THE PRODUCTION AND CONTROL OF FUNCTIONAL ELECTRICAL STIMULATION SWING-THROUGH GAIT

by

Benjamin Wolf Heller BA, MA (Cantab)

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Contains one computer disc.

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ABSTRACT

This thesis addresses some of the issues involved in the synthesis of swing-through gait by functional electrical stimulation (FES).

A general introduction is given to paraplegic gait, then the following areas are reviewed in detail: previous production of FES swing-through gait; biomechanical and energetics analyses of swing-through gait; general techniques for controlling FES gait; and the use of machine-learning techniques.

Trained, non-impaired subjects wearing adjustable braces are used to model the movement patterns of FES swing-through gait. It is found that flexing the knees during the body-swing phase of swing-through gait reduces the energy cost of the gait.

Hardware and software are developed to allow the production of FES swing-through gait in paraplegics with mid and low thoracic lesions of the spinal cord. The kinematic parameters of the resulting gait are assessed. It is found that the gait is faster than both knee-ankle-foot-orthosis (non FES) gait and reciprocal FES gait. This constitutes the first demonstration of FES free-knee swing-through gait in a spinal cord injured population.

A symbolic inductive learning program, *Empiric*, is described. This program uses 'fuzzy' weighting to cope with uncertainty in the training data. This technique is found to offer improved classification performance (on artificially generated data) over both the orthodox (non-weighted) approach and an alternative weighting strategy.

The fuzzy inductive learning technique is compared with a multi-layer perceptron type neural network for identifying the invariants (rules) that describe muscle activation during normal human gait. Both techniques are found to successfully model the muscular activation; the inductive learning technique has the advantage of producing explicit rules which are easily understood.

The fuzzy inductive learning technique is applied to data obtained from the (previously mentioned) model of swing-through gait, in an attempt to mimic the control strategies used by the unimpaired subjects. It is found that the gait is best modelled with simple rule-sets, based on only one sensor. It is argued that this technique allows the automatic derivation of control strategies for FES gait: in particular, it allows the subjects' movement intentions to be determined. It is suggested that this 'intention detection' provides a more natural interface between a paraplegic subject and an FES control system than the techniques which are currently used.

Man is on the threshold of breaking past the discontinuity between himself and machines. Bruce Mazlish 'The Fourth Discontinuity'*

*In Kranzberg, Melvin and Davenport (eds.): *Technology and Culture*, New York, New American Library, 1972.

INSTRUCTIONS FOR USE OF ACCOMPANYING FLOPPY DISC

A floppy disc is contained in a pocket on the front cover of this thesis. It contains the following files:

EMPIRIC.PAS, ALIGN.PAS, GAIT.PAS

This is the source code for programs described in this thesis.

GEN_BEN.TPU, GRAFWIND.TPU, TIMEDATE.TPU, WINDOWS.TPU

'Unit' files, required to compile the above programs.

EMPIRIC.EXE, ALIGN.EXE, GAIT.EXE

'Run-time' versions of the above.

The programs are written in *Turbo Pascal V5* (Borland Ltd). They are described in more detail in the main body of this thesis.

The disc can be read on any computer running *DOS* (Microsoft Corporation, V 3.0 or higher) with a 1.2 Mbyte 5¼" floppy disc drive.

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PUBLICATIONS ARISING FROM THIS WORK

REVIEWED JOURNALS

HELLER B.W., Rijkhoff N.J.M., Veltink P.H., Rutten W.L.C. and Andrews B.J.: Predicting muscle activation during walking by means of rule-based inductive learning and neural networks. Submitted to *Biological Cybernetics*

GRANAT M.G., Heller B.W., Nicol D.J., Andrews B.J. (in print): Improving limb flexion using the flexion withdrawal reflex in FES gait. *Journal of Biomedical Engineering* August 1991.

HELLER B.W., Granat M.H., Andrews B.J.: The Production of Free-Knee Swing-Through Gait Using Surface FES. Submitted to *Archives of Physical Medicine and Rehabilitation*

PUBLIC REPORTS

KIRKWOOD C.A. and Heller B.W. (1990): Inductive methods in movement analysis. In Starita A. (ed.) (1990): *Ground rules for the formalisation of the biomedical movement analysis knowledge.* Public report forming CAMARC (AIM project A 1012) deliverable A to the CEC - DG XIII.

HELLER B.W. (1990): Algorithm for inductive learning program 'EMPIRIC'. In Woltring H.J. (ed.) (1990): *Software quality, and software packages for functional movement analysis.* Public report forming CAMARC (AIM project A 1012) deliverable H to the CEC - DG XIII.

HELLER B.W. and Andrews B.J. (1990): Prospects for the future use of data-driven methods in movement analysis; In Starita A. (ed.) (1990): *Formalisation of the biomedical movement analysis knowledge.* Public report forming CAMARC (AIM project A 1012) deliverable B to the CEC - DG XIII.

HELLER B.W. and Paul J.P. (1990): Statistical methods in motion analysis. In: Woltring H.J. (ed.) (1990): *Models, Connection with experimental apparatus and relevant DSP techniques for functional movement analysis.* Public report forming CAMARC (AIM project A 1012) deliverable F to the CEC - DG XIII.

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CONFERENCE PAPERS (Published in conference proceedings)

HELLER B.W., Andrews B.J. (1989): An analysis of swinging gaits and their synthesis using functional electrical stimulation. *Proceedings of the Third Vienna International Workshop on Functional Electrostimulation.* Baden-Baden, Vienna, September 1989.

HELLER B.W., GRANAT M.H., Kirkwood C.A. and Delargy M. (1990): Preliminary studies of swing-through gait using FES. *Proceedings of Tenth International Conference - Advances in External Control of Human Extremities.* Dubrovnik, August 1990.

HELLER B.W., Andrews B.J. and Rijkhoff N.J.M.: Inductive cloning of a state model for normal gait. *IEEE EMBS Conference* Orlando, Florida, USA, November 1991.

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TERMINOLOGY AND ABBREVIATIONS

Terminology

Some machine learning terms are introduced below.

Attribute: a dimension of variation on the vector that describes an *example*.

Class: the subset of the problem domain to which each example belongs (also known as the **concept**).

Counter example: an *example* with a similar *description* but different *class* label to one or more other examples.

Decision tree: a directed graph representing the sequentially ordered decision rules produced by one type of *inductive learning program*. It can be described by a *rule-set*. Because a decision-tree based inductive learning program is used in this work, the terms 'decision tree' and 'rule-set' will be used synonymously.

Description: the *attribute* vector associated with an example.

Error rate: the percentage of examples from either the *training set* or the *testing set* that are misclassified by a *rule-set*.

Example: an instance within a particular problem domain, consisting of an *attribute* vector and a *class* label.

Expert: someone experienced in the problem domain, who is able to create or select an appropriate *training set*.

Inductive learning program: A computer program that searches a *training set* of *examples* to find a collection of general rules (a *rule-set*) that explains the training data, and can be used to make predictions on new data.

Performance: An assessment of how well the rule-set classifies *training* or *testing* data; a common measure is the *error rate*.

Production rule: a rule of the form

IF *attribute* > *threshold* THEN a ELSE b

where a and b either represent *classes* or further production rules.

Rule-based controller: A controller in which the knowledge required to control a plant is represented semantically as-well-as/instead-of numerically.

Rule-set: The *production rules* produced by an *inductive learning program* for a particular problem domain. The rule-set contains the information necessary to map the *description* of an example on to a particular *class*. Because a decision-tree based inductive learning program is used in this work, the terms 'decision tree' and 'rule-set' will be used synonymously.

Testing set: a collection of representative *examples*, independent of the *training set* that are used to assess the *performance* of a *rule-set*.

Threshold: a hyper-plane perpendicular to an *attribute* axis that is used to partition a set of *examples* into two subsets.

Training set: a collection of representative *examples* selected by an *expert* used by the *inductive learning program* to induce a *rule-set* describing a particular problem domain.

Abbreviations

ADC:	analogue to digital converter
AFO:	ankle foot orthosis
EMG:	electromyogram
FSR:	force sensitive resistor
FRO:	floor reaction orthosis
HGO:	hip guidance orthosis (trade-name *Para-walker*)
HKAFO:	hip-knee-ankle-foot orthosis
IR:	infra-red
KAFO:	knee-ankle-foot orthosis
RGO:	reciprocating gait orthosis (trade-name *LSU-RGO*)
SCI:	spinal cord injury / spinal cord injured

CHAPTER 1. INTRODUCTION

1.1. SPINAL CORD INJURY

A severe injury of the spinal cord undoubtably constitutes one of the most devastating calamities in human life (Guttman, 1976). Everyday functions such as temperature control, bowel and bladder management and pressure relief, which are taken for granted by the normal individual, become the life-or-death responsibility of the spinal-cord-injured individual. Other problems associated with severe spinal-cord-injury (SCI) are loss of sensation, impaired sexual function, contractures, disuse osteoporosis and muscle atrophy (Bedbrook, 1985; Guttman, 1976). The annual incidence of SCI (in the United States) is estimated to be approximately 500 per million (Capildeo and Maxwell, 1984); this incidence is not uniform across all age ranges and both sexes, but is highly skewed to males in the 19-25 group. Modern rehabilitation techniques allow paralysed individuals to live for almost a normal life-span (Bedbrook, 1985). Nevertheless, the inability to stand or walk still alienates the paralysed person from the community in which she or he lives and wishes to make an active contribution; it also incurs a large financial price due to the cost of lifetime care and the loss of earnings. Society is becoming more aware of the special needs of this population, and environmental adaptations such as wheelchair access to (and facilities in) public buildings help to reduce the **handicap** resulting from this **disability** (World Health Organisation, 1980); however, these adaptations will never be a complete solution. Phillips's (1991) comments on *Disabilities Expo 88* at the Los Angeles Convention Centre are pertinent:

> *What a majority of these paralyzed people were* [sic] *really looking for was an alteration of their disability so that they could more normally function (in an unaltered environment). What the great majority of the exhibitors were offering was an alteration of their environment so that they could more normally function (with an unaltered disability).*

The 'cure', spinal cord regeneration, will not be available in the near future (Phillips, 1991), despite some encouraging results (Bjorklund and Stenevi, 1979). Instead, there are a number of orthotic and prosthetic devices which help to reduce the level of disability arising from spinal cord injury. These devices will be reviewed in the following section (1.2).

Region	Muscle group	Innervation
Trunk	Rectus abdominus	
	Upper	T7-9
	Lower	T10-12
	Back dorsal	T1-S3
	Back lumbar	T1-S3
	Internal oblique	T7-L1
	External oblique	T5-11
Hip	Sartorius	L1-3
	Iliopsoas	L1-3
	Adductors	L2-4
	External rotators	L3-S2
	Internal rotators	L4-S1
	Tensor fascia latae	L4-S1
	Gluteus medius	L4-S1
	Gluteus maximus	L5-S2
Knee	Hamstrings	
	Inner	L4-S1
	Outer	L5-S3
	Quadriceps	L2-4
Ankle-foot	Anterior tibial	L4-5
	Extensor digitorum longus	L5-S1
	Extensor hallucis longus	L5-S1
	Peroneus brevis	L5-S1
	Peroneus longus	L5-S2
	Gastroc soleus	L5-S1
	Posterior tibial	L5
	Flexor digitorum longus	S1-3
	Flexor hallucis longus	S1-2
	Intrinsic toe flexor	S2-3
	Extensor digitorum brevis	S2-3

Table 1.1 *Innervation of muscles of the trunk and lower limb; taken from Rieser et al. (1985)*

The deficit arising from spinal cord injury is determined both by the level and degree of injury. The *level* is defined as the vertebral body level at which the injury occurs; muscles innervated by nerves leaving the spinal column below the level of injury will be affected. The innervation level of the major trunk and lower extremity muscles is given in table 1.1 (from Reiser *et al.* [1985]). Paraplegics with lesions in the mid to low thoracic range (T5-T12) have full upper limb function and increasing degrees of control of trunk musculature (which is important for posture and gait); thus this is a suitable population for the restoration of standing or walking. The spinal cord terminates at the L1 vertebral level; below this level only lower-motor neurons are present (the cauda equina). Injury at or below the L1 level will thus result in damage to these lower motor neurons, leading to denervation of muscle. Denervated muscle cannot be easily excited by electrical stimulation and so subjects with lesions in lumbar or sacral regions are not at the present time suitable candidates for FES.

The *degree* of injury can be classified in various ways, the Frankel grading (Frankel *et al.*, 1969) being one of the most common.

a. Complete injury with no preservation of any motor or sensory function below the spinal cord lesion.
b. Preservation of sensation.
c. Preservation of some non-useful motor function.
d. Preservation of some useful motor function.
e. Complete recovery

The designation *motor complete* is used for individuals with lesions in Frankel groups (a) and (b).

1.2. ORTHOTIC AND PROSTHETIC AIDS FOR PARAPLEGIC STANDING AND WALKING

The benefits accruing to paraplegics from standing and walking may include such therapeutic gains as reduction in osteoporotic bone loss, relief of pressure on support areas, promotion of satisfactory renal and bladder function (through gravity assisted drainage), prevention of contractures, reduction in spasticity, prevention of obesity, cardio-vascular conditioning and psychological effects, in addition to the functional benefits (Guttman, 1976; Rowley and Edwards, 1987). These standing and walking functions are provided by devices which assist or replace the impaired functions - *orthoses* or *prostheses.*

The problems that need to be addressed in the design of effective orthotic or prosthetic ambulation systems for paraplegics are assigned to five categories by Stallard *et al.* (1989):

1. Independence: no assistance from a helper in donning and doffing or transferring from sitting to standing.
2. Energy cost.
3. Cosmesis: this is divided into disguising the orthosis, improving the style of walking, and the effectiveness of walking aids (e.g. crutches) with the orthosis.
4. Reliability.
5. Cost.

The relative importance of each of these categories will vary from subject to subject. For example, high energy cost may be less of an impediment to a young, active individual than to some-one older; similarly, the definition and importance of cosmesis will be subjective.

Various orthotic or prosthetic aids which are currently used to assist paraplegic ambulation are outlined in the subsequent sections.

1.2.1 Knee-Ankle-Foot Orthoses (KAFOs)

Also known as calipers, or long-leg braces, these orthoses maintain the wearers' ankles in neutral or slight dorsi-flexion, and their knees in extension. A paraplegic without hip control can stand using this orthosis by adopting a 'C' posture, in which the hips are pushed forwards and held in extension by the opposing forces due to gravity and ilio-femoral ligamental constraints. A paraplegic wearing KAFOs can walk by adopting either a swinging or a reciprocal style of gait (see section 1.3). The functionality of the gait depends on the user's motivation, strength and level of injury: Alvarez (1985) states that preserved proprioception at the hip, and some pelvic control via latissimus dorsi and the abdominal muscles, are prerequisites of a functional gait (implying a lesion at T12 or below).

Long-term follow-up studies have shown low rates of paraplegics' continued use of KAFOs following discharge from hospital (Mikelberg and Reid, 1981; Coghlan *et al.*, 1980; Stauffer *et al.*, 1978). Stauffer *et al.* (1978) conclude:

> *Ambulation with crutches and braces is not a realistic functional goal for the patient with complete thoracic paraplegia. Only those patients with grossly-incomplete thoracic paraplegia and at least good hip control or lower lumbar lesions are able to continue functional ambulation with braces and crutches.*

1.2.2 Reciprocating Gait Orthosis (RGO) and Hip Guidance Orthosis (HGO)

The lack of hip control in complete thoracic paraplegia has led to the development of orthoses that provide external control of the hip, whilst still permitting ambulation. The principle of reciprocally linking the hip joints in a HKAFO was originally developed in the late 1960s. Motloch described a gearing mechanism (Ontario Crippled Children's Centre, Toronto, Annual Report 1968) whilst Scruton (1971) utilised paired Bowden cables. Douglas *et al.* (1983) refined Scruton's design, producing the Louisiana State University Reciprocating Gait Orthosis (LSU-RGO or just RGO). This device consists of two linked KAFOs, a pelvic band and thoracic supports. Bowden cables reduce the degrees of freedom by preventing bilateral flexion or extension. Flexion at one hip joint is coupled to extension at the other, and vice versa. A release mechanism allows the hips to be uncoupled for donning/doffing and sitting. Andrews (1990) describes the use of a single, flexible, push-pull linear bearing which offers the advantages of reduced friction, no cable stretch and reduced number of components over Bowden cables.

The Parawalker or Hip Guidance Orthosis (HGO) (Rose, 1979) also constrains the motion of the hip-joint. Rigid hinges at the hip prevent adduction; thus, when the whole body is tilted laterally, the leg is lifted clear of the ground and can swing freely (due to gravity). There is no reciprocal linkage to prevent bilateral flexion.

Both the HGO and the RGO facilitate level-ground ambulation in paraplegics with thoracic lesions. However, the mechanical hardware, particularly that above the thigh, may impede activities of daily living such as transfer or toileting; they also make the braces cumbersome to don and doff. Most users do not regularly wear the braces for extended periods (in excess of 30 minutes), but predominantly use them for exercise (in which case they are donned and doffed for each session) (Cochrane and Whittle, 1989).

1.2.3 Neural Prostheses and Functional Electrical Stimulation.

These are defined by Hambrecht and Reswick (1977) as follows:

> *The term neural prostheses will be used to designate devices or techniques for supplementing or replacing lost function in neurologically impaired individuals. This can be accomplished by either direct transfer of information into the nervous system, by detection of neural signals for outward information transfer or a combination of the two. Functional Electrical Stimulation (FES) is a neural prosthetic technique that utilizes stimulation of neural tissue for inward information transfer.*

There have been attempts to treat muscle paralysis by the use of electricity for over 2000 years; by the 19th century, Duchenne was able to stimulate nerves by the use of surface electrodes placed over nerve trunks and motor points and was able to allow a paraplegic to stand up (Geddes, 1984; McNeal, 1987). The recent history (following Liberson *et al.*'s [1961] application of stimulation to correct foot drop in hemiplegic patients and Kantrowitz's [1963] demonstration of standing in a T7 complete paraplegic) has been reviewed in Vodovnik *et al.* (1981) and Kralj and Bajd (1989).

The restoration of gait in a complete spinal cord injured (SCI) subject by means of FES was reported by Brindley *et al.* in 1979. Kralj *et al.* (1983) reported the production of a simple reciprocal gait by means of four channels of surface stimulation; this gait was slow (speeds of about 0.15 m/s, 0.27-0.35 m/s and 0.03-0.04 m/s are reported for the three subjects) and should be termed stepping rather than walking, due to its quasi-static nature. There have been many attempts to improve the speed, appearance and reliability of FES walking - multi-channel implanted or percutaneous systems having been reported in a number of centres (Holle *et al.*, 1984; Donaldson, 1986; Marsolais and Kobetic 1987). Kralj *et al.* (1987A) reported the Yugoslavian experience with 45 complete paraplegics selected from about 500 admitted to a rehabilitation centre over a 10 year period: 16 achieved functional standing; 21 were able to take steps with the aid of parallel bars, a walker or crutches; and three were able to climb steps. Thirty patients continued to use the equipment at home.

FES techniques produce muscle contractions by delivering electrical stimulation to appropriate sites[1] by means of electrodes. These are of three major types:

a. Surface electrodes: muscles are stimulated transcutaneously by strategically placed electrodes. They have the advantage of being non-invasive, but the disadvantages of needing to be re-applied for each session, causing allergic reactions in some patients, changing their resistive properties as they dry-out, requiring large currents and voltages to excite action potentials, having low selectivity for individual muscles, and not being capable of exciting deeper muscles (such as iliopsoas, an important hip flexor). Because they are easily applied and non-invasive, they are ideal for testing stimulation strategies in laboratory situations, but not appropriate for long-term home use if large numbers of stimulation channels are required.

b. Percutaneous electrodes: these are intra-muscular electrodes that are implanted via a hypodermic needle, which is then withdrawn, leaving the electrode in position. The electrodes can be easily removed if they break or are no longer required. They have the following advantages over surface electrodes: they have better selectivity, they require much smaller currents, and they can access deeper muscle groups. They have few problems of infection (Marsolais and Kobetic [1987] report only seven infections in 969 electrodes implanted over a 36 month period), but may be liable to breakage (Marsolais and Kobetic [1987] report a 30 per cent electrode survival rate after one year, falling to 20 per cent after two years). Recent improvements in electrode design may reduce this failure rate (Handa [1989] reports a failure rate of 1.3% implanted electrodes in one year).

1 Motor points or alpha motor neurons for direct stimulation, cutaneous and other afferents for indirect (reflex) stimulation.

The electrode entry sites are unsightly, but may be hidden under clothing.

c. Fully implanted electrode systems: these are driven by implanted stimulators which are powered and controlled by radio signals transmitted transcutaneously. Once implanted, they require the minimum amount of preparation (only the application of a transmitter coil) and are thus suited for long-term applications. However, they require a surgical procedure to implant them, and have the disadvantage that any infection may not remain localised (as with percutaneous electrodes) but may spread through the entire system.

Muscle can either be activated **directly** (efferent pathways) or **indirectly** (afferent pathways). Indirect activation of hip, knee and ankle flexion via stimulation of the flexion-withdrawal reflex is often used to produce the swing-phase of gait (Nicol, 1990; Kralj *et al.*, 1983). The use of this reflex complicates the control of gait by introducing long-latencies, habituation and inappropriate co-contractions (Granat *et al.*, in press; Rudel *et al.*, 1989), but is often the only practical method of obtaining hip flexion with surface electrodes.

The advantages of FES over other orthotic or prosthetic aids are that muscle atrophy can be reversed (Fournier *et al.*, 1984), active contraction of the paralysed musculature may require less work from the able limbs (Cliquet, 1988) and circulatory and cardiovascular benefits may result from the activation of large muscle groups, such as the quadriceps. However, there are a number of drawbacks which include the relatively crude control and coordination of limb movement (compared to the RGO), rapid muscular fatigue leading to the possibility of falls, and the high degree of patient compliance required to participate in muscle strengthening and gait training regimes.

The control of FES activated movements is reviewed in section 2.4.

1.2.4 Hybrid Systems

Tomovic *et al.* (1972) first proposed the combination of FES with external mechanical bracing (which may or may not be powered) to produce a *hybrid* system that preserves the advantages and cancels the disadvantages of both individual techniques. Practical hybrid orthotic systems have been reported by

Andrews (1990), Solomonow *et al.* (1989), Andrews *et al.* (1988), Hausdorf and Durfee (1988), Jaeger *et al.* (1988), Petrofsky *et al.* (1985), Andrews and Bajd (1984) and Schwirtlitch and Popovic (1984).

The mechanical component of a hybrid system can reduce the number of degrees of freedom of the system, thus simplifying the control problem. It can also provide 'back-up' support in case of electrical failure or fatigue of stimulated musculature. A passive mechanical brace can provide the static forces necessary to maintain postural stability, whilst the electrically stimulated musculature provides the active forces necessary for movement, or correction of temporary instability. In this way, the problems of rapid fatigue of stimulated musculature and of high locomotion energy costs can be mitigated. Finally, the application of external mechanical bracing may protect delicate anatomical structures from injury or progressive deformation by excessive or prolonged forces.

Andrews and Baxendale (1986) reported a simple hybrid system that combined a floor reaction orthosis (FRO) (Saltiel, 1969) with electrical stimulation. The FRO is an AFO with a very stiff foot-plate, that passively maintains the knee in extension by shifting the ground-reaction-vector anterior to it. A sensor detects when the vector passes behind the knee, triggering a 'knee-extension-reflex'. This 'reflex' applies stimulation to the quadriceps muscles, actively maintaining extension until the vector returns in front of the knee.

1.3 AMBULATION IN SPINAL CORD INJURY

1.3.1 Crutches

Crutches have been used to aid locomotion for 5000 years (Epstein, 1937), and their design has changed little over that time (Rovick, 1982). Axillary crutches have traditionally been prescribed; however, complications arising from the use of this crutch (such as axillary artery thrombosis [Brooks and Fowler, 1964] and radial nerve compression [Rudin and Levine, 1951]) have recently led to the forearm (or elbow) crutch becoming widely used. Another crutch type, the cuff (or Canadian) crutch (American Academy of Surgeons, 1975) has a ring which bears on the biceps, thus providing more stability than the elbow crutch, but limiting elbow flexion. For a discussion of the relative merits of these crutch

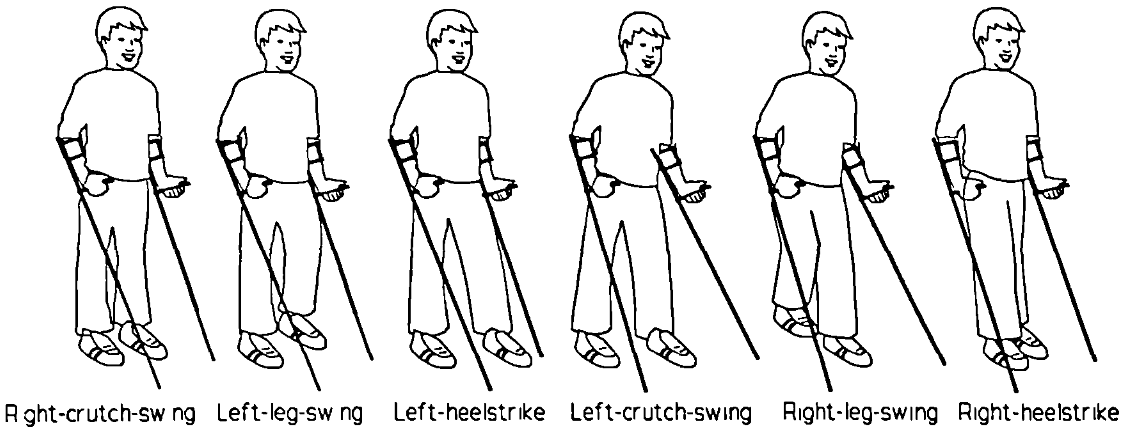

Figure 1.1 *Phases and events in the reciprocal gait cycle*

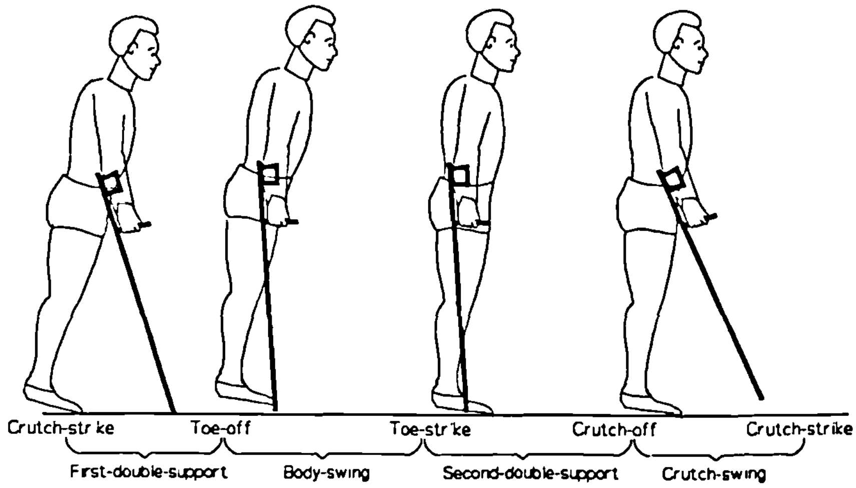

Figure 1.2 *Phases and events in the swing-to gait cycle*

types for swing-through gait see Stallard *et al.* (1978) and Sankarankutty *et al.* (1979).

1.3.2 Types of gait

There are two basic kinds of crutch-aided gait: reciprocating gait (sometimes called four point gait), and the family of swinging gaits (two point)[1]. In the following descriptions the assumption is made that the ambulator has two symmetrically impaired legs, although the swinging gaits may be performed with only one weight-bearing leg.

Reciprocating gait is so called because both feet and both crutches move reciprocally (see figure 1.1). When this gait is performed slowly there are always at least three points of contact with the ground: either both crutches and one foot, or both feet and one crutch. This leads to a gait that is always stable - the subject can stop in any phase of the gait cycle without falling. Bromley (1985) describes it thus:

> *This gait is the slowest and most difficult and is only achieved on crutches by the accomplished walkers. It facilitates turning and manoeuvring in confined spaces.*

Reciprocating gait is closer to normal human locomotion, and thus may be preferable cosmetically.

Swinging gaits differ in that both feet move simultaneously, followed by both crutches. Forward progression is made by alternately pivoting about the crutch tips whilst lifting and swinging the feet, then pivoting about the feet whilst lifting and swinging the crutches.
There are many different forms of swinging gait:

Swing-to gait (figure 1.2) is referred to as the 'universal gait' by Bromley (1985) because it is the simplest and safest. In this gait the crutches are placed on the ground in front of the body, the feet are raised off the ground by lifting the whole body with the arms, and the body is allowed to swing until it is level with the crutches. The feet are then lowered back to the ground and the crutches are advanced, completing the cycle.

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1 Three point gait, in which both crutches move simultaneously but each foot moves consecutively, is probably best classified as a reciprocating gait.

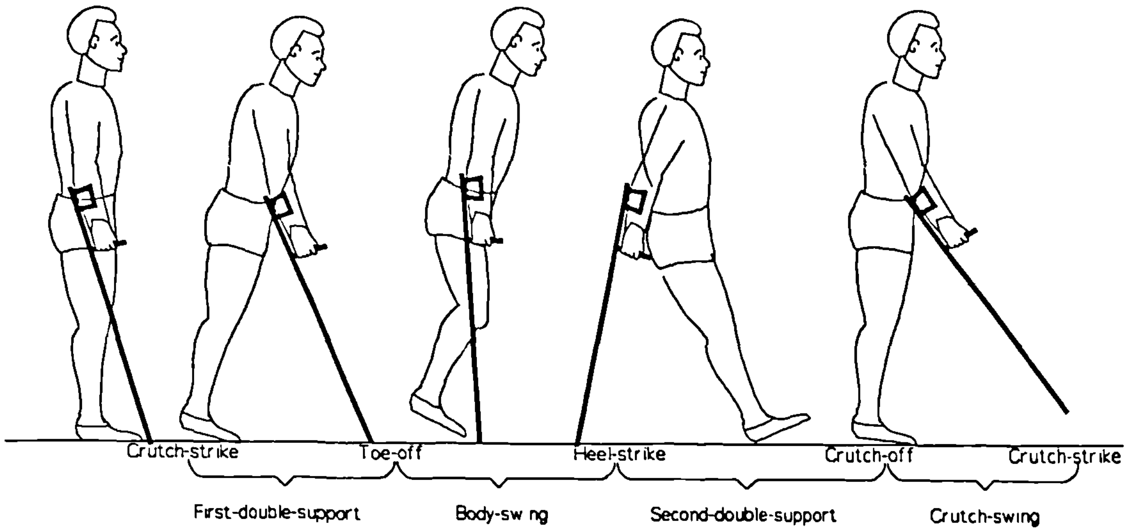

Figure 1.3 *Phases and events in the swing-through gait cycle*

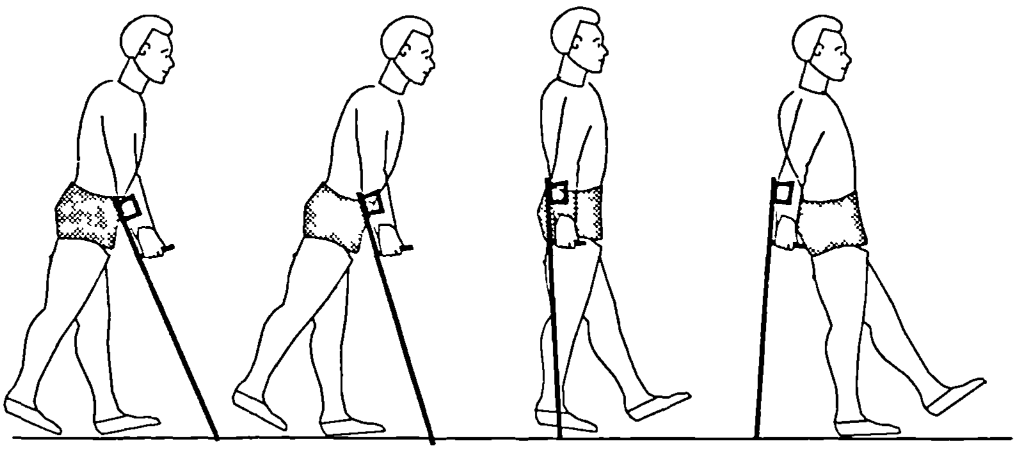

Figure 1.4 *Wheeling gait*

Swing-from gait is not generally practised (Rovick, 1982). It is similar to swing-to gait, except that it is initiated by the legs being placed on the ground in front of the crutches, with the crutches then being swung level with them.

Drag-to gait is a variation of swing-to; it is performed by ambulators (commonly obese) lacking the strength to raise their bodies a sufficient height to produce ground clearance (Stallard & Rose, 1978).

Swing-through gait (figure 1.3) has been described as:

> *The swing-through gait is the fastest and most useful gait pattern of the completely paralyzed person using long-leg braces and crutches.*
> (Bajd and Kralj, 1991)

> *...the fastest and most useful gait, though requiring skilled balance.*
> (Bromley, 1985)

> *...the swing-through gait offers the paraplegic patient the fastest and most graceful type of mobility. Clinical experience has shown that many paraplegics can be taught a skill of application and an economy of motion that make crutch walking very practical.*
> (Childs, 1964)

There are many variations of this gait, depending on the subject's strength, skill, level of lesion and degree of orthotic support. The type of gait that can be performed by a paraplegic who has no control at and distal to the hip, and who is using KAFOs will be described. In this gait the crutches are placed on the ground in front of the body (the *first period of double support*), and weight is transferred on to them from the feet. The body is then lifted by depressing the shoulders and extending the elbows, raising the feet off the ground (*toe off*), and the body is allowed to swing through and beyond the crutches (*body swing phase*). The feet land in front of the crutches (*heel strike*) initiating the *body stance phase* with a *second period of double support*. The body has sufficient momentum to allow it to continue moving forwards, pivoting about the foot-ground contact point and passing through the vertical position (*mid stance*). During this period the crutches are lifted (*crutch off*) and brought to a position in front of the body (*crutch strike*). Having returned to the double support position, the ambulator can either stop, or continue with the next stride whilst the body is still moving forwards, thus conserving some of the kinetic energy gained.

Wheeling (Nuzzo, 1989) (figure 1.4) is similar to swing-through gait, except one foot is held in front of the other. This can be achieved either by external bracing, or by the patient's own musculature (if they have sufficient control at the hip). During the stance phase of this gait, rollover occurs first for the trailing and then for the leading foot; in this way, the distance covered during stance is greater than that of swing-through gait (in which rollover takes place about only one pivot point). It has not been widely reported as a practical gait for paraplegics.

1.4. THE CASE FOR FES SWING-THROUGH GAIT IN THORACIC LEVEL PARAPLEGIA

Despite the sophistication of many of the FES reciprocal gait systems that have been developed to date, the resulting gait is rarely used outside the laboratory. Possible reasons for this are:

1. The many degrees of freedom that need to be controlled in order to produce an acceptably fast, dynamic gait, require a controller of a complexity beyond that of the present implementations.
2. The highly non-linear and time-varying nature of muscle (Bernotas *et al.*, 1986), and the inability to access suitable feedback signals such as muscle force and fatigue level compound the difficulties of controller design.
3. The high rates of fatigue in stimulated muscle, compared to muscle activation in normals (Levy *et al.*, 1990) limit the duration of the gait.
4. The large number of stimulation channels needed either necessitate major operations, with associated risk of infection if implanted electrodes are used, risk electrode breakage and many unsightly electrode exit points if percutaneous electrodes are used, or require excessive time to don and doff for surface electrodes.
5. Previously implemented FES reciprocal gaits have been non-dynamic in nature, leading to high energy costs as energy is wasted whilst the subject is stationary between steps (Marsolais and Edwards, 1988). This restricts the gait's usefulness when compared with wheelchair locomotion.

Thus the benefits to a paraplegic with a thoracic level lesion in using FES for locomotion, rather than a wheelchair, may not outweigh the costs.

An alternative to attempting more sophisticated solutions to the problem of producing FES gait, is to simplify the problem. Thus hybrid systems combine FES with external bracing to reinforce muscular contractions and reduce the degrees of freedom of the system. However, the benefits derived from the increased simplicity of control and reliability of these systems are offset by the additional time required to don and doff them, and the extra weight to be carried.

If a simpler mode of gait were to be utilised, the control problem could be simplified without the use of external bracing. The swinging gaits fulfill this requirement due to their lateral symmetry and stability, whereas reciprocal walking (as opposed to *stepping*) is unstable in both the anterior-posterior and medial-lateral planes (Bajd and Kralj, 1991). This lateral symmetry reduces the number of muscles that need to be stimulated and controlled by preventing the need for ab- or adduction. Swinging-gaits are, by their nature, dynamic, and thus can provide a fast and more energy efficient form of locomotion.

It is postulated that by using neural prostheses (FES) to replace neurological deficiencies in mid-thoracic subjects, it will be possible to produce functional swing-through ambulation for mid-thoracic level paraplegics (Heller and Andrews, 1989; Heller *et al.*, 1990).

1.5. INITIAL THESIS HYPOTHESIS AND OBJECTIVES

The initial hypothesis to be tested in this thesis is:

> **FES swing-through gait provides a practical and fast form of locomotion for SCI subjects with complete mid to low thoracic lesions. This gait offers speed and energy-cost advantages over both KAFO swing-through gait and FES reciprocal gait.**

Initial objectives to enable this hypothesis to be tested are:

1. Review any previous FES implementations of swinging gaits.
2. Review the literature on the energetics and biomechanics of pathological gaits to select the most efficient gait pattern to be produced.
3. Investigate methods for the design of controllers that will allow paraplegics with thoracic-level lesions to perform this gait.

CHAPTER 2. LITERATURE REVIEW

2.1 PREVIOUS PRODUCTION OF FES SWING-THROUGH GAIT

In an early report of electrically stimulated gait in complete paraplegia, Brindley *et al.* (1979) implanted electrodes on the bilateral femoral nerve trunks, the bilateral inferior gluteal nerves, and the right superior gluteal nerve[1] of a paraplegic with a T7 complete traumatic cord lesion; they also implanted electrodes bilaterally on the vastus medialis, intermedius and lateralis branches of the femoral nerve of a paraplegic with a T12 complete traumatic cord lesion. Prior to implantation, the T7 paraplegic could perform a swing-to gait and the T12 paraplegic could perform a swing-through gait with the aid of calipers. Following their operations, both learnt to achieve the same gaits (but less confidently) using the implants rather than their calipers. There was no report of the speed or range of the gait. After a 4 month training period the T7 paraplegic could walk for 15 minutes and the T12 paraplegic could walk for 5 minutes. There was no attempt to control the stimulation pattern, all muscles being permanently activated.

Holle *et al.* (1984) implanted 16 channel stimulators in two paraplegics, both with complete lesions at T9 and T12. Electrodes were attached to the femoral and infragluteal nerves in both subjects, in order to produce hip and knee extension. They report that '...both patients were able to stand up by themselves with the aid of crutches and were able to walk in a slow swinging-through gait and four-point gait for a distance up to 100 m'. There is no report of the control strategies (if any) that were applied. There is also no reported study of the parameters of the gait, or the conditions under which it was produced (straight-line or circular track, continuous walking or rest-breaks, laboratory or outdoors). One of the paper's contributors, Professor Herwig Thoma[2] reports the following:

> *Our experience* [in 1982-84] *was that swing-through has the advantage of a very simple and fast movement, but the disadvantage of (1) safety and (2) too much load on the upper extremities.*

---

1 This produced a weaker extensor action at the hip than was expected, which was insufficient to prevent episodes of hip buckling interrupting the gait, although it did reduce the frequency and severity of their occurrence.
2 Of the Biotechnical Laboratory of the Second Surgical University Clinic, Vienna.

Possible situations to benefit from this swing-through gait may be at home, e.g. walking to the bedroom from the toilet and especially in any kind of turning... For outdoors or distances more than a couple of metres I would not recommend this method. But note that these are personal experiences and not strict recommendations. If the patient is strong enough and trained, it may be a good solution. (Thoma, personal communication, 1991).

Marsolais and Kobetic (1987) report the implantation of percutaneous electrodes in eleven subjects (lesions from T4 to T11). Five of the subjects did not complete the implantation and gait training programme; Two of the remaining six subjects were able to walk 'with difficulty' using axillary crutches and a four point gait twenty-five months after implantation. One subject progressed to two-point (swing-through) gait at thirty months after implantation. No control strategies were reported and no assessment of the gait was given. Marsolais (1989, personal communication) reported that the (fixed-knee) swing-through gait was discontinued because of worries about the magnitude of the contact forces at heel-strike (although this was just a subjective impression, the forces were not measured).

