.02.012.
[314] A. Macaluso, M. A. Nimmo, J. E. Foster, M. Cockburn, N. C. McMillan, and G. D. Vito, 'Contractile muscle volume and agonist-antagonist coactivation account for differences in torque between young and older women', *Muscle Nerve*, vol. 25, no. 6, pp. 858–863, 2002, doi: 10.1002/mus.10113.
[315] M. Olinski, B. Lewandowski, and A. Gronowicz, 'Type synthesis and preliminary design of devices supporting lower limb's rehabilitation', *Acta Bioeng. Biomech.*, vol. 17, no. 1, 2015, doi: 10.5277/ABB-00219-2014-02.
[316] C. P. McGowan, R. R. Neptune, D. J. Clark, and S. A. Kautz, 'Modular control of human walking: Adaptations to altered mechanical demands', *J. Biomech.*, vol. 43, no. 3, pp. 412–419, Feb. 2010, doi: 10.1016/j.jbiomech.2009.10.009.
[317] C. P. McGowan, R. Kram, and R. R. Neptune, 'Modulation of leg muscle function in response to altered demand for body support and forward propulsion during walking', *J. Biomech.*, vol. 42, no. 7, pp. 850–856, May 2009, doi: 10.1016/j.jbiomech.2009.01.025.
[318] N. Dominici *et al.*, 'Locomotor Primitives in Newborn Babies and Their Development', *Science*, vol. 334, no. 6058, pp. 997–999, Nov. 2011, doi: 10.1126/science.1210617.
[319] R. R. Neptune, D. J. Clark, and S. A. Kautz, 'Modular control of human walking: A simulation study', *J. Biomech.*, vol. 42, no. 9, pp. 1282–1287, Jun. 2009, doi: 10.1016/j.jbiomech.2009.03.009.

[320] G. Cheron, A. Cebolla, F. Leurs, A. Bengoetxea, and B. Dan, 'Development and Motor Control: From the First Step on', in *Motor Control and Learning*, Springer, Boston, MA, 2006, pp. 127–139.
[321] C. K. Tan *et al.*, 'Differences in Muscle Synergy Symmetry Between Subacute Post-stroke Patients With Bioelectrically-Controlled Exoskeleton Gait Training and Conventional Gait Training', *Front. Bioeng. Biotechnol.*, vol. 8, 2020, doi: 10.3389/fbioe.2020.00770.
[322] L. Gizzi, J. F. ek Nielsen, F. Felici, Y. P. Ivanenko, and D. Farina, 'Impulses of activation but not motor modules are preserved in the locomotion of subacute stroke patients.', *J. Neurophysiol.*, vol. 106, no. 1, pp. 202–210, 2011, doi: 10.1152/jn.00727.2010.
[323] A. Holobar, D. Farina, and D. Zazula, 'Surface EMG Decomposition', in *Surface Electromyography : Physiology, Engineering, and Applications*, R. Merletti and D. Farina, Eds. John Wiley & Sons, Inc., 2016, pp. 180–209.
[324] H. Piitulainen, A. Holobar, and J. Avela, 'Changes in motor unit characteristics after eccentric elbow flexor exercise: Motor unit characteristics after exercise', *Scand. J. Med. Sci. Sports*, vol. 22, no. 3, pp. 418–429, Jun. 2012, doi: 10.1111/j.1600-0838.2010.01228.x.
[325] M. Chen, X. Zhang, and P. Zhou, 'A Novel Validation Approach for High-Density Surface EMG Decomposition in Motor Neuron Disease', *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 26, no. 6, pp. 1161–1168, Jun. 2018, doi: 10.1109/TNSRE.2018.2836859.
[326] D. Y. Barsakcioglu and D. Farina, 'A real-time surface EMG decomposition system for non-invasive human-machine interfaces', in *2018 IEEE Biomedical Circuits and Systems Conference (BioCAS)*, Oct. 2018, pp. 1–4, doi: 10.1109/BIOCAS.2018.8584659.
[327] M. Ghofrani Jahromi, H. Parsaei, A. Zamani, and M. Dehbozorgi, 'Comparative Analysis of Wavelet-based Feature Extraction for Intramuscular EMG Signal Decomposition', *J. Biomed. Phys. Eng.*, vol. 7, no. 4, pp. 365–378, Dec. 2017.
[328] Y. Ning, N. Dias, X. Li, J. Jie, J. Li, and Y. Zhang, 'Improve computational efficiency and estimation accuracy of multi-channel surface EMG decomposition via dimensionality reduction', *Comput. Biol. Med.*, vol. 112, p. 103372, Sep. 2019, doi: 10.1016/j.compbiomed.2019.103372.
[329] R. M. Enoka, 'Physiological validation of the decomposition of surface EMG signals', *J. Electromyogr. Kinesiol.*, vol. 46, pp. 70–83, Jun. 2019, doi: 10.1016/j.jelekin.2019.03.010.
[330] N. Suresh, Xiaoyan Li, Ping Zhou, and W. Z. Rymer, 'Examination of motor unit control properties in stroke survivors using surface EMG decomposition: A preliminary report', in *2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Boston, MA, Aug. 2011, pp. 8243–8246, doi: 10.1109/IEMBS.2011.6092032.
[331] L. C. Miller, C. K. Thompson, F. Negro, C. J. Heckman, D. Farina, and J. P. A. Dewald, 'High-density surface EMG decomposition allows for recording of motor unit discharge from proximal and distal flexion synergy muscles simultaneously in individuals with stroke', in *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Aug. 2014, pp. 5340–5344, doi: 10.1109/EMBC.2014.6944832.
[332] X. Li, A. Holobar, M. Gazzoni, R. Merletti, W. Z. Rymer, and P. Zhou, 'Examination of Poststroke Alteration in Motor Unit Firing Behavior Using High-Density Surface EMG

Decomposition', *IEEE Trans. Biomed. Eng.*, vol. 62, no. 5, pp. 1242–1252, May 2015, doi: 10.1109/TBME.2014.2368514.
[333] C. J. Lamoth, F. J. van Deudekom, J. P. van Campen, B. A. Appels, O. J. de Vries, and M. Pijnappels, 'Gait stability and variability measures show effects of impaired cognition and dual tasking in frail people', *J. NeuroEngineering Rehabil.*, vol. 8, p. 2, Jan. 2011, doi: 10.1186/1743-0003-8-2.
[334] F. Danion, E. Varraine, M. Bonnard, and J. Pailhous, 'Stride variability in human gait: the effect of stride frequency and stride length', *Gait Posture*, vol. 18, no. 1, pp. 69–77, Aug. 2003, doi: 10.1016/S0966-6362(03)00030-4.
[335] C. Hershler and M. Milner, 'An Optimality Criterion for Processing Electromyographic (EMG) Signals Relating to Human Locomotion', *IEEE Trans. Biomed. Eng.*, vol. BME-25, no. 5, pp. 413–420, Sep. 1978, doi: 10.1109/TBME.1978.326338.
[336] I.-S. Hwang, H.-M. Lee, R.-J. Cherng, and J.-J. J. Chen, 'Electromyographic analysis of locomotion for healthy and hemiparetic subjects—study of performance variability and rail effect on treadmill', *Gait Posture*, vol. 18, no. 1, pp. 1–12, Aug. 2003, doi: 10.1016/S0966-6362(02)00071-1.
[337] K. P. Granata, D. A. Padua, and M. F. Abel, 'Repeatability of surface EMG during gait in children', *Gait Posture*, vol. 22, no. 4, pp. 346–350, Dec. 2005, doi: 10.1016/j.gaitpost.2004.11.014.
[338] R. E. Richards, M. T. Thornton, and R. M. R. Delaney, 'EMG variance ratio—A useful clinical outcome measure?', *Gait Posture*, vol. 39, pp. S80–S81, Jun. 2014, doi: 10.1016/j.gaitpost.2014.04.111.
[339] F. Di Nardo *et al.*, 'A new parameter for quantifying the variability of surface electromyographic signals during gait: The occurrence frequency', *J. Electromyogr. Kinesiol.*, vol. 36, pp. 25–33, Oct. 2017, doi: 10.1016/j.jelekin.2017.06.006.
[340] F. D. Nardo *et al.*, 'The occurrence frequency: A suitable parameter for the evaluation of the myoelectric activity during walking', in *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Aug. 2015, pp. 6070–6073, doi: 10.1109/EMBC.2015.7319776.
[341] J. Perry and J. M. Burnfield, *Gait analysis: normal and pathological function*, 2nd ed. Thorofare, NJ: SLACK, 2010.
[342] D. H. Sutherland, 'The evolution of clinical gait analysis part l: kinesiological EMG', *Gait Posture*, vol. 14, no. 1, pp. 61–70, Jul. 2001, doi: 10.1016/S0966-6362(01)00100-X.
[343] E. Criswell and J. R. Cram, Eds., *Cram's introduction to surface electromyography*, 2nd ed. Sudbury, MA: Jones and Bartlett, 2011.
[344] G. Loeb, 'The Motor Unit and Muscle Action', *Princ. Neural Sci.*, Jan. 2000.
[345] F. Mokaya, B. Nguyen, C. Kuo, Q. Jacobson, A. Rowe, and P. Zhang, 'MARS: a muscle activity recognition system enabling self-configuring musculoskeletal sensor networks', Apr. 2013, doi: 10.1145/2461381.2461406.
[346] K. Ohta, Y. Tanaka, I. Kawate, and T. Tsuji, 'Human muscular mobility ellipsoid: End-point acceleration manipulability measure in fast motion of human upper arm', *J. Biomech. Sci. Eng.*, vol. 9, pp. 14–00207, Dec. 2014, doi: 10.1299/jbse.14-00207.
[347] 'Sensor Locations'. http://seniam.org/sensor_location.htm (accessed Feb. 13, 2019).
[348] 'Full Size Picture sartorius.jpg', *TheFreeDictionary.com*. https://medical-dictionary.thefreedictionary.com/_/viewer.aspx?path=MosbyMD&name=sartorius.jpg&url=https%3A%2F%2Fmedical-dictionary.thefreedictionary.com%2Fsartorius%2Bmuscles (accessed May 17, 2019).
[349] 'contraction | Origin and meaning of contraction by Online Etymology Dictionary'. https://www.etymonline.com/word/contraction (accessed Jun. 11, 2019).