These previous attempts to produce swing-through gait in spinal-cord injured subjects by means of FES have maintained extended knees throughout the gait cycle. This has the advantages of stability and ease of control, but requires more lift to achieve ground clearance, and hence more upper body effort than swing-through gait in which the knees are flexed during the body-swing phase (Wells [79], and this thesis). Swing-through gait is also considered less of a 'natural' gait than reciprocal walking. This may explain why, despite having been implemented by a number of research centres, FES swing through gait has not been adopted as a viable form of locomotion. This is in contrast to its popularity amongst active paraplegics who walk with knee-ankle-foot orthoses (Rovick, 1982). The present work is the first attempt to produce free-knee swing-through gait by means of FES.

2.2 BIOMECHANICAL ANALYSES OF SWING-THOUGH GAIT

Childs (1964) presents a qualitative analysis of one paraplegic subject performing swing-through gait. He gives some pre-crutch training exercises to prepare a SCI patient to perform the gait, and suggests that the patient maintain full elbow extension throughout the body-swing phase to minimise energy cost.

Peacock (1966) carried out a study of three unimpaired subjects performing one-legged swing-through gait (the other leg was held out of the way). Only one of the subjects had any previous experience of walking with crutches. He measured the EMG signal from a total of twenty-one muscles in the wrist, arm, shoulder-girdle, and trunk. Still photographs of the gait were also taken, but only used to describe the gait qualitatively. He showed high activity in the muscles of the arm and shoulder girdle during the swing phase. The fact that the subjects were untrained and were performing a one-legged gait in which they had full range of motion in their weight-bearing legs, lessens the relevance of this study to swing-through gait in paraplegia. Peacock asserted that, unlike the hip, the shoulder joint is not designed for weight-bearing and thus needs a high level of muscular activity to transmit sagittal-plane forces across it during the time the weight is on the hands (body swing-phase). This is one of the reasons why crutch walking is so energy intensive. He also showed differences in the geometry of the loaded shoulder joint between a trained gymnast (with well-developed shoulder girdle muscles, probably akin to a regular crutch ambulator) and one of the normal subjects. This would indicate that an untrained individual does not have the correct musculature to adequately simulate a regular swing-through ambulator.

Perry (1975), in another qualitative analysis, recognised the possibilities of swing-through gait for mid-thoracic paraplegics wearing KAFOs, but rejected it due to the potentially high energy costs and low stability:

> ...*But the energy expenditure* [of swing-to/through gait in T6-T9 paraplegics] *is too demanding for more than an exercise experience. There are basic deficits that prohibit making the task easier with training or devices. These are the absence of both sensation and active control of pelvis and hips and the presence of primitive spinal motor responses.*
>
> ...*Advancement of the body is also extremely challenging as his lack of lumbar and hip control means the motion must occur entirely at his shoulders. This makes the body one rigid lever with considerable weight distally because of the orthotic mass that is required to control limb 'spasticity' and accept the thrusts of abrupt loading from a swing-through gait.*

> *...With knees and ankles rigidly locked, the body and limbs must be lifted and swung in one large motion rather than by a sequence of controlled position changes at each joint. This makes the margin between stability and falling very narrow. The energy cost of walking in this fashion is so great that it is a strenuous athletic feat that leaves the person exhausted, even when performed by powerful healthy young men. Such walking is not a useful means of locomotion. The patient cannot travel far enough and is too tired to be effective when he has arrived.*

Her comments on the energy cost of the gait are not experimentally substantiated, nor are references to the literature given, but they are broadly in agreement with those found by other researchers (see section 2.3). The problems she identifies can be addressed by a combination of pharmacological and prosthetic solutions. Sensation can be restored through sensory feedback to innervated regions (Phillips CA, 1988; Andrews *et al.*, 1988). Spasticity can be controlled through the use of anti-spasmodic drugs such as *Baclofen*. FES control of hip and knee obviates the need for heavy orthoses, and allows active flexion at the hip, reducing the demand on the muscles of the shoulder. FES also allows the hip and knee to be individually flexed and extended, providing additional ground clearance. This relieves the need for lift from the upper-body and so further reduces the energy costs.

Shoup *et al.* (1974) performed a three-dimensional cinematographic analysis of four unimpaired, adult, male subjects performing swing-through gait at unspecified speed. They stated that '...[the subjects] were trained in the proper technique for swing-through gait...' but gave no details of the training regime. They chose a four link model to represent the gait, consisting of shank and foot, thigh, head and trunk, and arms and crutches. They presented graphs of the displacements of joint centres, and angles between body segments in the frontal and sagittal planes. These graphs were compared to the data for normal walking. The authors concluded that displacements in the frontal plane were smaller for swing-through gait than for normal walking. An exception was the lateral displacement of the crutch tips during body stance, which was necessarily large in order to allow the long axillary crutches to clear the ground. They suggested three areas in which research to improve the gait should be concentrated:

(a) The vertical motion of the upper body should be minimised by allowing the crutches to collapse slightly during the swing phase (perhaps by means of a spring). Shoup investigated this concept in a later paper (Shoup, 1980) and found the modified crutch could save up to 25% of energy costs. Unfortunately this is not appropriate for paraplegic swing-through gait with fixed knees, as the paraplegic must raise his upper body (by extension of the arm and depression of the shoulder) in order to obtain sufficient clearance for his feet to swing through. Any collapse of the crutch would have to be compensated for by increased upper body effort. The technique could be used if active knee flexion were to be restored by means of FES, for example.

(b) The shock associated with planting the crutch tips should be reduced to minimise fatigue and potential joint damage. This was investigated by Parziale and Daniels (1989) who found that a spring-loaded crutch led to a 24% reduction in peak stress, when compared to a standard axillary crutch. The tests were performed using unimpaired subjects. The same argument applies for the reduction in ground clearance caused when this device is used by paraplegics with fixed knees.

(c) The lateral motion of the crutch tips should be minimised by a crutch that actively shortened: how this was to be achieved was not specified. Elbow crutches are shorter and allow greater elbow flexion than the axillary crutches used in the study, so they need less lateral motion for ground clearance. They might be a better choice than a self shortening crutch with a complicated and heavy mechanism.

Wells (1979) claimed that the use of unimpaired subjects by Shoup *et al.* (*ibid*) was not a good model for paraplegics performing swing-through gait: the former have the full use of their legs, they can push-off, lengthen their stride by hip flexion and they can use hip and knee flexion to generate ground clearance during the swing phase. This is impossible for a paraplegic crutch user. He suggested that an unimpaired subject with artificially restricted mobility (by bracing) was a closer approximation to a disabled crutch user. He proceeded to examine the kinematics and mechanical energy variations of swing through gait at four different speeds ('slow', 'comfortable', 'fast' and 'as fast as you can'). He used three subjects, of which one was 'familiar' with crutch gait; the subjects were shown the gait and 'allowed to practice and obtain a basic proficiency' but no details of any formal training methodology were given. The kinematics of the movement were recorded by a single 16 mm cine camera. A force plate and a crutch-tip force transducer were used to identify the phases of the gait, but not to determine any kinetic quantities. He used the same four segment model as Shoup. His kinematic results show that as the level of (artificial) disability increases, the proportion of time spent in the double support phases increases and that spent in the body swing phase decreases. He used the technique of Winter (1979) to compute the whole body energy by taking the algebraic sum of the kinetic and gravitational potential energies of each segment. In this way he could estimate the amount of energy conserved in each segment, and thus the mechanical energy input needed to maintain the gait. The studies he performed on the one artificially-disabled subject showed that if the knees were locked, the potential energy variation of the trunk increased considerably. This is because, in the absence of knee flexion, the whole body must be raised in order to obtain sufficient ground clearance to swing the legs through. Wells found that *the internal mechanical expenditures of energy in swing-through gait are roughly equivalent to those presented by Winter (1979) for normal walking.* He argued that the reason swinging gaits are more tiring than normal gait, despite these similar values, is that this mechanical work is being done by the (less well adapted) muscles of the upper body rather than those of the legs.

Wells' suggested that an artificially-disabled subject is a good approximation to a disabled crutch walker. This is only true if the subject wears appropriate bracing. His 'universal' orthosis could lock the knee and hip (he does not specify if the ankle was also locked) but this is only a valid model for a paraplegic with similar braces; in the absence of spasticity and contractures, a paraplegic will walk with flaccid rather than stiff joints (i.e. negligible moments are produced at the joints). Also, for a valid comparison between the energetics of constrained and unconstrained walking, the same orthosis should be worn unlocked in the unconstrained tests; it is not clear if this occurred in Wells' tests.

Another difference between his subjects and genuine, experienced crutch ambulators, is mentioned by Rovick (1982), he points out that the latter will have well developed upper body musculature, with atrophied lower limbs[1]; whereas, in general, the able-bodied individual will demonstrate a different body type, less well adapted to the demands of crutch aided locomotion.

The use of mechanical, rather than physiological, energy cost as a measure of the total 'efficiency'[2] of the gait allows us to compare directly the energy costs of different gaits, rather than the energy costs of their implementation by humans (which depend on the efficiency of the human machine). This may be informative, but the physiological cost is still the factor which is relevant to the actual use of the gait. Wells makes no attempt to relate the two, but Burdett *et al.* (1983) found a high correlation ($r=0.79$) between the measure used by Wells and the true metabolic energy consumption (per unit time) of normal walking determined by oxygen consumption. However, they found a much lower correlation between the energy costs per-metre, indicating that purely mechanical measures should be treated with caution when used to predict true metabolic energy costs[3].

Rovick (1982 and 1988) performed a kinematic study of the body-swing phase of a T11-12 complete paraplegic who had 20 years experience of ambulating with a swing-through gait and KAFOs. There are a number of methodological weaknesses in his study:

- His method of determining the positions of joint centres was by marking a sheet of mylar placed over a 'freeze-frame' picture of the subject displayed on a monitor. Despite the precautions of using one eye and maintaining the head of the person performing the digitisation in a fixed position, parallax errors are likely, due to the thickness of the monitor screen.
- He used 4 cm diameter targets to mark the 'joint centres' (assumed to be fixed), but gave no indication of how the positions of these centres were determined.

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1 A paraplegic who either has chronic spasticity of his lower limbs, or who exercises them regularly with FES can prevent or reverse atrophy.
2 Strictly, the efficiency of gait on level ground is zero as no work is being done.
3 For example, the development of isometric force, such as that which is needed to prevent subluxation of the shoulder girdle during the body-swing phase, requires metabolic energy, but produces no mechanical work.

- The hip marker was attached to the subject's shorts, rather than directly to his skin. This makes the incorrect assumption that the movement of the clothing will match that of the skeletal landmark. It will also decrease marker stability and thus further increase the measurement error.
- He estimates that the measurement and transcription angular errors are 0.5 degrees, based on the scatter of the data compared to the smoothed curves. This assumes that the original angles form a band limited signal with no high frequency components above the cut off point of the filter, an assumption which Rovick does not justify. This technique will also only pick up high frequency, random errors; errors due to faulty marker placement, or parallax errors in the measurement or transcription will lead to undetectable, low frequency, systematic errors.
- His assumption of a normal weight distribution in the subject's legs is probably not valid, as there is likely to be a considerable reduction in muscle mass and some reduction in bone mass in a complete paraplegic 20 years post injury. This will lead to errors in the estimation of the centres of mass and moments of inertia for his model.
- His three-link model has severe shortcomings in that it doesn't allow for depression of the shoulders or extension of the elbows as a means of obtaining ground clearance. Consequently, the simulated foot trajectory passes beneath floor level, which is impossible in reality.
- He validates the model using a trial and error technique in which he estimates the applied moments at the joints, solves the direct dynamics problem to obtain the kinematic outputs, then compares these with the subject's measured movements and adjusts the model accordingly. It would be more efficient to obtain the moments at each joint by solving the inverse dynamics problem for the measured movements; if the moments were close to the postulated values (usually zero for the paralysed joints, variable for the innervated shoulder joint), then the model would be acceptable.

Despite these reservations, his qualitative finding that swing-through gait with KAFOs and flaccid hips can be modelled as a three link pendular system, with a forcing moment at the shoulder, is of interest in providing an simple model of the gait that may be understood by those teaching it clinically. He suggests that energy costs can be reduced by the use of crutches such as the Canadian (or ring top) crutch which relieves the triceps group by reducing the elbow flexing moment, or the saddle crutch (Taylor, 1883) which relieves the arms by helping to support the weight of the body mechanically. These crutches prevent the arms raising the body for ground clearance and are thus inappropriate for a paraplegic ambulator who cannot flex and extend his knees; however, their use would be possible if FES were used to actively flex the knees.

McGill and Dainty (1984) analysed eight unimpaired children performing a one legged swing-through gait without orthoses. They characterised the gait using 2 cine cameras recording at 20 Hz, a crutch that had been instrumented to measure axial loading, and a force plate. They compared an extension of Wells' model to ten segments (with the head/neck as a separate segment to the trunk) to a 9 segment model (with head and neck combined as one segment). They found no differences between the models in terms of the timing of segment energy fluctuations, and so used the nine segment model for their analysis. In order to examine the effects of crutch length on the gait energetics, each child was studied walking with crutches:

a. correctly adjusted according to the method of Cohen (1979)
b. set 4 cm longer than the value in a.
c. set 4 cm shorter than the value in a.

The technique they used to compare the different gaits was to calculate the instantaneous segmental potential and kinetic energies, and their time derivatives (power) (a similar technique to that used by Wells). By examining the total variations in energies, and the phase differences between kinetic and potential energies, they were able to identify (in an intuitive manner) inefficient gaits, and inefficient events within a particular gait. They found that crutch length changes of 4 cm had a considerable effect on the segmental energies, but that the most efficient length didn't always correspond to that predicted by Cohen's fitting formula. They also found that the (normalised) energy values for children were higher than those found for Wells for adults (although a different type of gait was being considered).

Stallard *et al.* (1980) used a force plate to measure the ground reaction forces both on the landing leg and on the crutches for one-legged swing-through gait in ten unimpaired adults. They found that the inter-subject average of peak vertical reaction force applied to the leg was 1.32 times body weight. They reported this to be 16 per cent higher than equivalent values for normal walking. They interpreted these results to indicate caution in the prescription of one leg swing-through gait in subjects with diseased bone and joints in the lower limb. This note of caution should also extend to paraplegic swing-through gait due to the propensity of paraplegics to develop osteoporotic weakening in the bones of their lower limbs, (Guttman, 1976). However, if a two-legged swing-through gait is performed, and equal sharing of load through both lower limbs is assumed, then the maximum force through each leg will be halved, *bringing it to below normal values.*

Wilson and Gilbert (1982) attempted to determine the vertical loads on the hands and the lateral forces at the axilla for thirty-one unimpaired subjects performing swing-through gait with axillary crutches. They only measured the lateral forces between the ground and the crutches, and made a number of approximations and assumptions to derive the required values. These included assuming that the hands provided no lateral force or twisting moment at the crutch handle, that accelerations were small, and that the angle between one crutch and the ground, measured in the plane of both crutches, remained constant throughout 5 gait runs. They did not justify these assumptions and thus their conclusions that up to 3.4 times body-weight is taken through the hands should be treated with much caution.

Reisman *et al.* (1985) used more sophisticated motion analysis equipment (a force plate and three high-speed cine cameras) to investigate the effect of varying the crutch handle position (and thus the elbow flexion angle) on the elbow-extension moment. They also made the assumptions that inertial forces could be ignored, and that no twisting moments were transmitted to the crutches from the wrists via the hands. Their study is interesting in that they judged the quality of the gait by the size of the elbow extending moment. They also recommend that an examination of the biomechanics of the shoulder during crutch gait may be illuminative.

Goh *et al.* (1986) performed a biomechanical study of one-legged swing-through gait. They used a force-plate, an instrumented crutch and a *VICON* kinematic analysis system; however, they did not report the kinematic analysis. They found that the peak vertical component of the ground reaction force on the weight-bearing leg during body-stance was 121.6 % of body weight, which is higher than for normal gait. They sounded a similar note of caution to that of Stallard *et al.* regarding the use of the gait by patients with unsound lower limbs.

Opila *et al.* (1987) used crutches that had been instrumented to measure three components of force, and a three-dimensional TV-based kinematic measuring system, to determine the flexion-extension moments at the elbow and shoulder, and the ab/adduction moment at the shoulder, for four low-thoracic paraplegics performing KAFO swing-through gait with elbow crutches. She found extending moments of up to 0.10 Nm per Newton body weight - values as large as those found at the hip in normal, unaided gait. However, unlike the hip (and elbow), the shoulder also requires muscular actions to transmit sagittal plane forces. Thus shear forces at this joint are also important, but were not reported in this study.

2.3 THE ENERGETICS OF SWING-THOUGH GAIT

The human body releases energy by the oxidisation of food; the amount of energy produced is related to the amount of oxygen consumed. Thus, by measuring the difference in the amounts of inhaled and exhaled oxygen, it is possible to determine the amount of energy released. One litre of oxygen is associated with the release of 4.83 kcal or 20.2 kJ of energy for an average diet (Fisher and Gullickson, 1978)[1]. The reliable standard for measuring oxygen consumption is the Douglas Bag combined with volumeter and gas analysis.

The use of oxygen consumption to determine energy expenditure during locomotion is a well established procedure: McDonald (1961) has reviewed

1 The amount of energy associated with one litre of oxygen varies according to the type of food being oxidised (e.g. carbohydrates, fats, proteins). For accurate calorific equivalents, the respiratory quotient (the ratio of CO_2 produced to O_2 consumed) must be measured. However, if tests on the same subject are performed in a short period of time (less than one hour for example), the respiratory quotient will remain approximately constant and intra-subject comparisons will be valid.

literature for normal walking dating from 1912 to 1958. There are two main methods of reporting results:

- energy expended per kilogram body-weight per second, termed *energy consumption* by Nene and Patrick (1989). The term *energy consumption rate* will be used in this thesis.
- energy expended per kilogram body-weight per metre moved, termed *energy cost* by Nene and Patrick. The term *energy cost per metre* will be used in this thesis.

The first term can be thought of as a measure of the cardiovascular demand of a gait. It determines the **possibility** of a particular subject using a particular gait mode. The second term is more a measure of the 'efficiency' of a gait. It determines the **practicality** of using the gait in a particular situation. For example, a particular gait mode may have a low energy consumption rate, and thus be **possible** for many subjects, but if it is also very slow (thus high energy cost per metre) then it is of little **practical** use. Conversely, a gait that has a high energy consumption rate may only be performed by the very fittest subjects, but if it is sufficiently fast it may provide them with a practical gait form. This is depicted graphically in figure 2.1.

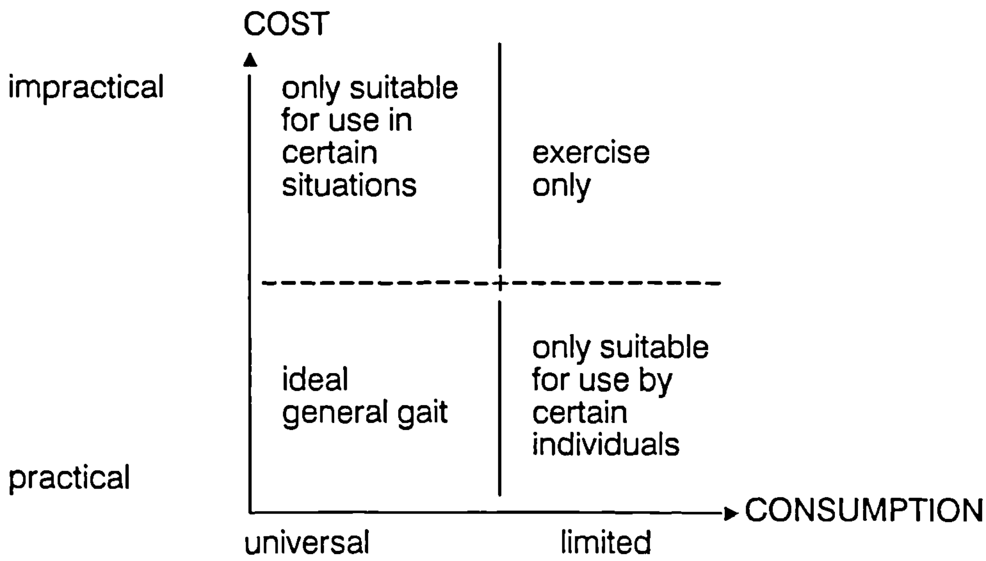

Figure 2.1: How the energy cost/m and consumption rate of a gait specify its use.

Although energy cost per metre, energy consumption rate and velocity are not independent for a single subject (energy consumption rate is the product of energy cost per metre and velocity), the **mean** values are independent. If a study quotes only the mean values from a group of subjects all three parameters must be given.

Gordon and Vanderwalde (1956) conducted the first study of the energy requirements of paraplegic locomotion. They found that the energy consumption rate of paraplegics walking at 0.45 m/s was 5.8 times more than their basal energy consumption rate. They felt that the subjects would not be able to sustain this level of output for long periods. Gordon (1956) concluded that ambulation with braces was not practical for paraplegics with cord lesions above T12.

Clinkingbeard *et al.* (1964) studied paraplegics with thoracic- and lumbar-lesions who had been ambulating for an average of 18 months. Those with thoracic level lesions (two at T4 and two at T12) walked at an average speed of 0.08 m/s. Their energy consumption rate was less than that of an unimpaired subject walking at 1.3 m/s (indicating perhaps that the major constraining factor on their speed was not energy consumption rate but some other factor such as balance or upper body fatigue). However, their energy **cost per metre** was nine times that of an unimpaired subject walking at his most comfortable walking speed. Three lumbar paraplegics were also studied (two at L1 and one at L2); their average speed was 0.33 m/s and their energy **cost per metre** was one third that of the thoracic level lesions. Clinkingbeard *et al.* also studied a further 11 paraplegics undergoing gait training as part of their rehabilitation programmes; they demonstrated a reduction in oxygen cost per metre in the first four weeks of training, with the improvements then leveling out.

McBeath *et al.* (1974) measured the metabolic energy costs per metre of ten unimpaired subjects performing both swing-through crutch gait and normal walking. They found the self-selected velocity for swing-through gait to be three quarters of that of normal walking, and the energy **cost per metre** and **consumption rate** (at 1 m/s) to be 78% greater. It should be born in mind that these subjects had full use of their limbs, and thus these values represent a **maximum** bound for the efficiency attainable by FES assisted gait in paraplegics (although if insufficient swing-through training was provided [the training regime was not specified] then there might still be room for improvement).

Cerny *et al.* (1980) compared the energy demands of KAFO swing-through gait with that of a wheelchair for ten adults with low-level spinal cord injuries. Three of these subjects walked regularly (two with lesions at T12 and one with a lesion at L1). Cerny *et al.* concluded that KAFO walking was significantly more inefficient than wheelchair propulsion. They suggested that it was only appropriate for athletic individuals who were capable of walking at 0.9 m/s and who were willing to work under anaerobic conditions. This conclusion ignores other factors that may affect the decision to use a wheelchair, such as psychological concerns. Additionally, even if a wheelchair is used as the major form of locomotion, it may be advantageous to be able to walk without it under certain circumstances (e.g. to avoid obstructions).

Fisher and Patterson (1981) examined the energy demands of eight unimpaired subjects performing swing-through gait at various speeds. They found that the energy **consumption rate** and **cost per metre** was approximately two times that of normal walking at the same speed. In addition, their subjects performed arm and leg ergometry to determine the rates of maximum oxygen uptake (VO_{2max}) for upper and lower body work. Fisher and Patterson suggested that if swing-through gait is regarded as primarily an upper body exercise (which is not the case for subjects with full use of their legs) then 0.67-0.83 m/s is the maximum speed at which the gait remains aerobic (i.e. it can be sustained). This compares with a normal comfortable walking speed of 1.3 m/s. They recommended upper-extremity endurance training as a pre-requisite for crutch walking (although this training was not given to their subjects).

Merkel *et al.* (1984) examined the energy expenditure of eight paraplegics (C7 to T12) who had been trained to walk with KAFOs for at least eight weeks. They found that there was a significant reduction in energy **consumption rate** when using the *Scott-Craig* KAFO (in which both legs are linked by a bilateral cross bar) compared to a standard KAFO. They found that the energy **cost per metre** of ambulating with *Scott-Craig* KAFOs was 5 times greater than that of normal walking, and that of ambulating with standard KAFOs was 7.7 times greater than that of normal walking.

Chantraine *et al.* (1984) compared the energy expenditure of four paraplegics who had recently completed a course of rehabilitation, but were unaccustomed to using braces, with another three who had used KAFOs for more than four years. They found that the subjects who were accustomed to walking with KAFOs walked on average 5 times faster than the unaccustomed group, and that their energy **cost per metre** was almost 5 times smaller. They interpreted these results as demonstrating the importance of the training effect for paraplegic ambulation.

The effect of training was also investigated by Nejad (1990). She examined five normals performing swing-through gait and found that following a systematic training regime, their physiological cost index (PCI, a measure of energy cost per metre based on heart-rate) (MacGregor, 1981) decreased, and their step length and speed increased. This supports the findings of Chantraine *et al.* and Clinkingbeard *et al.* indicating the importance of training for crutch-aided gaits, and suggests that one should be cautious in interpreting results from tests performed on untrained subjects. In addition, Nejad attempted to determine the effect on PCI of artificially disabling ankle and knee joints, but her results were inconclusive due to methodological problems.

Tesio *et al.* (1991) argued that, when comparing the energy **costs** of pathological gaits with normal walking, the speeds at which the comparisons are made is important. They plotted energy costs per metre of amputee, hemiplegic and paraplegic gaits (obtained from the literature) against speed, and fitted second order regression lines to obtain the **minimum** energy values. They then compared these minima with the values for normal walking at the same speeds. They found that the speed at which the energy cost per metre of paraplegic gait was a minimum was 0.83 m/s. The cost per metre was only 9% higher than that of normal walking at the same speed. They used this result, and similar ones for amputee and hemiplegic gait, to support their argument that inefficiency in pathological gaits is not a direct result of the pathology. Instead, they postulated that inefficiency is mainly due to the low speeds attainable in pathological gaits limiting the conservation of mechanical energy from one cycle to the other. Their arguments are interesting, but somewhat artificial. It is more valid to compare the energy cost per metres of different gaits at the preferred speed of each one, as these values reflect the real costs of their use.

The improvement in crutch gait due to training is apparent from Nejad's, Clinkingbeard's and Chantraine's studies. However, only Nejad reports a systematic training regime for her subjects (the regular, long-term, use of crutches, such as in Chantraine's study, may also be regarded as training). The results from other investigations, particularly those on unimpaired subjects, may represent a partly-trained gait with consequent higher energy demands.

The role of knee flexion in reducing the need for swing-phase ground clearance and in reducing the moment of inertia of the swing-leg is well-known for reciprocal gait (e.g. Saunders *et al.*, 1953). However, no study has systematically varied a subject's degree of (artificial) disablement and observed the effect on oxygen consumption during swing-through gait. It is therefore hard to directly quantify how the loss of this gait component will affect the energetics of the gait.

2.4. THE CONTROL OF FES GAIT

This section will explore the control issues involved in the synthesis of FES gait. It will start by discussing the hierarchical nature of the processes involved in the production of movements (both normal and impaired). The second section will review methods of implementing FES controllers and the third section and fourth sections will explore ways of deriving these controllers.

2.4.1. Models of the Movement Process

There are an estimated 792 degrees of freedom in the human body (Tomovic and Bellman, 1970). Nearly 700 skeletal muscles can be controlled to produce movement (Tortora and Anagnostakos, 1987 p. 218). Each muscle is further sub-divided into a sizable number of independent motor units. There is a similarly large amount of **information** about the movements available from muscle spindles, Golgi tendon organs, joint kinesthetic receptors, pressure receptors, cutaneous nerves and vision. This plethora of control outputs and feedback information makes the control problem seem an intractable one; however, this difficulty is avoided by the hierarchical organisation of the motor control system (Stelmach and Diggles, 1982), in which fundamental goals are specified at the highest levels, and decisions on detail are added at subordinate levels. Brooks (1979) describes the hierarchy as going from the general to the particular: general decisions to act, strategies for how to act, preparations for movement execution, and combination of tactical detail. This hierarchical approach allows more economical use of the higher levels (Bernstein's 'economy principle', [Bernstein, 1967]), and a substantial reduction in the quantity of information that must pass between levels. The flow of movement instructions in this hierarchy is not purely 'top-down', but may be transformed through multiple feedback and feedforward interactions at many different levels of the central nervous system (Stelmach and Diggles, 1982; Brooks, 1979).

There is also evidence for parallel interaction, in which control responsibility at each level is spread among a number of interacting structures (Posner and McLeod, 1982; Arbib, 1981). Models of motor control are reviewed in Stelmach and Diggles (1982).

The control rules can take place at varying levels of consciousness. For example, in a complex, unfamiliar movement sequence, each element may need to be **consciously** controlled (the 'slow mode' of Mulder and Geurts [1991]); whilst as skill increases, or for genetically pre-programmed movements (such as breathing), more of the processing load is performed by coordinative structures ('fast mode'). Thus, in the absence of environmental impediments, walking is generally a **sub-conscious** (fast mode) activity. Other control rules will be activated at **non-conscious** (spinal) levels; these include the control loops associated with stretch and force receptors, the triggering of spinal reflexes, and may even include some complex movement patterns such as walking (Grillner, 1975; Bussel, 1988).

Mulder and Geurts (1991) state that the ability to control movements at a non-cognitive level results in a decreased reaction time, and a greater ability to perform simultaneous cognitive tasks (such as obstacle avoidance, planning, talking) due to reduced inter-task interference. It is therefore desirable that an FES ambulator can control her/his walking via the same (fast) mode of control as a non-impaired ambulator.

2.4.1.1. Effect of spinal cord injury

A lesion of the spinal cord interrupts the flow of ascending and descending information. The amount of disruption this causes will depend on the level and nature of the lesion: an upper-motoneuron lesion will leave many structures intact, and thus allow movement processes using these preserved structures (such as spinal reflexes) to continue. Movement processes originating above the lesion, but requiring activation of structures below it, will be prevented from occurring. However, it was stated that there may be parallel activation of coordinative structures during a movement, in particular, postural stabilisation always precedes voluntary movement (Mulder and Geurts, 1991). Thus, the postural precursors of a voluntary movement may still be functional, even though the movement cannot occur.

If the afferent pathways (which provide information about the consequences of a movement) are interrupted, then the movement may still be performed, but will be less precise (Bizzi *et al.*, 1976).

2.4.1.2. Application to FES control systems

Coburn (1984) states that any bioengineering alternative to the normal locomotor system must follow similar, hierarchical, strategies from goal selection at the top down to the control of single motor units. Similar hierarchical schemes have been proposed in the field of motor rehabilitation to describe the control of man-machine systems (Tomovic, 1969; Stanic *et al.*, 1974; Kralj, 1975; Chizeck *et al.*, 1988B). The model of Kralj (1975) is illustrative and is reproduced below.

I level of decision

↓ ↑

II level of coordination

↓ ↑

III level of execution

These models share the characteristics of having a high level decision (mode selection) process which is performed by the subject, a central coordinative or supervisory level that translates the movement decisions into the required joint trajectories (states) in the correct sequence, and low level subsystem controllers that generate the actual stimulation sequences required to achieve the desired joint trajectories (in an open or closed loop manner). The low-level controllers implement a set of control laws or rules which are active whilst that state is active. Tomovic (1969) calls these lowest levels the 'control of continuous variables'. The supervisory level activates or deactivates these low-level controllers. The decision level selects the appropriate supervisory controllers (e.g. stand-up/stand/sit-down, reciprocal walking, swing-through walking).

The man-machine interface is the mechanism by which the subject's control decisions are communicated to the machine and also the way the machine feeds back information to the subject.

2.4.1.3. Manual and automatic control

The man-machine interface in FES gait may occur at two different levels, which define the *manual* and *automatic* modes of control.

In the automatic mode (called the menu mode by Kralj *et al.* [1987]) the subject selects pre-programmed sequences, which then proceed automatically (Marsolais and Kobetic, 1983; Holle *et al.*, 1984). The man-machine interface takes place between the higher (decision) and central (coordinative) levels of control, with coordination and all lower levels being performed by the machine. This approach allows the simple addition and modification of stimulation patterns, and facilitates the use of many channels of stimulation. The walking sequences are preset (although they may be triggered by various sensors). Modifications (training) are performed by re-programming the controllers. Much of the knowledge of how to produce the gait (skill) lies in the controller rule-base, thus a subject may perform a complex gait pattern with minimal training. This gait is of a automaton form, requiring minimal cognitive effort by the subject (although s/he must ensure that her/his voluntary movements are coordinated with the automatic ones); thus it parallels the subconscious control of normal gait. There has, as yet, been no development of control systems that can identify and anticipate obstacles in the environment; thus, the subject must manually select different gait modes for obstacle avoidance.

In the manual mode (called the trigger mode by Kralj *et al.* [1987]), the subject explicitly controls the activation of each channel of stimulation (e.g. Kralj *et al.*, 1983). The man-machine interface takes place between the central (coordinative) and lower (execution) levels of control. The coordinative role is performed by the subject, who has access to environmental information and can thus provide versatile control (Kralj *et al.*, 1987). The integration of voluntary and FES produced movements is simplified, with the subject initiating them both. The subject may have no direct (apart from visual) information about the consequences of a movement, but this can be provided through sensory feedback to innervated regions (Phillips CA, 1988; Andrews *et al.*, 1988). Modifications of the movement (training) are directly learnt and performed by the subject. This mode requires more cognitive input, and thus may prevent the performance of simultaneous cognitive tasks. It may require much subject training to produce a fast control mode. The number of stimulation channels is limited by the lack of suitable control inputs, and by the prohibitive cognitive burden.

A quantification of the *autonomy* of a *cybernetic actuator* (in this case an FES control system) is given by Tomovic and McGhee (1966): they define the *measure of autonomy* to be the inverse of the average sum of the number of binary decisions per unit time made at a conscious level and the average number of binary output changes fed back to the conscious level. They state that it is desirable to minimise this figure because the rate at which humans are able to make conscious decisions is very low. They term this the *maximal autonomy* principle.

2.4.1.4. Intention detection

The man-machine interface can be **explicitly** controlled by a subject pressing appropriate switches. An alternative approach is **implicit** control, in which preparatory activations or movements of the subject's preserved motor structures are associated with appropriate movements of the stimulated structures. This is termed *intention detection* (Andrews *et al*, 1987). Liberson *et al*'s (1961) heel switch for correction of hemiplegic drop-foot detects weight shift away from the foot and thus can be considered as an indicator of the intention to step. A more sophisticated system for paraplegic gait was reported by Graupe *et al.* (1983). They detected characteristic patterns in the EMG activation of the erector spinae muscle in mid-thoracic paraplegics that corresponded to the postural adjustments made prior to performing simple movements (stand, sit, right leg swing, left leg swing). The detection of these patterns triggered the production of the appropriate movements by FES. The remainder of the movement followed a fixed time course. Graupe *et al.* described the EMG signals as providing a *posture mapping* of the upper trunk. The technique has inherent safety in that if the posture is incorrect a step cannot be taken, even if the subject desires it. If the system incorrectly detects the desire to step, the posture will still be correct, and so the subject should not fall (Graupe *et al.*, 1984).

Tomovic *et al.* (1987) detected the intention to initiate a step by a shift in the position of the body-weight vector away from the swing leg. This shift is controlled by the arms and is a natural precursor of taking a step.

Andrews *et al.* (1988) described the use of force sensors mounted on crutches and insoles to detect the intention to step. They derived the following rules from observing the gait of a skilled paraplegic ambulator:

IF the contralateral crutch is loaded
AND the contralateral foot is loaded
AND the ipsilateral foot is unloaded[1]
THEN initiate FLEXION (swing) of the ipsilateral leg.

Once triggered, the flexion stimulation was maintained until the hip angle exceeded a pre-set threshold. The requirement of three conditions being satisfied before flexion is triggered may make this rule-set more reliable than one using only one condition.

Hefftner *et al.* (1988) suggest that EMG, force and limb position signals may be used for the detection of intention. They give a set of criteria that an EMG signal has to meet to form a useful command signal. These criteria may be extended to other forms of signal, and are listed below (original text italicised):

1. *Reliability: The method must be able to differentiate between a user-generated [EMG] command signal and background [EMG] noise, as well as between different commands.*
2. *Versatility: The method should not be limited to specific [electrode]* sensor *locations. It should be possible to modify and adapt these for each patient, depending on the level of the lesion, the strength of the remaining active muscles, and the degree of control over these muscles.*
3. *Repeatability: When using a [myoelectric] control system, the user is required to perform a specific predefined muscle contraction in order to activate a command. As it is inconceivable that exactly the same contraction can be performed repeatedly, the method of [EMG] processing must be relatively insensitive to small variations in*

1 By the subject shifting his/her bodyweight.

the [*EMG*] sensor *time signature and/or signal level due to inconsistencies in the movement performed.*

4. Computation delay: The total response time from the patient's initiation of a command by his above-lesion [*EMG*] musculature *to the subsequent limb function activation by electrical stimulation must be kept within 0.5 s*[1]*, as a longer time delay will be noticeable and unacceptable to the patient. The system must attempt to minimize the response time.*

5. [*Electrode*] sensor *considerations:* [*With surface electrodes being used,*] *the number of* [*electrodes*] sensors *required by the control system should be kept to a minimum. This could contribute to the system being simple, convenient to use, and cost effective. The method of* [*EMG*] signal *processing should also not be excessively sensitive to small variations in the* [*EMG*] signal [*signature*] *due to small changes in* [*electrode*] sensor *placement, although naturally some level of accuracy in the placing of* [*electrodes*] sensors *will be required.*

6. Patient training: The patient should be able to produce the required [*EMG signatures*] sensor outputs *reliably and repeatedly with a minimum of training. The movements or muscle contractions required to produce these* [*EMG signatures*] outputs *should, once learned by the patient, be natural and convenient to the patient, and not require excessive limb movements.*

These applications have used intention detection to trigger the start of particular movement sequences (phases) in the gait cycle, thus forming an alternative way of controlling a manual controller. If condition (6) above holds, then the above-lesion movements will be a natural part of the gait cycle (such as movement of a crutch) and may be performed at a subconscious level (fast mode). Thus by using intention detection as the man-machine interface, it is possible to combine the benefits of the reduced cognitive burden associated with the automatic mode of control (maximum autonomy principle) with the anticipative power and versatility of manual control. If the preparatory action is also associated with the voluntarily elicited components of gait, then the synchronisation of voluntary and automatic movements is guaranteed.

1 This delay seems too long for a dynamic gait (rather than quasi static 'stepping'). A more appropriate figure might be 0.1 s.

It is clear that for the subject to provide the control input to initiate phases of the gait cycle, s/he must have access to information about the movement. However, due to the nature of the subject's lesion, this information may not be available for some phases of gait. For example, in swing-through gait, the knee extensors must be active at the end of the body-swing phase to prevent the subject's knees buckling. If the subject has preserved proprioception and sensation below the lesion, then she/he will be able to identify the appropriate time to stimulate the knee extensors. A subject without these senses must rely on visual or other indirect information (such as shoulder motion) about the movement. Rather than using manual triggering of knee extension, it would be more appropriate in this case to use a sensor on the subject's shoe to detect heel-strike (or better still, the imminence of heel-strike[1]), and thus **automatically** initiate knee extension. Thus it is postulated that the difference between automatic and intention-detected manual control modes depends on whether the sensor responds to signals originating above or below the lesion. This difference may not always be clear cut; for example, when a foot switch is unloaded during stance this may represent a subject's intention to step[2]. The same sensor may be used to detect the end of the step, but in this case, the exact moment of heel-strike will not directly reflect the subject's intention, but will be determined by the interaction of the trajectory of the foot with the ground. The latter case would be an example of automatic control.

It is postulated that, in general, the choice of control method to trigger a gait phase will depend on the nature of the phase, the availability of a suitably coordinated above-lesion signal, and the quality of relevant sensory information available to the subject.

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1 In a dynamic gait, the knee extensors may need to be activated before the foot contacts the ground. Such a sensor does not exist in normal human gait (if vision is excluded) and so the moment of heel-strike must be predicted by a proprioceptive awareness of the foot position (or possibly just the elapsed time in the swing phase) and a knowledge of the terrain, leading to stumbles on uneven ground.
2 If the subject's body is held rigid by stimulation, then the weight distribution may be controlled by pressing on the crutches.