[350] N. Nazmi *et al.*, 'A Review of Classification Techniques of EMG Signals during Isotonic and Isometric Contractions', *Sensors*, vol. 16, no. 8, p. 1304, Aug. 2016, doi: 10.3390/s16081304.
[351] L.-Q. Zhang, G. Wang, T. Nishida, D. Xu, J. A. Sliwa, and W. Z. Rymer, 'Hyperactive tendon reflexes in spastic multiple sclerosis: Measures and mechanisms of action', *Arch. Phys. Med. Rehabil.*, vol. 81, no. 7, pp. 901–909, Jul. 2000, doi: 10.1053/apmr.2000.5582.
[352] R. M. Enoka and J. Duchateau, 'Physiology of Muscle Activation and Force Generation', in *Surface Electromyography : Physiology, Engineering, and Applications*, R. Merletti and D. Farina, Eds. John Wiley & Sons, Inc., 2016, pp. 1–29.
[353] P. Haggard, 'Conscious intention and motor cognition', *Trends Cogn. Sci.*, vol. 9, no. 6, pp. 290–295, Jun. 2005, doi: 10.1016/j.tics.2005.04.012.
[354] J. C. Eccles, 'The initiation of voluntary movements by the supplementary motor area', *Arch. Für Psychiatr. Nervenkrankh.*, vol. 231, no. 5, pp. 423–441, Jul. 1982, doi: 10.1007/BF00342722.
[355] S. Boncompagni, 'Severe muscle atrophy due to spinal cord injury can be reversed in complete absence of peripheral nerves', *Eur. J. Transl. Myol.*, vol. 22, Dec. 2012, doi: 10.4081/ejtm.2012.1799.
[356] 'Differential Amplifier - an overview | ScienceDirect Topics'. https://www.sciencedirect.com/topics/computer-science/differential-amplifier (accessed Jun. 10, 2019).
[357] A. Farinha, S. Kellogg, K. Dickinson, and T. Davison, 'Skin Impedance Reduction for Electrophysiology Measurements Using Ultrasonic Skin Permeation: Initial Report and Comparison to Current Methods', *Biomed. Instrum. Technol.*, vol. 40, no. 1, pp. 72–77, Jan. 2006, doi: 10.2345/0899-8205(2006)40[72:SIRFEM]2.0.CO;2.
[358] L. Altimari, J. L. Dantas, M. Bigliassi, T. Kanthack, A. Moraes, and T. Abrao, 'Influence of Different Strategies of Treatment Muscle Contraction and Relaxation Phases on EMG Signal Processing and Analysis During Cyclic Exercise', 2012.
[359] G. Morey-Klapsing, A. Arampatzis, and G. P. Brüggemann, 'Choosing EMG parameters: comparison of different onset determination algorithms and EMG integrals in a joint stability study', *Clin. Biomech.*, vol. 19, no. 2, pp. 196–201, Feb. 2004, doi: 10.1016/j.clinbiomech.2003.10.010.
[360] A. Shafti *et al.*, 'Comfort and Learnability Assessment of a New Soft Robotic Manipulator for Minimally Invasive Surgery', Aug. 2015, vol. 2015, doi: 10.1109/EMBC.2015.7319482.
[361] T. Sarkodie-Gyan, H. Yu, M. Bogale, N. Hernandez, and M. Pirela-Cruz, 'Application of Multiple Sensor Data Fusion for the Analysis of Human Dynamic Behavior in Space: Assessment and Evaluation of Mobility-Related Functional Impairments', *J. Biomed. Sci. Eng.*, vol. 10, pp. 182–203, Jan. 2017, doi: 10.4236/jbise.2017.104015.
[362] F. Stival, 'Subject-independent modeling of sEMG signals for the motion of a single robot joint through GMM modelization', 2015.
[363] A. Burden, 'Surface electromyography', *Biomech. Eval. Mov. Sport Exerc.*, Jan. 2008.
[364] D. M. Bojanic, B. D. Petrovacki-Balj, N. D. Jorgovanovic, and V. R. Ilic, 'Quantification of dynamic EMG patterns during gait in children with cerebral palsy', *J. Neurosci. Methods*, vol. 198, no. 2, pp. 325–331, Jun. 2011, doi: 10.1016/j.jneumeth.2011.04.030.
[365] C. Kendell, E. D. Lemaire, Y. Losier, A. Wilson, A. Chan, and B. Hudgins, 'A novel approach to surface electromyography: an exploratory study of electrode-pair selection based on signal characteristics', *J. NeuroEngineering Rehabil.*, vol. 9, no. 1, p. 24, Apr. 2012, doi: 10.1186/1743-0003-9-24.

[366] H. M. Al-Angari, G. Kanitz, S. Tarantino, and C. Cipriani, 'Distance and mutual information methods for EMG feature and channel subset selection for classification of hand movements', *Biomed. Signal Process. Control*, vol. 27, pp. 24–31, May 2016, doi: 10.1016/j.bspc.2016.01.011.

[367] Q. Xu, Y. Quan, L. Yang, and J. He, 'An Adaptive Algorithm for the Determination of the Onset and Offset of Muscle Contraction by EMG Signal Processing', *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 21, no. 1, pp. 65–73, Jan. 2013, doi: 10.1109/TNSRE.2012.2226916.

[368] D. Yang, Q. Huang, W. Yang, and H. Liu, 'EMG Onset Detection Based on Teager–Kaiser Energy Operator and Morphological Close Operation', in *Intelligent Robotics and Applications*, 2015, pp. 257–268.

[369] S. Márquez-Figueroa, Y. S. Shmaliy, and O. Ibarra-Manzano, 'Analysis and Smoothing of EMG Signal Envelope Using Kalman and UFIR Filtering under Colored Measurement Noise', *MATEC Web Conf.*, vol. 292, p. 04002, 2019, doi: 10.1051/matecconf/201929204002.

[370] T. D'Alessio and S. Conforto, 'Extraction of the envelope from surface EMG signals', *IEEE Eng. Med. Biol. Mag.*, vol. 20, no. 6, pp. 55–61, Dec. 2001, doi: 10.1109/51.982276.

[371] H. Xie and Z. Wang, 'Mean frequency derived via Hilbert-Huang transform with application to fatigue EMG signal analysis', *Comput. Methods Programs Biomed.*, vol. 82, no. 2, pp. 114–120, May 2006, doi: 10.1016/j.cmpb.2006.02.009.

[372] W. M. B. W. Daud, A. B. Yahya, C. S. Horng, M. F. Sulaima, and R. Sudirman, 'Features Extraction of Electromyography Signals in Time Domain on Biceps Brachii Muscle', *Int. J. Model. Optim.*, pp. 515–519, 2013, doi: 10.7763/IJMO.2013.V3.332.

[373] A. Balbinot and G. Favieiro, 'A Neuro-Fuzzy System for Characterization of Arm Movements', *Sensors*, vol. 13, no. 2, Art. no. 2, Feb. 2013, doi: 10.3390/s130202613.

[374] A. Phinyomark, P. Phukpattaranont, and C. Limsakul, 'Feature reduction and selection for EMG signal classification', *Expert Syst. Appl.*, vol. 39, no. 8, pp. 7420–7431, Jun. 2012, doi: 10.1016/j.eswa.2012.01.102.

[375] Md. R. Ahsan, M. I. Ibrahimy, and O. O. Khalifa, 'Neural Network Classifier for Hand Motion Detection from EMG Signal', in *5th Kuala Lumpur International Conference on Biomedical Engineering 2011*, vol. 35, N. A. A. Osman, W. A. B. W. Abas, A. K. A. Wahab, and H.-N. Ting, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2011, pp. 536–541.

[376] J. Drapała, K. Brzostowski, A. Szpala, and A. Rutkowska-Kucharska, 'Two stage EMG onset detection method', *Arch. Control Sci.*, vol. 22, no. 4, pp. 427–440, Dec. 2012, doi: 10.2478/v10170-011-0033-z.

[377] P. Bonato, T. D'Alessio, and M. Knaflitz, 'A statistical method for the measurement of muscle activation intervals from surface myoelectric signal during gait', *IEEE Trans. Biomed. Eng.*, vol. 45, no. 3, pp. 287–299, Mar. 1998, doi: 10.1109/10.661154.

[378] S. Micera, G. Vannozzi, A. M. Sabatini, and P. Dario, 'Improving detection of muscle activation intervals', *IEEE Eng. Med. Biol. Mag.*, vol. 20, no. 6, pp. 38–46, Nov. 2001, doi: 10.1109/51.982274.

[379] G. Severini, S. Conforto, M. Schmid, and T. D'Alessio, 'Novel formulation of a double threshold algorithm for the estimation of muscle activation intervals designed for variable SNR environments', *J. Electromyogr. Kinesiol.*, vol. 22, no. 6, pp. 878–885, Dec. 2012, doi: 10.1016/j.jelekin.2012.04.010.

[380] A. Merlo, D. Farina, and R. Merletti, 'A fast and reliable technique for muscle activity detection from surface EMG signals', *IEEE Trans. Biomed. Eng.*, vol. 50, no. 3, pp. 316–323, Mar. 2003, doi: 10.1109/TBME.2003.808829.