2.4.2. The Implementation of FES Controllers

2.4.2.1. Low-level controllers

Low-level FES controllers may be implemented in either an open- or closed-loop manner. An open-loop control system attempts to control a system output by controlling its input, without reference to the actual value of the output. A closed-loop control system uses the error between the desired output of a system and the measured output[1] to adjust the control input to that system in a direction so as to reduce the error. Closed-loop systems are thus less susceptible to uncertainties in the system input-output response. Electrically stimulated muscle is a highly non-linear and position-dependent time-varying system (Chizeck *et al.*, 1988B). Joint motion is also subject to a number of external influences (external forces and loadings, perhaps arising from the subject's voluntary movements), and internal influences (preserved spinal reflexes). Thus open-loop control is prone to be inaccurate. However, for simple, manually controlled systems (such as that described by Kralj *et al.* [1983]), the visual feed-back loop allows the subject a sufficient degree of control. Other open-loop control systems have been reported by Marsolais and Kobetic (1987), Mizrahi *et al.* (1985) and Cybulski *et al.* (1985).

Closed-loop FES controllers have been described by many authors, some have attempted to control force (Chizeck *et al.*, 1988A; Wilhere *et al.*, 1985; Crago *et al.*, 1980) and others to control position (Ewins *et al.*, 1988; Stanic and Trnkoczy, 1974; Vodovnik *et al.*, 1967). Some authors have used adaptive control techniques to attempt to track changing muscle parameters (Itakura *et al.*, 1988; Bernotas *et al.*, 1987; Kljajic and Trnkoczy, 1978). Closed-loop controllers theoretically produce more accurate joint positioning than open-loop controllers; they should also reduce energy consumption and fatigue if muscle is only activated sufficiently to produce the required movement (Mulder, 1991). However, closed-loop controllers are not without their difficulties, these include the problems of ensuring stability in the face of varying system characteristics, the high computational cost of some of the more sophisticated control strategies, and the problems of finding suitable robust and reliable sensors (the use of sensors in FES is reviewed by Crago *et al.* [1986]).

1 Or more generally, a function of the error and time.

Non-numerical or *rule-based* controllers can also be used at this low level of control; when the sensor inputs match the conditions of a rule then the control actions corresponding to that rule are performed. Thus control outputs only occur in response to particular sensor patterns, and the joint trajectories do not follow an exact pre-defined trajectory, but one which is bounded by the activation of rules. This parallels the role of biological reflexes and so has been termed *artificial reflex control* (Tomovic, 1984). A simple knee-extension artificial reflex was used to control standing by Andrews *et al* (1987).

2.4.2.2. Mid-level controllers

The middle (coordinating) level of control involves the (explicit or implicit) development of a discrete event model of the task under control. This level must determine which state the system is in based on processed input commands and sensor measurements, and direct the low-level controllers accordingly (Chizeck *et al.*, 1988B). Following the early work of Tomovic and McGhee (Tomovic, 1969; McGhee, 1968; Tomovic and McGhee, 1966) the *finite state machine* (Moore, 1964) has been used to model these processes. In this technique, rules determine when the *events* (transition conditions) that correspond to transfers from one state to the next occur. Thus starting from any one state, it is only possible to move to a pre-defined subset of the universe of possible states.

The finite state approach allows gait characteristics to be distinguished without reference to the physical properties of the system (McGhee and Meisel, 1966). Once the system is described then it can be controlled by using the outputs of the finite-state model to select the appropriate low-level controllers, which then produce the required trajectories. A finite state description of a gait mode consists of a set of *states* (representing the activation of low-level controllers), a set of possible *transitions* (which states can be reached directly from a particular state) and the *events* or *rules* (sensor patterns) associated with these transitions.

Finite-state based controllers for FES standing or gait have been described by Mulder (1991), Andrews (1988) and Simon *et al.* (1987). The finite-state technique has been no more than a convenient way to describe the gait, with the actual coding of the controller still needing to be performed in standard computing languages. However, programming tools have recently been developed that allow the direct implementation of finite-state modelled controllers (Phillips, 1990; Abbas *et al.*, 1988).

Pattern matching control (Tomovic *et al.*, 1981; Tomovic *et al.*, 1982) is an alternative representation of mid-level control, in which rules determine which **state** the system is in (rather than the transitions between states). The rules corresponding to a state (class) can fire at any time. Thus it is possible to move from any state directly to any other possible state.

If it is known *a priori* that the low-level operations must be performed in a particular sequence, then the finite-state approach is preferable to pattern matching control as it can guarantee that this sequence is followed.

2.4.3. The Derivation of FES Control Strategies

This section will explore methods for deriving mid-level, coordinating FES controllers. The implementation of the corresponding low-level controllers can be via open- or closed-loop techniques. The aim of these techniques is to (explicitly or implicitly) produce an **optimal** gait pattern, where the criteria of optimality is a function of factors such as speed, energy consumption, fatigue, effort in voluntary musculature, safety and cosmesis.

2.4.3.1. Hand-crafted rules

Control rules are written based on the experimenters' previous experience. The quality of the resulting gait may then be assessed, adjustments performed and the process repeated in an iterative fashion until a satisfactory gait is achieved. The assessment can vary from simple qualitative judgements (based on visual appraisal aided by video tape) to complete automation, involving sophisticated motion analysis equipment. This 'trial and error' technique cannot guarantee a formally optimal gait, and has the drawback of requiring the subject's presence at every iterative cycle. The group of Marsolais in Cleveland, USA, uses this method (e.g. Marsolais and Kobetic, 1987).

2.4.3.2. Formal mathematical modelling

A comprehensive neuro-musculo-skeletal model is formed, and used to adapt the stimulation sequence by some search technique (e.g. dynamic programming [Yamaguchi and Zajac, 1990]); the aim being to minimise a cost function. Various cost functions that have been reported include the time integral of moment as a predictor of fatigue (d'Hollosy, 1991), the energy production of stimulated muscle (Khang and Zajac, 1991) and the magnitude of bone bending moments (Kralj *et al.*, [1987B]). The model can be adjusted for each subject (who does not have to be present whilst the optimisation is taking place). However, the high complexity of the system and the difficulty of obtaining accurate model parameters require many assumptions and approximations to be made. Thus, a solution which is optimal for the model cannot be guaranteed optimal for a paraplegic subject. This method of developing a controller is termed *model driven* and the type of knowledge obtained is *deep knowledge* because it includes an understanding of the (simplified) causal relationships that govern the system. For more details see Koopman (1989) or Hatze (1984).

2.4.3.3. 'Cloning'[1] the rules of an expert

A complex movement can be improved with training: in this way, the acquisition of skills can be considered as an optimisation process taking place at a number of levels in the central nervous system - the cerebral cortex, subcortical nuclei, supraspinal centres and spinal cord (Gawronski, 1967). A skilled practitioner will develop a set of motor control rules that are near optimal (where rules can be considered as associations between equivalence classes of environmental situations and equivalence classes of motions or

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1 *Clone* - a thing produced in imitation of, or closely resembling, another (*Oxford English Dictionary*, 2nd Edition)

actions [Jagacinski *et al.*, 1987]). If these rules (skills) can be copied by an expert system, they can be used to form a controller to reproduce the near optimal movements[1]. Winter (1989) states:

> *What needs to be recognised is that any FES microprocessor system is replacing the CNS and therefore must mimic the same strategies that the intact CNS uses.*

This approach is termed *data driven* and the type of knowledge obtained is *heuristic* or *shallow* as there is no understanding of the causal relationships in the system, which is considered as a 'black box'. This technique avoids the need to develop complex mathematical models of the gait; thus, it provides a direct method to develop near-optimal automatic controllers. It is the strategy which will be adopted in this in this work.

The validity of this approach depends both on the presence of invariant features in the locomotion of normals, and also that these can be identified (cloned) and used to reproduce a similar gait. Some justification for this view is found in the motor control literature. Stelmach and Larish (1980) hypothesise that automation of action (the 'fast mode' of Mulder and Geurts [1991]) corresponds to

> *...the development of an automatic sequence such that the contextual situation triggers the necessary action from an appropriate response class*

Schmidt (1985) concluded that there appear to be invariant timing patterns in complex learned movements, and when the movements are speeded up, the relative timings remain constant. Schmidt commented that where such invariants could be found, inferences could be made about the nature of the motor control underlying the behaviour. Das and McCollum (1988) stated that these invariant structures allowed the variable yet robust accomplishment of the locomotion process. They also considered that where invariants were found, this would allow prediction of the nature of the control process. Arendt-Nielsen

1 It is unlikely that exactly the same criteria of optimality will hold for unimpaired and FES gait, given the different mechanisms of muscular contraction. However, the assumption is made that the two forms are 'close enough' for the technique to be valid.

et al. (1991) found that the shape of the EMG profile (therefore its features) was maintained for changes in walking speed, despite changes in amplitude.

In order to clone experts' skills, some understanding of the psychological bases of skills is required. Anderson's (1980) introduction to his chapter on 'cognitive skills' (quoted in Michie *et al.* [1990]) distinguishes between cognitive and motor skills:

> *1. Our knowledge can be categorised as declarative knowledge and procedural knowledge. Declarative knowledge comprises the facts we know: procedural knowledge comprises the skills we know how to perform.*
>
> *2. Skill learning occurs in three steps: (1) cognitive stage, in which a description of the procedure is learned; (2) an associative stage, in which a method for performing the skill is worked out, and (3) an autonomous stage in which the skill becomes more and more rapid and automatic.*
>
> *3. As a skill becomes more automatic, it requires less attention and we may lose our ability to describe the skill verbally.*
>
> *4. Skills can be represented by sets of productions. Each production consists of a condition and an action. The condition is a general description of the circumstances under which the production should apply. The action consists of both the external behavior and the changes to be made in memory if the production applies.*

Thus the problem of 'cloning' the experts' rules becomes one of identifying the **productions** that link measurable **conditions** to executable **actions.** Unfortunately, point three suggests that the expert may not be able to articulate these skills (procedural knowledge). This is supported by the observations of Polanyi (1973) on the influence of tacit knowledge in human motor behaviour (cited in Davids and Myers [1990]) that, 'because it is personal, much of the skill of an expert is inarticulable and may be best picked up by an apprentice latently through observational learning'. Davids and Myers (*ibid.*) support this in a review of the literature on the learning of process control tasks:

> *With experience, individuals improve the ability to achieve specified targets but show little improvement in the ability to articulate how performance is attained. Thus, the knowledge which guides performance appears to be ~ ~ 'implicit' rather than 'explicit' since it has been noted that individuals become skilled in system control long before observable gains in verbalizable knowledge occur.*

This is a situation analogous to the 'Feigenbaum Bottleneck' of artificial intelligence (the difficulty of manually eliciting knowledge from an expert). The solution adopted in the artificial intelligence domain is to use an alternative way of obtaining the knowledge - 'learning by example', in which the expert system produces its own rules from general principles extracted from the training data presented to it. This *inductive* approach is the one adopted by Michie *et al.* (1990), and Kirkwood *et al.* (1989).

The techniques available for extracting knowledge from training data will be considered in the next section.

2.4.4. Techniques for 'Cloning' the Rules of an Expert

2.4.4.1. Pattern repetition

The simplest technique is to record and reproduce output patterns from an expert. For example, Oderkerk and Inbar (1991) recorded angular trajectories in the lower limbs for non-impaired individuals walking at different speeds. They then used these as reference signals to be tracked by closed-loop joint-angle controllers, in order to

> *...impose* [sic] *the desired walking cycle on the* [leg trajectory of the] *paraplegic subject.*

An alternative, open loop, approach is to use EMG patterns recorded from non-impaired subjects as a way of directly defining stimulation output patterns (Marsolais and Kobetic, 1987; Saito *et al.*, 1990).

Both of these approaches impose time-invariant patterns on the gait, and cannot be considered as more than a superficial 'cloning' of knowledge. The resulting gait will be inflexible and incapable of responding to the demands of the subject and the environment (other than in a gross manner such as switching to different patterns according to the subject's explicit control instructions). These approaches also compel SCI subjects to walk with the same cadence as unimpaired ambulators.

2.4.4.2. Inductive learning

There has been much recent focus in the artificial intelligence domain into machines which can automatically acquire knowledge, without needing to be explicitly told (Clark, 1990). This approach can offer a better method of eliciting knowledge from an expert than the explicit articulation of rules (Michalski and Chilauski, 1980). Thus it may be an appropriate technique for the automatic derivation of FES rule-based control systems.

The nature of inductive learning is to find invariant features (generalisations) that describe one concept and distinguish it from others. This approach is suited to the identification of invariant features within a variable gait cycle, and so it is the approach to be adopted in this study. A review of inductive learning techniques is given in section 2.5.1.

It should be noted that the induced rules (or invariant features) used to discriminate states within the gait cycle do not necessarily represent the actual rules used in the human motor control system. In fact, the simple production-rule representation of knowledge will be a very crude approximation of the massively parallel processing capabilities of the human motor control system. The rule-based controller provides an **emulation** rather than a **replication** of the true neuro-physiology.

2.5. MACHINE LEARNING

Michie (1988) suggests three criteria for machine learning. The *weak criterion* states that machine learning occurs when:

> *a system uses sample data to generate an updated basis for improved performance on subsequent data.*

The *strong criterion* requires than in addition the system

> *can communicate its internal updates in explicit symbolic form.*

The *ultra-strong* criterion further requires that the updates be communicated in *operationally effective* form, i.e. in a form which allows an expert to utilise them to improve her/his performance.

The strong criterion excludes those approaches such as neural networks, statistical and evolutionary techniques that store knowledge in an implicit **numerical** rather than explicit **symbolic** fashion[1].

Early machine learning work focussed on games and the 'pole balancing'[2] paradigm: Michie *et al.* (1990) describe Donaldson's work of 1960, in which he demonstrated a machine which learnt how to balance a pole by imitating a skilled human controller, the derived rules being encoded as lists of numerical coefficients. The seminal work in this field is the *BOXES* algorithm of Michie and Chambers (1968), so called because the state-space was partitioned into hyper-cuboids ('boxes') by hyper-planes perpendicular to each state variable. Each 'box' was associated with a learning agent ('demon') which learnt how to make a control decision (left or right). The learning mechanism (**reinforcement learning**) was based on rewarding the demon for making a move with a successful outcome ('success' depending on the subsequent time after the move before the pole fell). Thus the control decisions for the whole problem were accrued by learning what to do in each situation (region of the state-space). The control rules learnt by *BOXES* may be translated into production rules by means of symbolic inductive learning

1 Although there has been some work on the explanation of learned networks in a symbolic manner by Gallant (1988) and Kononenko (1989).

2 Also referred to as an *inverted pendulum* or as a *pole and cart system*.

techniques (Bain [1990], and Sammut [1988]); this allows them to be easily comprehended, and facilitates their grafting on to existing controller rule-bases.

The 'trial and error' nature of this type of learning makes it unsuitable for direct application in FES control of human gait, as the cost of failure (falling) is much higher. However, once the system has learnt the fundamental control rules, more subtle performance indicators could be introduced (such as speed, reduction of contact forces, degree of stability, etc.). This would allow **incremental** improvement and adaptation of the control strategies. The fundamental rules may be learnt 'risk-free' by using a system simulation[1] (which need not be a perfect model), by using causal rules based on approximations of the system dynamics, or by using rules obtained from an expert. The latter method could involve the expert explicitly articulating the rules, or teaching by example[2].

2.5.1. Inductive Learning

The machine learning technique which has received the most attention and has been the most commercially successful to date (Clark, 1990) is the inductive rule learning paradigm. This is described by Diettrich and Michalski (1981) as:

> *...a search for plausible general descriptions (inductive assertions) which explain the given input data and are useful for predicting new data*

The mechanism is described by Clark as being:

> *...based on a simple pattern recognition model of learning, in which correlations between observable features and some final classification are sought for.*

This process is described as 'heuristic classification' by Clancey (1984). It is based on the seminal 'concept learning systems' of Hunt *et al.* (1966), later

1 Michie's original work was also on a simulated inverted pendulum.

2 Chambers and Michie (1969) described an extension to the original BOXES work which allowed human cooperation on the task. Interestingly, they found that the machine could out-perform its human 'expert' trainer.

developed into the ID3 algorithm by Quinlan (1983), which is the basis of many machine learning systems, e.g. *Assistant* (Kononenko *et al.*, 1984) and *ACLS* (Paterson and Niblett, 1982). They all have the common feature of classifying examples by means of a decision tree. This tree is 'grown' in stages: initially, all examples are at the first (root) node of the tree; if there is more than one class of example then the attribute test that will 'best' split the data is found, that test is placed at the current node, and left and right branches are added corresponding to the result of the test. This is repeated until only examples of one class remain at each leaf node of the tree[1]. Different algorithms vary in their technique for finding the 'best' test: the types of possible technique are described by Ben-Basset (1982) as being rules derived from information measures, distance measures or dependence measures. However, Mingers (1989a) found that the accuracy of the induced rule-sets (on independent testing sets) was roughly the same irrespective of what technique was chosen (although the rule-set size did vary). The method used to select the best test in this study is mutual information - an information measure (see methods section).

As an alternative to inducing decision trees, the *AQ* algorithm (Michalski, 1983) generates a set of production rules. These may be directly incorporated into expert systems based on the production rule paradigm, and may be more comprehensible than large decision trees[2], but they are more susceptible to noise than ID3 type algorithms (Shapiro and Eckroth, 1987 p. 471).

2.5.2. Inductive Learning in the Presence of Uncertainty or Noise

Inductive learning algorithms assume that any patterns in the training examples are due to genuine invariances in the data, which can be used to induce consistent rules. However, real-world data (especially from a domain as complex as the human cognitive-motor system) contains errors and uncertainty (noise), which lead to the generation of counter examples to the true, consistent patterns in the data. This noise can be due to a number of causes:

1. **Attribute error**: There may be sufficient measurement errors in the data attributes to take them over attribute thresholds.

---

1 This process is called 'top down induction of decision trees' - TDIDT by Quinlan (1986).
2 It is possible to convert a decision tree into a set of production rules (Quinlan, 87).

2. **Class error**: If the class is determined by mapping one or more continuous variables on to a number of discrete levels, then measurement error in these variables may lead to incorrect classification.
3. **Modelling error**: The error may represent genuine causal patterns in the system, but either the necessary attributes cannot or have not been measured[1], or their effects cannot be adequately modelled by the knowledge representation paradigm employed by the inductive learning algorithm (e.g. a system whose parameters were time varying could not be easily modelled by a decision tree, even if time were included as an explicit attribute).
4. **System variability**: There is genuine random variability in the system being modelled. There may be difficulty in deciding whether noise is due to genuine system variability, or just insufficient information (modelling error). The present study involves modelling of cognitive processes which are affected by system variability due to the nature of 'free will'.

Inductive learning programs initially search for the most general rules (covering the largest number of examples), the most specific (covering the smallest number of examples) being found last. These later rules are more susceptible to noise than rules based on large example numbers. This will not be apparent from the training data, but will lower the predictive accuracy of the rules on unseen, test data. Thus as the size of the rule-set increases, its predictive power may reduce. This is referred to as *over-fitting* of the rules to the data (Watkins, 1987) or *over-particularisation* (Kirkwood, 1989). Thus Occam's razor (the principle that the best explanation is the simplest possible one that fits the data) applies to induction, i.e. minimality is desirable.

Four techniques for reducing the effects of noise are reviewed by Clark (1990):

Data filtering: Only representative examples are selected for the training set: selection can be by a human expert, or automatically.

1 The 'butterfly effect' (Lorenz, 1979) of 'chaos' theory (Gleick, 87) tells us that as the level of modelling accuracy that we require increases, so does the quantity of variables that we have to measure, and the precision with which we have to measure them in order to obtain that accuracy. Hence to obtain 'perfect' accuracy we would have to perfectly measure an infinite quantity of variables.

Pre-pruning: The general to specific nature of the search for rules allows the process to be terminated before all the training examples are classified, once the level of reliability is judged to have fallen below acceptable levels (reliability can be gauged from the number of examples supporting the current hypothesis). This is the technique used by Kirkwood (1989).

Post-pruning: The rule search is allowed to continue until all examples are covered, then the rules which are deemed unreliable (according to some pre-defined criterion) are removed. The advantage of this is that the performance of the pruned and unpruned versions of the rule-set can be directly compared. The performance of a number of post-pruning techniques is compared in Mingers (1989b)[1].

Corroborative rule application: All rules are allowed to contribute towards classification, with different weights attached to their decisions. Quinlan (1987) suggests how a degree of corroboration may be introduced between branches in a decision tree. This may degrade the comprehensibility of the rule-set (Clark, 1990).

There is another type of uncertainty that can affect the induction of classification rules from training examples - genuine uncertainty (not due to measurement errors) as to the class of a training example, caused by ambiguity in the class definitions. This is best described by the fuzzy set theory outlined in the following section.

2.5.3. The Application of Fuzzy Set Theory to Inductive Learning

Fuzzy sets were introduced by Zadeh (1965) as a means of describing 'real-world' systems in which classification is not precise, but depends on human judgements and perceptions. An often quoted example is the set of 'tall men': a

1 The present work uses a form of post-pruning, as the decision tree grows, its performance is assessed on an independent testing set. The tree which has minimum error on this testing set is adopted.

man who is 2 metres tall is undoubtedly a member of the set, one who is 1.5 metres tall is undoubtedly not, but the situation is less clear for one who measures 1.75 metres. The fuzzy set theory addresses this ambiguity by allowing differing degrees of set membership: elements have a continuous range of membership ranging from zero (not belonging to the set) to one (definitely belonging to the set).

If X is an interval, containing all possible values of a variable x (e.g. X represents the possible range of men's heights, x is the height of a specific man) and F is a fuzzy set defined in interval X (e.g. F could represent the set of tall men) then the grade of membership of x in F is given by the real number $\mu_F(x)$, known as the membership function. For conventional ('crisp') sets, the membership function can only assume the values zero and one; for fuzzy sets, it can vary **continuously** within this range. Thus, crisp sets can be thought of as a special case of fuzzy sets. It is important to remember that membership functions do not represent statistical probabilities, but are an attempt to quantify the ambiguity arising from subjective terms such as 'tall', 'hot', 'expensive', etc.

The application to the inductive learning problem is apparent when one considers that many real world classifications are not 'crisp', but are, in fact, the result of applying (often arbitrary) thresholds to continuous variables. As an illustration, consider the example given by James (1985) - the induction of decision rules to predict the gender of infants, based on their heights and weights. This is clearly a crisp classification with minimal uncertainty attached to the discrimination. However, if the problem is changed to become one of predicting infant height based on gender and weight, or of predicting weight based on gender and height, a degree of ambiguity (fuzziness) is introduced. This arises from the quantisation of the continuous measures 'height' and 'weight' into discrete classes such as 'small-medium-tall' or 'light-medium-heavy'. There are various solutions to this problem:

1. Define arbitrary crisp thresholds on the continuous measure, and use these to form discrete classes. This approach will be 'brittle' in the presence of noise - an example near the boundary of one class may appear to be in the adjacent class, and thus become a counter-example to the correct rule.

2. Filter the data by choosing only those training examples which **definitely** satisfy the crisp definitions (i.e., only consider the data of those children who are definitely small, medium or tall). This approach has the disadvantage of 'throwing away' those training examples that do not definitely fall into only one category: e.g., the data of a child whose height lies between small and medium may not add information to discriminate between those classes, but it does contains information to discriminate between tall and small, and also between tall and medium.

3. Define a very large number of quantisation levels (very small, quite small, slightly small, etc.). This approach leads to increased decision tree complexity, reduced comprehensibility, and reduced robustness (as the rules for each class will only be formed from a small number of examples).

4. Explicitly consider the fuzzy membership of each training example in each class when forming classification rules. This approach requires modification of the inductive learning algorithm to allow it to cope with fuzzy class membership, it is a technique which is explored later in this thesis.

Note: in some circumstances it may be relevant for the decision tree to give a fuzzy output (classification). However, in the context of designing rule-based controllers a 'de-fuzzified' output (Postlethwaite, 1990) is required; thus, only fuzziness in the training example classes will be considered.

The literature contains some applications of fuzzy set ideas to inductive learning algorithms: Bergadano *et al.* (1987) describe a knowledge acquisition system with a very general form, intended for the pattern analysis domain. They allow for errors and noise in the training data by associating each example with an 'evaluation' μ (which represents the degree of confidence in the example). Each induced rule is allocated a corresponding evaluation. However, they specifically do not allow for non mutually-exclusive classes. Thus, their technique is not suited to the present problem (in which each training example is considered to have the same validity, but to be a fuzzy member of more than one class).

Anfa *et al.* (1988) present an algorithm based on Pawlak's (1982) rough set model of inductive learning. They allow each example to have a fuzzy weighting function (supplied by the expert) which determines the grade of membership of the example in the concept (class) it represents. Again, each example is only associated with one concept (class).

Kienitz (1990) suggests an algorithm which induces production rules in a similar manner to ID3. His algorithm allows each **attribute** to be described in a linguistic, fuzzy manner (e.g. 'X is very A'), but again does not allow for fuzzy **class** membership.

2.5.4. Previous Relevant Applications of Inductive Learning

Kirkwood *et al.* (1989) described the application of the *Disciple* inductive learning program to the problem of classifying kinematic and kinetic data obtained from normal walking into four phases (classes). They showed that this was possible using only 3 attributes (left metatarsal force, left knee angle and left heel force) from the available 12; thus, the technique could identify redundancy in the attribute set. They compared *Disciple*'s assessment of the relative importance of sensors and sensor combinations with the intuitive assessment of five FES researchers and found that the rankings tended towards the exact opposite. They assert:

> *The most significant implication of this is that the most intuitively obvious sensor to use in such an application may not be the best.*

They suggest that this technique may be used in an FES rule-based control system for the discrimination of (pre-defined) phases in the gait cycle.

The above work represents the use of inductive learning to map one set of sensor values on to another (the phases in the gait cycle were defined as occurring at singularities in the bilateral hip and knee goniometer outputs) rather than a 'cloning' of the skills of the subject[1]. Michie *et al.* (1990) investigated such skill transfer for a dynamical control task - the inverted pendulum. Using the C4.5 rule induction program (a derivative of Quinlan's C4 [Quinlan, 1987]) they induced control rules obtained from a trained subject, and used these to construct an automatic controller. They found that the automatic controller was able to predict the behavior of its human trainer on unseen testing data. They also found that it had a similar performance when substituted for the human trainer (in terms of number of crashes and goal achievement). However, the machine's performance exhibited what they called 'clean-up' - the ranges of variation of the four state variables describing the system[2] were reduced by a mean of 69% when compared to the human's performance. They suggest that the clean-up effect may allow 'skill grafted' controllers to outperform their original human trainers, as they avoid the time lags, inattention and other inconsistencies characteristic of human operators.

As a test of the validity of the technique for extracting valid rules from records of a subject's performance, Michie *et al.* created an 'artificial subject', using the rules given by Makarovic (1990). The performance of this artificial subject was corrupted by imposing noise and a time lag at the output (to simulate human imperfections). The inductive learning program then attempted to reconstruct the original rules. The performance of the reconstructed rule-set was similar to that of the original artificial subject, and, significantly, the structures of the two rule-sets were similar. Michie *et al.* consequently state:

> *We feel safe in concluding that the reconstructions obtained from human-generated traces prima facie show the logical structure of hidden representations in the trained subject's skill memory.*

Kirkwood (1989, p.110; Kirkwood and Andrews, 1989) presents a direct application of the inductive learning technique to the FES domain. The *Disciple* program was used to mimic the control actions of a paraplegic with an

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1 Although there is not a clear distinction between simple pattern matching and true skill transfer, two necessary requirements for skill transfer would be:

a. The link between input and output variables must be through some degree of cognitive activity rather than being a fixed mechanical relationship.

b. There must be some significant variation in the time course of events in the training data (i.e. they should not all be consistent repetitive activities). If this condition is not met, 'brittle' rules may be generated due to casual correspondence of input and output events.

2 Pole angle and angular velocity, and linear displacement and velocity of the pole base.

incomplete[1] lesion at level C6 who had been trained to walk with simple, unilateral, two channel stimulation. In order to produce a continuous gait, the subject had learnt to anticipate the delay in activation of the flexion reflex (of the order of 200 ms [Granat, 1990]) by pressing the switch before hip flexion was required. There were two classes: 'switch on' (stimulation applied to peroneal [reflex] site) and 'switch off' (stimulation applied to quadriceps). Thus, the classes were directly determined by the state of the subject's hand-switch. The attributes consisted of forces between the subject's hands and the crutch grips, and forces measured at four points under each foot by means of instrumented insoles. Kirkwood found that an accurate rule-set could be induced using both crutch sensors and any two other sensors (however, such a controller was not implemented). He compared the induced rules with the previously derived intuitive rules for automatic control of stepping for the same subject given by Andrews *et al* (1988), and concluded that the induced rules were superior as they mimicked the subject's anticipation of the reflex latency, whilst the intuitive rules did not. Thus, the induced rules would allow a faster walking cadence.

2.5.5 Other Machine Learning Techniques

2.5.5.1. Cross correlation

Willemsem *et al.* (1990) used accelerometers in an attempt to automatically identify the swing and stance phases of hemiplegic gait, for the purpose of correcting foot-drop by peroneal nerve stimulation (Liberson *et al.*, 1961). They used a cross correlation technique to match accelerometer patterns to foot-switch outputs (which were used to identify the states).

The cross-correlation technique allows the matching of complex shapes (features) in the input data, but does not easily cope with multiple-dimensioned attribute vectors, and does not satisfy Michie's strong criterion for machine learning (the results are not communicable in symbolic form). Despite the superficial similarity between Willemsen *et al.*'s aims and those of the present thesis, their work is a simple attempt to predict the output of one sensor by

1 This subject was unusual in having both preserved proprioception and sensation in his paralysed limb (Brown-Sequard syndrome). This knowledge of the state of the limb had enabled him to learn a very effective gait. He was an 'ideal' subject from which to 'clone' rules.

means of another, rather than a cloning of rules from their experimental subjects; the link between gait state and stimulation was intuitive (stimulation was defined as occurring at heel-off).

2.5.5.2. Statistical techniques

Kirkwood (1989) compared inductive learning with **linear discriminant analysis,** a widely used statistical technique for multi-variate classification problems. He used data from a number of domains, and concluded that the classification performance of the inductive learning technique was as good as, or better than, that of linear discriminant analysis, and the inductive technique had the following additional advantages:

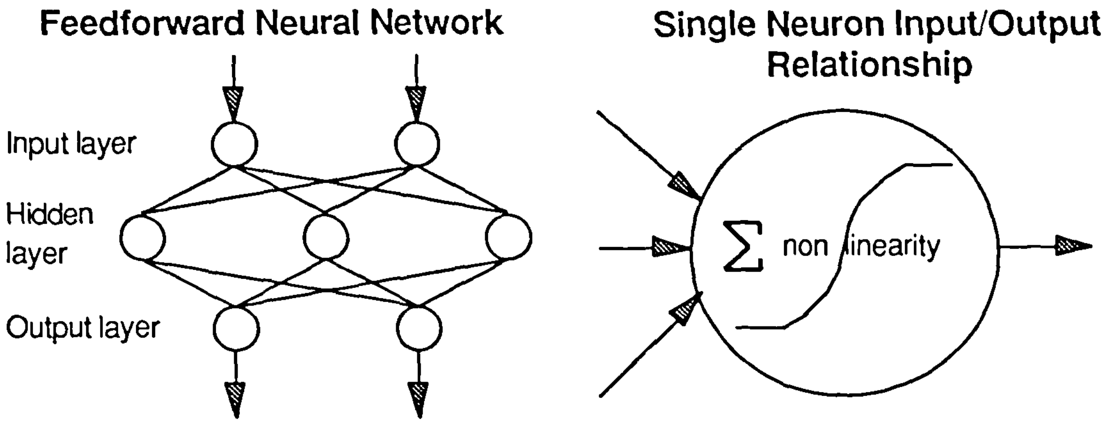
1. It allowed the user to control the error rate (rule-set size).
2. It was much less computationally expensive.
3. It gave an indication of sensor importance.

The statistical techniques do not satisfy Michie's 'strong' or 'ultra-strong' criteria for machine learning, i.e. they cannot communicate their knowledge in a manner that is symbolically comprehensible.

2.5.5.3. Regression trees

These are similar to the classification trees described in section 2.5.1 in that they have a binary tree structure. However, they are used to predict the value of a **continuous** variable rather than non-ordered continuous classes. This makes them eminently suitable for problems such as that given in 5.4.3, in which the desired output is a numerical variable (EMG activation). The alternative approach of dividing the continuous variable into a series of sub-ranges, and calling each an independent class is inferior in that ordering information is lost. Regression trees are described in Breiman *et al.* (1984).

In terms of reaching a yes/no control decision (as in section 5.5), the classification tree method is preferable. A complete FES control system might use classification rules for mid-level (supervisory) control and regression rules for low-level control of continuous variables (see section 2.4.1.2).



Redrawn in part from Willis *et al.* (1990)

Figure 2.2 *Neural-network structure*

2.5.5.4. Connectionist techniques

In these techniques knowledge is stored as weights associated with connections. The most common connectionist technique is that of neural networks. These are based on a (very simplified) approximation of the human brain and consist of a network of interconnected processing elements (analogous to biological neurons). Each element performs a weighted summation of signals from other elements (the connections being analogous to synapses) and produces an output according to a pre-defined input-output function[1]. This output may form the input to other elements, or may be a system output. 'Learning' involves modifying the weights of the interconnections between the elements in an iterative attempt to map the inputs to the correct outputs.

A number of different neural-network architectures have been proposed (Lippmann, 1987), but the most common (Willis *et al.*, 1990) is the 'feedforward' network. A typical feedforward network consists of one input and one output layer, with an arbitrary number (from zero upwards) of 'hidden' layers; each consisting of an arbitrary number of neurons (see figure 2.2).

Cybenko (1989) suggests that any continuous function can be approximated arbitrarily well by means of a feedforward network with at least two hidden layers and a fixed continuous non-linearity.

A common method of training the network is the 'back-error propagation' algorithm of Rumelhart and McClelland (1986), which is a gradient descent technique in which weights in the jth layer are adjusted according to information 'back propagated' from the $j+1th$ layer.

Comparison with symbolic (inductive) learning

Because their function is determined by their structure, the performance of machine learning methods will vary with the type of data they are tested on. Neural networks are better at 'X of N' functions (where at least X features out of a possible N must be present for an example to be a member of a class); symbolic learning techniques require very complex rule trees to solve these problems. Symbolic methods are better for singly sufficient attribute values of the 'IF A THEN B' kind (Mooney, 1990).

1 The sigmoid is a commonly used non-linear input-output function; although any function with a bounded derivative could be used (Rumelhart and McClelland, 1986).

A thorough comparison of the performance of symbolic learning (ID3) and connectionist (back-propagating neural network algorithm) techniques on **real-world** data was performed by Shavlik *et al.* (1991). They used five data sets to assess the algorithms' performances, reaching the following conclusions:

1. The neural network gave slightly higher classification accuracy than ID3 when tested on new examples.
2. The neural network could be significantly better on numerical data sets (this contradicts the findings of Weiss and Kapouleas [1989]).
3. The neural network was slightly more accurate when the examples were noisy or incompletely specified (however, the chi-squared pre-pruning method used for ID3 was probably less effective than post pruning techniques [Mingers, 1989b]).

Other differences were that ID3 could be trained 150 times faster, and classified new examples 10 times faster than the neural network (although the back-propagation technique may not be the fastest learning mechanism [Willis *et al.*, 1990]); the neural-network architecture (number of hidden layers, number of neurons) needed to be selected, which is considered 'more of an art than a science', and perhaps most importantly for the present application, the comprehensibility of the knowledge acquired by the symbolic learning technique was much higher.

2.6. SENSOR SUBSTITUTION

A separate but similar problem to the identification (cloning) of the relationships between sensor outputs and movement decisions is that of *sensor substitution*, i.e. how can the output(s) of one (or more) sensor(s) be used to predict the output of another. This may be necessary if the sensor to be substituted is expensive, unsightly, unreliable, heavy, awkward to don and doff, or if it interferes with the intended movements. The work of Willemsem *et al.* (1990) (cited in section 2.5.5.1), in which they attempted to relate accelerometer outputs to foot-switches using cross-correlation techniques, is an example of an attempt to substitute one sensor for another, less reliable, one. In that work the relationship between the sensors was determined empirically.

Symons *et al.* (1986) compared EMG signals from the bilateral latissimus dorsi, erector spinae, posterior deltoid and triceps muscles and foot-switches, crutch-forces and accelerometer readings obtained from incomplete SCI subjects ambulating at or above 30 m/min. They found that the timing and phasing of these signals showed intra-subject consistency, and many of them also showed inter-subject consistency. They suggested that the EMG and acceleration signals could be detected by completely implantable sensors, and thus may be suitable for future 'take-home' FES gait systems. This represents another empirical attempt to ascertain the relationship between sensors (However the empirical relationships were identified in an intuitive manner).

Simon *et al.* (1987) adopted a formal approach to deriving the relationship between sensors. They wished to use a strain-gauge sensor attached to the upright of an AFO to predict the bending moment at the knee (which was normally predicted by the combination of a force-plate and kinematic-measurement system). They calculated the theoretical relationship, and found a very close correlation ($R=0.99$) between the predicted and measured values.

The ability of inductive learning techniques to identify relationships between classes (the output of the sensor to be substituted) and attributes (the outputs of the substitute sensors) makes them well suited to this application. The work of Kirkwood *et al.* (1989) (cited in section 1.5.4) is an attempt to predict angular singularities at the bilateral hip and knee (i.e. goniometer outputs) from one unilateral knee goniometer and two foot-forces, using inductive techniques.

CHAPTER 3. THESIS AIMS AND OBJECTIVES

The initial hypothesis to be tested in this thesis was (section 1.5):

> **FES swing-through gait provides a practical and fast form of locomotion for SCI subjects with complete mid to low thoracic lesions. This gait offers speed and energy-cost advantages over both KAFO swing-through gait and FES reciprocal gait.**

Initial objectives to enable this hypothesis to be tested were:

1. Review any previous FES implementation of swinging gaits.
2. Review the literature on the energetics and biomechanics of pathological gaits to allow an efficient gait pattern to be produced.
3. Investigate methods for the design of controllers that will allow paraplegics with thoracic-level lesions to perform this gait.

In the light of the literature review, the following modified hypotheses were developed:

1. FES swing-through gait with active knee-flexion during the body-swing phase provides a faster form of locomotion than KAFO swing-through gait and FES reciprocal gait for SCI subjects with mid to low thoracic lesions.
2. It also has a lower energy cost (joules/metre) than the other two gaits.
3. It is possible to induce rules that describe human movements by using machine learning techniques to find invariants in the movement patterns.
4. Specifically, the study of trained and braced unimpaired subjects performing swing-through gait allows the induction of rules that describe this gait.
5. The induced rules allow the development of controllers for FES swing through gait.

6. These controllers allow the detection of a paraplegic subject's movement intentions, and thus permit a less cognitively demanding mode of control.
7. The application of fuzzy set concepts to inductive learning allows the induction of more robust rule-sets.
8. Inductive learning techniques provide an automatic means of identifying substitute sensors and assessing their utility.

In order to test the above hypotheses, the following objectives were identified:

1. Develop the hardware and software to allow the synthesis of FES swing-through gait.
2. Identify suitable mid-and low thoracic SCI subjects and train them to perform the gait.
3. Assess the resulting gait.
4. Modify the inductive learning program *Disciple* (Kirkwood, 1989) to include fuzzy example weighting and to permit realistic training-set sizes.
5. Use the program to identify invariants (rules) that describe human gait.
6. Develop a model of FES swing-through gait, using braced, unimpaired subjects.
7. Compare the energetics of swing-through gait with fixed and free knees using the model.
8. Use the inductive learning program to identify control rules from the model.

CHAPTER 4. METHODS AND MATERIALS

4.1. MODEL OF FES SWING-THROUGH GAIT

4.1.1. Subject Selection and Training

Five unimpaired male volunteers were selected to be trained in swing-through gait. Their details are listed below:

Subject	Age (year)	Height (m)	Body Mass (kg)
A	26	1.88	76.9
B	25	1.82	72.2
C	23	1.87	75.4
D	23	1.85	82.5
E	32	1.75	78.5

Height and mass were measured without shoes, with the subjects wearing light clothing.