[381] G. T. Allison, 'Trunk muscle onset detection technique for EMG signals with ECG artefact', *J. Electromyogr. Kinesiol.*, vol. 13, no. 3, pp. 209–216, Jun. 2003, doi: 10.1016/S1050-6411(03)00019-1.
[382] K. Bennell, M. Duncan, and S. Cowan, 'Effect of patellar taping on vasti onset timing, knee kinematics, and kinetics in asymptomatic individuals with a delayed onset of vastus medialis oblique', *J. Orthop. Res.*, vol. 24, no. 9, pp. 1854–1860, Sep. 2006, doi: 10.1002/jor.20226.
[383] M. L. T. M. Müller and M. S. Redfern, 'Correlation between EMG and COP onset latency in response to a horizontal platform translation', *J. Biomech.*, vol. 37, no. 10, pp. 1573–1581, Oct. 2004, doi: 10.1016/j.jbiomech.2004.01.004.
[384] W.-N. Chang, J. S. Lipton, A. I. Tsirikos, and F. Miller, 'Kinesiological surface electromyography in normal children: Range of normal activity and pattern analysis', *J. Electromyogr. Kinesiol.*, vol. 17, no. 4, pp. 437–445, Aug. 2007, doi: 10.1016/j.jelekin.2006.02.003.
[385] F. Hug and S. Dorel, 'Electromyographic analysis of pedaling: A review', *J. Electromyogr. Kinesiol.*, vol. 19, no. 2, pp. 182–198, Apr. 2009, doi: 10.1016/j.jelekin.2007.10.010.
[386] P. M. Vieira, J. F. Ferreira, P. R. Gomes, and C. S. Lima, 'An adapted double threshold protocol for spastic muscles', in *2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Aug. 2016, pp. 3630–3633, doi: 10.1109/EMBC.2016.7591514.
[387] G. Kamen and D. A. Gabriel, *Essentials of electromyography*. Champaign, IL: Human Kinetics, 2010.
[388] M. Lyu, C. Xiong, Q. Zhang, and L. He, 'Fuzzy Entropy-Based Muscle Onset Detection Using Electromyography (EMG)', in *Intelligent Robotics and Applications*, 2014, pp. 89–98.
[389] R. Bahadur and S. ur Rehman, 'A Robust and Adaptive Algorithm for Real-time Muscle Activity Interval Detection using EMG Signals', Aug. 2018, pp. 89–96, Accessed: Aug. 30, 2018. [Online]. Available: http://www.scitepress.org/DigitalLibrary/Link.aspx?doi=10.5220%2f0006536200890096.
[390] M. Amann, L. T. Proctor, J. J. Sebranek, D. F. Pegelow, and J. A. Dempsey, 'Opioid-mediated muscle afferents inhibit central motor drive and limit peripheral muscle fatigue development in humans', *J. Physiol.*, vol. 587, no. 1, pp. 271–283, 2009, doi: 10.1113/jphysiol.2008.163303.
[391] G. A. C. Abbud, K. Z. H. Li, and R. G. DeMont, 'Attentional requirements of walking according to the gait phase and onset of auditory stimuli', *Gait Posture*, vol. 30, no. 2, pp. 227–232, Aug. 2009, doi: 10.1016/j.gaitpost.2009.05.013.
[392] J. P. Clarys *et al.*, *REVIEW ARTICLE Critical Appraisal and Hazards of Surface Electromyography Data Acquisition in Sport and Exercise*. 2010.
[393] P. Kutilek, J. Hybl, J. Kauler, and S. Viteckova, 'Prosthetic 6-DOF arm controlled by EMG signals and multi-sensor system', in *Proceedings of 15th International Conference MECHATRONIKA*, Dec. 2012, pp. 1–5.
[394] M. R. Al-Mulla, F. Sepulveda, and M. Colley, 'A Review of Non-Invasive Techniques to Detect and Predict Localised Muscle Fatigue', *Sensors*, vol. 11, no. 4, Art. no. 4, Apr. 2011, doi: 10.3390/s110403545.
[395] K. P. Granata, D. A. Padua, and M. F. Abel, 'Repeatability of surface EMG during gait in children', *Gait Posture*, vol. 22, no. 4, pp. 346–350, Dec. 2005, doi: 10.1016/j.gaitpost.2004.11.014.

[396] R. Merletti and P. Parker, Eds., *Electromyography: physiology, engineering, and noninvasive applications*. Hoboken, NJ: IEEE/John Wiley & Sons, 2004.
[397] W. C. Jacobson, R. H. Gabel, and R. A. Brand, 'Surface vs. fine-wire electrode ensemble-averaged signals during gait', *J. Electromyogr. Kinesiol.*, vol. 5, no. 1, pp. 37–44, Jan. 1995, doi: 10.1016/S1050-6411(99)80004-2.
[398] D. Farina, D. F. Stegeman, and R. Merletti, 'Biophysics of the Generation of EMG Signals', in *Surface Electromyography : Physiology, Engineering, and Applications*, R. Merletti and D. Farina, Eds. John Wiley & Sons, Inc., 2016, pp. 1–24.
[399] R. H. Chowdhury, M. B. I. Reaz, M. A. B. M. Ali, A. A. A. Bakar, K. Chellappan, and T. G. Chang, 'Surface Electromyography Signal Processing and Classification Techniques', *Sensors*, vol. 13, no. 9, pp. 12431–12466, Sep. 2013, doi: 10.3390/s130912431.
[400] K. S. Frahm, M. B. Jensen, D. Farina, and O. K. Andersen, 'Surface EMG crosstalk during phasic involuntary muscle activation in the nociceptive withdrawal reflex', *Muscle Nerve*, vol. 46, no. 2, pp. 228–236, 2012, doi: 10.1002/mus.23303.
[401] D. Farina, R. Merletti, B. Indino, M. Nazzaro, and M. Pozzo, 'Surface EMG crosstalk between knee extensor muscles: Experimental and model results', *Muscle Nerve*, vol. 26, no. 5, pp. 681–695, 2002, doi: 10.1002/mus.10256.
[402] D. Farina and A. Holobar, 'Characterization of Human Motor Units From Surface EMG Decomposition', *Proc. IEEE*, vol. 104, no. 2, pp. 353–373, Feb. 2016, doi: 10.1109/JPROC.2015.2498665.
[403] R. Merletti, A. Botter, and U. Barone, 'Detection and Conditioning of Surface EMG Signals', in *Surface Electromyography : Physiology, Engineering, and Applications*, R. Merletti and D. Farina, Eds. John Wiley & Sons, Inc., 2016, pp. 1–37.
[404] P. Bartuzi, T. Tokarski, and D. Roman-Liu, 'The effect of the fatty tissue on EMG signal in young women', *Acta Bioeng. Biomech. Wroc. Univ. Technol.*, vol. 12, pp. 87–92, Jan. 2010.
[405] D. M. Pincivero, R. C. Green, J. D. Mark, and R. M. Campy, 'Gender and muscle differences in EMG amplitude and median frequency, and variability during maximal voluntary contractions of the quadriceps femoris', *J. Electromyogr. Kinesiol.*, vol. 10, no. 3, pp. 189–196, Jun. 2000, doi: 10.1016/S1050-6411(00)00003-1.
[406] D. Gradolewski, P. Tojza, J. Jaworski, D. Ambroziak, G. Redlarski, and M. Krawczuk, 'Arm EMG wavelet-based denoising system', in *Advances in Intelligent Systems and Computing*, vol. 317, 2015, pp. 289–295.
[407] A. van Boxtel, 'Filters for optimal smoothing of acoustic and electric blink reflex EMG responses to determine blink response magnitude', *Biol. Psychol.*, vol. 85, no. 2, pp. 299–305, Oct. 2010, doi: 10.1016/j.biopsycho.2010.07.017.
[408] R. N. Khushaba, S. Kodagoda, M. Takruri, and G. Dissanayake, 'Toward improved control of prosthetic fingers using surface electromyogram (EMG) signals', *Expert Syst. Appl.*, vol. 39, no. 12, pp. 10731–10738, Sep. 2012, doi: 10.1016/j.eswa.2012.02.192.
[409] I. F. J. Ghalyan, Z. M. Abouelenin, G. Annamalai, and V. Kapila, 'Gaussian Smoothing Filter for Improved EMG Signal Modeling', in *Signal Processing in Medicine and Biology: Emerging Trends in Research and Applications*, I. Obeid, I. Selesnick, and J. Picone, Eds. Cham: Springer International Publishing, 2020, pp. 161–204.
[410] S. N. Sidek and A. J. Haja Mohideen, 'Mapping of EMG signal to hand grip force at varying wrist angles', in *2012 IEEE-EMBS Conference on Biomedical Engineering and Sciences*, Dec. 2012, pp. 648–653, doi: 10.1109/IECBES.2012.6498069.
[411] E. A. Clancy, F. Negro, and D. Farina, 'Single-Channel Techniques for Information Extraction from the Surface EMG Signal', in *Surface Electromyography : Physiology,*

Engineering, and Applications, R. Merletti and D. Farina, Eds. John Wiley & Sons, Inc., 2016, pp. 91–125.
[412] E. A. Clancy and N. Hogan, 'Probability density of the surface electromyogram and its relation to amplitude detectors', *IEEE Trans. Biomed. Eng.*, vol. 46, no. 6, pp. 730–739, Jun. 1999, doi: 10.1109/10.764949.
[413] C. J. De Luca, L. Donald Gilmore, M. Kuznetsov, and S. H. Roy, 'Filtering the surface EMG signal: Movement artifact and baseline noise contamination', *J. Biomech.*, vol. 43, no. 8, pp. 1573–1579, May 2010, doi: 10.1016/j.jbiomech.2010.01.027.
[414] P. Merriaux, Y. Dupuis, R. Boutteau, P. Vasseur, and X. Savatier, 'A Study of Vicon System Positioning Performance', *Sensors*, vol. 17, no. 7, p. 1591, Jul. 2017, doi: 10.3390/s17071591.
[415] C. Yang *et al.*, 'Autonomous Gait Event Detection with Portable Single-Camera Gait Kinematics Analysis System', *Journal of Sensors*, Jan. 05, 2016. https://www.hindawi.com/journals/js/2016/5036857/ (accessed Jun. 23, 2020).
[416] E. Papi, U. C. Ugbolue, and P. J. Rowe, 'SYSTEM DEPENDENT DIFFERENCES IN THE ACCURACY OF GAIT KINEMATICS: A COMPARISON OF A MODERN 12 CAMERA VICON MX-GIGANET SYSTEM WITH AN OLDER 8 CAMERA VICON 612 SYSTEM', Brazil, 2013, p. 2.
[417] R. D. Tugui, D. Antonescu, M. I. Nistor, D. Bucur, and S. Kostrakievici, 'Gait Analysis in Cerebral Palsy Using Vicon System', *Proc. Manuf. Syst.*, vol. 7, no. 2, pp. 99–104, 2012.
[418] G. Ozkaya *et al.*, 'Three-dimensional motion capture data during repetitive overarm throwing practice', *Sci. Data*, vol. 5, no. 1, Art. no. 1, Dec. 2018, doi: 10.1038/sdata.2018.272.
[419] L. J. Millar, L. Meng, and P. J. Rowe, 'Routine clinical motion analysis: comparison of a bespoke real-time protocol to current clinical methods', *Comput. Methods Biomech. Biomed. Engin.*, vol. 22, no. 2, pp. 149–158, Jan. 2019, doi: 10.1080/10255842.2018.1541089.
[420] G. Shafiq and K. C. Veluvolu, 'Multimodal chest surface motion data for respiratory and cardiovascular monitoring applications', *Sci. Data*, vol. 4, no. 1, Art. no. 1, Apr. 2017, doi: 10.1038/sdata.2017.52.
[421] B. Carse, B. Meadows, R. Bowers, and P. Rowe, 'Affordable clinical gait analysis: An assessment of the marker tracking accuracy of a new low-cost optical 3D motion analysis system', *Physiotherapy*, vol. 99, no. 4, pp. 347–351, Dec. 2013, doi: 10.1016/j.physio.2013.03.001.
[422] J. R. Duque-Ramírez, J. D. Velez-Uribe, N. E. Gómez-Suárez, and R. D. Manrique-Hernández, 'Gait parameters in a sample of healthy Colombian adults aged between 18 and 25 years: a cross-sectional study', *Rev. Fac. Med.*, vol. 68, no. 1, Art. no. 1, Jan. 2020, doi: 10.15446/revfacmed.v68n1.71690.
[423] B. Sijobert, F. Feuvrier, J. Froger, D. Guiraud, and C. A. Coste, 'A sensor fusion approach for inertial sensors based 3D kinematics and pathological gait assessments: toward an adaptive control of stimulation in post-stroke subjects*', in *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Jul. 2018, pp. 3497–3500, doi: 10.1109/EMBC.2018.8512985.
[424] A. Szczesna, M. Blaszczyszyn, M. Pawlyta, and A. Michalczuk, 'Assessment of Gait Parameters in Virtual Environment', in *2018 IEEE 20th International Conference on e-Health Networking, Applications and Services (Healthcom)*, Sep. 2018, pp. 1–5, doi: 10.1109/HealthCom.2018.8531159.