All the subjects had previously participated in a series of gait and energetics experiments (Nejad, 1990), as part of which they had undergone the following swing-through gait training regime:

a. Pre-crutch body-lift exercise: a one hour exercise session which involved lifting the body off the ground by pressing on to parallel bars.
b. Pre-crutch resisted-trunk exercise: a similar, one hour exercise session, in which the trunk lifts were resisted by a physiotherapist.
c. Swing-to gait: a one hour series of five 100 m walks without braces, and five with braces.
d. Reciprocal gait: a one hour series of five 100 m walks without braces, and five with braces.
e. Swing-through gait: a one hour series of five 100 m walks without braces, and five with braces.

Further details of this training regime can be found in Nejad (1990).

One of the subjects (E) was unable to perform a confident swing-through gait, even after the training period, and was excluded from the study.

Figure 4.1 *Adjustable braces*

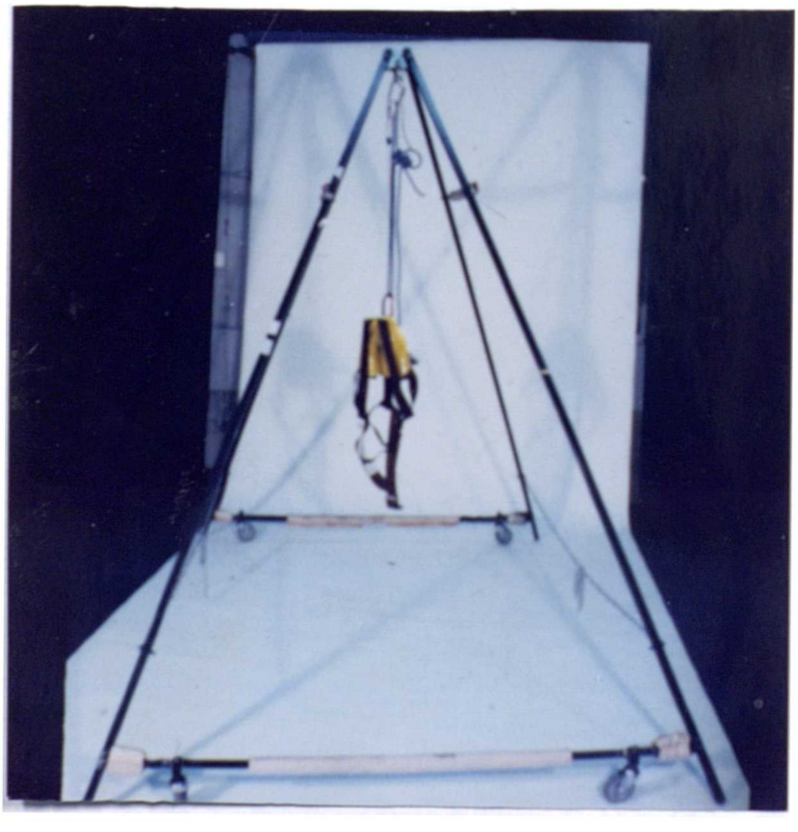


Figure 4.2 *Overhead support*

4.1.2. Adjustable Braces

The subjects wore the same adjustable braces in these tests as for those of Nejad (1990); the braces are illustrated in figure 4.1. These braces were constructed from the following standard orthotic components: a polypropylene foot-plate, adjustable for toe in/out; the base of the foot-plate was covered with a proprietary self-adhesive rubber sole, to provide grip on the smooth linoleum floor of the gait laboratory. The connection between the foot-plate and each of two stainless steel uprights allowed the ankle dorsi/plantar-flexion range to be adjusted (Otto Bock stainless steel double action ankle joint). The crural sections of the uprights were adjustable for length, and were attached to the femoral components by lockable hinge joints at the knee (Masser mild-steel manual ring lock). The femoral sections could also be lengthened or shortened. Aluminium posterior thigh and calf bands, padded with Plastozote, located the braces against the subject's legs. The braces were attached to the subject by means of adjustable velcro straps.

The brace alignment is listed below:

Foot to-in/toe-out: set to neutral.
Ankle dorsi/plantar-flexion range: fixed in neutral.
Knee hinges: locked or unlocked according to the test being carried out.
Length of crural sections: adjusted to align the knee joint with the anatomical axis of the extended knee.
Length of femoral sections: adjusted to bring the superior thigh strap as high up the thigh as possible, without interfering with the perineum.

Each brace had a mass of 1.8 kg.

4.1.3. Other Aspects of the Model

The un-impaired subjects walked using standard, adjustable elbow crutches, of mass 0.8 kg each. The crutch heights were adjusted to the correct position for each subject using the technique of Nejad (1990), which set the hand-grip to the height of the flexed wrist when the elbow was held in 30 degrees of flexion.

Further crutch height adjustments were made at the investigator's discretion.

The subjects wore lightweight, un-restricting clothing during these tests, and their own lightweight, laced, training shoes.

4.2. THE PRODUCTION OF FES SWING-THROUGH GAIT

4.2.1 Subject Selection

The subject selection criteria were as follows:

1. Mid- to low- thoracic, motor-complete lesion.
2. At least one year post-injury.
3. Lack of joint contractures.
4. Subject had already undergone an FES strengthening programme for the quadriceps muscle group, and was able to stand using electrical stimulation and a walking aid.
5. It was possible to elicit a flexion reflex from one of the five sites suggested by Kralj *et al.* (1981).
6. The subject was trained in the use of knee-ankle-foot orthoses for swing-to or swing-through gait (but s/he didn't necessarily have to walk regularly).
7. The subject was able to attend weekly training sessions.

Four subjects were initially selected for training in swing-through gait. Two subjects (C and D) were unable to complete the programme and so a fifth subject (E) was recruited; this subject also withdrew from the programme (for personal reasons) before completing all the tests. The subject details (at the time of selection) are given below:

Subject A: 28 years, female, complete T11 lesion.
Subject B: 22 years, male, complete T6 lesion.
Subject C: 35 years, male, complete T6 lesion.
Subject D: 33 years, male, complete T8 lesion.
Subject E: 27 years, male, complete T11 lesion.

All subjects were at least two years post injury.

4.2.2 Subject Training

All the subjects underwent a standardised training regime, supervised by a physiotherapist. Initially, a subject was trained to perform four point (reciprocal) gait using a rollator as a support device. Once the subject was walking confidently, s/he proceeded to swing-to gait in mobile parallel bars, followed by swing-to gait in a rollator; once the subject was judged to be adept at this gait, the training proceeded to the use of crutches.

Initial crutch training involved the subject standing with crutches. Crutch height (which had been initially set according to the guidelines of Nejad [1991], detailed in section 4.1.3) was adjusted for each subject, in order to produce the most stable standing position. The subject then advanced to taking single swing-through steps using crutches, and finally to continuous gait. Whenever a subject was standing, a nominated 'catcher' stood immediately behind him or her. Additionally, whenever a subject stood with crutches (which are less stable than a rolling walker), s/he wore an upper body harness (LecSave Ltd. Avon, UK) (figure 4.2) which was attached by a loop of 9 mm diameter mountaineering rope and karabiners (Wild Country Ltd., breaking force 24 000 N) to a specially developed mobile overhead support (figure 4.2, see appendix D for design details). These precautions ensured that if a subject fell, it was impossible for her/him to strike the ground. The karabiner was strain-gauged to determine if it was loaded (i.e. if the subject was using the harness to support her/his body-weight) during gait.

4.2.3 Stimulation Strategies

All stimulation was performed using self-adhesive surface electrodes (*Pals-Plus*, Axelgaard manufacturing Co, Ltd., Fallbrook, CA); each subject was given their own set of electrodes. The stimulator was an eight channel, constant-current (for voltages up to 180V), computer controllable device (described in Barnett, [1990]). The stimulator was controlled by an IBM *PC* compatible computer (Compaq Ltd.) via a digital input/output board (*PC-14A*, Amplicon Ltd., Brighton, UK). Analogue data were sampled via an analogue to digital (A/D) converter board (*PC-26A*, Amplicon Ltd.). A *Turbo Pascal* (version 5, Borland Ltd.) program, *Gait* controlled the stimulation parameters. The low-level routines that allowed *Gait* to communicate with the stimulator and A/D board were provided by the *Turbo Pascal* unit *Stimdriv* (Phillips, 1989).

The following muscle groups were used for the production of swing-through gait:

Knee extensors (quadriceps group): to prevent buckling of the knee during the body-stance period of the gait, and to produce knee extension during the late body-swing phase, immediately prior to heel-strike.

Knee flexors (hamstrings group): to generate knee flexion during the early body-swing phase of the gait, ensuring ground clearance.

Hip extensors (gluteus maximus): to prevent buckling of the hip ('jack-knifing') during stance, especially at heel-strike.

Hip flexors: to actively flex the hip during body-swing, thus helping to produce ballistic knee flexion, and increase stride length. Due to the difficulty of recruiting the deep iliopsoas (hip flexing) muscle directly (efferent stimulation) with surface stimulation, hip flexion was produced indirectly (afferent stimulation) by the flexion reflex. This stimulation was usually applied at the peroneus superficialis site (Kralj *et al.*, 1981), although occasionally other sites were found to give a better response. The excitation of the flexion reflex also produced knee flexion, although this had to be augmented by direct stimulation of the knee flexors. For some subjects, at some sites, the inappropriate knee **extension** response described by Rudel *et al.* (1989) was observed.

The locations of the electrodes were as follows:

1. **Right flexor reflex**: usually at the right peroneus superficialis site. Small electrodes[§] were used. The active electrode was sited distally to the indifferent electrode, with a separation of approximately 5 cm. The precise location of the electrodes was determined by using a motor-point locator (an electrode that could be held and moved against the subjects skin to find the best stimulation site).

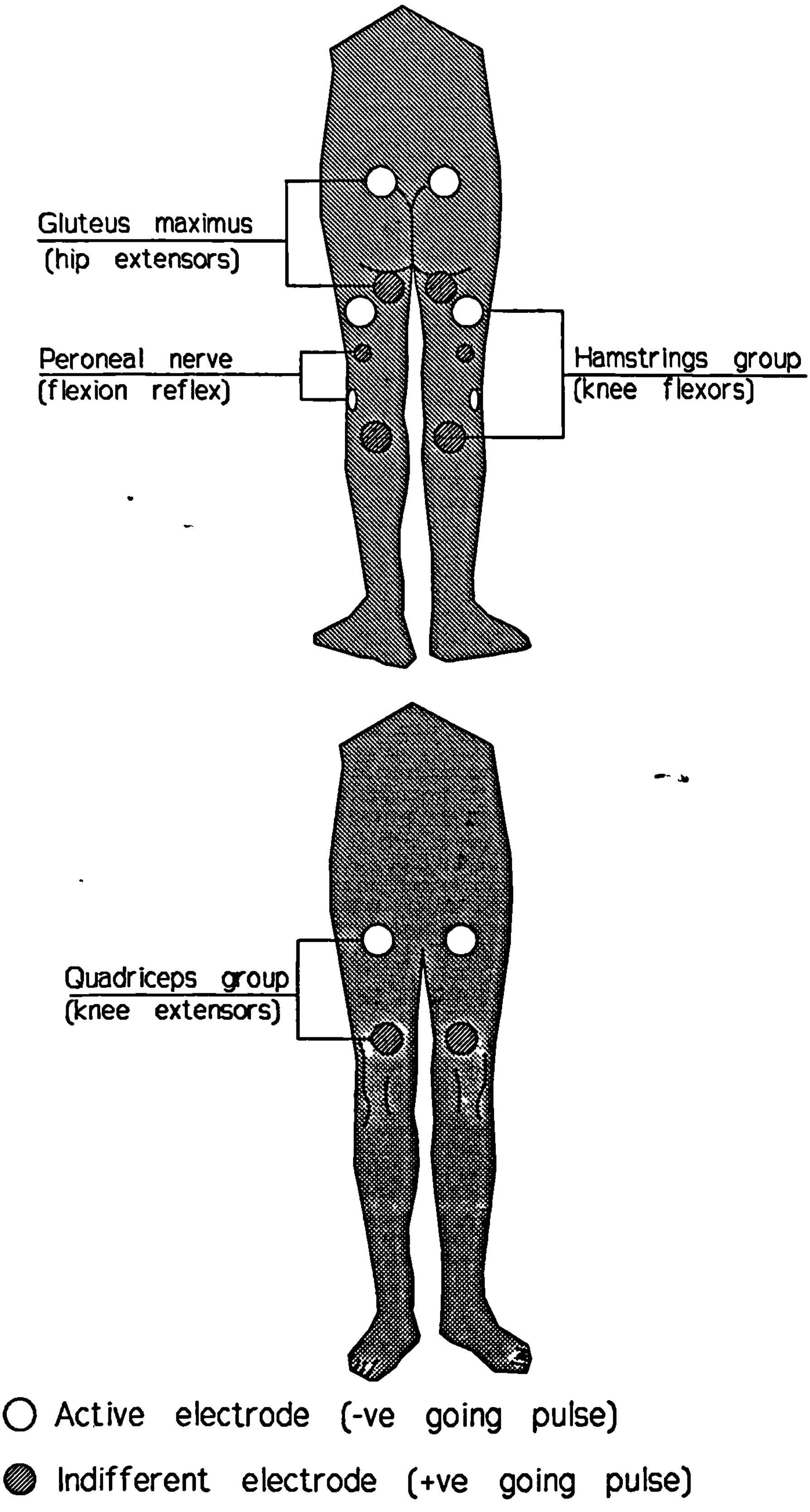


Figure 4.3 *Electrode sites for swing-through gait*

3. **Right quadriceps**: the active electrode was placed over the supposed site of the femoral nerve, the indifferent electrode was located medially, roughly 5 cm superior to the patella. Both electrodes were large*.
5. **Right hamstrings**: the large active electrode was placed medially on the right posterior thigh, just inferior to the right buttock. The indifferent electrode (also large) was placed just superior to the right popliteal hollow, in an attempt to additionally recruit the Gastrocnemius muscle.
7. **Right gluteus maximus**: the large active electrode was placed near the right posterior-superior-iliac-spine. The large indifferent electrode was placed inferior to the buttock, just medial to the proximal hamstring electrode.

§ The small electrode was circular and 1.25 inches in diameter.
* The large electrode was circular and 3 inches in diameter.

Electrodes 2,4,6,8 were placed in similar, contralateral positions to electrodes 1,3,5,7 above. These electrode sites are shown in figure 4.3.

Each subject was fitted with polypropylene ankle-foot orthoses (AFOs), cast in a neutral angle, which were worn inside the subjects' shoes. These prevented dorsi-flexion at the ankle during stance and foot-drop during swing. However, their use precluded the generation of push-off using active plantar-flexion.

4.2.4. Other Equipment

The subjects used elbow crutches which had been strain-gauged to measure axial force. These crutches were calibrated using a force plate (Kistler Ltd.) at the start of each session. The crutch length was adjusted to the optimum found for each subject in section 4.1.3.

Two switches were used for manual control of the gait. One was attached to a crutch hand-grip, in a position which allowed it to be easily operated by the subject. The other was held by an experimenter, who could operate it if a subject preferred not to control the gait.

Figure 4.4 *Equipment trolley*

All gait trials were recorded on to video tape (Panasonic NV-MS90 camcorder to Panasonic NV FS90 HQ video cassette recorder); the computer output was superimposed on the picture at the time of recording by a 'gen-lock' card (*EGA-lock*, Vine Micros Ltd.). This facility allowed the active state of each stimulation channel, and the value of each sensor, to be recorded on every video frame (every 40 ms).

Two subjects (A and B) preferred their feet to be fastened together; this was done by an velcro strap that was adjusted until the subject was comfortable.

The computer, amplifiers, camera and video-recorder and monitor were mounted on a specially designed mobile trolley (figure 4.4).

4.2.5. The Investigators' Roles

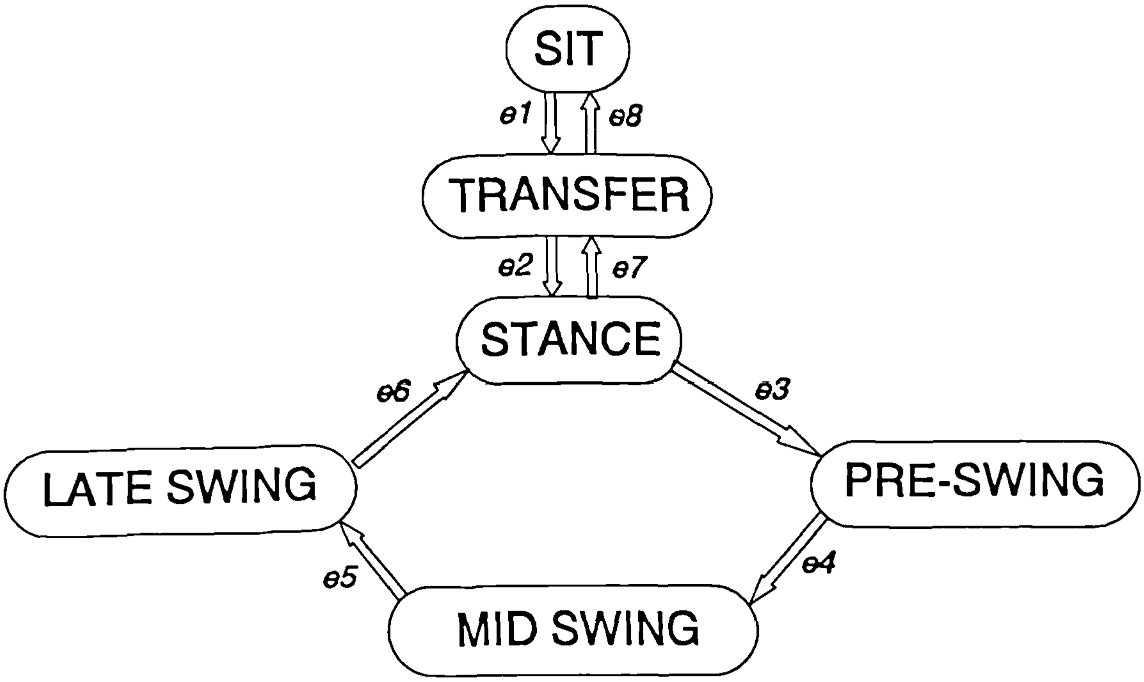
Each investigator had a specified role during the training and testing sessions. These are listed below:

a. Investigator A walked behind the paraplegic subject and caught or steadied her/him if s/he overbalanced. This investigator was also responsible for attaching the subject to the overhead safety support, and releasing her/him when s/he sat down.

b. Investigator B walked backwards in front of the subject, facing towards her/him. This investigator pulled the overhead support, ensuring its apex was always directly above the subject; s/he also assisted the subject in sit/stand transfers.

c. Investigator C propelled and steered the instrumentation trolley, ensuring that the subject always remained in view of the camera. This investigator also operated the computer, activating the key that triggered sit/stand transfer.

d. Investigator D was responsible for removing the subject's wheelchair once s/he was standing, and replacing it before a stand-sit manoeuvre.



<u>STATES</u>

SIT: no stimulation
TRANSFER: **Quads** ramps up or down
STANCE: **Gluts** and **Quads**
PRE-SWING: **Gluts** and **Quads** and **Reflex**
EARLY-SWING: **Reflex** and **Hams**
LATE-SWING: **Quads** and **Reflex**

<u>EVENTS</u>

e1: investigator presses key
e2: time-out
e3: subject presses switch
e4: both crutches loaded
e5: time-out
e6: time-out
e7: investigator presses key
e8: time-out

Quads = Quadriceps stimulation
Gluts = Gluteal stimulation
Reflex = Flexion withdrawal reflex (usually peroneal site)
Hams = Hamstrings stimulation

Figure 4.5 *State-transition diagram for swing-through gait*

4.2.6. Control of Stimulation

The program *Gait* was written to allow simple development, execution and modification of finite-state controller strategies. All states were implemented as procedures which were written in a uniform manner. Transition between states was controlled by the main program. The main program also performed tasks such as updating the video output and processing sensor signals; thus minimising the extraneous code that had to be included in each procedure. More details of the implementation of *Gait* can be found in appendix C.

The finite state control strategy was initially written intuitively, based on the insights obtained from a review of the literature on swing-through gait (section 2.2). It was then adapted over the course of the training period. Adaptation was an iterative process: the controller's performance was assessed from the video recording and the subjects' comments, modifications were then made, and the controllers performance was re-assessed following the next session.

The state transition diagram that was eventually obtained is shown in figure 4.5.

4.3. *EMPIRIC* - AN INDUCTIVE LEARNING PROGRAM

4.3.1. Information Theory Underlying Empiric Program

The inductive learning program *Empiric* is an implementation of the hierarchical mutual information classifier algorithm of Sethi and Sarvarayudo (1982). This algorithm forms a decision tree by maximising the average mutual information gain at each partitioning step. This section will explain these concepts and their implementation.

In information theory, *information* is regarded as the removal of uncertainty. Thus, the occurrence of a likely event conveys less information than that of an unlikely event as there is less *a priori* uncertainty of its occurrence. If an alphabet X (all possible source outputs) consists of J symbols, the jth symbol occurring with a probability of p_j, then the amount of information (in bits) associated with j is:

$$I_j = -\log_2 p_j \qquad (4.1)$$

Shannon's (1948) entropy[1] is defined as:

$$\mathrm{H(X)} = \sum_{j=1}^{J} p_j \log_2 \frac{1}{\mathrm{p}_j} \quad = \quad - \sum_{j=1}^{J} p_j \log_2 p_j \qquad (4.2)$$

Note: whilst it is generally accepted to write *H(X), H* is not a function of x, but of the probability distribution p (Blahut, 1987).

In information theoretic terms, entropy is a measure of the average amount of information gained per symbol received in an alphabet, it can also be considered as a measure of the uncertainty as to the identity of a symbol before it is received. If all symbols are equally likely then the *a priori* (before the symbol is received) uncertainty as to the symbol is a maximum; the entropy being equal to the log of the number of symbols[2]. If one symbol becomes much more likely than the rest, then the uncertainty falls and the entropy asymptotically approaches zero.

4.3.1.1. Mutual information

If a communication channel has an output alphabet Y, with a probability $P_{j|k}$ that the j-th symbol of X was transmitted, given that the k-th symbol of Y was received, then the uncertainty as to j on receiving k is:

$$H_{j,k} = -\log_2 P_{j|k} \qquad (4.3)$$

The *mutual information* is the reduction in uncertainty, i.e. the *a priori* uncertainty as to j less the *a posteriori* uncertainty upon receiving k:

$$I_{j,k} = -\log_2 P_j + \log_2 P_{j|k} = \log_2 \frac{P_{j|k}}{P_j} \qquad (4.4)$$

The *average mutual information* is then the product of $I_{j,k}$ and the joint

1 So called because the function is the same as that used in statistical mechanics for the thermodynamic quantity entropy.
2 When the logarithm is to base 2, the entropy is the minimum number of bits required to perfectly encode the alphabet.

probability of (j,k) occurring, summed over all possible (j,k), i.e. :

$$I(X|Y) = \sum_{k=1}^{K} \sum_{j=1}^{J} p_{j,k} \log_2 \frac{P_{j|k}}{P_j} \qquad (4.5)$$

The inductive learning problem is to choose a threshold t on an attribute a to discriminate between a set of examples Z with class values X. Y is obtained by applying the production rule:

'IF $a > t$ THEN $y \rightarrow 1$ ELSE $y \rightarrow 0$'

to an example z with class value x, i.e. the two possible values of Y are either 0 for attribute values below the threshold, or 1 for values above it. K is equal to 2, J is equal to the number of classes. $I(X|Y)$ is then the average mutual information gain for threshold t on attribute a at node N. By comparing this value with those obtained for all possible thresholds on all possible attributes at that node, it is possible to select the best discrimination rule (i.e. the rule which gives the greatest gain in information/reduction in uncertainty) at that node. In the absence of true values for the probabilities, estimates are made based on the data in the training set (for a fuller description of this see appendix A).
To obtain the average mutual information for all the nodes in the decision tree T, the product of $I(X|Y)$ at a node and p_k, the probability of being at that node must be summed for all nodes:

$$I(X|T) = \sum_{k=1}^{K} p_k I_k(X_k|Y_k) \qquad (4.6)$$

4.3.1.2. Error rates

If the decision tree is to have a probability of classification error P_e, for J classes, then we can calculate I_{min}, the minimum average mutual information required, as follows:
The average mutual information may be written:

$$I(X|Y) = H(X) - H(X|Y) \qquad (4.7)$$

The maximum value[1] of $H(X|Y)$ is given by Fano's inequality (Fano, 1963):

$$H(X|Y) \leq H(P_e) + P_e \log_2 (J\text{-}1)$$

substituting this in 4.7:

$$I(X|Y) \geq H(X) - H(P_e) - P_e \log_2 (J\text{-}1) \qquad (4.8)$$

This represents the minimum gain in mutual information that will be provided by a decision tree having an error rate P_e. Thus, expanding for $H(X)$ and $H(P_e)$, I_{min} becomes :

$$I_{min} = -\sum_{j=1}^{J} p_j \log_2 p_j + P_e \log_2 P_e + (1\text{-}P_e)\log_2 (1\text{-}P_e) - P_e \log_2 (J\text{-}1) \qquad (4.9)$$

Once the cumulative mutual information provided at each node exceeds this value, the decision tree has achieved the required error rate.

4.3.1.3. Incorporation of fuzzy class membership

The equations for the mutual information gain at each node will now be modified to allow for the uncertainty associated with the fuzzy class membership (see section 2.5.3).

Each example e (total N) is considered to be a member of each class j simultaneously, with a membership value $\mu_{e,j}$. Xie and Bedrosian (1984) give the following expression for the entropy associated with a fuzzy set from a binary source:

$$H_{tot}(p_1, p_0, \mu) = -p_1 \log_2 p_1 - p_0 \log_2 p_0 + \frac{1}{N} \sum_{e=1}^{N} S(\mu_e)$$

where S is Shannon's function:

$$S(\mu_e) = -\mu_e \log_2 \mu_e - (1 - \mu_e)\log_2 (1 - \mu_e)$$

1 The maximum uncertainty occurs if all errors are equally likely.

Extending this for a source X, with J classes:

$$H_{tot}(X) = -\sum_{j=1}^{J}(p_j \log_2 p_j + \frac{1}{N}\sum_{e=1}^{N}\mu_{e,j}\log_2 \mu_{e,j}) \qquad (4.10)$$

Thus, the *a priori* uncertainty associated with a fuzzy source can be seen to have two components, one due to the uncertainty as to class membership $H(X)$, and one due to the fuzziness of the source $H_F(X)$. If the fuzzy membership value is understood to represent the probability that the associated concept (class) is true, then we can calculate a mean membership value μ_j, which represents the probability of membership of class j, i.e $p_j \equiv \mu_j$:

$$\mu_j = \frac{1}{N}\sum_{e=1}^{N}\mu_{e,j} \qquad (4.11)$$

Where N is the total number of examples,
Thus, the total entropy at the input to the channel is given by 4.2:

$$H_{tot}(X) = -\sum_{j=1}^{J}\mu_j \log_2 \mu_j + H_F(X) \qquad (4.12)$$

Similarly, the *a posteriori* uncertainty results from the uncertainties due to class membership and fuzziness at the output to the channel. The mean membership value on class j of the T examples that are below the threshold (fail the discrimination rule) is:

$$\mu_{jbelow} = \frac{1}{T}\sum_{e=1}^{T}\mu_{e,j} \qquad (4.13)$$

and for the N-T that are above the threshold (pass the discrimination rule):

$$\mu_{jabove} = \frac{1}{N-T}\sum_{e=N-T}^{N}\mu_{e,j} \qquad (4.14)$$

Thus the total conditional entropy $H_{tot}(Y)$ at the output of the channel is:

$$-\sum_{j=1}^{J}(\frac{T}{N}\mu_{jbelow}\log_2\mu_{jbelow} + \frac{N-T}{N}\mu_{jabove}\log_2\mu_{jabove}) + H_F(Y) \qquad (4.15)$$

The average mutual information provided by the discrimination rule is given by:

$$I(X|Y) = H_{tot}(X) - H_{tot}(Y) \qquad (4.16)$$

The partitioning rule does not change the fuzziness of an example between input and output. Thus, the total fuzziness at the output is the same as that at the input, $H_F(Y) = H_F(X)$ and these terms in 4.12 and 4.15 will cancel when substituted into 4.16. Noting that $\mu_j \log_2 \mu_j$ in 4.12 can be re-written as:

$$\left(\frac{T}{N}\mu_{jbelow} + \frac{N\text{-}T}{N}\mu_{jabove}\right)\log_2 \mu_j \qquad (4.17)$$

and substituting 4.15 in 4.16, the following expression for $I(X|Y)$ is obtained:

$$\sum_{j=1}^{J}\left(\frac{T}{N}\mu_{jbelow}\log_2\frac{\mu_{jbelow}}{\mu_j} + \frac{N\text{-}T}{N}\mu_{jabove}\log_2\frac{\mu_{jabove}}{\mu_j}\right) \qquad (4.18)$$

This expression is, in fact, equivalent to equation 4.5 if each example e were simply replicated $\mu_{e,j}$ times in each class j.
Thus, the simplest implementation of fuzzy class membership would require each example to be repeated ROUND ($Q\,\mu_{e,j}$) times in the training file, where $1/Q$ represents the desired resolution of the fuzzy membership function, and ROUND (z) is a function that returns the nearest integer to the real value z. This would not require any modifications to the existing algorithm. In practice, constraints of file and memory size make this impractical. An alternative technique is to include J membership values with each training example, each one representing the example's degree of membership in class j, and to modify the algorithm accordingly. This is the approach used in the inductive learning program *Empiric*; however, to conserve memory, each example is only allowed to have non-zero membership values in two classes. Details of the implementation can be found in appendix A.

4.3.2. Development of *Empiric*

An algorithm for a hierarchical classifier using the (non-fuzzy) mutual information measures described in the previous section was published by Sethi and Sarvarayudo (1982). Kirkwood implemented this algorithm in the program *Disciple* (Kirkwood *et al.*, 1989). The program *Empiric* (one who derives knowledge from experience alone) is a development from *Disciple.* The original program was re-written to maximise memory usage, improve processing efficiency and allow fuzzy weighting of examples. Specifically:

- The generation of a separate example-list containing all the examples associated with a node (suggested in the original Sethi and Sarvarayudo paper) was replaced by using one example-list, with a pointer identifying the node at which each example is presently located.

- Every example now has a weight W_z associated with it. This is equivalent to (but more efficient than) replicating each example W_z times.

- Each example can now have two class labels simultaneously (fuzzy class membership).

- Sethi and Sarvarayudo (*ibid*) suggested that the algorithm had a recursive structure, thus Kirkwood chose a recursive implementation. In fact, the loop structure used in *Empiric* is more efficient.

- A more efficient, successive approximation sorting procedure was used.

- Procedures to allow batch processing of files were introduced.

- The facility to save and re-load rule-sets (both in ASCII and binary format) was added.

- The program was made more 'user friendly'.

These changes have allowed the maximum number of examples to be increased from the 50 of *Disciple* to 20 000[1]. The program is described in appendix A, and the source code is included on an *IBM PC* compatible disc accompanying this thesis.

4.4. THE CLONING OF CONTROL RULES FOR SWING-THROUGH GAIT

The method for inducing a rule-based FES controller is reported in this section. Data collected from subjects skilled in performing the movement is used to train the inductive learning algorithm. It is assumed that these patterns are near optimal, and that the 'cloned' rules would also produce near optimal movements when used to control FES activation of paralysed muscles in spinal cord injured subjects. The problem consists of recognising (discriminating) classes (events or states within the gait cycle) based on the values of a sensor (attribute) set. The particular movement type implemented is swing-through gait; section 5.3 describes the collection of the movement data used to train the inductive learning algorithm.

4.4.1. Type of Controller

There are two possible models of rule-base controller, *pattern matching* and *finite state* (see section 2.4.2). A finite state model was previously used in the control of FES swing-through gait (section 4.2.6). Thus, this approach will be used for the induced controller to be developed in this thesis. This type of controller requires transition rules to be induced (representing the decision to move between states); whereas the decision tree produced by the inductive learning algorithm is more suited to the implementation of pattern matching controllers (where the rules directly determine the system state). This is resolved by inducing separate rule trees in the region of each transition event. The rule-set that discriminates the new state from the original state is used to form the transition rules between the two states in the finite state controller. Thus a separate decision tree must be induced for every state in the movement,

1 This number will be reduced if there are more than 10 (maximum 16) attributes, or if the full 640 kB of PC memory is not available.

representing the transition events to all succeeding states.

4.4.2. Determination of the State Transitions

The gait cycle must be deconstructed into separate states. Although these may be defined arbitrarily or from the characteristics inherent in the data, the most appropriate states to implement in this case are those previously used in the FES swing-through gait controller (section 4.2.6). This allows direct integration of the induced rules into the existing controller. The two critical state transitions are those between late stance and the initiation of swing (the end of the first period of double-support), and between late swing and early stance (the start of the second period of double-support). The first is important as it marks the end of the only stable state in the cycle (the subject may stop at the end of stance, but once swing is initiated s/he must continue until the next stance period). The second is important as correct timing of knee extensor activation at the end of swing is critical: if it is delayed it may lead to the subject falling following heel strike, premature activation may lead to the feet contacting the ground during mid-swing.

It is necessary to distinguish these state transitions in the training data. Kirkwood used two techniques to do this: in the first, analysis of normal walking (Kirkwood, 1989, p.99), he defined the state transitions as occurring at major joint flexion singularities (i.e. where the joint trajectories change from flexing to extending), a similar technique to that originally used by Tomovic and McGhee (1966); this provided a simple method of determining state transitions. However, it is not the most appropriate technique for the direct induction of control rules for FES activation as:

- The changes in joint angles will lag behind the activation of the corresponding musculature; thus, a controller based on this principle will always be delayed in initiating stimulation.

- There will be times when joint angle changes occur passively (without the need for muscular activation), due to ballistic motion or external force actions. There will also be times when muscular contractions do not produce an associated change in joint angle, such as when joint movement is prevented by ligamentous or

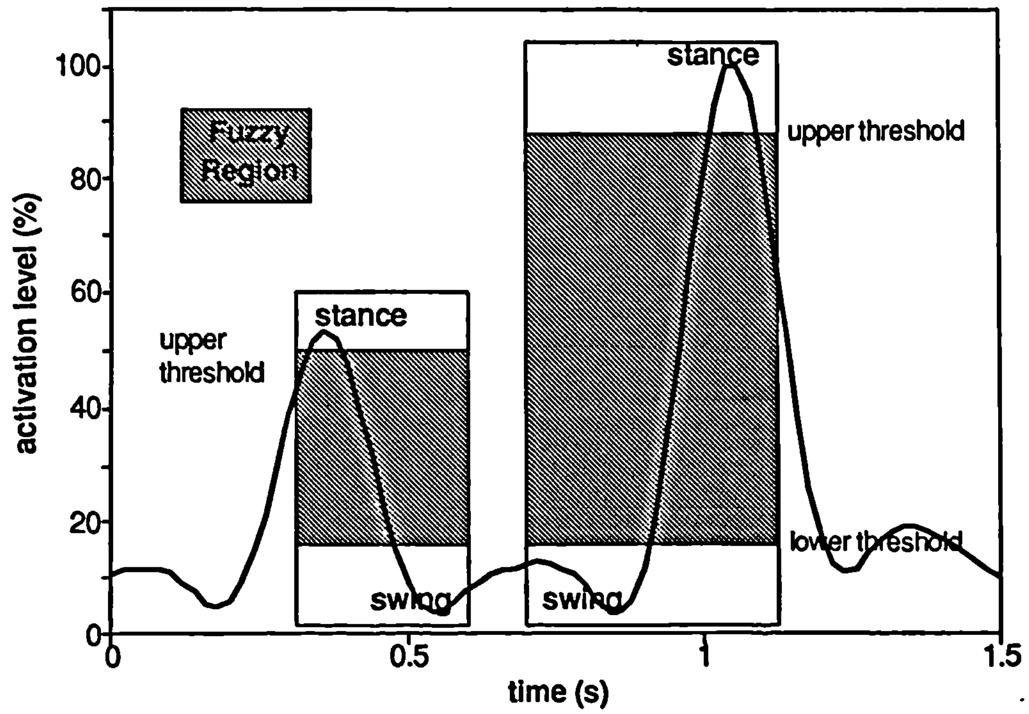
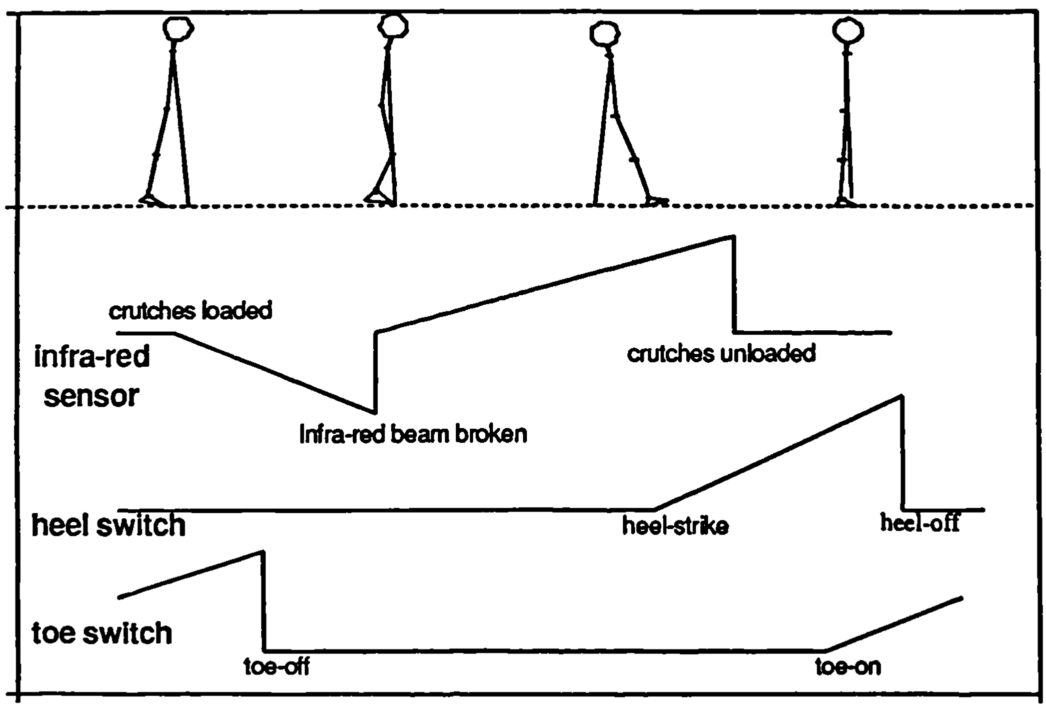


Figure 4.6 *How the quadriceps EMG defines states in the gait cycle*



Figures 4.7 a,b,c *Processed sensor outputs*

antagonist constraints. Thus, a controller based on joint angle events may apply stimulation when it is inappropriate, or fail to apply it when it would be appropriate.

The second approach of Kirkwood involved mimicking the control actions of a paraplegic with an incomplete lesion, who had been trained to walk with simple, unilateral, two channel stimulation (Kirkwood, 1989, p.110). He used the output of the subject's hand-switch to directly determine the classes. This approach required a trained subject who could manually control the FES system. The 'ideal' subject for this approach is one who has complete motor loss, but preservation of all sensation and proprioception[1] (This corresponds to Frankel's paraplegia grading b [Frankel *et al.*, 1969]). This subject could then be trained to control FES swing-through gait by means of hand switches. Such a subject was not available to us, and the reliance on one would limit the generality of the approach. Indeed, the aim of the present work is to program the knowledge required for the optimum production of gait **into the controller rulebase** and thus avoid the necessity of a subject learning these rules.

An appropriate signal to automatically define the states for an FES controller is the activation levels of the actual muscles to be controlled[2]. Thus, singularities in the EMG traces were used to determine the state transition events. Specifically, the fall in the activation of quadriceps group as the knee began to flex was used to determine the initiation of the swing state. Similarly, the rise in quadriceps EMG level as the leg was braced prior to heel strike defined the initiation of the stance state (see figure 4.6). A fixed number of samples (examples) in the region of each transition were used to form each training set (see section 4.4.4).