[425] S. Roeles *et al.*, 'Gait stability in response to platform, belt, and sensory perturbations in young and older adults', *Med. Biol. Eng. Comput.*, vol. 56, no. 12, pp. 2325–2335, Dec. 2018, doi: 10.1007/s11517-018-1855-7.
[426] A. E. Markham, K. A. Service, J.-D. Collins, and P. H. Sessoms, 'Learning and Long-Term Retention of Task-Specific Training in a Non-injured Population Using the Computer Assisted Rehabilitation Environment (CAREN)', in *Serious Games, Interaction and Simulation*, Cham, 2017, pp. 99–108, doi: 10.1007/978-3-319-51055-2_13.
[427] A. Kalron, I. Fonkatz, L. Frid, H. Baransi, and A. Achiron, 'The effect of balance training on postural control in people with multiple sclerosis using the CAREN virtual reality system: a pilot randomized controlled trial', *J. NeuroEngineering Rehabil.*, vol. 13, no. 1, p. 13, Mar. 2016, doi: 10.1186/s12984-016-0124-y.
[428] Y. Ma, Y. Liang, X. Kang, M. Shao, L. Siemelink, and Y. Zhang, 'Gait Characteristics of Children with Spastic Cerebral Palsy during Inclined Treadmill Walking under a Virtual Reality Environment', *Appl. Bionics Biomech.*, vol. 2019, p. 8049156, 2019, doi: 10.1155/2019/8049156.
[429] K. L. Hsieh, R. C. Sheehan, J. M. Wilken, and J. B. Dingwell, 'Healthy individuals are more maneuverable when walking slower while navigating a virtual obstacle course', *Gait Posture*, vol. 61, pp. 466–472, Mar. 2018, doi: 10.1016/j.gaitpost.2018.02.015.
[430] E. I. Baron, M. Miller Koop, M. C. Streicher, A. B. Rosenfeldt, and J. L. Alberts, 'Altered kinematics of arm swing in Parkinson's disease patients indicates declines in gait under dual-task conditions', *Parkinsonism Relat. Disord.*, vol. 48, pp. 61–67, Mar. 2018, doi: 10.1016/j.parkreldis.2017.12.017.
[431] S. Kimel-Naor, A. Gottlieb, and M. Plotnik, 'The effect of uphill and downhill walking on gait parameters: A self-paced treadmill study', *J. Biomech.*, vol. 60, pp. 142–149, Jul. 2017, doi: 10.1016/j.jbiomech.2017.06.030.
[432] M. Eltoukhy, J. Oh, C. Kuenze, and J. Signorile, 'Improved kinect-based spatiotemporal and kinematic treadmill gait assessment', *Gait Posture*, vol. 51, pp. 77–83, Jan. 2017, doi: 10.1016/j.gaitpost.2016.10.001.
[433] L. D. Duffell, N. Hope, and A. H. McGregor, 'Comparison of kinematic and kinetic parameters calculated using a cluster-based model and Vicon's plug-in gait', *Proc. Inst. Mech. Eng. [H]*, vol. 228, no. 2, pp. 206–210, Feb. 2014, doi: 10.1177/0954411913518747.
[434] L. Meng, L. Millar, C. Childs, and A. Buis, 'A strathclyde cluster model for gait kinematic measurement using functional methods: a study of inter-assessor reliability analysis with comparison to anatomical models', *Comput. Methods Biomech. Biomed. Engin.*, vol. 0, no. 0, pp. 1–10, Jun. 2020, doi: 10.1080/10255842.2020.1768246.
[435] 'Lower body modeling with Plug-in Gait - Nexus 2.5 Documentation - Documentation | VICON'. https://docs.vicon.com/display/Nexus25/Lower+body+modeling+with+Plug-in+Gait (accessed Mar. 02, 2018).
[436] D. Levine, J. Richards, M. Whittle, and M. Whittle, Eds., *Whittle's gait analysis*, 5th ed. Edinburgh ; New York: Churchill Livingstone/Elsevier, 2012.
[437] N. T. Pickle, A. M. Grabowski, A. G. Auyang, and A. K. Silverman, 'The functional roles of muscles during sloped walking', *J. Biomech.*, vol. 49, no. 14, pp. 3244–3251, Oct. 2016, doi: 10.1016/j.jbiomech.2016.08.004.
[438] J. R. Franz and R. Kram, 'The effects of grade and speed on leg muscle activations during walking', *Gait Posture*, vol. 35, no. 1, pp. 143–147, Jan. 2012, doi: 10.1016/j.gaitpost.2011.08.025.

[439] A. R. den Otter, A. C. H. Geurts, T. Mulder, and J. Duysens, 'Speed related changes in muscle activity from normal to very slow walking speeds', *Gait Posture*, vol. 19, no. 3, pp. 270–278, Jun. 2004, doi: 10.1016/S0966-6362(03)00071-7.
[440] A. L. Hof, H. Elzinga, W. Grimmius, and J. P. K. Halbertsma, 'Speed dependence of averaged EMG profiles in walking', *Gait Posture*, vol. 16, no. 1, pp. 78–86, Aug. 2002, doi: 10.1016/S0966-6362(01)00206-5.
[441] V. L. Gray, C. L. Pollock, J. M. Wakeling, T. D. Ivanova, and S. J. Garland, 'Patterns of muscle coordination during stepping responses post-stroke', *J. Electromyogr. Kinesiol.*, vol. 25, no. 6, pp. 959–965, Dec. 2015, doi: 10.1016/j.jelekin.2015.09.003.
[442] G. Moisan, M. Descarreaux, and V. Cantin, 'Muscle activation during fast walking with two types of foot orthoses in participants with cavus feet', *J. Electromyogr. Kinesiol.*, vol. 43, pp. 7–13, Dec. 2018, doi: 10.1016/j.jelekin.2018.08.002.
[443] K. Watanabe, M. Kouzaki, M. Ogawa, H. Akima, and T. Moritani, 'Relationships between muscle strength and multi-channel surface EMG parameters in eighty-eight elderly', *Eur. Rev. Aging Phys. Act.*, vol. 15, no. 1, p. 3, Apr. 2018, doi: 10.1186/s11556-018-0192-z.
[444] M. Piasecki, A. Ireland, D. Stashuk, A. Hamilton-Wright, D. A. Jones, and J. S. McPhee, 'Age-related neuromuscular changes affecting human vastus lateralis: Age-related neuromuscular changes affecting human vastus lateralis', *J. Physiol.*, vol. 594, no. 16, pp. 4525–4536, Aug. 2016, doi: 10.1113/JP271087.
[445] L. L. Menegaldo, 'Real-time muscle state estimation from EMG signals during isometric contractions using Kalman filters', *Biol. Cybern.*, vol. 111, no. 5, pp. 335–346, Dec. 2017, doi: 10.1007/s00422-017-0724-z.
[446] K. Manal and W. Rose, 'A general solution for the time delay introduced by a low-pass Butterworth digital filter: An application to musculoskeletal modeling', *J. Biomech.*, vol. 40, no. 3, pp. 678–681, Jan. 2007, doi: 10.1016/j.jbiomech.2006.02.001.
[447] R. Baker, *Measuring Walking: A Handbook of Clinical Gait Analysis*. London, UNITED KINGDOM: Mac Keith Press, 2013.
[448] R. Baker, 'Temporal spatial data, the gait cycle and gait graphs', p. 8.
[449] M. L. Harris-Love, L. W. Forrester, R. F. Macko, K. H. C. Silver, and G. V. Smith, 'Hemiparetic Gait Parameters in Overground Versus Treadmill Walking', *Neurorehabil. Neural Repair*, Mar. 2001, doi: 10.1177/154596830101500204.
[450] E. R. Da, M. R. Kunzler, M. F. Bobbert, J. Duysens, and F. P. Carpes, '30 min of treadmill walking at self-selected speed does not increase gait variability in independent elderly.', *J. Sports Sci.*, vol. 36, no. 11, pp. 1305–1311, Jun. 2018, doi: 10.1080/02640414.2017.1375139.
[451] J. M. Hausdorff, 'Gait dynamics, fractals and falls: Finding meaning in the stride-to-stride fluctuations of human walking', *Hum. Mov. Sci.*, vol. 26, no. 4, pp. 555–589, Aug. 2007, doi: 10.1016/j.humov.2007.05.003.
[452] G. Allali *et al.*, 'Gait phenotype from mild cognitive impairment to moderate dementia: results from the GOOD initiative', *Eur. J. Neurol.*, vol. 23, no. 3, pp. 527–541, Mar. 2016, doi: 10.1111/ene.12882.
[453] H. B. Menz, M. D. Latt, A. Tiedemann, M. M. S. Kwan, and S. R. Lord, 'Reliability of the GAITRite® walkway system for the quantification of temporo-spatial parameters of gait in young and older people', *Gait Posture*, vol. 20, no. 1, pp. 20–25, Aug. 2004, doi: 10.1016/S0966-6362(03)00068-7.
[454] G. Yavuzer, Ö. Öken, A. Elhan, and H. J. Stam, 'Repeatability of lower limb three-dimensional kinematics in patients with stroke', *Gait Posture*, vol. 27, no. 1, pp. 31–35, Jan. 2008, doi: 10.1016/j.gaitpost.2006.12.016.

[455] F. Stief, H. Böhm, K. Michel, A. Schwirtz, and L. Döderlein, 'Reliability and Accuracy in Three-Dimensional Gait Analysis: A Comparison of Two Lower Body Protocols', *J. Appl. Biomech.*, vol. 29, no. 1, pp. 105–111, Feb. 2013, doi: 10.1123/jab.29.1.105.
[456] J. L. McGinley, R. Baker, R. Wolfe, and M. E. Morris, 'The reliability of three-dimensional kinematic gait measurements: A systematic review', *Gait Posture*, vol. 29, no. 3, pp. 360–369, Apr. 2009, doi: 10.1016/j.gaitpost.2008.09.003.
[457] R. Merletti, B. Afsharipour, J. Dideriksen, and D. Farina, 'Muscle Force and Myoelectric Manifestations of Muscle Fatigue in Voluntary and Electrically Elicited Contractions', in *Surface Electromyography : Physiology, Engineering, and Applications*, R. Merletti and D. Farina, Eds. John Wiley & Sons, Inc., 2016, pp. 273–310.
[458] J. Mickelborough, M. L. van der Linden, R. C. Tallis, and A. R. Ennos, 'Muscle activity during gait initiation in normal elderly people', *Gait Posture*, vol. 19, no. 1, pp. 50–57, Feb. 2004, doi: 10.1016/S0966-6362(03)00016-X.
[459] H. P. Goodkin and W. T. Thach, 'Cerebellar Control of Constrained and Unconstrained Movements. II. EMG and Nuclear Activity', *J. Neurophysiol.*, vol. 89, no. 2, pp. 896–908, Feb. 2003, doi: 10.1152/jn.00115.2002.
[460] J. H. Hollman, M. K. Watkins, A. C. Imhoff, C. E. Braun, K. A. Akervik, and D. K. Ness, 'Complexity, fractal dynamics and determinism in treadmill ambulation: Implications for clinical biomechanists', *Clin. Biomech.*, vol. 37, pp. 91–97, Aug. 2016, doi: 10.1016/j.clinbiomech.2016.06.007.
[461] C. A. Byrne, D. T. O'Keeffe, A. E. Donnelly, and G. M. Lyons, 'Effect of walking speed changes on tibialis anterior EMG during healthy gait for FES envelope design in drop foot correction', *J. Electromyogr. Kinesiol.*, vol. 17, no. 5, pp. 605–616, Oct. 2007, doi: 10.1016/j.jelekin.2006.07.008.
[462] C. A. Francis, A. L. Lenz, R. L. Lenhart, and D. G. Thelen, 'The Modulation of Forward Propulsion, Vertical Support, and Center of Pressure by the Plantarflexors during Human Walking', *Gait Posture*, vol. 38, no. 4, pp. 993–997, Sep. 2013, doi: 10.1016/j.gaitpost.2013.05.009.
[463] K. S. Button *et al.*, 'Power failure: why small sample size undermines the reliability of neuroscience', *Nat. Rev. Neurosci.*, vol. 14, no. 5, pp. 365–376, May 2013, doi: 10.1038/nrn3475.
[464] J. Faber and L. M. Fonseca, 'How sample size influences research outcomes', *Dent. Press J. Orthod.*, vol. 19, no. 4, pp. 27–29, 2014, doi: 10.1590/2176-9451.19.4.027-029.ebo.
[465] Z. S. Nasreddine *et al.*, 'The Montreal Cognitive Assessment, MoCA: A Brief Screening Tool For Mild Cognitive Impairment', *J. Am. Geriatr. Soc.*, vol. 53, no. 4, pp. 695–699, 2005, doi: 10.1111/j.1532-5415.2005.53221.x.
[466] F. M. Collen, D. T. Wade, G. F. Robb, and C. M. Bradshaw, 'The Rivermead Mobility Index: A further development of the Rivermead Motor Assessment', *Int. Disabil. Stud.*, vol. 13, no. 2, pp. 50–54, Jan. 1991, doi: 10.3109/03790799109166684.
[467] M. R. Schindl, C. Forstner, H. Kern, H. T. Zipko, M. Rupp, and U. A. Zifko, 'Evaluation of a German version of the Rivermead Mobility Index (RMI) in acute and chronic stroke patients', *Eur. J. Neurol.*, vol. 7, no. 5, pp. 523–528, 2000, doi: 10.1046/j.1468-1331.2000.t01-1-00108.x.
[468] H.-M. Chen, C.-L. Hsieh, S. K. Lo, L.-J. Liaw, S.-M. Chen, and J.-H. Lin, 'The Test-Retest Reliability of 2 Mobility Performance Tests in Patients With Chronic Stroke', *Neurorehabil. Neural Repair*, vol. 21, no. 4, pp. 347–352, Jul. 2007, doi: 10.1177/1545968306297864.

[469] S. Lennon and L. Johnson, 'The modified Rivermead Mobility Index: validity and reliability', *Disabil. Rehabil.*, vol. 22, no. 18, pp. 833–839, Jan. 2000, doi: 10.1080/09638280050207884.
[470] 'Trigno Wireless System Users Guide (MAN-012-2-3)'. Delsys Inc, Jul. 2012, [Online]. Available: www.delsys.com.
[471] 'TRIGNO EMG System 4-Channel FSR Adapter User's Guide'. Delsys Inc.
[472] R. Oshana, 'Chapter 1 - Introduction to Digital Signal Processing', in *DSP for Embedded and Real-Time Systems*, R. Oshana, Ed. Oxford: Newnes, 2012, pp. 1–14.
[473] 'Trigno Wireless Biofeedback System'. Delsys Inc, 2019, [Online]. Available: www.delsys.com/emgworks.
[474] J. L. Bartlett and P. H. Sessoms, 'Preferred walking speed in a virtual environment', Jan. 2011, p. 2.
[475] A. Lees, J. Vanrenterghem, G. Barton, and M. Lake, 'Kinematic response characteristics of the CAREN moving platform system for use in posture and balance research', *Med. Eng. Phys.*, vol. 29, no. 5, pp. 629–635, Jun. 2007, doi: 10.1016/j.medengphy.2006.06.004.
[476] L. Hak *et al.*, 'Stepping strategies used by post-stroke individuals to maintain margins of stability during walking', *Clin. Biomech.*, vol. 28, no. 9, pp. 1041–1048, Nov. 2013, doi: 10.1016/j.clinbiomech.2013.10.010.
[477] L. Hak, H. Houdijk, P. van der Wurff, M. R. Prins, M. J. Beek, and J. H. van Dieën, 'Stride frequency and length adjustment in post-stroke individuals: Influence on the margins of stability', Feb. 2015. https://www.ingentaconnect.com/content/mjl/sreh/2015/00000047/00000002/art00004 (accessed Mar. 25, 2020).
[478] E. H. Sinitski, E. D. Lemaire, N. Baddour, M. Besemann, N. L. Dudek, and J. S. Hebert, 'Fixed and self-paced treadmill walking for able-bodied and transtibial amputees in a multi-terrain virtual environment', *Gait Posture*, vol. 41, no. 2, pp. 568–573, Feb. 2015, doi: 10.1016/j.gaitpost.2014.12.016.
[479] D. H. Gates, B. J. Darter, J. B. Dingwell, and J. M. Wilken, 'Comparison of walking overground and in a Computer Assisted Rehabilitation Environment (CAREN) in individuals with and without transtibial amputation', *J. NeuroEngineering Rehabil.*, vol. 9, no. 1, p. 81, Nov. 2012, doi: 10.1186/1743-0003-9-81.
[480] G. J. Barton, M. B. Hawken, R. J. Foster, G. Holmes, and P. B. Butler, 'The effects of virtual reality game training on trunk to pelvis coupling in a child with cerebral palsy', *J. NeuroEngineering Rehabil.*, vol. 10, no. 1, p. 15, Feb. 2013, doi: 10.1186/1743-0003-10-15.
[481] K. Aminian, B. Najafi, C. Büla, P.-F. Leyvraz, and Ph. Robert, 'Spatio-temporal parameters of gait measured by an ambulatory system using miniature gyroscopes', *J. Biomech.*, vol. 35, no. 5, pp. 689–699, May 2002, doi: 10.1016/S0021-9290(02)00008-8.
[482] D. McGrath, B. R. Greene, K. J. O'Donovan, and B. Caulfield, 'Gyroscope-based assessment of temporal gait parameters during treadmill walking and running', *Sports Eng.*, vol. 15, no. 4, pp. 207–213, Dec. 2012, doi: 10.1007/s12283-012-0093-8.
[483] J. Taborri, E. Palermo, S. Rossi, and P. Cappa, 'Gait Partitioning Methods: A Systematic Review', *Sensors*, vol. 16, no. 1, p. 66, Jan. 2016, doi: 10.3390/s16010066.
[484] I. P. I. Pappas, T. Keller, S. Mangold, M. R. Popovic, V. Dietz, and M. Morari, 'A reliable gyroscope-based gait-phase detection sensor embedded in a shoe insole', *IEEE Sens. J.*, vol. 4, no. 2, pp. 268–274, Apr. 2004, doi: 10.1109/JSEN.2004.823671.