In order to induce a robust rule-base in the presence of attribute noise, (triangular) fuzzy weighting was applied to the examples within each training set. The region to which the fuzzy membership function was applied is also given in figure 4.6. The first and last sample, and upper and lower thresholds for each training set were adjusted by means of an interactive graphics program *Align* (appendix B).

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1 Or possibly in the future, restoration through FES.

2 Perry (67) also used EMG activation levels to split the gait cycle into different states in her description of gait. Marsolais and Kobetic (1983, 1987) and Saito *et al.* (1990) used normal EMG patterns to suggest suitable fixed timing patterns for FES activation, see section 2.4.4.1.

4.4.3 Selection of Attributes

The attributes chosen to describe the gait need to a) reflect the state of the gait cycle (an attribute whose variations are unrelated to the classes being predicted is of no use); and b) represent a quantity which can be measured with a practical sensor. The variable-selective nature of the induction algorithm will reject attributes which do not fulfill criterion a. Criterion b involves questions of cost, robustness, reliability, repeatability, size, weight, safety, etc. A sensor which may not be practical at present may become so following technical advances. In order not to restrict the sensor set to those that were readily available at the time of performing the experiment, sensor outputs were simulated from the data collected from the *VICON* system, force plates and instrumented crutches. The advantages of a such a simulated sensor set are:

1. The subject does not have to be fitted with and carry a large number of sensors.
2. Any sensor which has a low information content can be rejected without having to build or buy it (saving time and money).
3. Sensors which are not yet available can be tested, if they prove useful they can then be developed.
4. Practical limitations associated with sensors (such as noise and limited resolution) are avoided. However, it is also possible to include the effect of these limitations in the simulation and so investigate the degradation due to non-ideal sensors.
5. The effect of different sensor failure modes (such as open or closed circuit failures) can be simulated.

The disadvantages of simulation are that the use of motion analysis equipment (force plate, *VICON* system) fixed in the laboratory, rather than carried by the subject, restricts the measurement volume: typically, it is only possible to record from one gait cycle per run. Also, the time-consuming reconstruction and analysis of the kinematic data obtained from the *VICON* system limits the number of runs that can be performed.

The sensors which were simulated are listed below:

a. toe switch
b. heel switch
c. torso inclination sensor
d. crutch inclination sensor
e. crutch axial force sensor
f. crutch infra-red beam
g. shoulder elevation
h. centre of pressure insole
i. ankle moment sensor
j. ankle axial acceleration
k. ankle transverse acceleration
l,m,n. hip goniometer (and first and second time derivatives)
o,p,q. knee goniometer (and first and second time derivatives)

These will now be described in detail:

a. **toe switch:** a simple switch placed under the anterior foot. This sensor is processed to give timing information about the stance phase (see figure 4.7a).

b. **heel switch:** a similar switch to above, which is placed under the posterior foot. This sensor is also processed to give timing information about the stance phase (see figure 4.7b).

c. **torso inclination sensor:** an inclinometer, possibly located in a stimulator or power-pack on the subjects back or chest.

d. **crutch inclination sensor:** either an inclinometer located on one crutch, or a potentiometer connected to a crutch rocker bottom (the latter would only give valid readings when the crutch was in contact with the ground).

e. **crutch axial force sensor:** strain gauges and corresponding amplifiers connected to one crutch to measure axial force (as the gait is symmetrical, the force in both crutches was assumed to be equal[1]).

f. **crutch infra-red beam:** a sensor consisting of an infra-red transmitter/receiver pair mounted one on each crutch. When the

1 If the crutch loading is markedly asymmetrical this indicates an incorrect step and so a set of 'recovery' states should be triggered. Such a consideration was outside the scope of this work.

crutches are loaded (see above) and the beam is broken, this indicates that the legs are passing between the crutches during the body-swing phase of the gait. This signal is processed to give timing information about the swing phase (see figure 4.7c). This sensor had not been constructed previously; the simulation technique allowed its performance to be evaluated before construction.

g. **shoulder elevation:** a sensor that detects elevation or depression of the shoulders, possibly by means of a sprung linear potentiometer, fixed to the mid back, and attached to a strap passing over the shoulder(s).

h. **centre of pressure insole:** a sensor that measures the position of the centre of pressure acting through it, mounted either under the shoe, or inside it. Possibly consisting of a matrix of small force sensitive switches (Péruchon, 1989, Kirkwood and Andrews, 1988).

i. **ankle moment sensor:** a sensor that detects the bending moment at the subject's ankle. It can be implemented by strain gauging the subject's ankle-foot orthosis (AFO)[1].

j. **ankle axial acceleration:** an accelerometer placed near the subject's ankle (probably on the AFO), aligned parallel to the shank - assumed to be unaffected by inclination.

k. **ankle tangential acceleration:** a similar accelerometer, aligned perpendicular to the first, and in the plane formed by the shank and the foot.

l. **hip goniometer:** a goniometer mounted at the hip to detect flexion/extension.

m,n. **first and second time derivatives:** either tachometers and acceleration sensors, or hardware/software derivatives of the above sensor.

o,p,q. **knee goniometer (and first and second time derivatives):** similar to l,m,n above.

The calculations to synthesise these sensors from the kinematic and kinetic data were performed by the program *Align* (appendix B). The

1 This is only valid if a moment cannot be transmitted through the subject's ankle joint, i.e. if there is no plantar-flexion contracture or arthrodesis of the joint.

algorithms for their synthesis are given in appendix B. The output of *Align* consisted of the each example class and fuzzy weightings, together with the corresponding sensor values (attributes). The output was in the *Empiric* data format (appendix A). Sample outputs of all sensors for one gait run are given in appendix B.

Of the seventeen sensors listed above, the six corresponding to the hip and knee angles and their derivatives were not used to train *Empiric*, as, for the transitions being considered, their values were not independent of the classes their examples are members of. For example, the knee flexes at the start of swing, leading to a change in the knee angle sensor output, but this may reflect activation of the hamstrings group rather than predicting it. This problem of causality is addressed by eliminating attributes that are directly affected by the state transitions being considered. The simulated centre of pressure insole and ankle moments sensors were also not used, as their simulations were only valid for the periods when the subjects feet were entirely over the force platform (see appendix B), which would have reduced the number of valid training runs. Thus, nine sensors were actually considered for predicting the gait events.

4.4.4 Assessing the Rule-set Performance

The method for determining the performance of a rule-set should be appropriate for the problem domain being considered. The most common technique is to simply quantify the number of examples misclassified. It may be preferable to include an estimate of the likely 'cost' of misclassifying an example: this can be simply achieved for the swing-through data by using the weightings associated with each example to define its cost. If the output of a rule-set is used to predict a continuously varying pattern (for example, the EMG traces of section 5.4.3), then a measure of the difference in 'shape' may be appropriate, such as the RMS error between actual and reconstructed outputs. The present work predicts states transition in swing-through gait, the induced rules being used to construct a rule-based controller. The most appropriate measure of performance for such a controller is the timing error between the predicted and actual occurrences of the state transitions. As the spacing between examples is 20 ms, *e*, the number of examples misclassified represents the magnitude (i.e. without a sign) of the time difference between the actual and predicted transitions. If data from R runs is included in each testing set, the mean magnitude of timing error T_{av} is given in milliseconds by:

$$\frac{20}{R} \sum_{i=1}^{R} e_i$$

If the data from each run contains n examples[1], then the percentage error-rate is given by:

$$E = \frac{100}{R \cdot n} \sum_{i=1}^{R} e_i$$

Thus $T_{av} = \dfrac{E \cdot n}{5}$ (4.19)

That is, if the data from each testing set run contains the same number of examples, the mean magnitude of timing error can be obtained from the percentage error rate, **without modification to the program.** The simple measure of percentage error-rate can be used to select the best rule-sets as it is proportional to the mean magnitude of timing error (eqn. 4.19).

1 There were 13 examples from each run used to form the (initiation of) swing data set, and 16 examples from each run used to form the (initiation of) stance data set.

CHAPTER 5. EXPERIMENTAL DESIGN

5.1. OXYGEN CONSUMPTION STUDY OF SWING-THROUGH GAIT

5.1.1. Subject Selection

Four male and four female subjects were selected to participate in this study; their Their details are listed below:

CODE	SEX	AGE	MASS	HEIGHT
A1	F	21	60kg	1.76m
B1	M	33	71kg	1.71m
C1	F	20	73kg	1.80m
D1	F	21	69kg	1.74m
E2	F	29	52kg	1.60m
F2	M	26	68kg	1.79m
G2	M	24	76kg	1.85m
H2	M	25	76kg	1.85m

The mean age was 25 years.
The code suffix '1' indicates that the subject performed swing-through gait with locked knees first; the suffix '2' indicates that the subject performed swing-through gait with unlocked knees first.

All subjects were experienced in performing swing-through gait. All were fully able-bodied, with no history of musculoskeletal, cardiovascular, neurological or respiratory disorders (to their own knowledge).

5.1.2. Apparatus

The following equipment was used in the collection of the oxygen samples:

i. **Mouthpiece**: a sterilised rubber mouthpiece.
ii. **Nose-clip**: a sprung clip, designed to prevent nasal breathing.
iii. **Respiratory system**: a two-way valve that allowed the inspiration of atmospheric air and the collection of expired air.

iv. **Tubing**: a 1.5 m length of flexible, corrugated plastic tubing, running from the respiratory system to the aluminium tap.

v. **Aluminium tap**: a three-limb tap with one limb connected to the tube, one connected to the Douglas bag, and one open to the atmosphere. This allowed the expired air to be either collected or discarded.

vi. **Douglas Bag**: a large, gas-impermeable, flexible plastic bag with a capacity of 200 l.

The following equipment was used in the analysis of the samples:

i. **Volumeter**: Parkinson-Cowan industrial volume meter.

ii. **Thermometer**: mercury thermometer incorporated within the volumeter.

iii. **Oxygen analyser**: *Servomax.*

iv. **Vacuum suction equipment**: Hoover Ltd.

The following equipment was used in the production of swing-through gait:

i. **Crutches**: adjustable aluminium elbow crutches.

ii. **Braces**: adjustable braces (see section 4.1.2).

5.1.3. Experimental Procedure for Gait

The gait tests took place in the large sports hall of the University of Strathclyde, Glasgow. This is a large, well lit and ventilated hall measuring 20 m by 10 m.

On arrival at the hall the subjects were asked to lie supine on a mattress for 10 minutes. After 5 minutes, heart-rate was monitored every minute to determine the resting heart rate. After 7.5 minutes, the subject inserted the mouthpiece (under supervision), attached the nose-clip and was instructed to continue to breath normally. Exhalation was initially to the atmosphere, whilst the subject became used to breathing through the mouthpiece. After 8 minutes (i.e. 30 seconds after inserting the mouthpiece), the tap was turned and the expired air was collected for the final 2 minutes of rest. This air was immediately analysed.

The subjects were then fitted with the adjustable orthoses and were given the following instructions:

> *Follow the outlined course at your own preferred, constant speed, not the speed of the investigators. The valve will be held up for you in front of your face and the Douglas Bag will be carried for you and kept out of your way. The test will last for five minutes; you may stop at any stage if you feel that you need to.*

The subject then had the mouthpiece re-inserted and began to walk around the designated path. One investigator walked alongside the subject, supporting the Douglas Bag, another investigator recorded distance and time. Both investigators walked to the side of the subject and did not interfere with her/his gait pattern.

The subject walked for five minutes continuously; for the last two minutes the aluminium tap was turned and the expired air was collected.

The subject was freed of all gas collection apparatus and returned to supine lying. This second rest period lasted for five minutes, or until the subject's heart rate fell to its resting level, whichever was longer.

After this rest period, the subject stood and was re-fitted with the gas collection apparatus (with a new Douglas bag). If the first walk had been with free knees, the knees were now locked, and vice-versa. The second five minute walk was performed in the same manner as the first. All apparatus was removed at the end of this test period.

5.1.4. Gaseous Analysis Procedure

The Douglas bag was attached to the volumeter and the analyser probe was inserted in to the circuit. The tap attached to the Douglas bag was opened and the air was pushed through the volumeter by rolling up the bag. The oxygen analyser reading was constantly monitored, and its lowest value was recorded. The volume and temperature readings were noted at the end of the flow.

After use, each Douglas bag was emptied of all residual air by vacuuming through the aluminium tap, which was closed immediately after this was completed.

5.2. EVALUATION OF FES SYNTHESISED SWING-THROUGH GAIT

The synthesised gaits were assessed as follows:

5.2.1. Distance Trials

The following tests were performed at Phillipshill Hospital, Glasgow (the location of the West of Scotland Spinal Injuries Unit).

The gait trials took place along a long, straight corridor with a level floor. Each subject walked along the corridor until s/he became fatigued. Personnel were the same as in 4.2.5; however, additionally, investigator (d) recorded the number of strides that each subject took, using a tally counter. The subjects' heart rates were monitored during the tests (using the *SportsTester PE 3000* ECG telemetry unit, Polar-Electro fitness technology, Finland) to ensure that they did not reach potentially dangerous levels.

5.2.2. Experiments Using the *VICON* Motion Analysis System

The following tests were performed in the gait laboratory of the Bioengineering Unit, University of Strathclyde. The walkway was approximately 10 m long and consisted of level, smooth, linoleum tiles. All previous training had taken place along this walkway. For each subject, the kinematic parameters of the gait cycle were recorded by means of the *VICON* TV based motion analysis apparatus (Oxford Metrics Ltd.).

Lightweight polystyrene spherical (25 mm diameter), retro-reflective markers (Oxford Metrics Ltd) were attached over the following landmarks[1]:

a. 'Toe' (fifth metatarsal head)
b. 'Heel' (inferior posterior aspect of shoe)
c. 'Ankle' (lateral malleolus)
d. 'Knee' (lateral epicondyle of femur)

1 These marker positions are similar to those used by Wells (1979), with modifications to account for the use of elbow rather than axillary crutches in this study.

e. 'Hip' (greater trochanter)[1]
f. 'Shoulder' (acromion)
g. 'Ear' (temporomandibular joint)
h. 'Elbow' (lateral epicondyle of humerus)
i. 'Hand' (lateral aspect of crutch hand-grip)

Additionally, a marker was placed at the crutch tip.

The markers were attachment by double-sided adhesive tape (3M Ltd.). All markers were placed on the right side of the subjects body (the symmetrical nature of the gait permitted a unilateral analysis to be performed). The position of each segment was defined by the markers on its proximal and distal joints. This did not permit segment rotations to be measured, but was justified due to the planar nature of swing-through gait for all segments except the crutches and arms during crutch swing (Shoup *et al.*, 1974).

Four cameras were positioned so as to allow any marker to be seen by at least two cameras in every TV frame (a necessary condition for the reconstruction of the 3-D coordinates). The marker positions were sampled at 50 Hz (the fastest rate allowed by the *VICON* system).

Each subject wore shorts and a T-shirt. The markers were attached either directly to the subject's skin (wherever possible, above bony prominences so as to minimise movement) or on to an orthosis (AFO, crutch) or shoe. Clothing was secured with adhesive tape (*Durapore*, 3M Ltd.) to prevent it obscuring markers.

The subjects wore lightweight, 'training' shoes, without heels; these were slightly over-sized to allow AFOs to be worn. They were securely laced.

Once all the markers were attached, an initial calibration test was performed. The subject stood (using FES stimulation and a rollator) on a force platform (Kistler Ltd.), which was in the centre of the measurement volume. An investigator standing on the TV system's 'blind side' (i.e. the opposite side of the subject to the cameras) assisted the subject in maintaining a neutral stance (fully extended knees, neutral hip angle, upright trunk). The angles measured

1 Cappozzo (1990) reports the maximum errors during normal reciprocal walking between a marker on the greater trochanter and the (kinematically determined) hip joint centre as being 14mm in the medio-lateral direction and 4mm vertically. Calculations based on the average body segment dimensions of Contini (1972) suggest this would lead to maximum errors of less than 2 degrees in the estimation of the knee angle and less than 3.5 degrees in the estimation of the hip angle. A major component of Cappozzo's error may be due to rotation of the femur, which will not occur in swing-through gait

by the *VICON* system were used as the zero reference angles in subsequent analyses. The subject's weight was determined from the force platform output.

The subjects were then asked to proceed along the walkway at a self-selected ('comfortable') speed, using a swing-through gait. They typically achieved two complete strides before reaching the measurement area, the third, fourth and fifth strides being recorded. They continued for a further two strides before stopping.

Each subject performed a number of trials, separated by 5 minute (seated) rest-breaks, until quadriceps fatigue precluded any further trials. The subject then had a 30 minute rest-break, in which they were offered non-alcoholic refreshments.

Once a subject had performed the FES swing-through trials, the electrodes were removed and s/he was asked to walk (using KAFOs) in either a swing-to or swing-through gait (whichever s/he was confident in performing). This gait was also measured, and served as a comparison to the FES-assisted gait.

The investigators had the same roles as in 4.2.5; additionally, a further investigator (e) initiated the *VICON* data capture when the subject reached the measurement area.

Only two of the subjects (A and B) were able to complete these tests, the third subject (E) having previously withdrawn from the programme.

5.3. THE COLLECTION OF SWING-THROUGH TRAINING FILES FROM UNIMPAIRED SUBJECTS

5.3.1. Measurement of Kinematic Variables

The position and orientation of each body-segment was measured using the *VICON* TV based motion analysis system. Marker and camera positioning was as described in section 5.2.2. The subjects wore shorts, T-shirts and light-weight, securely-laced training shoes. As in section 5.2.2, a preliminary calibration was performed with each subject standing in the anatomical position (but with slightly abducted arms to avoid obscuring the hip marker). The marker positions were sampled at 50 Hz.

5.3.2. Measurement of Foot Contact Forces

Contact forces between the subjects' feet and the ground were determined by means of a piezo-electric force-plate (Kistler Ltd.) with dimensions of 600 mm (anterior-posterior) and 400 mm (medial-lateral), which was mounted in the walkway. The signals from this force-plate were amplified, then sampled by a 12 bit analogue to digital converter (ADC) in the *VICON* system. Conversion of these values to actual forces was performed by the *AMASS* motion analysis software package (Oxford Metrics Ltd.), supplied with the *VICON* apparatus. Calibration constants for the force plate were taken from the computer file BIOGEN.DES which had been created by Messrs Steven Millbank, Michael Hall and Zuheir Marmar at the Bioengineering Unit, University of Strathclyde.

5.3.3. Measurement of Crutch Axial Loadings

A pair of standard elbow crutches had been previously instrumented with strain gauges in a full bridge configuration. These were used to measure axial crutch loads during gait. Calibration of the crutches and their amplifiers was performed immediately prior to any test. The calibration procedure involved attaching retro-reflective markers near the top and bottom of a crutch (so that the vector between the markers was parallel to the crutch axis). An investigator then applied varying loads through each crutch in turn by pressing it against the force-plate. The three-dimensional positions of both markers and the three components of force were recorded by the *VICON* motion analysis system. The amplified strain gauge outputs were sampled by the *VICON* ADC (see previous section) at 50 Hz. The dot product of the force vector and the crutch axial vector, divided by the magnitude of the crutch vector, gave the component of the force that was parallel to the crutch axis. This was calculated at each sampling instant. The calibration constants (offset and gain) were calculated by a linear regression of the strain gauge output (independent variable) against the axial force (dependent variable).

The crutch heights were adjusted to the correct position for each subject using the technique of Nejad (1990) (see section 4.1.3). Further height adjustments were made at the investigator's discretion.

5.3.4. Measurement of Muscular Activation

Muscle activation was determined by means of surface[1] electromyogram (EMG) signals. These were measured using a commercial, 8 channel, radio-telemetry device (MIE Ltd.), with a bandwidth of approximately 200 Hz[2]. The system consisted of small, bi-polar pre-amplifiers mounted (by double-sided tape) close to the electrode site, wired to a telemetry unit worn on a belt at the waist. Electrode sites halfway between the centre of a muscle's innervation zone and its distal tendon were used, as recommended by Basmajian and De Luca (1985, p.64). For the quadriceps group, a location approximately midway along the anterior thigh was chosen. The position was adjusted until voluntary activation of the quadriceps produced a satisfactory response. The bi-polar electrodes were positioned approximately 3 cm apart in a line parallel to the supposed direction of the muscle fibres (parallel to the thigh axis). The electrode site was prepared by first removing any hair using a disposable razor, then abrading the area with fine abrasive paper. The electrodes were attached to the skin by means of small, disposable, circular adhesive pads which adhered to the electrode circumference. A small quantity of electrode gel (Mingograf Electrode Cream, Siemens Elema AB, Sweden) was then injected between the electrode and the skin by means of a syringe. The earth was a 7.5 cm diameter self-adhesive electrode (Axelgaard manufacturing Co, Ltd., Fallbrook, CA) which was attached to the subject's back, immediately superior to the telemetry unit.

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1 Basmajian and De Luca (1985, p.36) suggest the use of surface rather than indwelling electrodes for kinesiological studies of superficial muscles (such as the quadriceps group).

2 Various recommended upper 3dB points for amplification of surface EMG are 1000 Hz (Winter, 1979), 600 Hz (Hof, 1984) and 500 Hz (Basmajian and De Luca, 1984). However, as the EMG signal is being used to determine timing, rather than level of activation, and as most of the signal power is concentrated between 20 and 200 Hz (Winter, *ibid*), the lower bandwidth should not adversely affect the results.

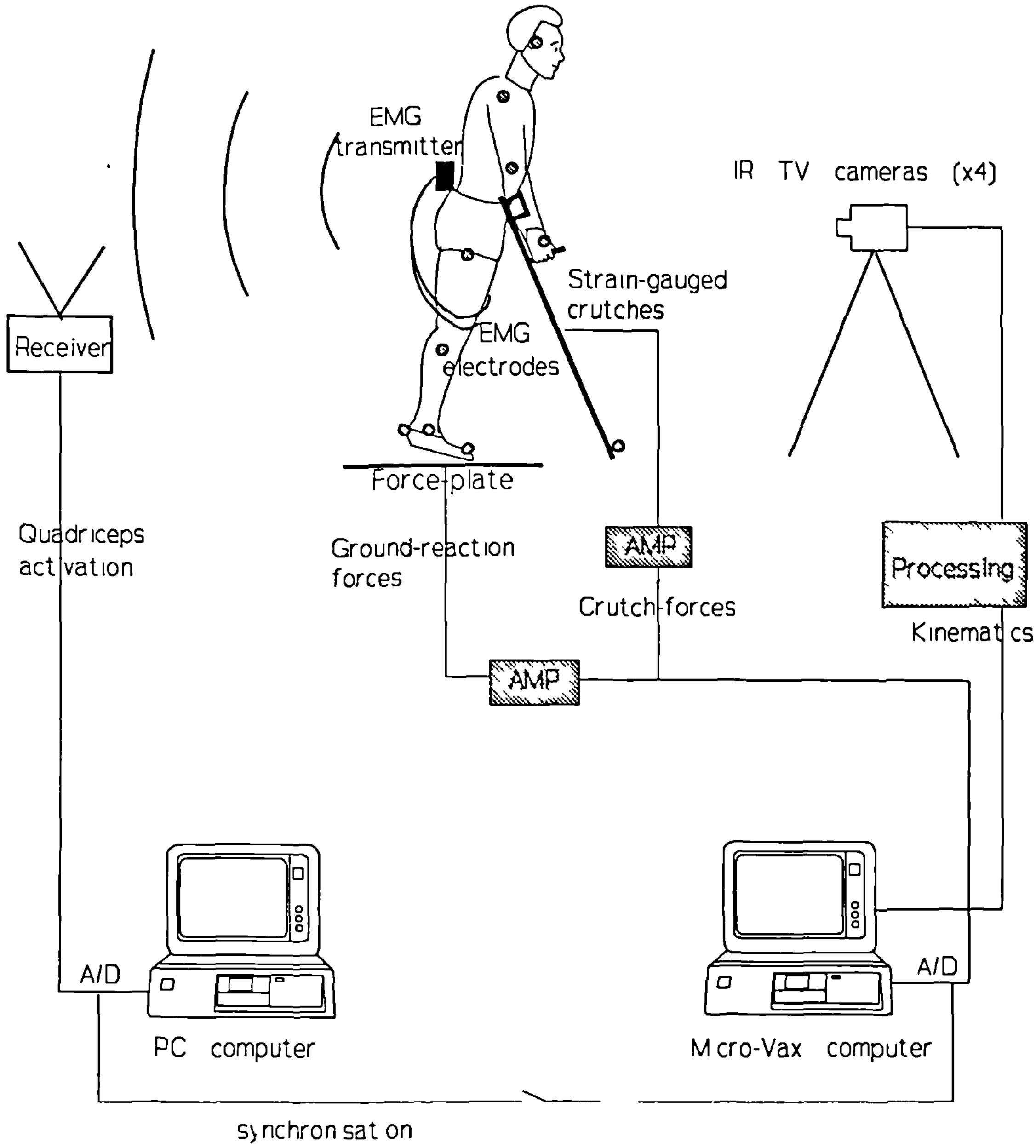

Figure 5.1 *Experimental setup for study of unimpaired swing-through gait*

5.3.4.1. Processing the EMG signal[1]

The output from the telemetry receiver was sampled at 400 Hz[2] into an IBM *AT* compatible computer (Compaq Ltd) by the computer program *Acquire* (Phillips, 1988) using a 12 bit ADC (*PC26A*, Amplicon Ltd.). The EMG signal was synchronised with the data collected by the *VICON* device by means of a switch that placed a 1 V DC signal on one channel of each ADC when it was pressed. This switch was pressed once during each collection, and the corresponding data points allowed both sets of sampled data to be synchronised. A block diagram of the experimental set-up is given in figure 5.1.

The lower 3 dB frequency of the surface EMG signal is approximately 20 Hz (Winter, 1979); any lower frequency components represent movement artifacts. To remove these artifacts, the data was digitally high-pass filtered using a 39 term symmetrical (19 terms on either side of the central point) finite impulse response (FIR) high-pass filter with a cut-off frequency of 20 Hz (this filter is described in more detail in appendix G). The filtered data was then digitally full-wave rectified and low-pass filtered (smoothed) to obtain the envelope shape. The latter stage is the most critical and will be explained in detail. The frequency content of human gait is bounded, with various authors suggesting different cut-off frequencies; for example, Winter (1974) found that 99.7 % of the signal power of leg and foot markers (for normal walking) was below 6 Hz; Antonsson and Mann (1985) found that 98 % of the signal power in force plate readings was below 10 Hz; Cappozzo *et al.* (1975) found that overall, gait could be represented by the first five terms in a Fourier series (approximately 5 Hz), and that the knee angle in level walking could be represented by the first three terms (3 Hz). Unfortunately, the random 'noise' in the EMG signal (caused by individual motor unit action potentials) can also have frequency components in this range. If the high cut-off frequency of the smoothing filter is too low, then genuine muscle activation features will be lost;

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1 This processing was performed off-line, using programs written in *Turbo Pascal* (Borland Ltd.) running on a *IBM AT* compatible computer with a '386 processor.

2 According to Shannon's sampling theorem, this is the **minimum** sampling rate that can be used to characterise a signal with frequency components up to 200 Hz. For a faithful reproduction of the input signal, a rule of thumb is that the actual sampling rate used should be two to three times this figure. However, Because of computer memory restrictions, the higher rate was not used. This is justified because the on/off timing of the muscle activation is required, rather than an exact representation of the raw signal. If there were any components above 200 Hz in the raw signal, then these would be aliased; however any aliased frequencies would have to approach DC (i.e. the original signal would be around 400 Hz) before they significantly affected the reconstructed muscle timing.

if the cut-off frequency is too high, then spurious features will be added (Hof, 1984). The correct choice of cut-off frequency, and the sharpness of the cut-off transition, are thus essential for the study of fast movements. They can only be determined with *a-priori* knowledge of the signal characteristics. A preliminary investigation was performed to assess the optimal high cut-off frequency for quadriceps activation during swing-through gait, and is described in appendix G. This led to the choice of a 199 term symmetrical FIR filter, with a cut-off frequency of 4 Hz.

5.3.5. Conduct of a Gait Test

All tests were performed in the gait laboratory of the Bioengineering Unit, University of Strathclyde. The walkway was approximately 10 m long and consisted of level, smooth, linoleum tiles. Two force-plates were set approximately halfway along the walkway, they were similarly tiled, and were flush with the walkway surface.

Each subject was fitted with the adjustable braces (with knees joints initially unlocked), markers and EMG electrodes as described above. S/he then stood on the force-plate whilst the static calibration test was performed. The subject then re-familiarised her/himself with walking in a swing-through gait whilst wearing the brace. This practice continued until the investigators were satisfied that the subject could safely and confidently perform the gait.

Each subject completed a number of runs, consisting of two strides before the measurement area was reached, one measured stride, and two subsequent strides before stopping. The subjects were specifically asked not to aim for the force-plate, but to look straight ahead at a point on the far wall. An investigator determined if the subject's feet had struck the force-plate correctly; if they had not, then the trial was repeated from a different starting position. This was repeated until a minimum of three, and preferably five (depending on time and fatigue) successful runs had been completed. The subject had a 15 minute rest before proceeding to the fixed-knee trials.

During these trials, the knee-locks on the adjustable braces were closed once the subject was standing. Further practice was obtained, and, if necessary, the heights of the crutches were increased to provide more ground clearance. The subject then performed stiff-legged swing-through gait trials until a further three to five successful runs were completed.

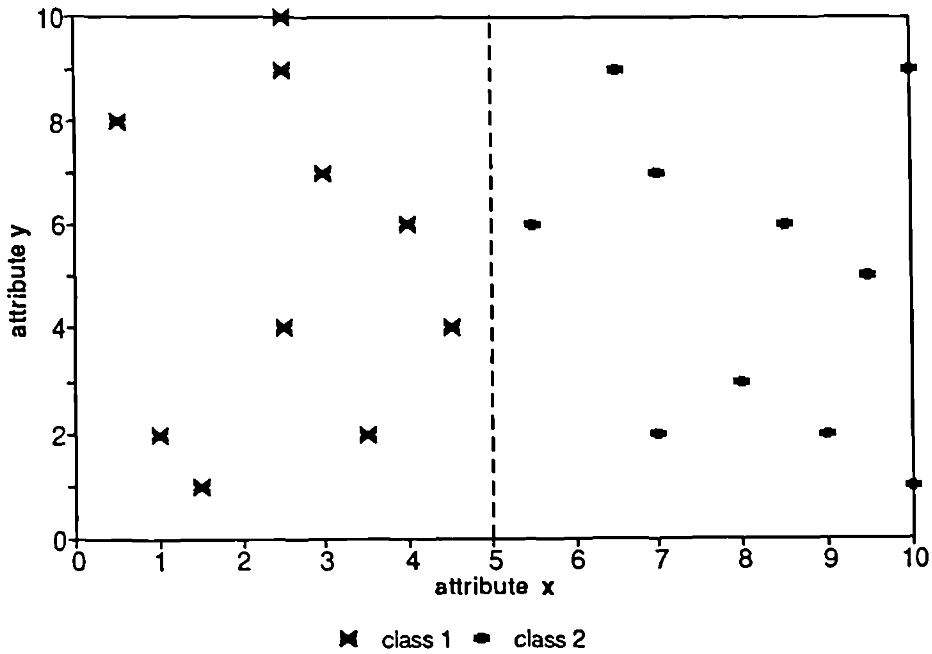

Figure 5.2 *Artificial data-set one*

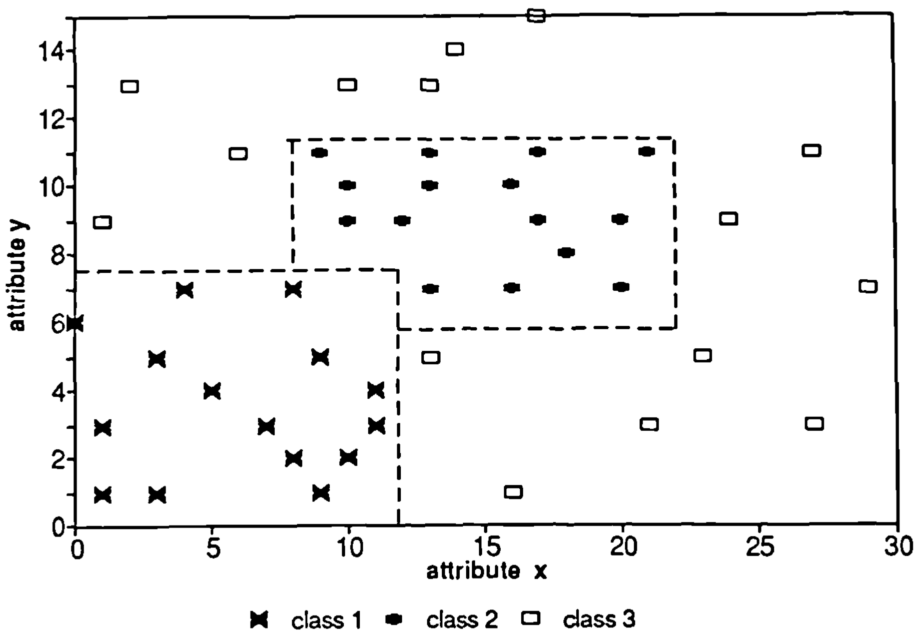

Figure 5.3 *Artificial data-set two*

5.4. PRELIMINARY INDUCTIVE LEARNING EXPERIMENTS

5.4.1. Initial Evaluation of *Empiric*

The inductive learning program *Empiric* was tested on three sets of artificial data to verify its correct function.

The first (figure 5.2) was a simple, two attribute, two class set, that required only one rule to classify it. These data were taken from Kirkwood (1989).

The second set (figure 5.3) was also taken from Kirkwood. It was a two attribute, three class problem, which required the use of both attributes to classify the data.

The third data set was less trivial. It was designed to test the performance of the program on a large, complex, data set, but to still produce a decision tree that could be understood intuitively. Firstly, 1024 examples were generated, numbered from 0 to 1023. Each example was then assigned to one of eight classes according to its number, i.e. examples 0 to 127 formed class one, 128 to 255 formed class two, etc. Seven attributes were constructed by assigning each a value of 1 or 0, corresponding to the seven most significant bits of the example number (figure 5.4). It was possible to uniquely classify this data set using only 7 rules involving the most significant 3 bits, thus the remaining bits were redundant.

As a variation of this 64 was added to each example number before calculating its attributes. Consequently, the data set required 15 rules to classify it, involving the most significant 4 bits.

5.4.2. Assessment of *Empiric's* Performance on a Noisy Data Set

In order to test the program's classification performance in the presence of different degrees of uncertainty (noise), the following example set was constructed:

The third artificial data-set (described in the previous section) was modified by adding 32 to each example number before calculating its attributes; 23 rules and 5 attributes (bits) were required to correctly classify this data set.

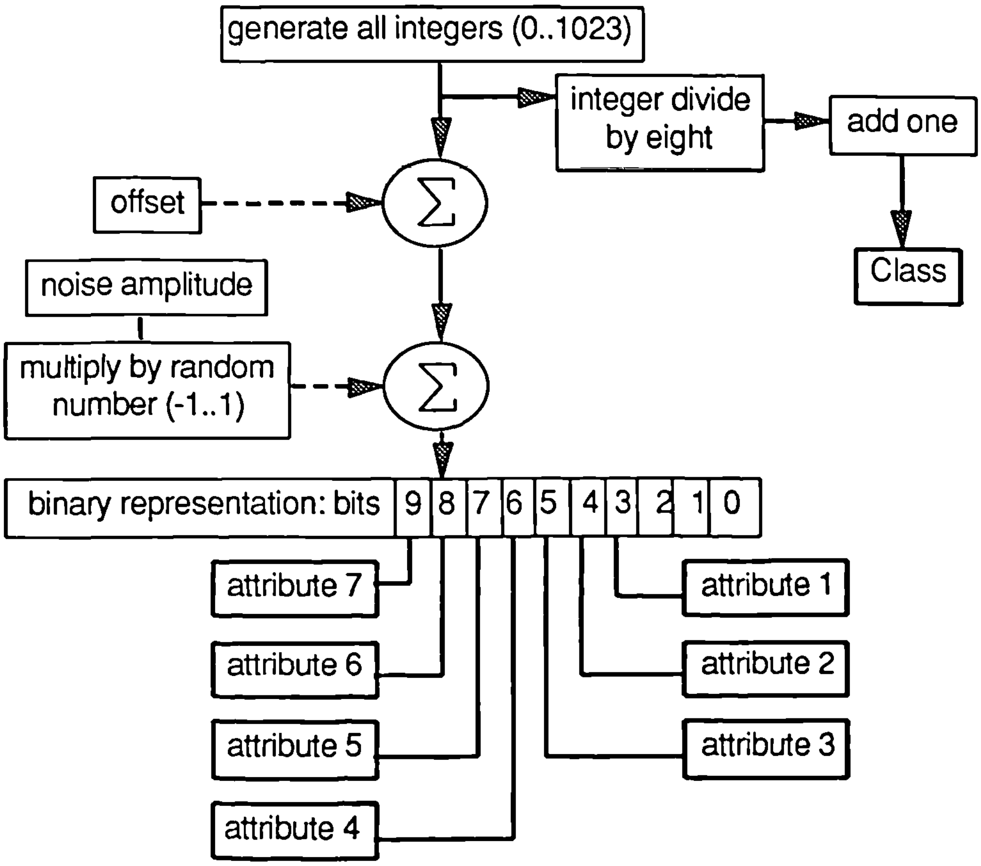

Figure 5.4 *The generation of artificial data-set three*

Each number was additionally contaminated with pseudo-random noise at various amplitudes, before the attributes were calculated. This technique simulated uncertainty in the attribute values. The examples nearest class boundaries were most likely to have sufficient noise to remove them into the next class, causing them to become counter-examples to the correct rules. This is analogous to the process of classifying a genuine continuous signal (e.g. an EMG recording) into arbitrary classes in the presence of noise.

The amplitude of the noise was set at 32, 64, 96, 128, 160, 192, 224 and 256 for various experiments. Rule trees were induced with 8, 16, 32, 64 and 128 rules at each noise level.

The performance of the rule-sets was assessed by determining how well they classified the original, uncontaminated data. The measure of performance was the proportion of examples that were misclassified.

This was repeated 50 times for each size of rule-set, to obtain a measure of the distribution of the error rates. The total number of rule-sets generated was:

9 (noise levels) x 5 (rule-set sizes) x 50 (repetitions) = 2250.

Empiric was modified to allow these calculations to take place automatically. The whole process took approximately 5 hours on a 16 MHz '386 IBM PC compatible computer.

The same tests were repeated for fuzzy and quadratic[1] weightings of the examples, to assess the effect these modifications had on the program's susceptibility to noise.

5.4.3. Classification of EMG Data From Normal Gait

The data of Veltink *et al.* (1990) were kindly made available by the authors. The following details of its collection (at the Roessingh Rehabilitation Centre, Enschede, The Netherlands) were obtained from one of the authors, Nico J. Rijkhoff.

> The data were recorded from a healthy, male, non-impaired individual, by instrumenting his right hip and knee with 'flexible goniometers' *(Penny and Giles Ltd)*. These angular data were sampled at

1 Quadratic weighting involved using a quadratic function to weight the central terms higher than those at the edge of the class.