[485] R. Moe-Nilssen and J. L. Helbostad, ‘Estimation of gait cycle characteristics by trunk accelerometry’, *J. Biomech.*, vol. 37, no. 1, pp. 121–126, Jan. 2004, doi: 10.1016/S0021-9290(03)00233-1.
[486] J. K. Lee and E. J. Park, ‘Quasi real-time gait event detection using shank-attached gyroscopes’, *Med. Biol. Eng. Comput.*, vol. 49, no. 6, pp. 707–712, Jun. 2011, doi: 10.1007/s11517-011-0736-0.
[487] D. Gouwanda and A. A. Gopalai, ‘A robust real-time gait event detection using wireless gyroscope and its application on normal and altered gaits’, *Med. Eng. Phys.*, vol. 37, no. 2, pp. 219–225, Feb. 2015, doi: 10.1016/j.medengphy.2014.12.004.
[488] D. Novak *et al.*, ‘Automated detection of gait initiation and termination using wearable sensors’, *Med. Eng. Phys.*, vol. 35, no. 12, pp. 1713–1720, Dec. 2013, doi: 10.1016/j.medengphy.2013.07.003.
[489] I. P. I. Pappas, M. R. Popovic, T. Keller, V. Dietz, and M. Morari, ‘A reliable gait phase detection system’, *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 9, no. 2, pp. 113–125, Jun. 2001, doi: 10.1109/7333.928571.
[490] C. M. Senanayake and S. M. N. A. Senanayake, ‘Computational Intelligent Gait-Phase Detection System to Identify Pathological Gait’, *IEEE Trans. Inf. Technol. Biomed.*, vol. 14, no. 5, pp. 1173–1179, Sep. 2010, doi: 10.1109/TITB.2010.2058813.
[491] D. Novak *et al.*, ‘Early recognition of gait initiation and termination using wearable sensors’, in *2012 4th IEEE RAS EMBS International Conference on Biomedical Robotics and Biomechatronics (BioRob)*, Jun. 2012, pp. 1937–1942, doi: 10.1109/BioRob.2012.6290277.
[492] P. Catalfamo, S. Ghoussayni, and D. Ewins, ‘Gait Event Detection on Level Ground and Incline Walking Using a Rate Gyroscope’, *Sensors*, vol. 10, no. 6, Art. no. 6, Jun. 2010, doi: 10.3390/s100605683.
[493] D. Gouwanda and A. A. Gopalai, ‘A robust real-time gait event detection using wireless gyroscope and its application on normal and altered gaits’, *Med. Eng. Phys.*, vol. 37, no. 2, pp. 219–225, Feb. 2015, doi: 10.1016/j.medengphy.2014.12.004.
[494] M. R. Patterson, E. Delahunt, K. T. Sweeney, and B. Caulfield, ‘An Ambulatory Method of Identifying Anterior Cruciate Ligament Reconstructed Gait Patterns’, *Sensors*, vol. 14, no. 1, pp. 887–899, Jan. 2014, doi: 10.3390/s140100887.
[495] P. C. Formento, R. Acevedo, S. Ghoussayni, and D. Ewins, ‘Gait Event Detection during Stair Walking Using a Rate Gyroscope’, *Sensors*, vol. 14, no. 3, pp. 5470–5485, Mar. 2014, doi: 10.3390/s140305470.
[496] K. T. Özgünen, U. Çelik, and S. S. Kurdak, ‘Determination of an Optimal Threshold Value for Muscle Activity Detection in EMG Analysis’, *J. Sports Sci. Med.*, vol. 9, no. 4, pp. 620–628, Dec. 2010.
[497] ‘Distribution function: E-Learning Platform for IFM’. http://daad.wb.tu-harburg.de/?id=271 (accessed Mar. 29, 2018).
[498] F. Di Nardo, A. Mengarelli, E. Maranesi, L. Burattini, and S. Fioretti, ‘Gender differences in the myoelectric activity of lower limb muscles in young healthy subjects during walking’, *Biomed. Signal Process. Control*, vol. 19, no. Supplement C, pp. 14–22, May 2015, doi: 10.1016/j.bspc.2015.03.006.
[499] Y. P. Ivanenko, R. E. Poppele, and F. Lacquaniti, ‘Five basic muscle activation patterns account for muscle activity during human locomotion’, *J. Physiol.*, vol. 556, no. 1, pp. 267–282, doi: 10.1113/jphysiol.2003.057174.
[500] S. A. Fraser, K. Z. H. Li, R. G. DeMont, and V. B. Penhune, ‘Effects of Balance Status and Age on Muscle Activation While Walking Under Divided Attention’, *J. Gerontol. Ser. B*, vol. 62, no. 3, pp. P171–P178, May 2007, doi: 10.1093/geronb/62.3.P171.

[501] A. Gallina, C. L. Pollock, T. M. Vieira, T. D. Ivanova, and S. J. Garland, 'Between-day reliability of triceps surae responses to standing perturbations in people post-stroke and healthy controls: A high-density surface EMG investigation', *Gait Posture*, vol. 44, pp. 103–109, Feb. 2016, doi: 10.1016/j.gaitpost.2015.11.015.

[502] A. Forner-Cordero, C. Itiki, R. S. Souza, J. C. M. C. Lourenço, and H. I. Krebs, 'Experimental assessment of gait with rhythmic auditory perturbations', in *5th IEEE RAS/EMBS International Conference on Biomedical Robotics and Biomechatronics*, Aug. 2014, pp. 282–286, doi: 10.1109/BIOROB.2014.6913790.

[503] R. D. Stout, M. W. Wittstein, C. T. LoJacono, and C. K. Rhea, 'Gait dynamics when wearing a treadmill safety harness', *Gait Posture*, vol. 44, pp. 100–102, Feb. 2016, doi: 10.1016/j.gaitpost.2015.11.012.

[504] J. R. Franz and R. Kram, 'Advanced age affects the individual leg mechanics of level, uphill, and downhill walking', *J. Biomech.*, vol. 46, no. 3, pp. 535–540, Feb. 2013, doi: 10.1016/j.jbiomech.2012.09.032.

[505] J. D. Ortega and C. T. Farley, 'Effects of aging on mechanical efficiency and muscle activation during level and uphill walking', *J. Electromyogr. Kinesiol.*, vol. 25, no. 1, pp. 193–198, Feb. 2015, doi: 10.1016/j.jelekin.2014.09.003.

[506] S. Carda, M. Invernizzi, A. Baricich, G. Cognolato, and C. Cisari, 'Does altering inclination alter effectiveness of treadmill training for gait impairment after stroke? A randomized controlled trial', *Clin. Rehabil.*, vol. 27, no. 10, pp. 932–938, Oct. 2013, doi: 10.1177/0269215513485592.

[507] E. Akoopie, B. C. Kleven, and T. Koch, 'Neuromuscular Adaptations Following Slope Walking in Individuals Post-Stroke', *UNLV Theses Diss. Prof. Pap. Capstones*, May 2018, [Online]. Available: https://digitalscholarship.unlv.edu/thesesdissertations/3560.

[508] R. Mohammadi, S. Talebian, C. P. Phadke, M. S. Yekaninejad, and M.-R. Hadian, 'Effects of Treadmill Incline and Speed on Ankle Muscle Activity in Subjects After a Stroke', *Arch. Phys. Med. Rehabil.*, vol. 97, no. 3, pp. 445–453, Mar. 2016, doi: 10.1016/j.apmr.2015.10.088.

[509] A. Mengarelli, E. Maranesi, L. Burattini, S. Fioretti, and F. Di Nardo, 'Co-contraction activity of ankle muscles during walking: A gender comparison', *Biomed. Signal Process. Control*, vol. 33, pp. 1–9, Mar. 2017, doi: 10.1016/j.bspc.2016.11.010.

[510] W. J. Hurd, T. L. Chmielewski, M. J. Axe, I. Davis, and L. Snyder-Mackler, 'Differences in normal and perturbed walking kinematics between male and female athletes', *Clin. Biomech.*, vol. 19, no. 5, pp. 465–472, Jun. 2004, doi: 10.1016/j.clinbiomech.2004.01.013.

[511] T. H. Cruz and Y. Y. Dhaher, 'Impaired lower limb muscle synergies post-stroke', in *2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Sep. 2009, pp. 3956–3959, doi: 10.1109/IEMBS.2009.5333669.

[512] J. R. Franz and R. Kram, 'How does age affect leg muscle activity/coactivity during uphill and downhill walking?', *Gait Posture*, vol. 37, no. 3, pp. 378–384, Mar. 2013, doi: 10.1016/j.gaitpost.2012.08.004.

[513] G. Grazzi *et al.*, 'Outdoor Reproducibility of a 1-km Treadmill Walking Test to Predict Peak Oxygen Uptake in Cardiac Patients':, *J. Cardiopulm. Rehabil. Prev.*, vol. 37, no. 5, pp. 347–349, Sep. 2017, doi: 10.1097/HCR.0000000000000266.

[514] H. J. P. Fokkenrood, M. M. L. van den Houten, S. Houterman, J. C. Breek, M. R. M. Scheltinga, and J. A. W. Teijink, 'Agreements and Discrepancies between the Estimated Walking Distance, Nongraded and Graded Treadmill Testing, and Outside Walking in Patients with Intermittent Claudication', *Ann. Vasc. Surg.*, vol. 29, no. 6, pp. 1218–1224, Aug. 2015, doi: 10.1016/j.avsg.2015.02.011.

[515] H. J. P. Fokkenrood, M. M. L. van den Houten, S. Houterman, J. C. Breek, M. R. M. Scheltinga, and J. A. W. Teijink, 'Agreements and Discrepancies between the Estimated Walking Distance, Nongraded and Graded Treadmill Testing, and Outside Walking in Patients with Intermittent Claudication', *Ann. Vasc. Surg.*, vol. 29, no. 6, pp. 1218–1224, Aug. 2015, doi: 10.1016/j.avsg.2015.02.011.

[516] G. A. Power, B. H. Dalton, K. J. Gilmore, M. D. Allen, T. J. Doherty, and C. L. Rice, 'Maintaining Motor Units into Old Age: Running the Final Common Pathway', *Eur. J. Transl. Myol.*, vol. 27, no. 1, Mar. 2017, doi: 10.4081/ejtm.2017.6597.

[517] L. B. Verdijk *et al.*, 'Characteristics of Muscle Fiber Type Are Predictive of Skeletal Muscle Mass and Strength in Elderly Men', *J. Am. Geriatr. Soc.*, vol. 58, no. 11, pp. 2069–2075, Nov. 2010, doi: 10.1111/j.1532-5415.2010.03150.x.

[518] C. J. McNeil, T. J. Doherty, D. W. Stashuk, and C. L. Rice, 'Motor unit number estimates in the tibialis anterior muscle of young, old, and very old men', *Muscle Nerve*, vol. 31, no. 4, pp. 461–467, 2005, doi: 10.1002/mus.20276.

[519] M. Divjak, B. Šimunič, K. Koren, M. Gerževič, R. Pišot, and A. Holobar, 'Surface EMG Analysis of Age-related Changes in Motor Unit Firing Rates of Triceps Surae During Isometric Plantar Flexion', in *2018 IEEE-EMBS Conference on Biomedical Engineering and Sciences (IECBES)*, Dec. 2018, pp. 96–101, doi: 10.1109/IECBES.2018.8626617.

[520] M.-J. Chung and M.-J. J. Wang, 'The change of gait parameters during walking at different percentage of preferred walking speed for healthy adults aged 20–60 years', *Gait Posture*, vol. 31, no. 1, pp. 131–135, Jan. 2010, doi: 10.1016/j.gaitpost.2009.09.013.

[521] D. P. Manning and C. Jones, 'The effect of roughness, floor polish, water, oil and ice on underfoot friction:: current safety footwear solings are less slip resistant than microcellular polyurethane', *Appl. Ergon.*, vol. 32, no. 2, pp. 185–196, Apr. 2001, doi: 10.1016/S0003-6870(00)00055-7.

[522] C. Aschan, M. Hirvonen, E. Rajamäki, T. Mannelin, J. Ruotsalainen, and R. Ruuhela, 'Performance of slippery and slip-resistant footwear in different wintry weather conditions measured in situ', *Saf. Sci.*, vol. 47, no. 8, pp. 1195–1200, Oct. 2009, doi: 10.1016/j.ssci.2009.01.006.

[523] G. Gard, G. Berggård, P. Rosander, and A. Larsson, 'Pedestrians perceptions of community walking with anti-slip devices – An explorative case study', *J. Transp. Health*, vol. 11, pp. 202–208, Dec. 2018, doi: 10.1016/j.jth.2018.09.001.

[524] I.-J. Kim, H. Hsiao, and P. Simeonov, 'Functional levels of floor surface roughness for the prevention of slips and falls: Clean-and-dry and soapsuds-covered wet surfaces', *Appl. Ergon.*, vol. 44, no. 1, pp. 58–64, Jan. 2013, doi: 10.1016/j.apergo.2012.04.010.

[525] A. Shumway-Cook, A. E. Patla, A. Stewart, L. Ferrucci, M. A. Ciol, and J. M. Guralnik, 'Environmental Demands Associated With Community Mobility in Older Adults With and Without Mobility Disabilities', *Phys. Ther.*, vol. 82, no. 7, pp. 670–681, Jul. 2002, doi: 10.1093/ptj/82.7.670.

[526] R. M. Lamont, M. E. Morris, M. H. Woollacott, and S. G. Brauer, 'Community Walking in People with Parkinson's Disease', *Parkinson’s Disease*, Nov. 29, 2011. https://www.hindawi.com/journals/pd/2012/856237/ (accessed Jul. 20, 2020).

[527] K. R. Gottshall and P. H. Sessoms, 'Improvements in dizziness and imbalance results from using a multi disciplinary and multi sensory approach to Vestibular Physical Therapy – a case study', *Front. Syst. Neurosci.*, vol. 9, 2015, doi: 10.3389/fnsys.2015.00106.

[528] A. L. V. Coelho and C. A. M. Lima, 'Assessing fractal dimension methods as feature extractors for EMG signal classification', *Eng. Appl. Artif. Intell.*, vol. 36, pp. 81–98, Nov. 2014, doi: 10.1016/j.engappai.2014.07.009.

[529] Y. Xue and Z. Ju, 'SEMG based Intention Identification of Complex Hand Motion using Nonlinear Time Series Analysis', in *2019 9th International Conference on Information Science and Technology (ICIST)*, Hulunbuir, China, Aug. 2019, pp. 357–361, doi: 10.1109/ICIST.2019.8836817.
[530] M. Chakraborty and D. Parbat, 'Fractals, chaos and entropy analysis to obtain parametric features of surface electromyography signals during dynamic contraction of biceps muscles under varying load', in *2017 2nd International Conference for Convergence in Technology (I2CT)*, Mumbai, Apr. 2017, pp. 222–229, doi: 10.1109/I2CT.2017.8226125.
[531] Y. Wu and R. Song, 'Effects of Task Demands on Kinematics and EMG Signals during Tracking Tasks Using Multiscale Entropy', *Entropy*, vol. 19, no. 7, p. 307, Jun. 2017, doi: 10.3390/e19070307.
[532] E. Conte *et al.*, 'Chaos, Fractal and Recurrence Quantification Analysis of Surface Electromyography in Muscular Dystrophy', *World J. Neurosci.*, vol. 05, no. 04, pp. 205–257, 2015, doi: 10.4236/wjns.2015.54022.
[533] D. Ghosh, S. Dutta, S. Chakraborty, and S. Samanta, 'Chaos Based Quantitative Electro-Diagnostic Marker for Diagnosis of Myopathy, Neuropathy and Motor Neuron Disease', *J. Neurol. Neurosci.*, vol. 8, 2017, doi: 10.21767/2171-6625.1000226.
[534] P. Carvalho, P. Gil, J. Henriques, L. Eugenio, and M. Antunes, 'Low complexity algorithm for heart sound segmentation using the variance fractal dimension', in *IEEE International Workshop on Intelligent Signal Processing, 2005.*, University of Algarve Portugal, 2005, pp. 194–199, doi: 10.1109/WISP.2005.1531657.
[535] M. S. Singh, R. Pasumarthy, and V. Talasila, 'Time Series Analysis of Surface EMG Signal - Linear, Non Linear and Chaotic Approaches', in *2019 Fifth Indian Control Conference (ICC)*, Jan. 2019, pp. 442–447, doi: 10.1109/INDIANCC.2019.8715550.
[536] S. Behnia, J. Ziaei, M. Ghiassi, and A. Akhshani, 'Nonlinear Dynamic Approach of Heartbeats Based on the Grudzin ski-Żebrowski's Model', *Chin. J. Phys.*, vol. 53, no. 7, pp. 120702–1, Dec. 2015, doi: 10.6122/CJP.20150904.
[537] S. S. Cury *et al.*, 'Fractal dimension analysis reveals skeletal muscle disorganization in mdx mice', *Biochem. Biophys. Res. Commun.*, vol. 503, no. 1, pp. 109–115, Sep. 2018, doi: 10.1016/j.bbrc.2018.05.189.
[538] A. Ancillao, M. Galli, C. Rigoldi, and G. Albertini, 'Linear correlation between fractal dimension of surface EMG signal from Rectus Femoris and height of vertical jump', *Chaos Solitons Fractals*, vol. 66, pp. 120–126, Sep. 2014, doi: 10.1016/j.chaos.2014.06.004.
[539] E. Brzozowska and M. Borowska, 'Selection of Phase Space Reconstruction Parameters for EMG Signals of the Uterus', *Stud. Log. Gramm. Rhetor.*, vol. 47, no. 1, pp. 47–59, Dec. 2016, doi: 10.1515/slgr-2016-0046.
[540] M. Borowska, E. Brzozowska, P. Kuć, E. Oczeretko, R. Mosdorf, and P. Laudański, 'Identification of preterm birth based on RQA analysis of electrohysterograms', *Comput. Methods Programs Biomed.*, vol. 153, pp. 227–236, Jan. 2018, doi: 10.1016/j.cmpb.2017.10.018.
[541] H. Xiao, W. Zhi-zhong, and R. Xiao-mei, 'Classification of surface EMG signal with fractal dimension', *J. Zhejiang Univ. Sci. B*, vol. 6, no. 8, pp. 844–848, Aug. 2005, doi: 10.1007/BF02842447.
[542] D. L. Streiner, 'Correction for Multiple Testing', *CHEST J.*, vol. 140, no. 1, pp. 16–18.
[543] R. A. Armstrong, 'When to use the Bonferroni correction', *Ophthalmic Physiol. Opt.*, vol. 34, no. 5, pp. 502–508, 2014, doi: 10.1111/opo.12131.

[544] A. S. P. Sousa, A. Silva, and R. Santos, 'Ankle anticipatory postural adjustments during gait initiation in healthy and post-stroke subjects', *Clin. Biomech.*, vol. 30, no. 9, pp. 960–965, Nov. 2015, doi: 10.1016/j.clinbiomech.2015.07.002.
[545] A. Danielsson, C. Meirelles, C. Willen, and K. S. Sunnerhagen, 'Physical Activity in Community-Dwelling Stroke Survivors and a Healthy Population Is Not Explained by Motor Function Only', *PM&R*, vol. 6, no. 2, pp. 139–145, 2014, doi: 10.1016/j.pmrj.2013.08.593.
[546] J. D. Lewsey *et al.*, 'Sex Differences in Incidence, Mortality, and Survival in Individuals With Stroke in Scotland, 1986 to 2005', *Stroke*, vol. 40, no. 4, pp. 1038–1043, Apr. 2009, doi: 10.1161/STROKEAHA.108.542787.
[547] V. Arnao and V. Caso, 'Sex-Related Differences of Acute Stroke Unit Care: Results from the Austrian Stroke Unit Registry':, *Women's Health*, Sep. 2014, doi: 10.2217/WHE.14.44.
[548] P. Santalucia *et al.*, 'Sex differences in clinical presentation, severity and outcome of stroke: Results from a hospital-based registry', *Eur. J. Intern. Med.*, vol. 24, no. 2, pp. 167–171, Mar. 2013, doi: 10.1016/j.ejim.2012.10.004.
[549] L. M. Decker, F. Cignetti, and N. Stergiou, 'Wearing a safety harness during treadmill walking influences lower extremity kinematics mainly through changes in ankle regularity and local stability', *J. NeuroEngineering Rehabil.*, vol. 9, no. 1, p. 8, Feb. 2012, doi: 10.1186/1743-0003-9-8.
[550] J. Fung, C. L. Richards, F. Malouin, B. J. McFadyen, and A. Lamontagne, 'A Treadmill and Motion Coupled Virtual Reality System for Gait Training Post-Stroke', *Cyberpsychol. Behav.*, vol. 9, no. 2, pp. 157–162, Apr. 2006, doi: 10.1089/cpb.2006.9.157.
[551] M. Rensink, M. Schuurmans, E. Lindeman, and T. Hafsteinsdóttir, 'Task-oriented training in rehabilitation after stroke: systematic review', *J. Adv. Nurs.*, vol. 65, no. 4, pp. 737–754, 2009, doi: 10.1111/j.1365-2648.2008.04925.x.
[552] J. Mehrholz, B. Elsner, C. Werner, J. Kugler, and M. Pohl, 'Electromechanical-assisted training for walking after stroke.', *Cochrane Database Syst. Rev.*, vol. 7, 2013.
[553] L. Ada, C. M. Dean, J. M. Hall, J. Bampton, and S. Crompton, 'A treadmill and overground walking program improves walking in persons residing in the community after stroke: a placebo-controlled, randomized trial', *Arch. Phys. Med. Rehabil.*, vol. 84, no. 10, pp. 1486–1491, Oct. 2003, doi: 10.1016/S0003-9993(03)00349-6.
[554] S. Mudge and N. S. Stott, 'Outcome measures to assess walking ability following stroke: a systematic review of the literature', *Physiotherapy*, vol. 93, no. 3, pp. 189–200, Sep. 2007, doi: 10.1016/j.physio.2006.12.010.
[555] C. Krishnan *et al.*, 'Learning New Gait Patterns is enhanced by specificity of training rather than progression of task difficulty', *J. Biomech.*, vol. 88, pp. 33–37, May 2019, doi: 10.1016/j.jbiomech.2019.03.014.
[556] L.-S. Giboin, M. Gruber, and A. Kramer, 'Task-specificity of balance training', *Hum. Mov. Sci.*, vol. 44, pp. 22–31, Dec. 2015, doi: 10.1016/j.humov.2015.08.012.
[557] T. G. Balshaw, G. J. Massey, T. M. Maden-Wilkinson, N. A. Tillin, and J. P. Folland, 'Training-specific functional, neural, and hypertrophic adaptations to explosive- vs. sustained-contraction strength training', *J. Appl. Physiol.*, vol. 120, no. 11, pp. 1364–1373, Apr. 2016, doi: 10.1152/japplphysiol.00091.2016.
[558] C. Cho, W. Hwang, S. Hwang, and Y. Chung, 'Treadmill Training with Virtual Reality Improves Gait, Balance, and Muscle Strength in Children with Cerebral Palsy', *Tohoku J. Exp. Med.*, vol. 238, no. 3, pp. 213–218, 2016, doi: 10.1620/tjem.238.213.
[559] R. B. van Dijsseldonk, L. A. F. de Jong, B. E. Groen, M. Vos-van der Hulst, A. C. H. Geurts, and N. L. W. Keijsers, 'Gait Stability Training in a Virtual Environment