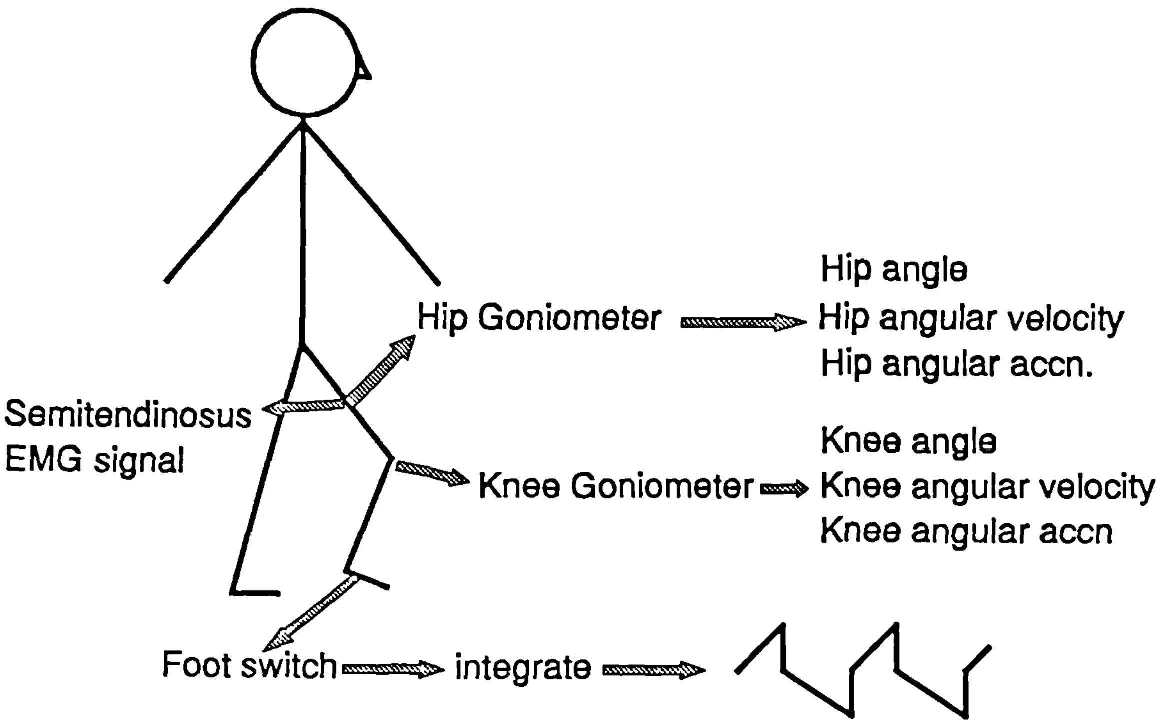

Figure 5.5 *The collection of reciprocal walking data*

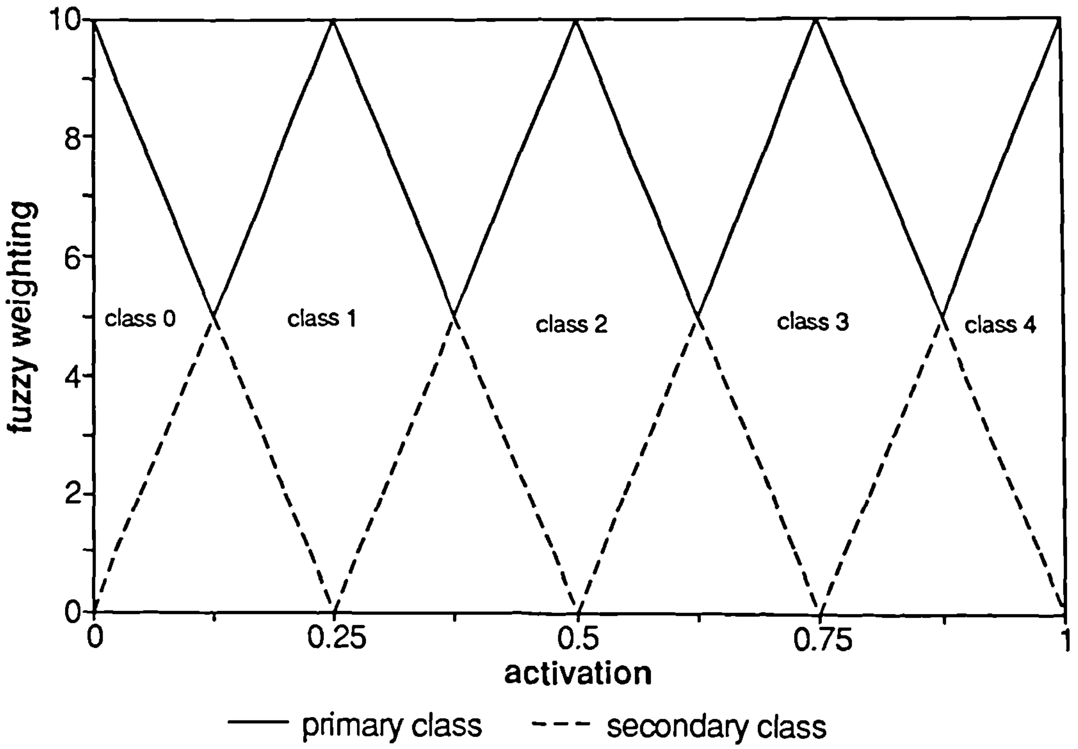

Figure 5.6 *Fuzzy weighting of EMG vs. activation level*

50 Hz by a 12-bit data acquisition card (*Analog Devices* RTI-815) installed in an IBM PC compatible computer. They were low-pass filtered at a cut-off frequency of 5 Hz by a finite impulse response (FIR) filter, then doubly differentiated using a second FIR filter. Foot-floor contact was determined by monitoring electrical resistance between metal plates under the feet and a conducting rubber floor; this signal was then integrated to give information about the time spent in that phase of the gait cycle (figure 5.5).

Activation patterns of the ipsilateral semitendinosus muscle (one of the hamstring muscles, responsible for knee flexion) were determined by means of bipolar surface-EMG electrodes. This signal was rectified and low-pass filtered using a second-order Butterworth filter with a 25 Hz cut-off frequency, prior to being sampled at 200 Hz. The EMG signal was further low-pass filtered off-line, using a 57 coefficient FIR filter with a 5 Hz cut-off frequency and zero phase-shift.

The subject performed 4 or 5 double steps at each of two self-selected speeds: natural speed and a faster speed. The data were recorded once a steady-state gait had been established.

The filtered data (hip and knee angles, angular velocities, angular accelerations and integrated foot contacts) from three trials at each speed were combined and used as the **training set**. The muscular activation signal was quantised into five levels (an arbitrary choice) and each one was taken as an independent class. A **fuzzy** weighting was used to assign class membership of each activation level to each quanta: each example was considered to be a member of both its actual class and the next nearest class. The triangular fuzzy membership value varied with the position of the example within the class as follows:

$$\mu(x,u) = 1 - |x - M(u)|/Q \quad \text{for } |x - M(u)| < Q$$
$$\mu(x,u) = 0 \quad \text{otherwise.}$$

where: $\mu(x,u)$ is the membership value of an example with value x in class u.
Q is the size of a quantum (the difference between adjacent quantisation levels)
$M(u)$ is the value of the midpoint of class u
$M(u)$ is given by: $M(u) = (u - 1)Q$

The variation of $\mu(x,u)$ with x is shown in figure (5.6).

Two different rule-sets were induced from the training data: one which had 3 rules (7 nodes) and a more complex one which had 31 rules (63 nodes). Both rule-sets were then used to classify each example in the **testing** sets, and the predicted and actual classes were compared.

5.4.4. Use of Neural Networks

The ability of neural networks techniques to model the EMG activation patterns was determined[1]. Computations were performed on an IBM-PC compatible computer using the *Nworks* software package (*Neural Works Inc.*). A multi-layer perceptron network with supervised learning via back-propagation (Lippman, 1987) was used in this study. At the beginning of the training session, the weights of the nodes were randomised between -0.1 and 0.1. The input signals and the corresponding output activation patterns were applied to the network at each time step, and the weights of the nodes were adapted via the back-propagation algorithm. The learning coefficient was set to 0.9 and the smoothing factor to 0.6 (Rumelhart and McClelland, 1986). The complete training set was applied to the network 30 times.

Two different networks were generated, one with one hidden layer and one with two hidden layers (figure 2.2). The attributes of the testing set were then applied to the inputs of the networks, and the predicted activation levels were obtained at the outputs. The predicted and measured outputs were compared.

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1 This work was performed in collaboration with Nico J.M. Rijkhoff at the Biomedical Engineering Division of the Department of Electrical Engineering, University of Twente, The Netherlands.

5.5. THE INDUCTION OF RULES FOR SWING-THROUGH GAIT

The inductive learning program was applied to induce control rules for swing-through gait from the data collected from trained, non-impaired subjects. This data was presented as simulated sensor outputs, generated by the program *Align* (see Appendix B, this appendix also contains simulated sensor outputs from one trial). Not all trials by all subjects were usable (transmission between the EMG telemetry unit and its receiver was sometimes unreliable). A total of 14 usable trials was obtained for the initiation of stance, and 10 for the initiation of swing.

5.5.1. Determination of the Optimal Attribute Sets for Training Data

The optimal rule-set may consist of rules formed from any number of sensors/attributes, ranging from one sensor up to the use of the entire set. The total number of possible combinations is:

$$\sum_{r=1}^{n} \frac{n!}{(n-r)!r!}$$

where n is the total number of sensor/attributes (9 in this case) and r is the number used. This is equivalent to the expansion of the binomial expression $(a+b)^n - 1$, with a,b equal to 1. Thus the sum becomes simply 2^n-1, or 511 combinations for $n = 9$.

For each total number of attributes (1 to 9), various sizes of rule-sets were generated for all possible attribute combinations, and the error rate of each one was assessed on the **training** set. This was performed for both the prediction of the onset of stance and that of swing

5.5.2. Determination of Optimal Rule-set Size and Attribute Set for Testing Data

If rule-sets of different sizes are induced for the same attributes, and then tested on the **training** set used to form them, accuracy will increase with rule-set size. However, if there is uncertainty (noise) in the data, additional rules will begin to map the local noise, rather than any genuine patterns within the data. If the rule-set is tested on an independent **testing set**, then the additional, non-general rules will not produce an improvement in classification accuracy but may degrade it. Thus, as the rule-set complexity increases, **generalisation** gives way to **over-particularisation.** If a graph of classification accuracy on the testing set is plotted against rule-set size, the minimum error rate should correspond to the optimal number of rules required to represent any general trends in the data.

To investigate the effect of changing rule-set size on the swing-through data, a procedure ('batch') was added to *Empiric*. This procedure performed the following functions: The 10 individual files representing the (initiation of) swing were split at random into training and testing sets, each containing 5 files. Rule-sets of sizes 1, 2, 4, 8, 16 and 32 rules were then constructed for the training set, and tested on the testing set. The process was repeated 100 times to minimise any bias in the testing or training sets. The mean error-rate and its standard error were calculated for each rule-set size.

As there are 511 different combinations of 9 sensors, a comprehensive exploration of each possible attribute combination would require the induction of:

511 (combinations) x 100 (repetitions) x 6 (rule-set sizes) $\approx 3 \times 10^5$

rule-sets for a comprehensive study. This would have required several days of processing on the computing equipment that was available. To reduce this figure, the heel switch was not used to indicate the initiation of swing (as swing is always initiated after heel-off, so the heel switch conveys no information), and the toe switch was not used for the beginning of stance (stance occurs before the toe switch closes). Also, the maximum number of separate attributes used in any rule-set was limited to 4, rather than 9 (the results of section 6.3.4.2 justified this choice). This left 152 possible combinations. The efficiency of the batch processing was improved by using a ruleset with n rules as the basis for a ruleset with $2n$ rules, thus avoiding the duplication of calculations for rule-sets of different sizes (see appendix A).

This was also performed for the 14 (initiation of) stance files (split into training and testing sets each containing 7 files).

The approach of this section constitutes a form of 'post-pruning' (Mingers, 1989b): the performance of the rule-tree is assessed at different stages of its growth and the tree with the best performance (lowest error-rate) is selected. Thus, unreliable ('brittle') rules in the larger trees will be rejected.

5.5.3. The Generality of the Induced Rules

The intention behind this work is to produce rules with universal applicability rather than ones which are specific to the subject they are obtained from. For this reason, examples from a group of subjects were used to train *Empiric*. The hypothesis behind this approach was that the rules specific to each subject will be smoothed out leaving only general rules. However, if the subjects use completely disparate strategies, rather than 'variations on a theme', inductive learning will not be able to induce a valid rule-set to cover the examples[1]. There is some evidence that different subjects do adopt similar motor-control strategies (e.g. Arendt-Nielsen *et al.*, 1991), and this may be expected due to the constraints associated with performing a particular gait (the gait events must follow in a fixed order, there must be a smooth progression of the centre of gravity, contact forces must be minimised, etc.).

To assess the degree of generality in the rules obtained in this study, a series of rule-trees were induced for the best attribute combinations (found in section 5.5.2). For each attribute combination, for each example file, one rule tree was generated from all the remaining example files for the whole group, and one was generated just from the remaining example files for that subject. The difference in performance of the rule-sets gives an indication of the specificity of each subject's strategy. There was only one example file for subject B for the stance-to-swing transition, and thus that subject was excluded.

5.5.4. Comparison with Experts' Ratings of Sensor Importance

The ability of a single sensor (or a combination of sensors) to model the gait can be determined from the minimum testing-set error rate (see previous section) of the decision tree formed from that sensor. This allows the sensors to be ranked in order of importance. To compare this ranking with that produced by experts in the field, the following study was performed.

A questionnaire was produced that described each sensor and the required state-transitions (swing and stance). This was circulated to international experts in the field of biomechanics through the electronic-mail discussion list *Biomch-L* (Bogert and Woltring, 1989), and to some local experts.

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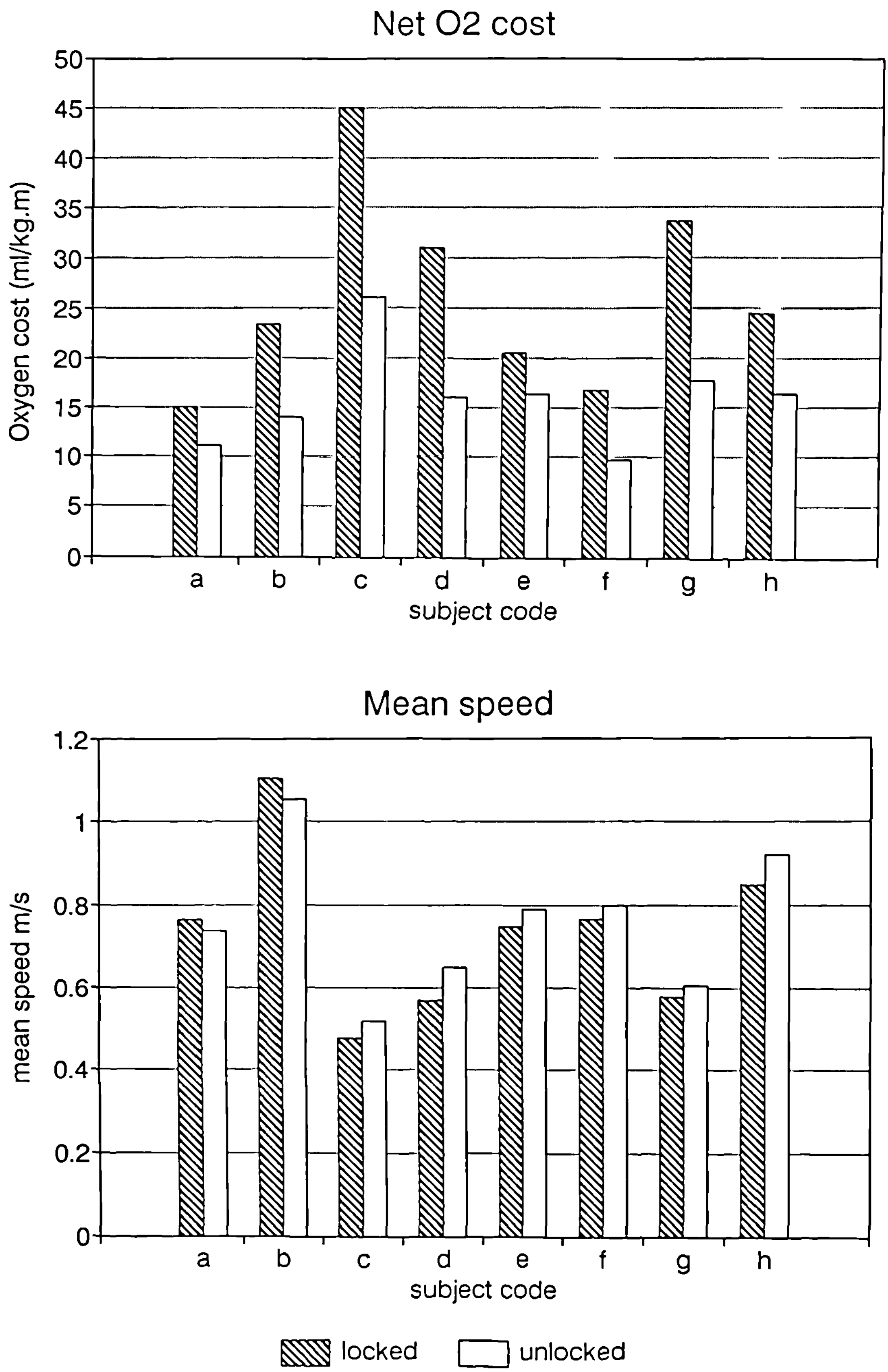
1 Just such a disparity is reported in Sammut *et al.* (1992) in which pilots either controlled a (simulated) air-plane's height by use of the throttle or by use of the elevators.

Each respondent was asked to rank the sensors according to how well they thought each would predict each state transition. Replies were received via electronic-mail. The questionnaire is reproduced in Appendix H.



Figures 6.1 and 6.2 *Comparison of fixed and free knee swing-through – unimpaired subjects*

CHAPTER 6. RESULTS

6.1. RESULTS FROM OXYGEN CONSUMPTION STUDIES

Oxygen consumption was calculated by multiplying the volume of air collected by the difference between the oxygen volume fraction of atmospheric air (0.209) and that of the collected expired air.

The resting oxygen consumption rate and the velocities of the eight unimpaired subjects performing swing-through gait are presented in table 6.1. The columns 'net oxygen consumption' were calculated by subtracting the resting oxygen consumption rate from the rates measured during gait. The columns 'net oxygen cost' were obtained by dividing the net oxygen consumption results by the subject's mass and gait velocity, and multiplying by 1000 (to convert to ml/kg.m). The 'cost ratio' is the cost per metre for unlocked-knees divided by the cost for locked knees.

The net energy costs for fixed and free knees are plotted in figure 6.1. The corresponding measured velocities are plotted in figure 6.2.

The free-knee energy costs for each subject are more likely to be lower than those for fixed knees at a significance level of 1% (non-parametric sign test). The free-knee self-selected velocities for each subject are more likely to be higher than those for fixed knees at a significance level of 5% (non-parametric sign test).

6.2. RESULTS OF FES SWING-THROUGH GAIT TRIALS

6.2.1. Distance Trials

The maximum range, overall speed, average stride time and average stride length for each subject performing FES swing-through gait are displayed in table 6.2. The speed was obtained by dividing the total distance travelled by the total time taken; the average stride length was obtained by dividing the total distance travelled by the number of strides; the average stride time was obtained by dividing the total time by the number of strides.

At no time in any of the trials did a subject's heart-rate exceed 150 beats per minute (the pre-determined maximum value).

subject	resting consmptn	net consmptn l/min		speed m/s		net O2 cost ml/kg.m		cost ratio
code	l/min	L	UL	L	UL	L	UL	UL/L
a	0.15	0.69	0.49	0.76	0.74	15.13	11.15	0.74
b	0.18	1.83	1.04	1.11	1.05	23.34	13.96	0.60
c	0.13	1.58	0.99	0.48	0.52	45.04	26.00	0.58
d	0.15	1.21	0.72	0.57	0.65	31.02	16.12	0.52
e	0.19	0.80	0.68	0.75	0.79	20.48	16.43	0.80
f	0.23	0.88	0.53	0.77	0.80	16.79	9.68	0.58
g	0.13	1.47	0.81	0.58	0.61	33.61	17.63	0.52
h	0.19	1.58	1.15	0.85	0.92	24.44	16.40	0.67
mean				0.73	0.76			0.63
std				0.18	0.16			0.10

L = locked knees
UL = unlocked knees
'net' figures are raw readings with resting O2 consumption subtracted

Table 6.1 *Oxygen used by unimpaired subjects performing fixed and free knee swing through gait*

subject (lesion level)	distance walked (m)	time (s)	speed (m/s)	mean stride length (m)	mean stride time (s)
A (T11)	55.50	138	0.40	1.26	3.15
B (T6)	43.30	144	0.30	1.08	3.60
E (T11)	50.60	133	0.38	1.13	2.97

Table 6.2 *Parameters obtained from distance walking trials for three complete paraplegic subjects performing FES assisted swing-through gait*

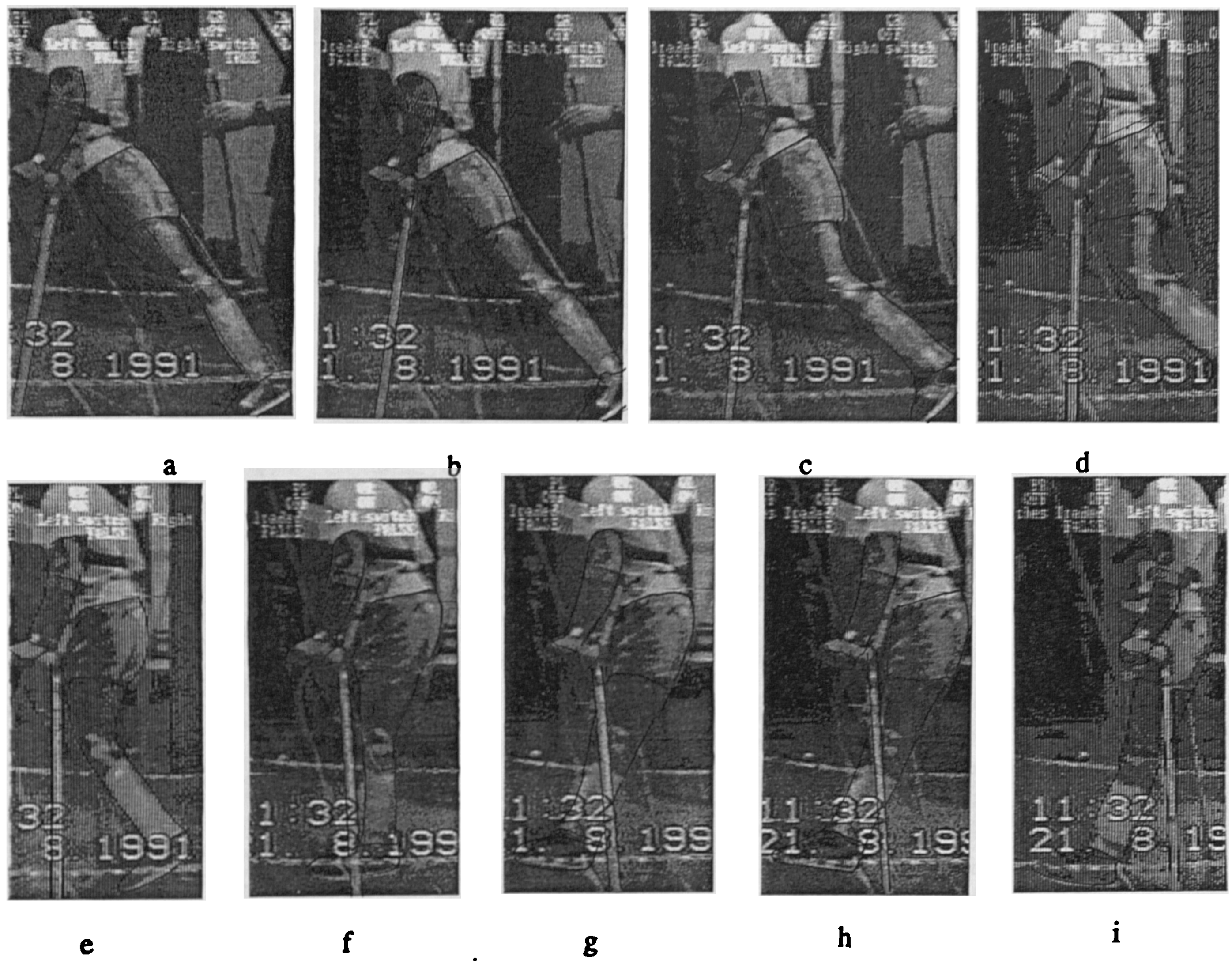


Figure 6.3 *T6 paraplegic performing FES swing-through gait; the separation between frames is 0.2 s*

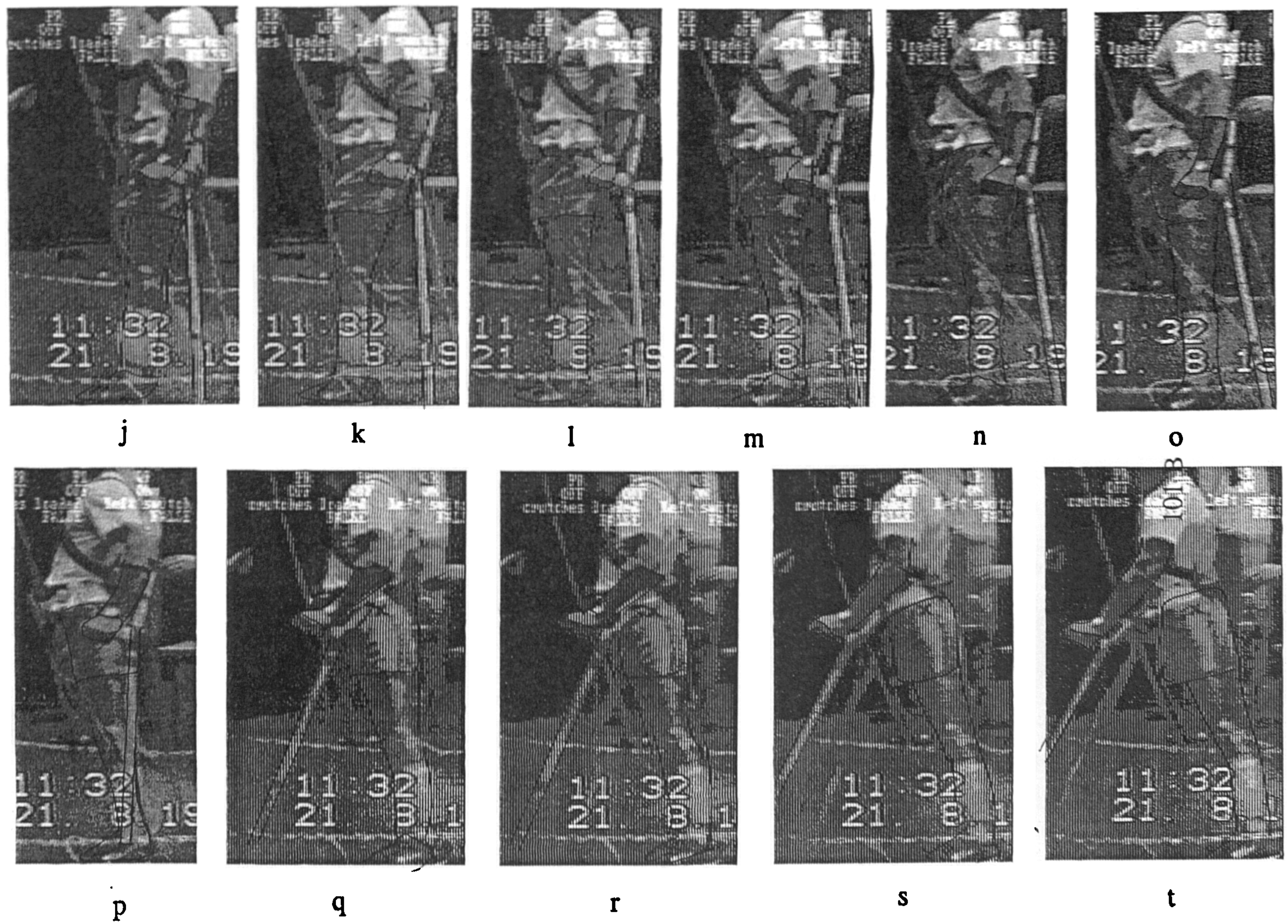


Figure 6.3 cont.

subject and gait type	total strides	overall speed (m/s)	mean stride length (m) +/- 1 SD	mean stride time (s) +/- 1 SD	mean body swing time (s) +/- 1 SD	mean crutch swing time (s) +/- 1 SD	mean 1st double support time (s) +/- 1 SD	mean 2nd double support time (s) +/- 1 SD	double stance ratio (percent)	mean maximum knee flexion (degree)	mean maximum hip flexion (degree)	mean distance beyond crutches (m)
A (1)	7	0.43 *(0.54)*	1.19 +/- 0.07 *(1.24)*	2.75 +/- 0.33 *(2.28)*	0.74 +/- 0.07 *(0.72)*	0.64 +/- 0.06 *(0.58)*	0.93 +/- 0.19 *(0.66)*	0.43 +/- 0.17 *(0.32)*	49.7% *(43.0%)*	10.0 +/- 5.3 *(4.6)*	43.4 +/- 2.3 *(43.0)*	0.51 +/- 0.05 *(0.57)*
A (2)	6	0.32 *(0.45)*	1.17 +/- 0.08 *(1.17)*	3.63 +/- 0.93 *(2.62)*	0.77 +/- 0.12 *(0.88)*	0.68 +/- 0.22 *(0.74)*	1.76 +/- 0.80 *(0.9)*	0.43 +/- 0.23 *(0.1)*	60.2% *(38.2%)*	N/A	34.5 +/- 3.4 *(29.7)*	0.48 +/- 0.03 *(0.49)*
B (1)	8	0.35 *(0.45)*	1.13 +/- 0.05 *(1.11)*	3.24 +/- 0.69 *(2.48)*	0.71 +/- 0.15 *(0.68)*	0.49 +/- 0.12 *(0.64)*	1.22 +/- 0.59 *(0.76)*	0.82 +/- 0.36 *(0.4)*	63.0% *(46.8%)*	50.9 +/- 6.9 *(49.7)*	42.8 +/- 3.3 *(45.3)*	0.25 +/- 0.07 *(0.24)*
B (3)	9	0.27 *(0.39)*	0.52 +/- 0.10 *(0.69)*	1.94 +/- 0.39 *(1.78)*	0.34 +/- 0.03 *(0.36)*	0.40 +/- 0.04 *(0.46)*	0.57 +/- 0.13 *(0.56)*	0.63 +/- 0.28 *(0.4)*	61.8% *(53.9%)*	N/A	25.1 +/- 2.6 *(27.4)*	N/A
F (4)	4	1.08 *(1.12)*	1.76 +/- 0.05 *(1.82)*	1.64 +/- 0.06 *(1.62)*	0.70 +/- 0.06 *(0.64)*	0.67 +/- 0.02 *(0.66)*	0.18 +/- 0.03 *(0.22)*	0.09 +/- 0.01 *(0.1)*	16.5% *(19.8%)*	65.5 +/- 5.0 *(67.7)*	46.4 +/- 2.8 *(49.7)*	0.87 +/- 0.03 *(0.92)*
F (2)	3	0.96 *(1.02)*	1.60 +/- 0.06 *(1.66)*	1.67 +/- 0.08 *(1.62)*	0.72 +/- 0.07 *(0.66)*	0.67 +/- 0.03 *(0.68)*	0.19 +/- 0.01 *(0.18)*	0.09 +/- 0.02 *(0.1)*	16.8% *(17.3%)*	N/A	47.4 +/- 0.5 *(47.9)*	0.77 +/- 0.08 *(0.76)*

Subject A is a T11 complete paraplegic
Subject B is a T6 complete paraplegic
Subject F is unimpaired
Figures in italics are for the single fastest stride

Table 6.3 *Temporal and distance parameters of FES swing-through gait (type 1), KAFO swing-through/swing-to gait (types 2/3) and AFO swing-through gait (unimpaired subject, type 4)*

6.2.2. Stride by Stride Trials

The following parameters are presented in table 6.3:

- the mean of the maximum angle of knee flexion in each stride.
- the mean of the maximum angle of hip flexion in each stride.
- overall speed.
- mean stride length.
- mean stride time.
- mean times for body swing, crutch swing, first double-support period and second double-support period.
- the overall ratio of double-support time to stride time.
- the mean of the maximum distance that the ankle marker was in front of the crutch-tip marker in each stride.

These results were obtained by examining the kinematic output of the *VICON* device as follows:

Stride length was defined as the distance moved by the toe marker in one stride, a stride being defined as taking place between two consecutive toe-off events. All gait phases were as defined in figure 1.3. Gait events were determined from the kinematic data: toe-off occurred when the toe vertical coordinate began to rise sharply; heel-strike occurred when the heel vertical coordinate reached its minimum value; crutch-off and crutch plant were similarly determined from the crutch vertical coordinate. The overall speed was obtained by dividing the sum of all stride lengths (total distance covered) by the sum of all stride times (total time taken). The overall ratio of double-support time to total-stride time was obtained by dividing the sum of all first and second double-support times by the sum of all stride times. Values of all the above parameters for the fastest strides of each gait type for each subject are also presented.

The knee angle was obtained from the kinematic output of the *VICON* device by calculating the angle between the projections of the hip-knee vector and the knee-ankle vector on to a sagittal plane. The hip angle was similarly obtained by projecting the shoulder-hip and hip-knee vectors on to the same plane. These angles were corrected by subtracting the corresponding 'zero' angles obtained in the initial calibration tests.

The video recording of the T6 subject performing swing-through gait (with the sensor and stimulation status superimposed on it) was 'frame-grabbed' (with an *ITEX* frame grabber, supplied by Amplicon Ltd., Brighton) at five-frame intervals (0.2 s). The resulting images were laser-printed and are displayed in figure 6.3. The quality of the reproduction is poor and so the outlines of the lower-limbs and crutches were enhanced by tracing around their edges with a black pen.

Equivalent results were obtained from one trained, unimpaired subject (subject B) wearing an adjustable brace (see section 4.1.2) and performing both free and fixed knee swing-through gait. These results are also presented in table 6.3. The protocol for these tests is described in section 5.3.

All calculations were performed using the *Quattro Pro* spreadsheet program (Borland Ltd.), on an IBM *AT* compatible computer.

No forces were detected in the strain-gauged karabiner during any of the gait trials (except on the few training runs when the subjects fell and were suspended in the harness).

6.3. RESULTS OF INDUCTIVE LEARNING EXPERIMENTS

6.3.1. Initial Evaluation of *Empiric*

The decision trees generated for artificial data sets 1 to 3 are shown in figures 6.4, 6.5 and 6.6a. The more complex tree for the modified artificial data set 3 (in which each example had an offset of 64) is shown in figure 6.6b.

6.3.2. Performance on a Noisy Data Set

For the noise-contaminated data set, the mean percentage of misclassified examples (with standard errors of the mean) are plotted against noise amplitude in figures 6.7a to 6.7e for rule-set sizes from 8 to 128 rules. The results for quadratic weighting, fuzzy weighting and no weighting are plotted on the same graphs for comparison.

To examine the relationship of error to rule-set size for different weighting strategies, the same data are plotted as error against rule-set size in figures 6.8a to 6.8e, for error levels from 32 to 160.

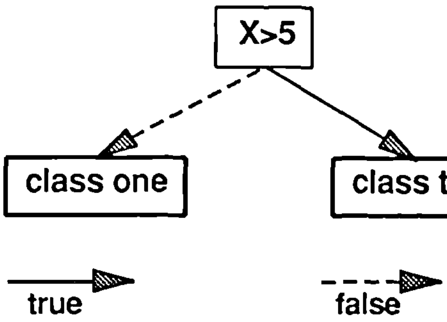


Figure 6.4 *Decision tree for artificial data-set one*

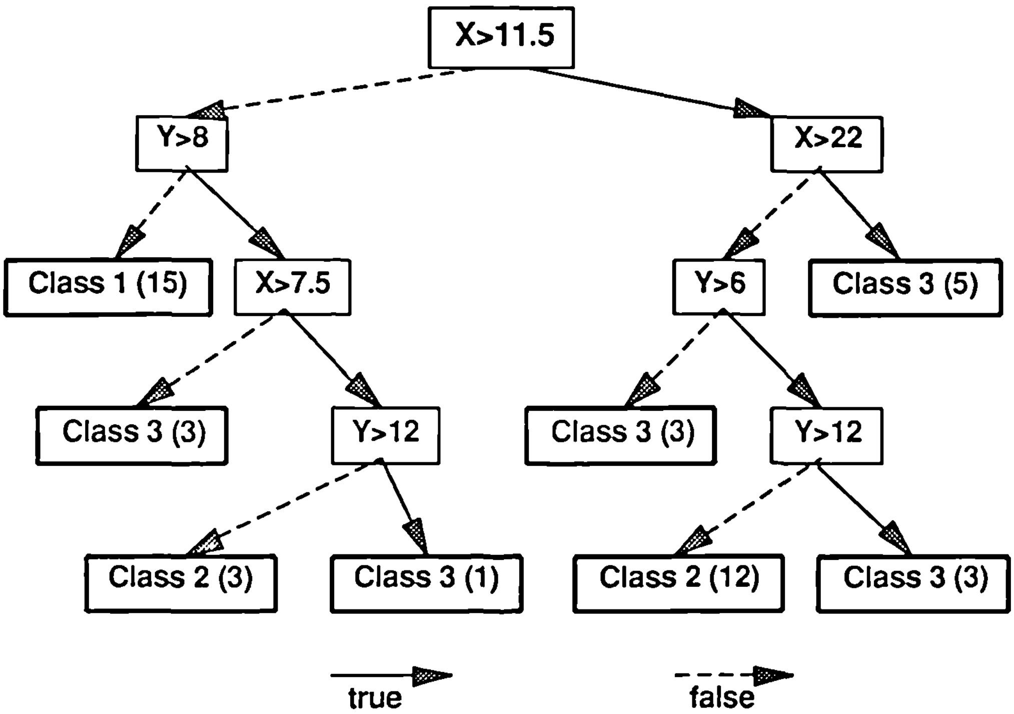


Figure 6.5 *Decision tree for artificial data-set two*

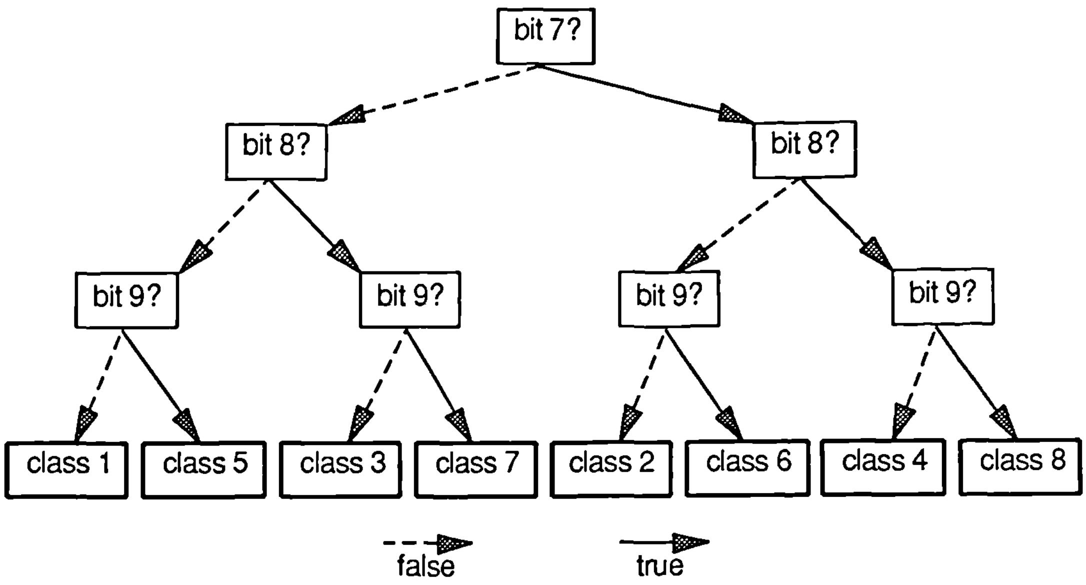


Figure 6.6a *Decision tree for artificial data-set three, no offset*

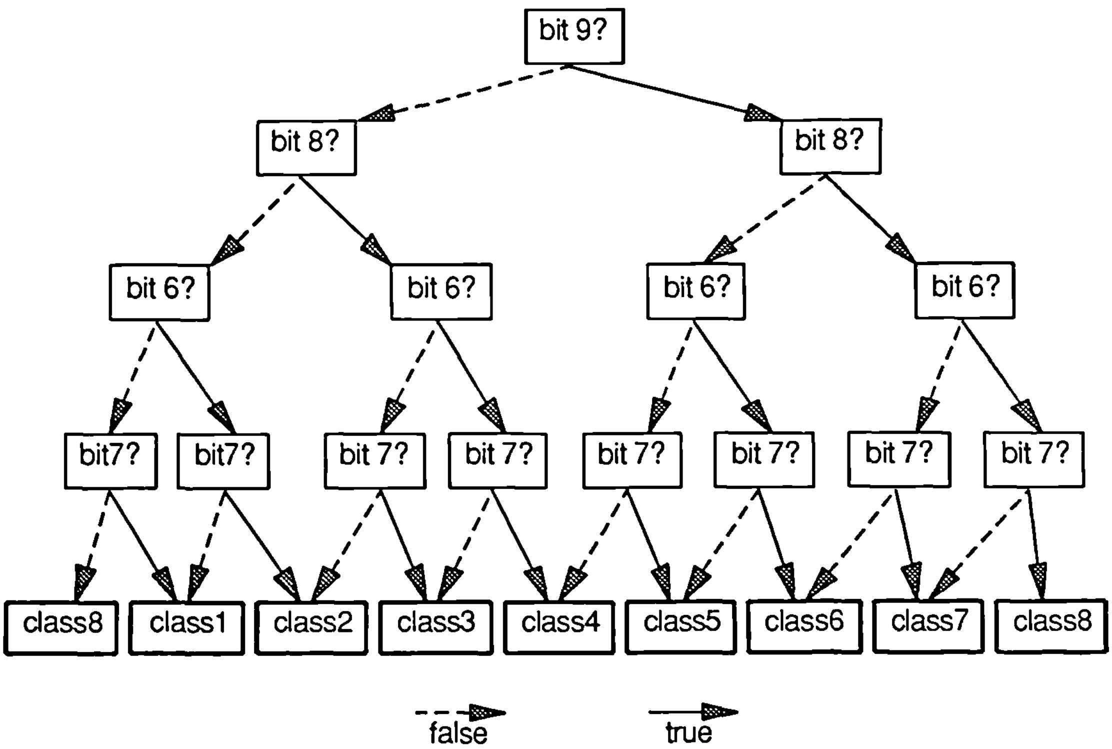
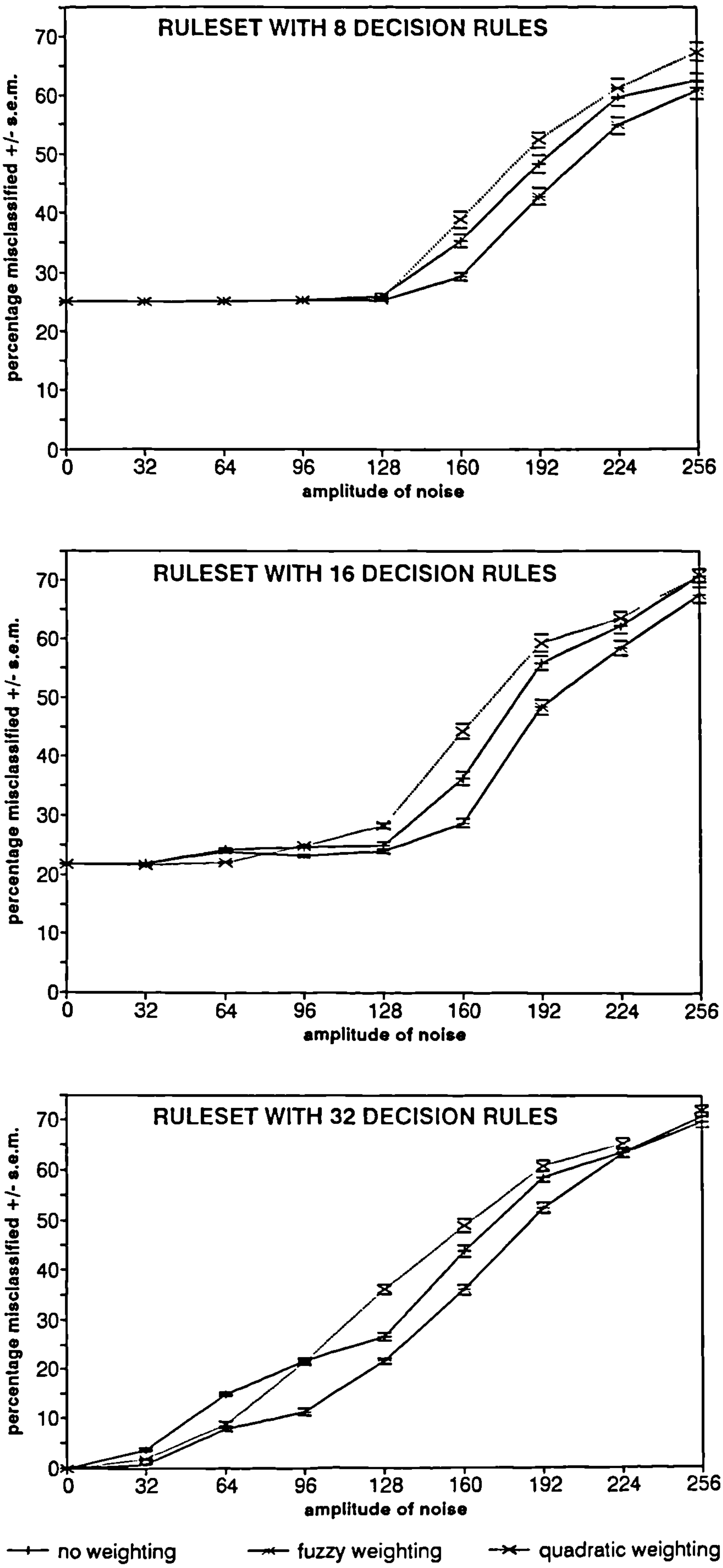
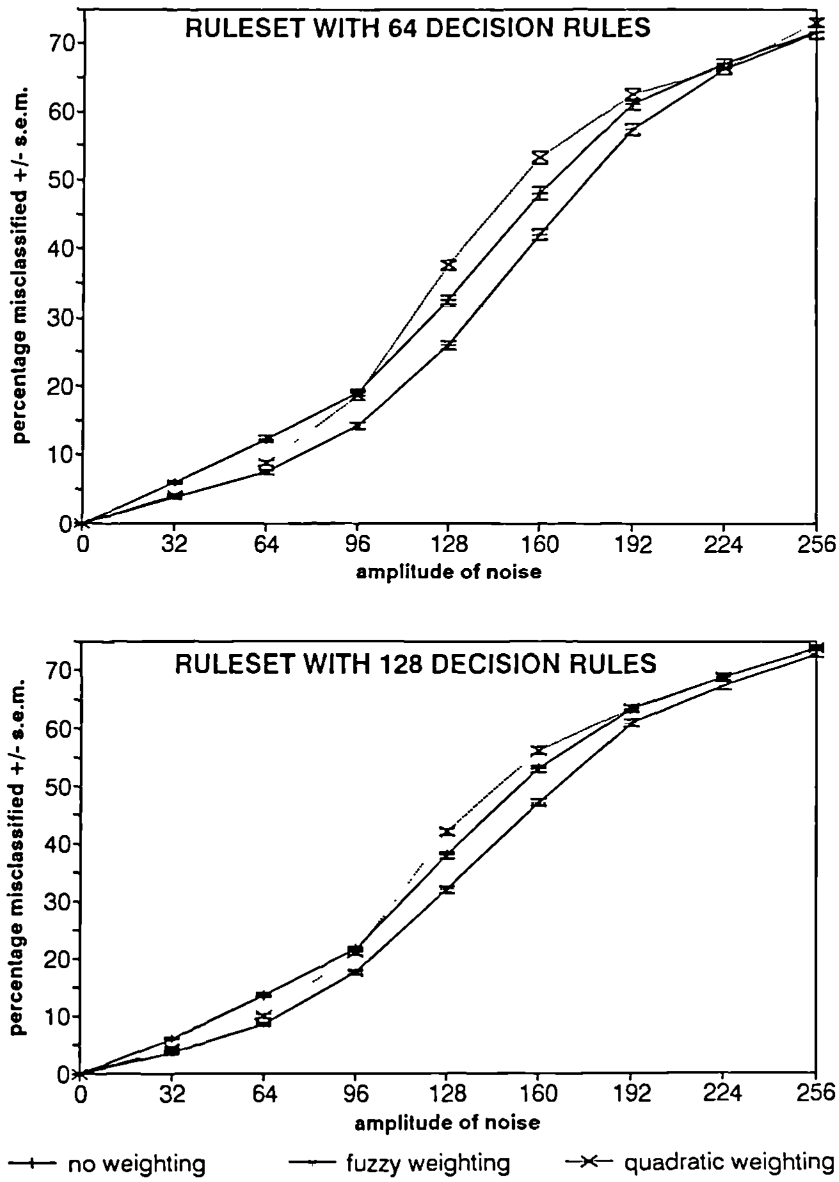


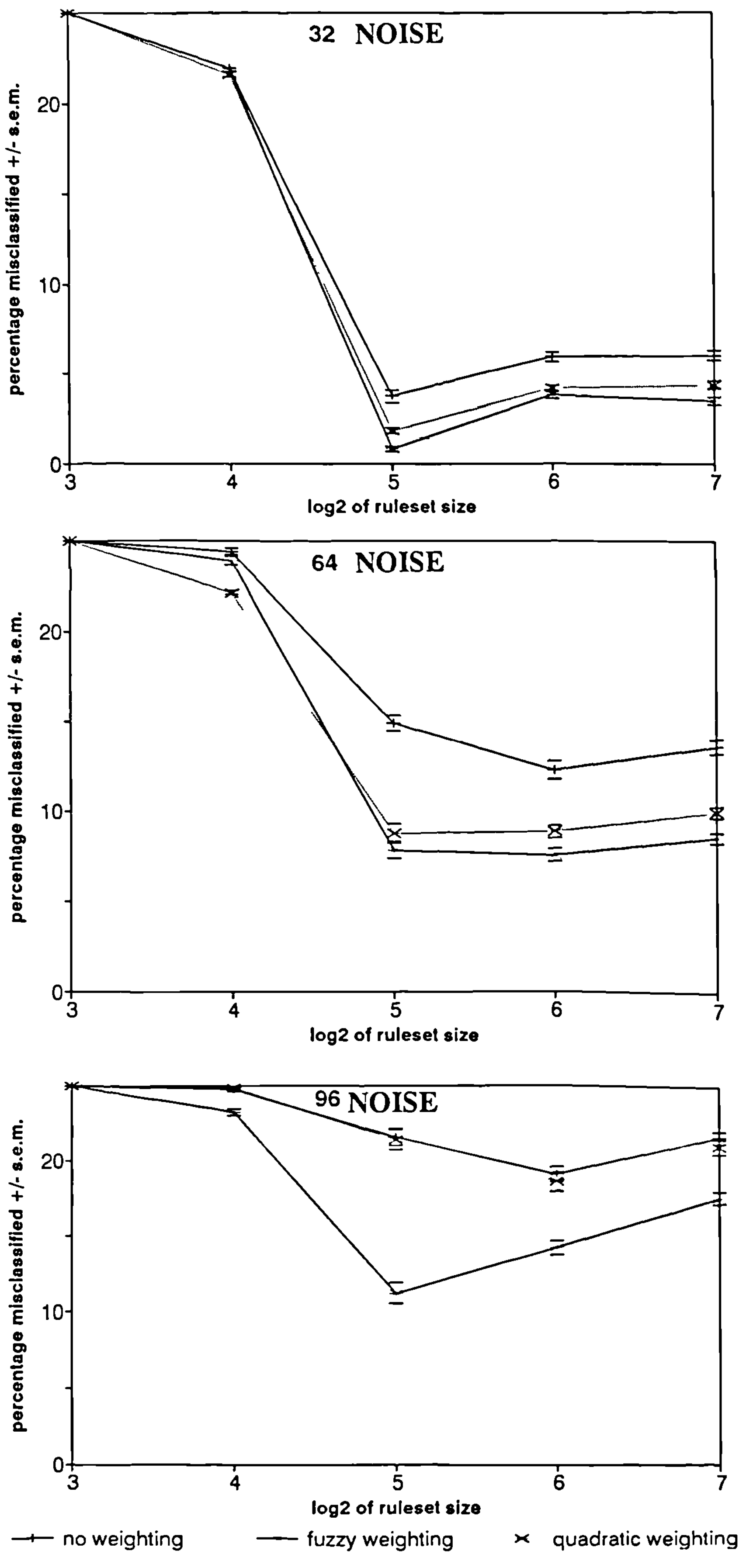
Figure 6.6b *Decision tree for artificial data-set three, 32 offset*



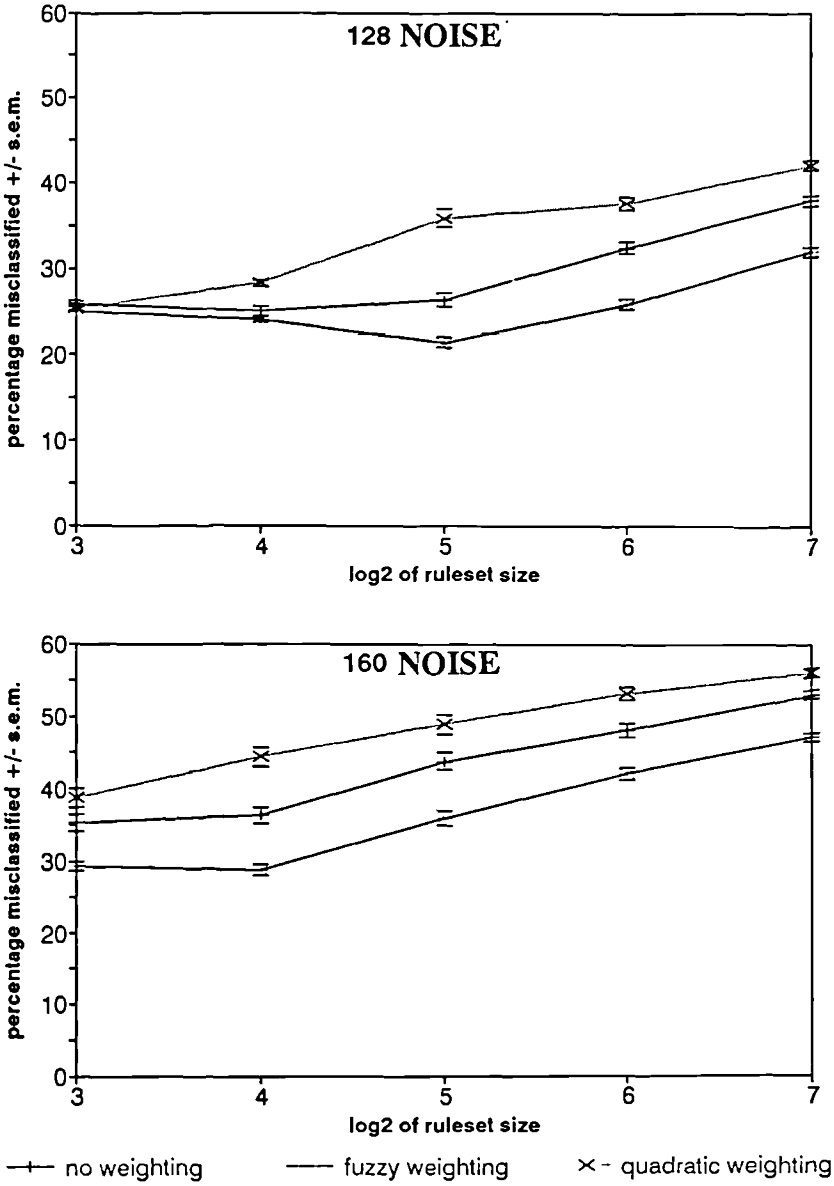
Figures 6.7 a,b,c *Error vs. noise level for contaminated data-sets, bars represent one standard deviation of the mean.*



Figures 6.7 d,e *Error vs. noise level for contaminated data-sets. Horizontal bars represent one standard deviation of the mean.*



Figures 6.8 a,b,c *Error vs rule-set size for contaminated data-set. Horizontal bars represent one standard deviation of the mean.*



Figures 6.8 d,e *Error vs rule-set size for contaminated data-set. Horizontal bars represent one standard deviation of the mean.*

amplitude of noise	number of rules				
	8	16	32	64	128
32	F=N F=Q Q=N	F=N Q>>F Q>>N	F>>N F>>Q Q>>N	F>>N F>Q Q>>N	F>>N F>>Q Q>>N
64	F=N F=Q Q=N	F>>N Q>>F Q>>N	F>>N F>Q Q>>N	F>>N F>>Q Q>>N	F>>N F>>Q Q>>N
96	F=N F=Q Q=N	F>>N F>>Q N>Q	F>>N F>>Q Q>N	F>>N F>>Q Q>N	F>>N F>>Q Q>N
128	F>Q F>>N Q>N	F>N F>>Q N>>Q	F>>N F>>Q N>>Q	F>>N F>>Q N>>Q	F>>N F>>Q N>>Q
160	F>>N F>>Q N>Q	F>>N F>>Q N>>Q	F>>N F>>Q N>>Q	F>>N F>>Q N>>Q	F>>N F>>Q N>>Q
192	F>>N F>>Q N>Q	F>>N F>>Q N>Q	F>>N F>>Q N>Q	F>>N F>>Q N>>Q	F>>N F>>Q N>Q
224	F>>N F>>Q N>Q	F>N F>>Q N>Q	F>N F>Q N>Q	F>N F>Q Q>N	F>N F>Q N>Q
256	F>>Q F>N N>>Q	F>N F>Q N>Q	F>N F>Q N>Q	F>N F>Q N>Q	F>N F>Q N>Q

KEY
F...Fuzzy weighting
Q...Quadratic weighting
N...No weighting
=...is equal to
>...is better than
>>...is significantly (3%) better than

Table 6.4 *Table of performance of different weighting strategies for the noisy artificial rule-set. `Better' performance implies a lower error rate. The significance level is 3%.*

Table 6.4 compares the performance of the different weighting strategies for each noise/rule-set size combination. The significance levels were obtained by calculating the test statistic:

$$T = \frac{(x_1 - x_2)}{\sqrt{(s_1^2/n_1 + s_2^2/n_2)}}$$

Where x_1, x_2 are the sample means for two different weighting strategies.
s_1, s_2 are the sample standard deviations.
n_1, n_2 are the sample sizes (50 in this case).

If T was larger than 2.326, x_1 was greater than x_2 with a certainty of 99 per cent (single tailed test). This is valid (i.e. the sample standard deviation is a good estimate of the population standard deviation) because n_1 and n_2 are large (see Petrie [1987]). As three paired comparisons are being made from the same set of data, the significance level is multiplied by three (Wetherill, 1981), i.e. the significance level becomes 3%.

6.3.3. Classification of EMG Data From Normal Gait and Comparison With Neural Networks

Two rule-sets (one small and one larger) were induced from the normal walking data. The small rule-set had 3 rules, the larger had 31 rules. The smaller decision tree is shown in figure 6.9.

The semitendinosus activation predicted by a) the small rule-set, b) the larger rule-set, c) the small neural network and d) the larger neural network, for the slow walking testing set, are plotted with the actual activation level in figures 6.10a to 6.10d. Similar graphs are plotted for the faster testing set in figures 6.11a to 6.11d.

The following comparisons between predicted and measured outputs were made for both decision trees and both neural networks.

a. The difference in the times of measured and reconstructed activations to cross 50% of the maximum value of each peak, at the start (onset) and end (offset) of each activation burst
b. The RMS error between measured and reconstructed activation patterns.

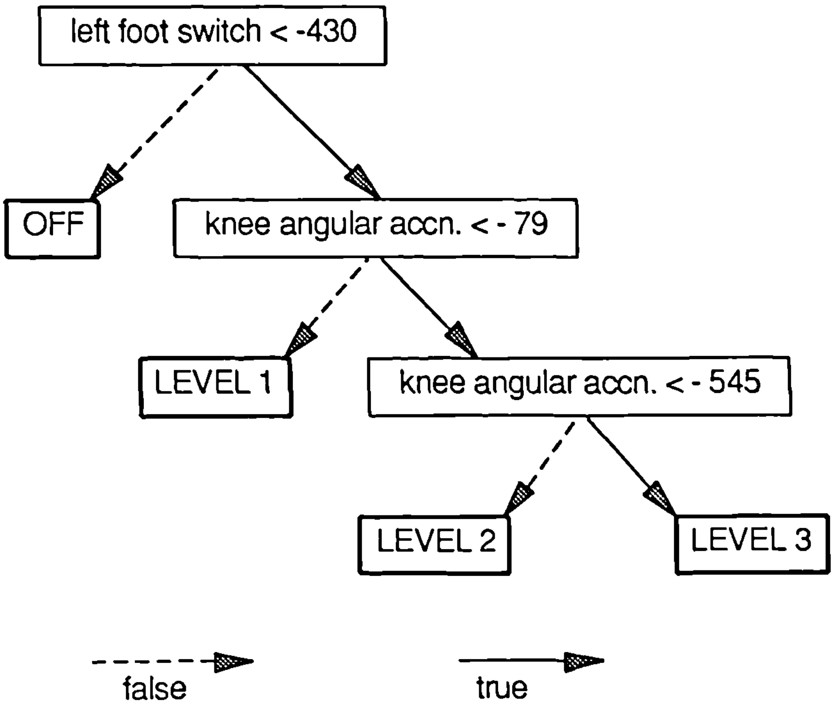
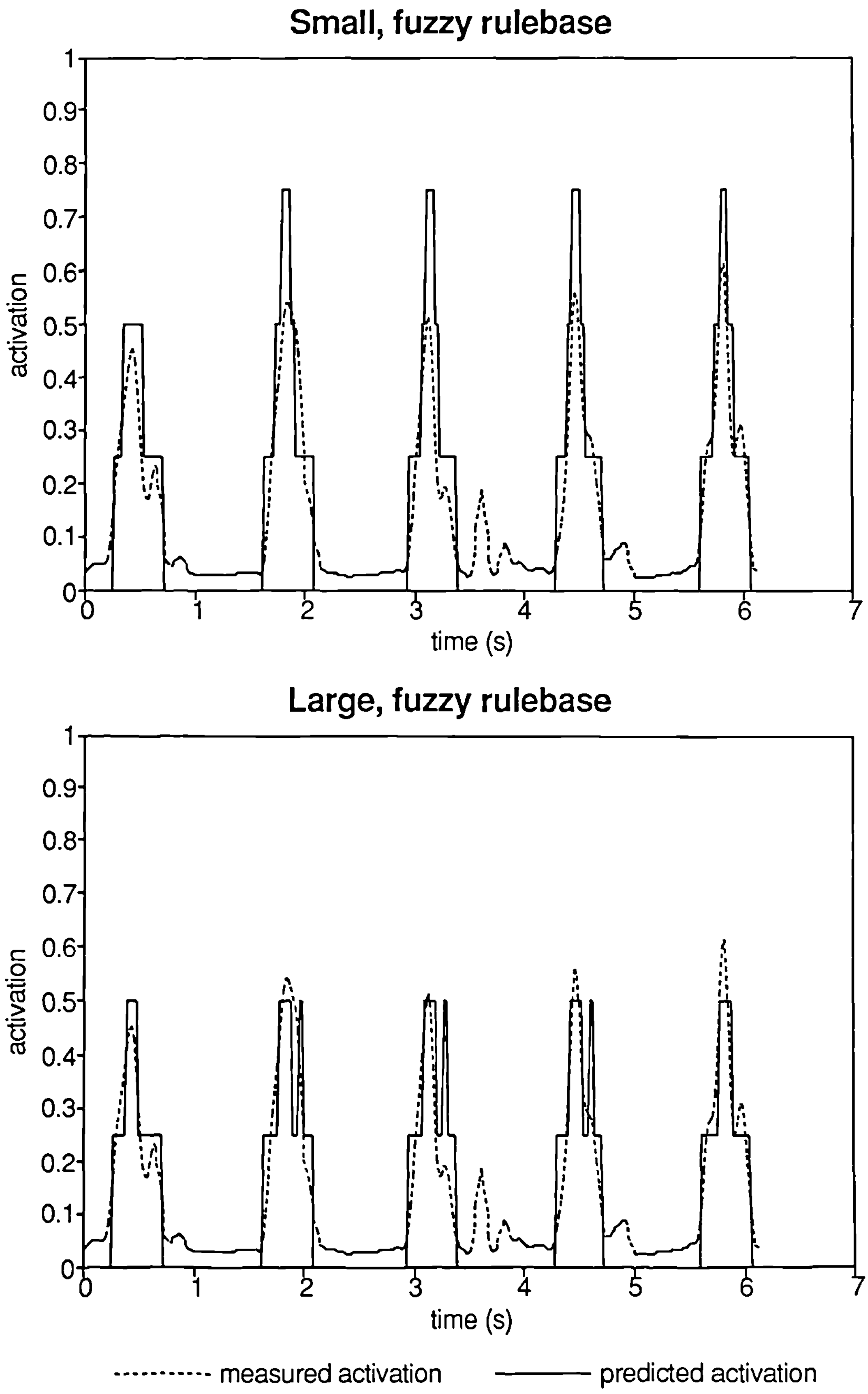
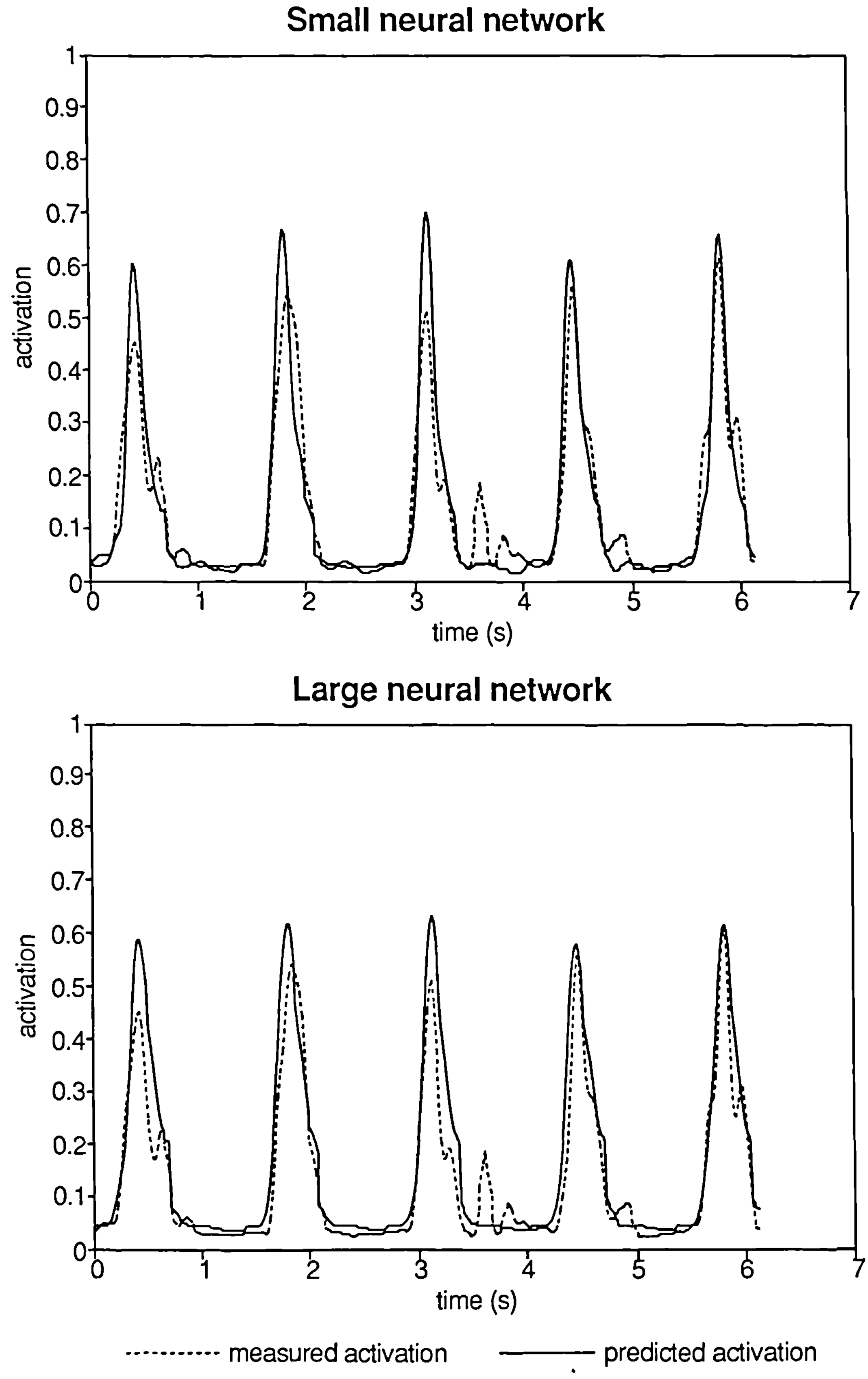


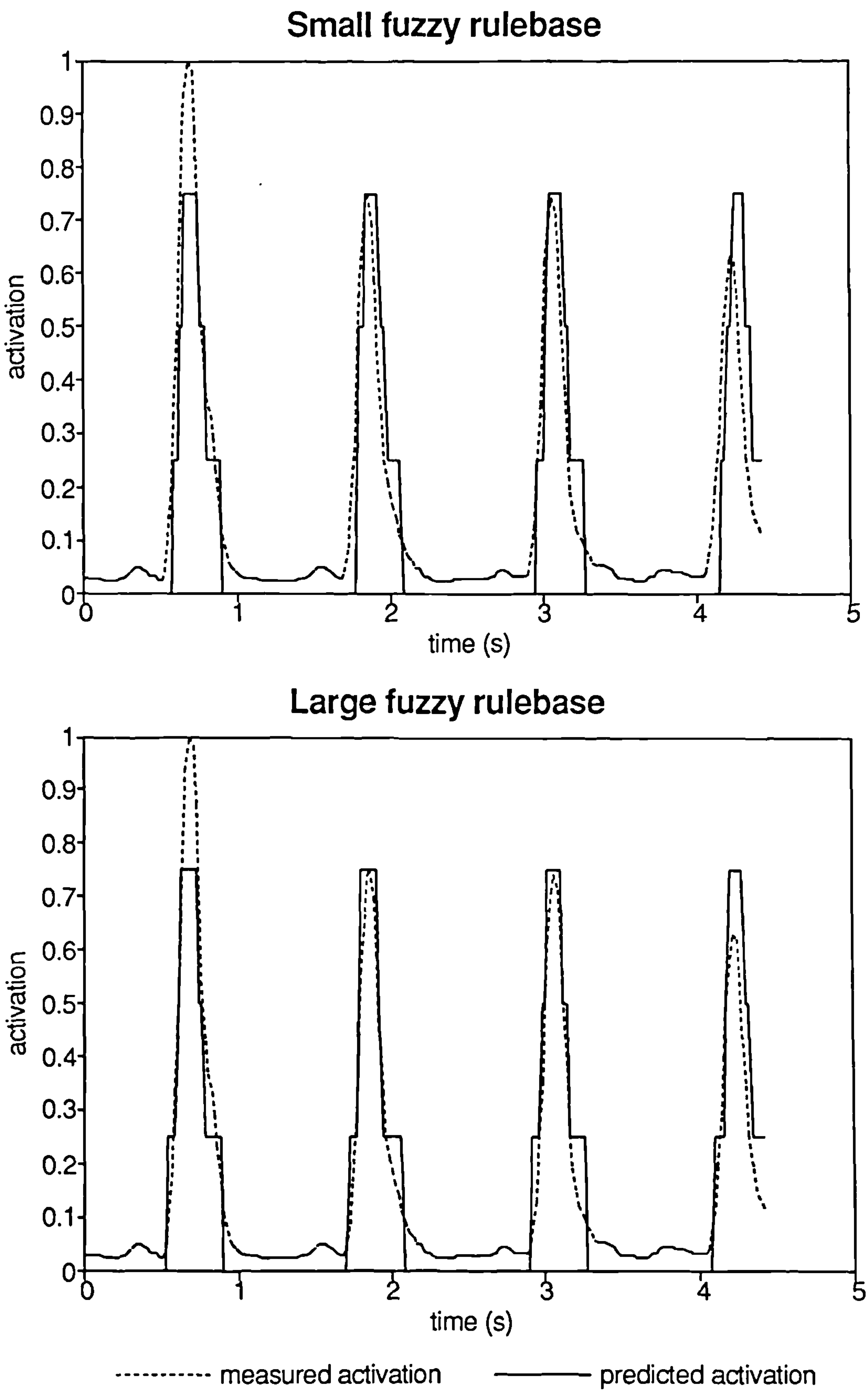
Figure 6.9 *Small decision tree for predicting semitendinosus activation during normal walking - formed using "fuzzy" weighting.*



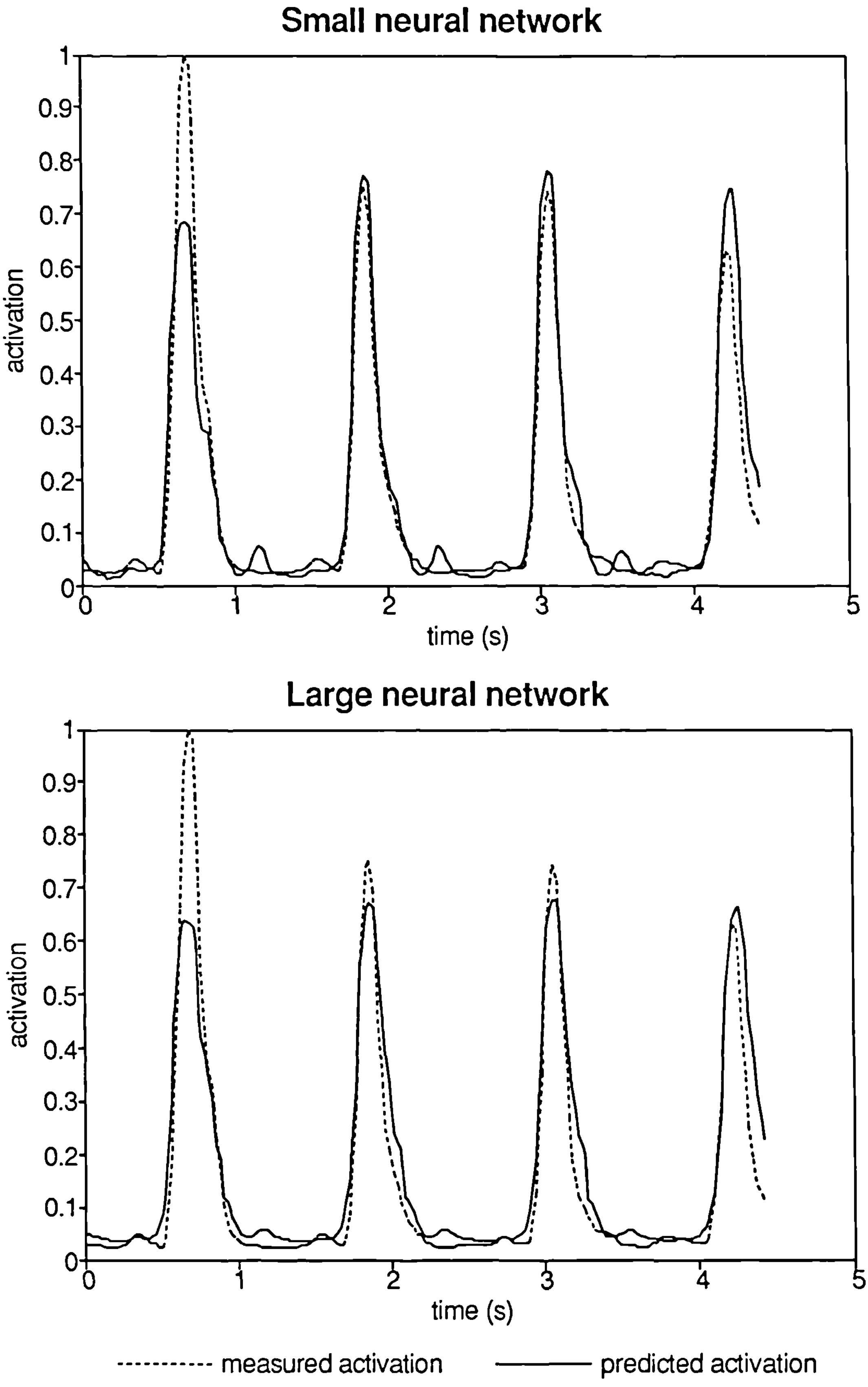
Figures 6.10 a,b *Predicted and measured semitendinosus activation - slow walking*



Figures 6.10 c,d *Predicted and measured semitendinosus activation - slow walking*



Figures 6.11 a,b *Predicted and measured semitendinosus activation - fast walking*



Figures 6.11 c,d *Predicted and measured semitendinosus activation - fast walking*

technique	speed	onset delay			offset delay		
		mean/ms	s.d./ms	number	mean/ms	s.d./ms	number
large fuzzy ruleset	slow	-8.0	16.0	5	4.0	19.6	5
small fuzzy ruleset	slow	-8.0	16.0	5	4.0	19.6	5
small neural network	slow	16.0	15.0	5	4.0	19.6	5
large neural network	slow	-16.0	15.0	5	4.0	19.6	5
large fuzzy ruleset	fast	-15.0	9.0	4	-7.0	25.0	3
small fuzzy ruleset	fast	35.0	17.0	4	0.0	16.0	3
small neural network	fast	5.0	17.0	4	0.0	16.0	3
large neural network	fast	-5.0	17.0	4	47.0	19.0	3

Table 6.5a *Turn-on or turn-off delay of reconstructed burst compared to original burst. Threshold is 10% of maximum value. A negative delay corresponds to an advance.*

technique	speed	number of bursts	integrated error mean %	s.d. %
large fuzzy ruleset	slow	5	4.4	11.9
small fuzzy ruleset	slow	5	20.8	11.6
small neural network	slow	5	5.8	10
large neural network	slow	5	25.5	8.8
large fuzzy ruleset	fast	4	15.8	17.2
small fuzzy ruleset	fast	4	3.7	14.4
small neural network	fast	4	8.7	16
large neural network	fast	4	13.9	16.1

Table 6.5b *Average error of the area under each reconstructed burst compared to the area under the original burst, expressed as a percentage of the area under the original burst. All the reconstructed bursts were too large.*

technique	speed	number of bursts	RMS error mean %	s.d. %
large fuzzy ruleset	slow	5	9.45	1.98
small fuzzy ruleset	slow	5	11.8	1.99
small neural network	slow	5	8.3	1.56
large neural network	slow	5	8.8	1.52
large fuzzy ruleset	fast	4	10.39	1.55
small fuzzy ruleset	fast	4	14.08	2.38
small neural network	fast	4	8.44	3.9
large neural network	fast	4	9.99	3.27

Table 6.5c *Average root-mean-square (RMS) error of each reconstructed burst relative to the original burst, expressed as a percentage of the maximum EMG value.*

c. The average difference in the time integral of each reconstructed and measured activation burst.

The results are presented in tables 6.5a to 6.5c.

6.3.4. Application to Swing-Through Data

6.3.4.1. Optimal attribute sets for training data

The error levels for the best attribute combinations at various rule-set sizes are plotted against the number of attributes used in figure 6.12 for the swing data and in figure 6.13 for the stance data. The same data is tabulated in tables 6.6 and 6.7, together with the sensors that formed each attribute combination. If a number of different attribute combinations achieved the same minimum error rate, only one combination was shown and the number of different combinations achieving the level was given.