Improves Gait and Dynamic Balance Capacity in Incomplete Spinal Cord Injury Patients', *Front. Neurol.*, vol. 9, Nov. 2018, doi: 10.3389/fneur.2018.00963.
[560] G. Aravind, A. Darekar, J. Fung, and A. Lamontagne, 'Virtual Reality-Based Navigation Task to Reveal Obstacle Avoidance Performance in Individuals With Visuospatial Neglect', *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 23, no. 2, pp. 179–188, Mar. 2015, doi: 10.1109/TNSRE.2014.2369812.
[561] J. Feasel, M. C. Whitton, L. Kassler, F. P. Brooks, and M. D. Lewek, 'The Integrated Virtual Environment Rehabilitation Treadmill System', *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 19, no. 3, pp. 290–297, Jun. 2011, doi: 10.1109/TNSRE.2011.2120623.
[562] C. L. Richards *et al.*, 'Gait Training after Stroke on a Self-Paced Treadmill with and without Virtual Environment Scenarios: A Proof-of-Principle Study', *Physiother. Can.*, vol. 70, no. 3, pp. 221–230, Aug. 2018, doi: 10.3138/ptc.2016-97.
[563] D. J. Clarke and A. Forster, 'Improving post-stroke recovery: the role of the multidisciplinary health care team', *J. Multidiscip. Healthc.*, vol. 8, pp. 433–442, Sep. 2015, doi: 10.2147/JMDH.S68764.
[564] S. P. Jones, C. Miller, J. M. E. Gibson, J. Cook, C. Price, and C. L. Watkins, 'The impact of education and training interventions for nurses and other health care staff involved in the delivery of stroke care: An integrative review', *Nurse Educ. Today*, vol. 61, pp. 249–257, Feb. 2018, doi: 10.1016/j.nedt.2017.11.024.
[565] J. Kim, A. Gravunder, C. J. Stanley, and H.-S. Park, 'Low-cost implementation of a self-paced treadmill by using a commercial depth sensor', in *2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Jul. 2013, pp. 874–877, doi: 10.1109/EMBC.2013.6609640.
[566] J. Kim, A. Gravunder, and H.-S. Park, 'Commercial Motion Sensor Based Low-Cost and Convenient Interactive Treadmill', *Sensors*, vol. 15, no. 9, Art. no. 9, Sep. 2015, doi: 10.3390/s150923667.
[567] J. L. Souman, P. R. Giordano, I. Frissen, A. D. Luca, and M. O. Ernst, 'Making Virtual Walking Real: Perceptual Evaluation of a New Treadmill Control Algorithm', *ACM Trans Appl Percept*, vol. 7, no. 2, p. 11:1-11:14, Feb. 2010, doi: 10.1145/1670671.1670675.
[568] G. D. Fulk, C. Reynolds, S. Mondal, and J. E. Deutsch, 'Predicting Home and Community Walking Activity in People With Stroke', *Arch. Phys. Med. Rehabil.*, vol. 91, no. 10, pp. 1582–1586, Oct. 2010, doi: 10.1016/j.apmr.2010.07.005.
[569] G. Boeing, 'Visual Analysis of Nonlinear Dynamical Systems: Chaos, Fractals, Self-Similarity and the Limits of Prediction', *Systems*, vol. 4, p. 37, Nov. 2016, doi: 10.3390/systems4040037.
[570] H. Nleminen and E.-P. Takala, 'Evidence-of-deterministic-chaos-in-the-myoelectric-signal.pdf', Jan. 1996. https://www.researchgate.net/profile/Esa-Pekka_Takala/publication/14546886_Evidence_of_deterministic_chaos_in_the_myoelectric_signal/links/5492e4e80cf2302e1d0745bf/Evidence-of-deterministic-chaos-in-the-myoelectric-signal.pdf (accessed Jun. 18, 2019).
[571] B. S. Raghavendra and D. Narayana Dutt, 'A note on fractal dimensions of biomedical waveforms', *Comput. Biol. Med.*, vol. 39, no. 11, pp. 1006–1012, Nov. 2009, doi: 10.1016/j.compbiomed.2009.08.001.
[572] Y. Ma, W. Shi, C.-K. Peng, and A. C. Yang, 'Nonlinear dynamical analysis of sleep electroencephalography using fractal and entropy approaches', *Sleep Med. Rev.*, vol. 37, pp. 85–93, Feb. 2018, doi: 10.1016/j.smrv.2017.01.003.
[573] N. Stergiou, Ed., *Nonlinear analysis for human movement variability*. Boca Raton: Taylor & Francis, Taylor & Francis, a CRC title, part of the Taylor & Francis imprint, a

member of the Taylor & Francis Group, the academic division of T&F Informa plc, 2016.
[574] E. Bradley and H. Kantz, 'Nonlinear time-series analysis revisited', *Chaos Interdiscip. J. Nonlinear Sci.*, vol. 25, no. 9, p. 097610, Sep. 2015, doi: 10.1063/1.4917289.
[575] 'Chaos Theory and the Logistic Map', *Geoff Boeing*, Mar. 26, 2015. https://geoffboeing.com/2015/03/chaos-theory-logistic-map/ (accessed Jan. 15, 2020).
[576] J. Theiler, 'Estimating fractal dimension', 1990, doi: 10.1364/JOSAA.7.001055.
[577] 'Fractales : la poussière de Cantor - Le BloGuen : art fractal, image, science, voyage, plongée'. http://www.blog.francis-leguen.com/fractales-la-poussiere-de-cantor/ (accessed Jun. 19, 2019).
[578] 'Fractal Foundation Online Course - Chapter 1 - FRACTALS IN NATURE'. http://fractalfoundation.org/OFC/OFC-10-3.html (accessed Jun. 19, 2019).
[579] H. Josiński, A. Świtoński, A. Michalczuk, and K. Wojciechowski, 'Phase space reconstruction and estimation of the largest Lyapunov exponent for gait kinematic data', Rhodes, Greece, 2015, p. 660006, doi: 10.1063/1.4912882.
[580] J. B. Dingwell, *Lyapunov Exponents*. 2006.
[581] J. C. van Swieten, P. J. Koudstaal, M. C. Visser, H. J. A. Schouten, and J. van Gijn, 'Interobserver agreement for the assessment of handicap in stroke patients.', p. 4.
[582] T. J. Quinn, J. Dawson, M. R. Walters, and K. R. Lees, 'Reliability of the Modified Rankin Scale: A Systematic Review', *Stroke*, vol. 40, no. 10, pp. 3393–3395, Oct. 2009, doi: 10.1161/STROKEAHA.109.557256.
[583] Broderick Joseph P., Adeoye Opeolu, and Elm Jordan, 'Evolution of the Modified Rankin Scale and Its Use in Future Stroke Trials', *Stroke*, vol. 48, no. 7, pp. 2007–2012, Jul. 2017, doi: 10.1161/STROKEAHA.117.017866.
[584] T. Quinn, J. Dawson, and M. Walters, 'Dr John Rankin; His Life, Legacy and the 50th Anniversary of the Rankin Stroke Scale.', *Scott. Med. J.*, vol. 53, no. 1, pp. 44–47, Feb. 2008, doi: 10.1258/RSMSMJ.53.1.44.
[585] Loewen S C and Anderson B A, 'Predictors of stroke outcome using objective measurement scales.', *Stroke*, vol. 21, no. 1, pp. 78–81, Jan. 1990, doi: 10.1161/01.STR.21.1.78.
[586] F. I. Mahoney, 'Functional evaluation: the Barthel index', *Md State Med J*, vol. 14, pp. 61–65, 1965.
[587] S. Shah, F. Vanclay, and B. Cooper, 'Improving the sensitivity of the Barthel Index for stroke rehabilitation', *J. Clin. Epidemiol.*, vol. 42, no. 8, pp. 703–709, Jan. 1989, doi: 10.1016/0895-4356(89)90065-6.
[588] Schmülling Susanne, Grond Martin, Rudolf Jobst, and Kiencke Peter, 'Training as a Prerequisite for Reliable Use of NIH Stroke Scale', *Stroke*, vol. 29, no. 6, pp. 1258–1259, Jun. 1998, doi: 10.1161/01.STR.29.6.1258.
[589] D. Cioncoloni *et al.*, 'Relationship between the modified Rankin Scale and the Barthel Index in the process of functional recovery after stroke', *NeuroRehabilitation*, vol. 30, pp. 315–22, Jun. 2012, doi: 10.3233/NRE-2012-0761.