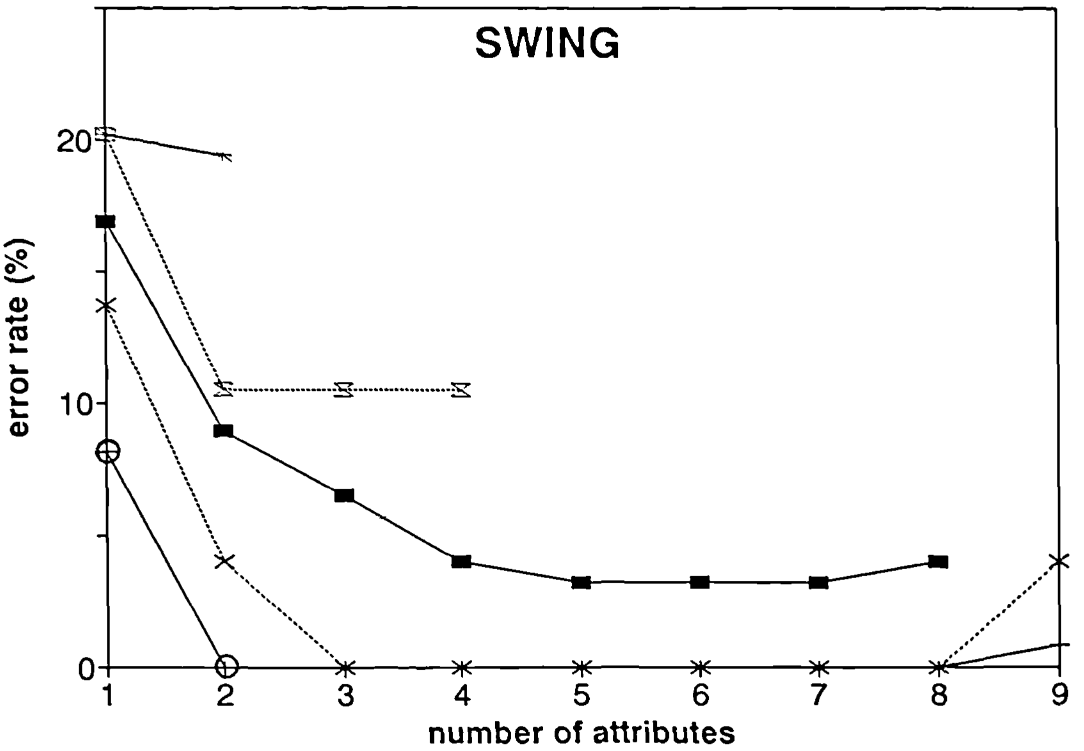
6.3.4.2. Optimal rule-set size and attribute set for testing data

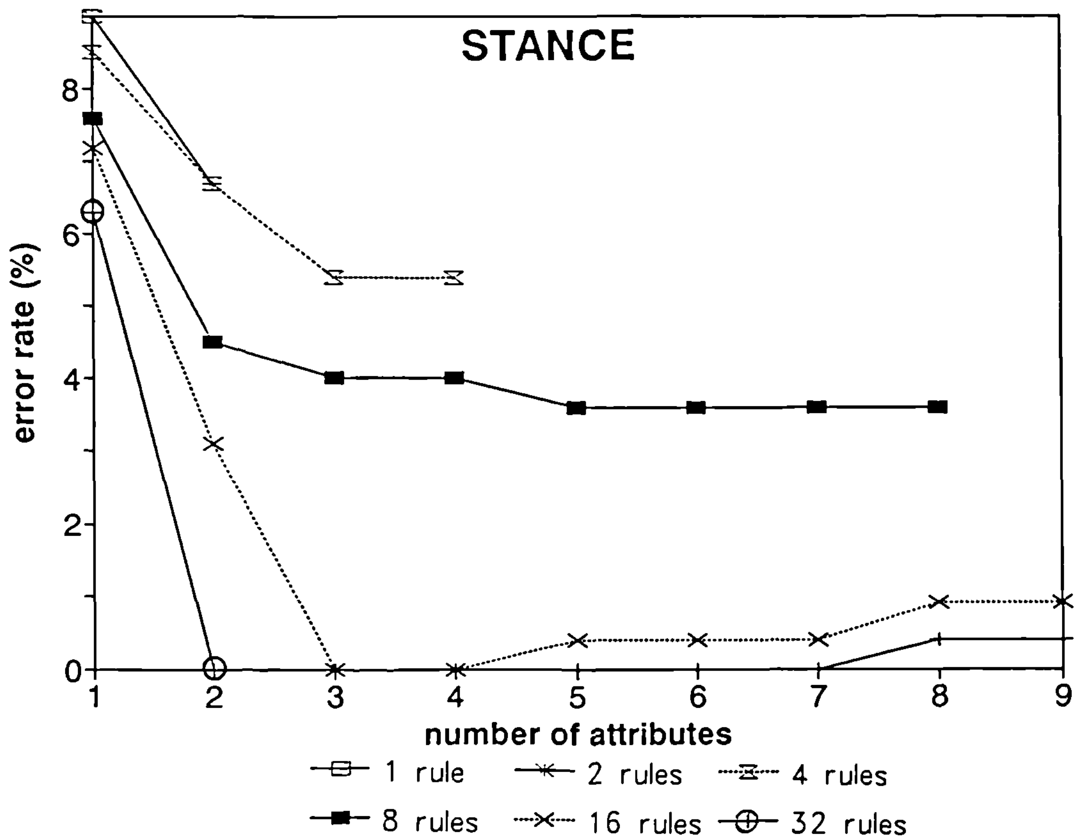
The lowest error rates (on the testing sets) of the best attribute combinations are plotted against the number of attributes in figure 6.14 for the swing data-set and in figure 6.15 for the stance data, for various rule-set sizes. The best combinations, together with their performances, are presented in tables 6.8 and 6.9.

The error rates achieved on training and testing sets are plotted against rule-set size for all single attributes, and the best attribute combinations, in figures 6.16a to 6.16i for the swing data, and figures 6.17a to 6.17j for the stance data.

6.3.4.3. Sample rule-sets

The rule-sets with the lowest error rates are displayed in figures 6.18a to 6.18c for the swing data, and figures 6.19a to 6.19e for the stance data. One run was excluded from the training set and was used as testing data. The induced rules





Figures 6.12, 6.13 *Error rate vs. number of attributes for various rule-set sizes on TRAINING SET.*

initiation of SWING						
number of attributes	number of rules					
	1	2	4	8	16	32
1	20.2 (1) d	20.2 (1) d	20.2 (1) d	16.9 (1) d	13.7 (2) d	8.1 (1) d
2		19.4 (1) ad	10.5 (1) cd	8.9 (1) gd	4.0 (1) cd	0.0 (4) cd
3			10.5 (5) bcd	6.5 (3) acd	0.0 (1) cdj	0.0 (29) acg
4			10.5 (11) bcgd	4.0 (6) acdf	0.0 (8) acgj	0.0 (68) abcg
5				3.2 (5) acdfk	0.0 (16) abcgj	0.0 (82) abcdg
6				3.2 (2) abcdfk	0.0 (16) abcgjk	0.0 (58) abcdfg
7				3.2 (5) abcdefk	0.0 (8) abcegjk	0.0 (23) abcdfgj
8				4.0 (3) abcdefjk	0.0 (2) abcdefjk	0.0 (4) abcdefgj
9					4.0 (1) abcdefgjk	0.8 (1) abcdefgjk

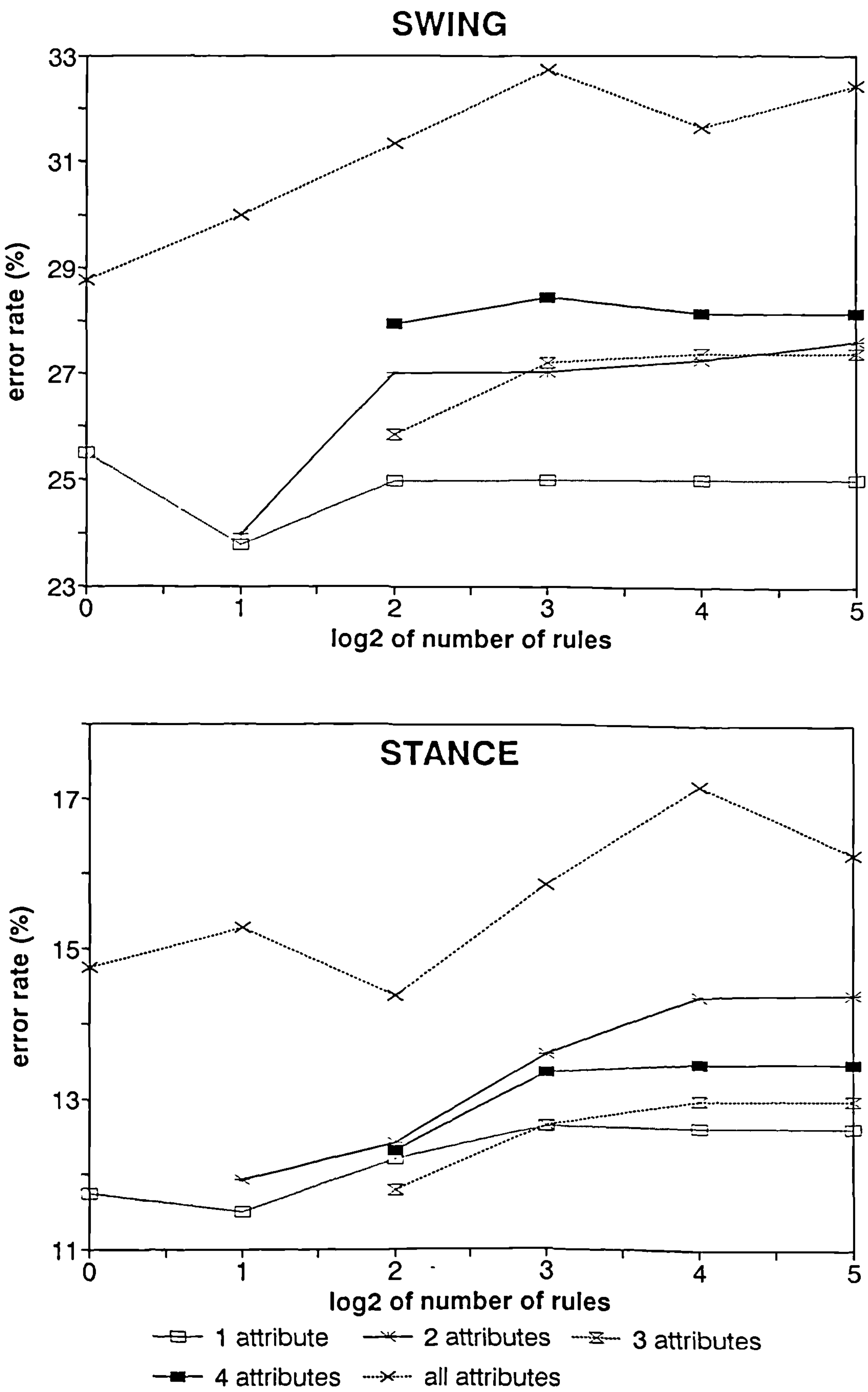
KEY	
a. toe switch	g. shoulder elevation
b. heel switch	h. centre of pressure insole *
c. torso inclination sensor	i. ankle moment sensor *
d. crutch inclination sensor	j. ankle axial acceleration
e. crutch axial force sensor	k. ankle tangential acceleration
f. crutch infra-red beam	* not used

Table 6.6 *Training set errors for the initiation of swing. Figures in parentheses are the number of alternative combinations achieving the same error rate.*

number of attributes	number of rules: 1	2	4	8	16	32
	initiation of STANCE					
1	9.0 (1) e	9.0 (1) e	8.5 (1) e	7.6 (1) e	7.2 (1) e	6.3 (1) d
2		6.7 (2) ce	6.7 (2) ce	4.5 (2) ce	3.1 (3) ce	0.0 (3) ce
3			5.4 (5) cej	4.0 (4) efj	0.0 (4) cej	0.0 (19) ace
4			5.4 (9) acej	4.0 (7) aefj	0.0 (3) acej	0.0 (40) abcg
5				3.6 (11) cdefk	0.4 (3) abcej	0.0 (40) abceg
6				3.6 (11) acdefk	0.4 (10) acdefk	0.0 (18) abcdgj
7				3.6 (9) abcdefk	0.4 (2) abcdefj	0.0 (4) abcdgjk
8				3.6 (5) abcdefgk	0.9 (4) abcdefgj	0.4 (8) abcdfgjk
9					0.9 (1) abcdefgjk	0.4 (1) abcdefgjk

KEY	
a. toe switch	g. shoulder elevation
b. heel switch	h. centre of pressure insole *
c. torso inclination sensor	i. ankle moment sensor *
d. crutch inclination sensor	j. ankle axial acceleration
e. crutch axial force sensor	k. ankle tangential acceleration
f. crutch infra-red beam	* not used

Table 6.7 *Training set errors for the initiation of stance. Figures in parentheses are the number of alternative combinations achieving the same error rate.*



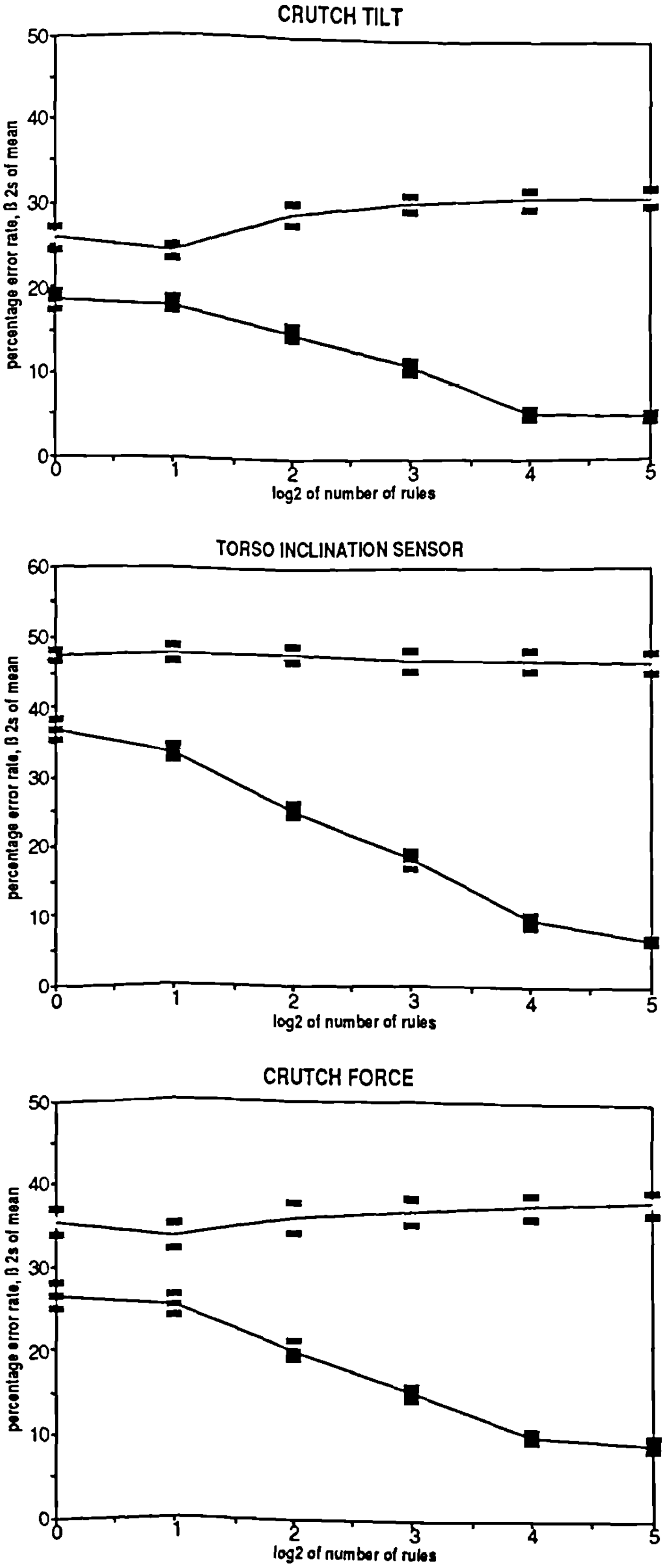
Figures 6.14, 6.15 *Error rate vs. rule-set size for various numbers of attributes on TESTING SET.*

number of rules	SWING number of attributes 1	2	3	4	9
0	25.5 f				
1	23.7 d	23.97 d,j			
2	24.98 f	27.02 a,d	25.84 c,d,j	27.96 c,d,e,k	
3	25 f	27.04 a,d	27.22 c,d,j	28.47 c,d,e,f	32.74 all
4	25 f	27.26 a,d	27.39 c,d,j	28.14 c,d,e,f	31.64 all
5	25 f	27.71 a,d	27.39 c,d,j	28.14 c,d,e,f	32.41 all

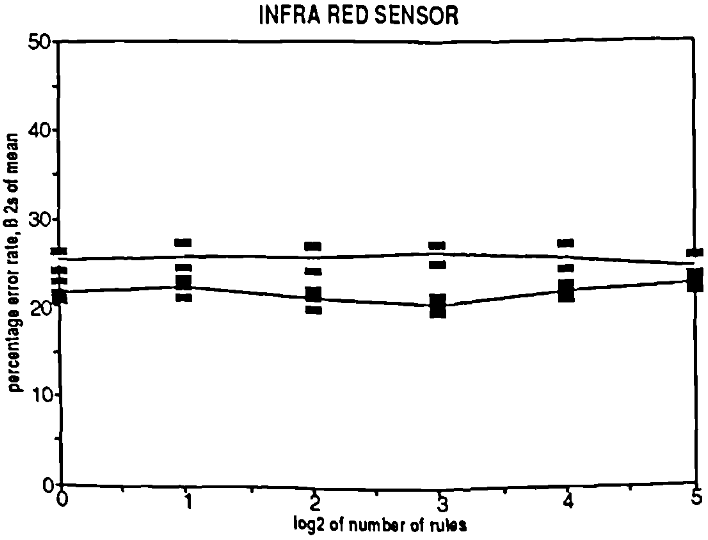
number of rules	STANCE number of attributes 1	2	3	4	9
0	11.74 e				
1	11.49 e	12.34 e,g			
2	12.19 e	12.41 b,e	11.77 c,e,j	12.31 c,e,j,k	
3	12.63 b	13.6 b,e	12.64 c,e,j	13.36 c,d,e,j	15.85 all
4	12.63 b	14.4 b,e	13.01 c,e,j	13.5 c,d,e,j	17.19 all
5	12.63 b	14.42 b,e	13.01 c,e,j	13.5 c,d,e,j	16.28 all

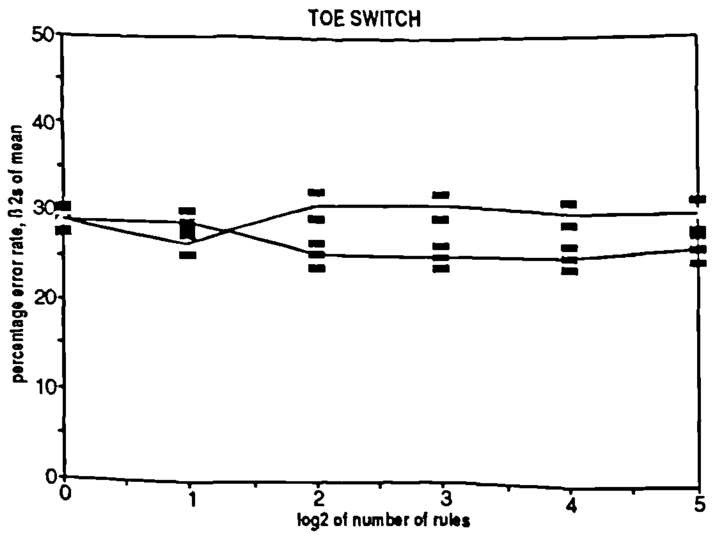
KEY	
a. toe switch	g. shoulder elevation
b. heel switch	h. centre of pressure insole *
c. torso inclination sensor	i. ankle moment sensor *
d. crutch inclination sensor	j. ankle axial acceleration
e. crutch axial force sensor	k. ankle tangential acceleration
f. crutch infra-red beam	* not used

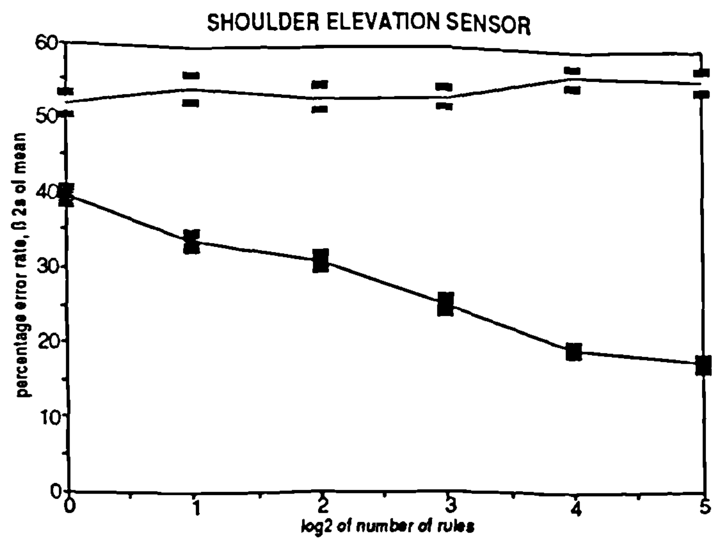
Tables 6.8 and 6.9 *The lowest testing set error for each rule-set size and number of attributes; the combination of sensors achieving this performance is shown in each case.*



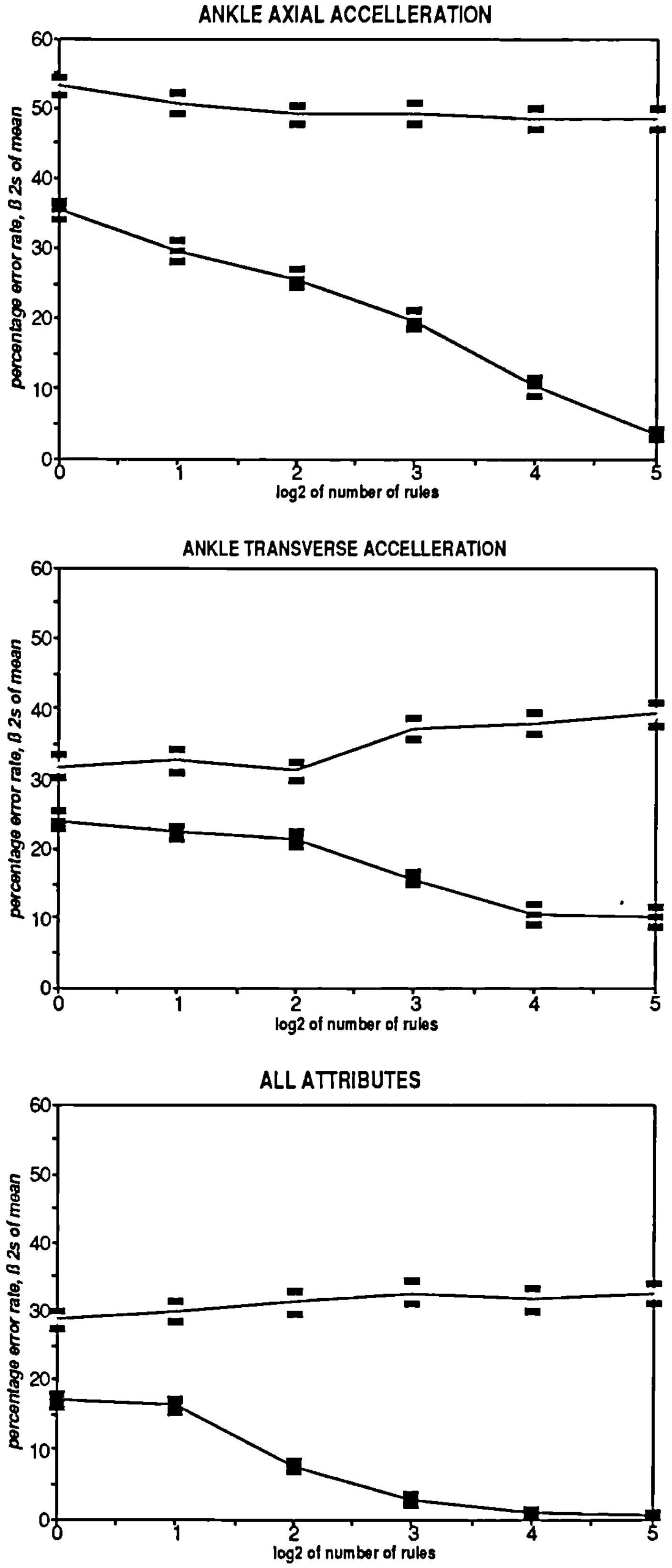
Figures 6.16 a,b,c *Error rates vs. rule-set size on training (lower trace) and testing sets for the initiation of SWING.*





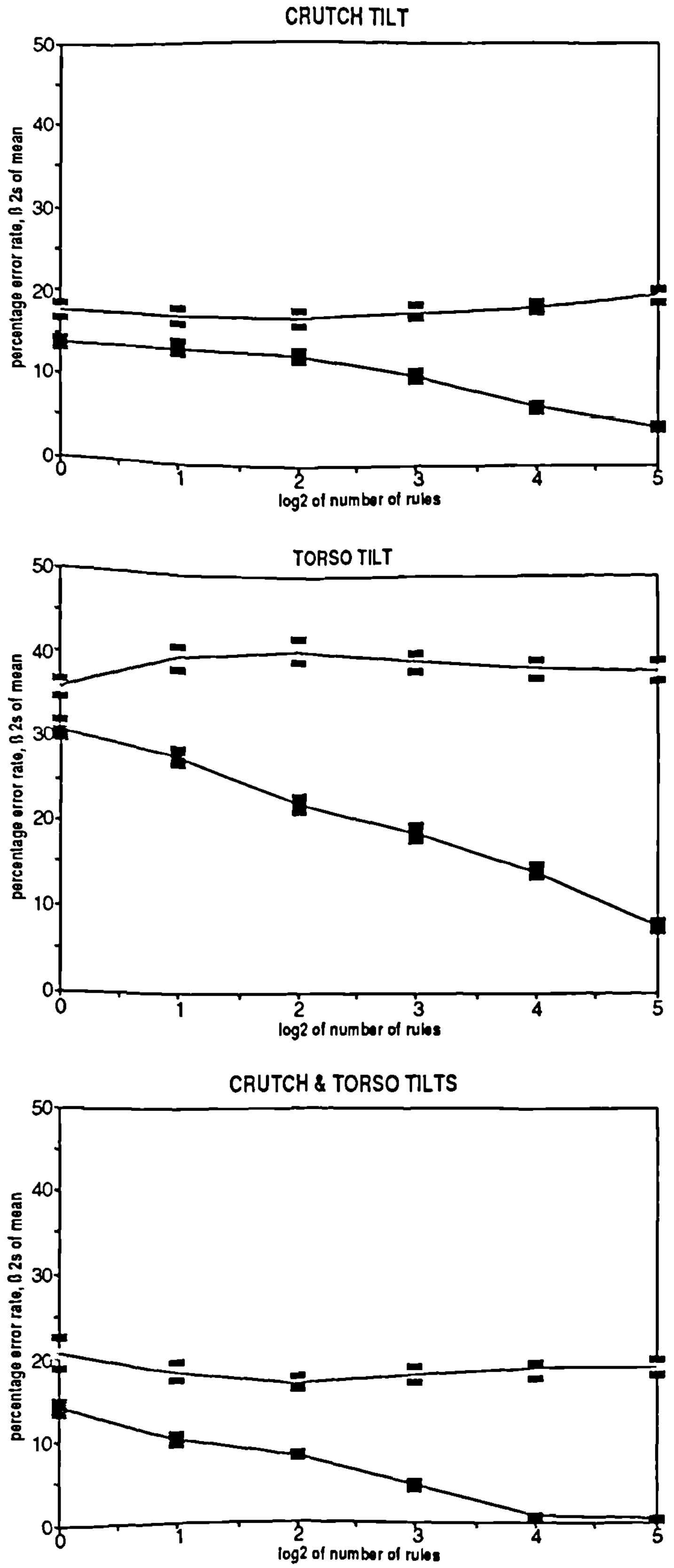


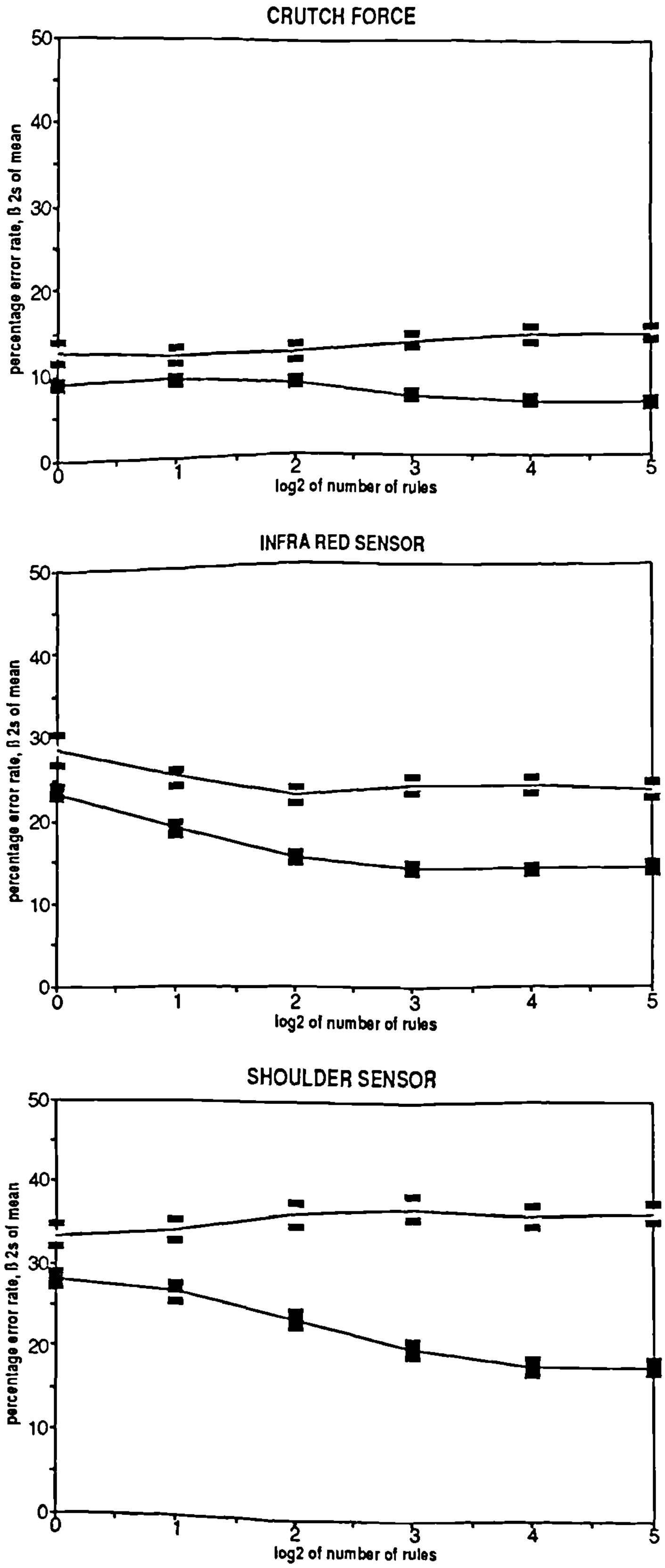
Figures 6.16 d,e,f, *Error rates vs. rule-set size on training (lower trace) and testing sets for the initiation of SWING.*



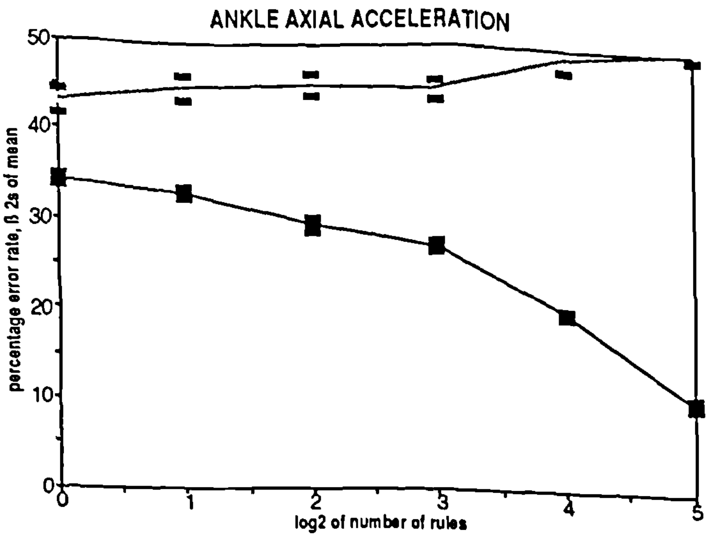
Figures 6.16 g,h,i *Error rates vs. rule-set size on training (lower trace) and testing sets for the initiation of SWING.*

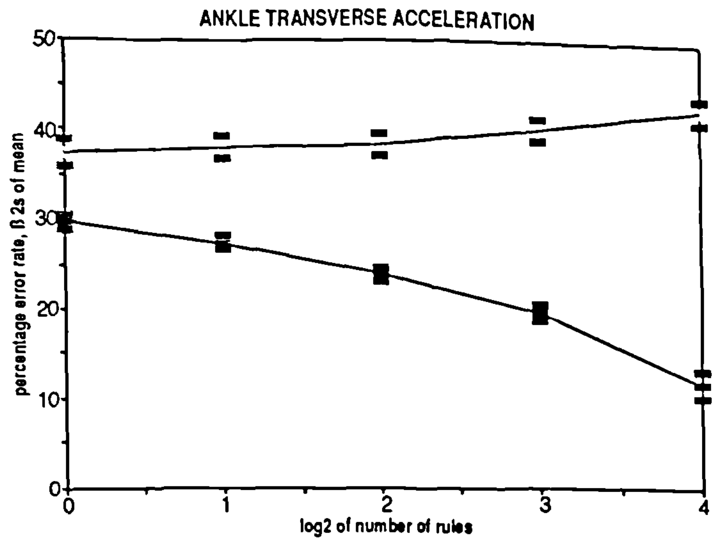
Figures 6.17 a,b,c *Error rates vs. rule-set size on training (lower trace) and testing sets for the initiation of STANCE.*

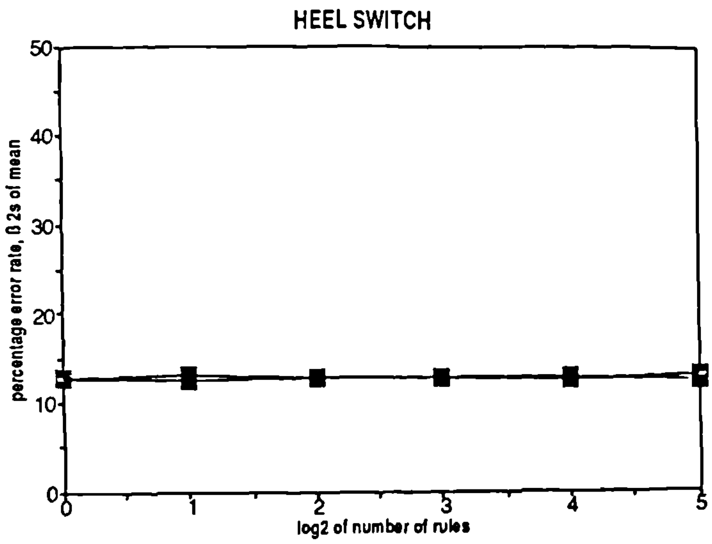




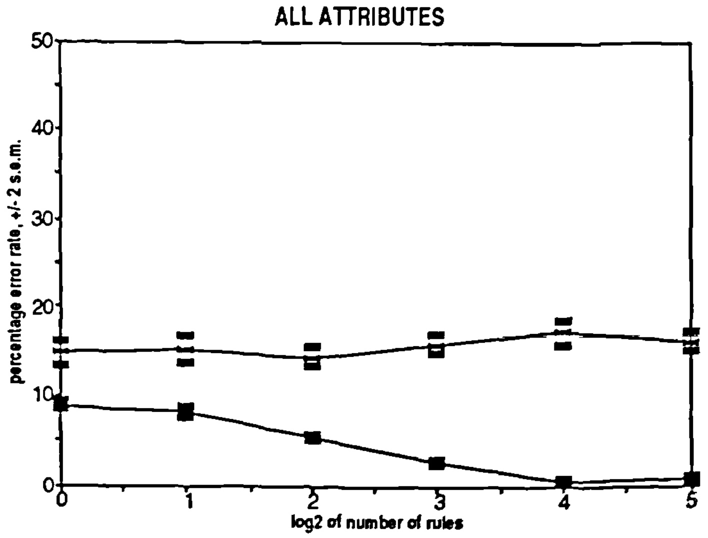
Figures 6.17 d,e,f *Error rates vs. rule-set size on training (lower trace) and testing sets for the initiation of STANCE.*







Figures 6.17 g,h,i *Error rates vs. rule-set size on training (lower trace) and testing sets for the initiation of STANCE.*



Figures 6.17 j *Error rates vs. rule-set size on training (lower trace) and testing sets for the initiation of STANCE.*

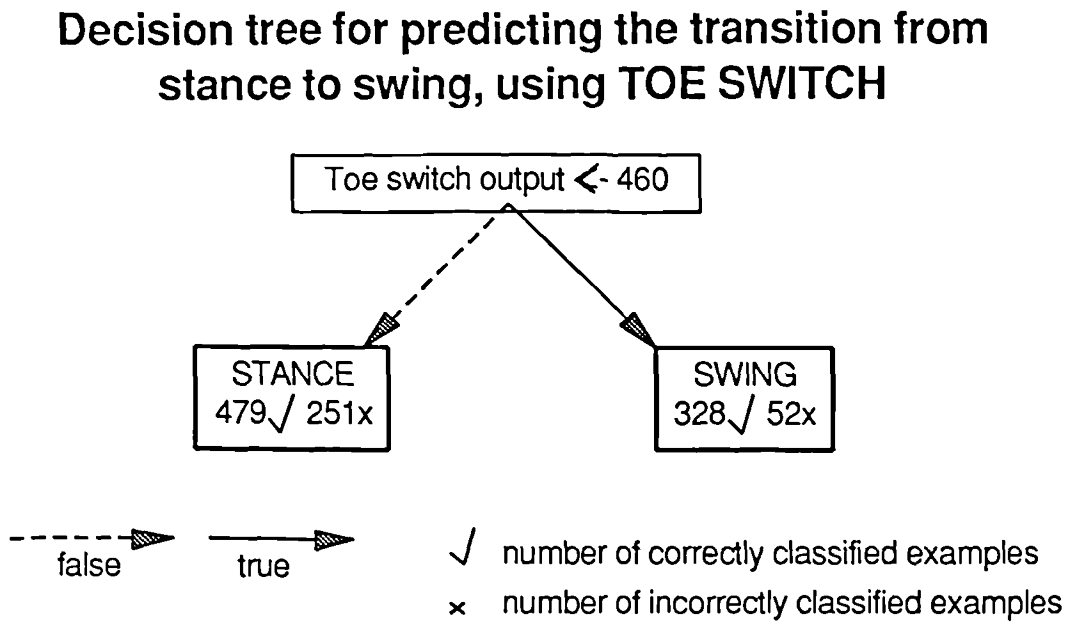


Figure 6.18 a

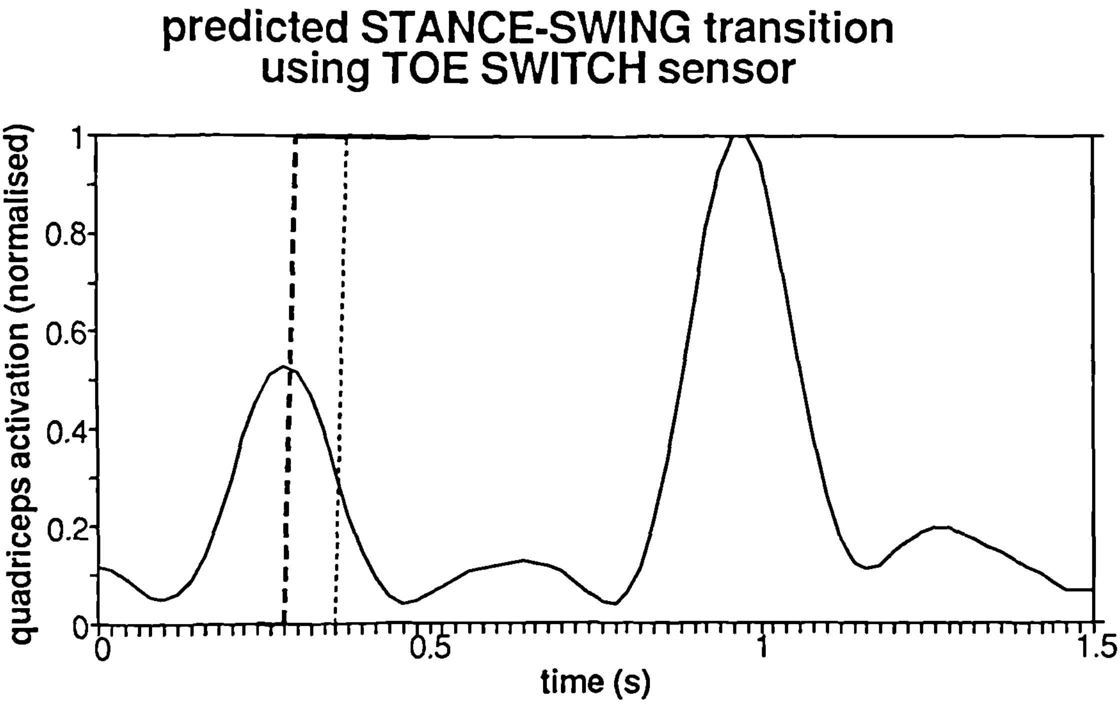
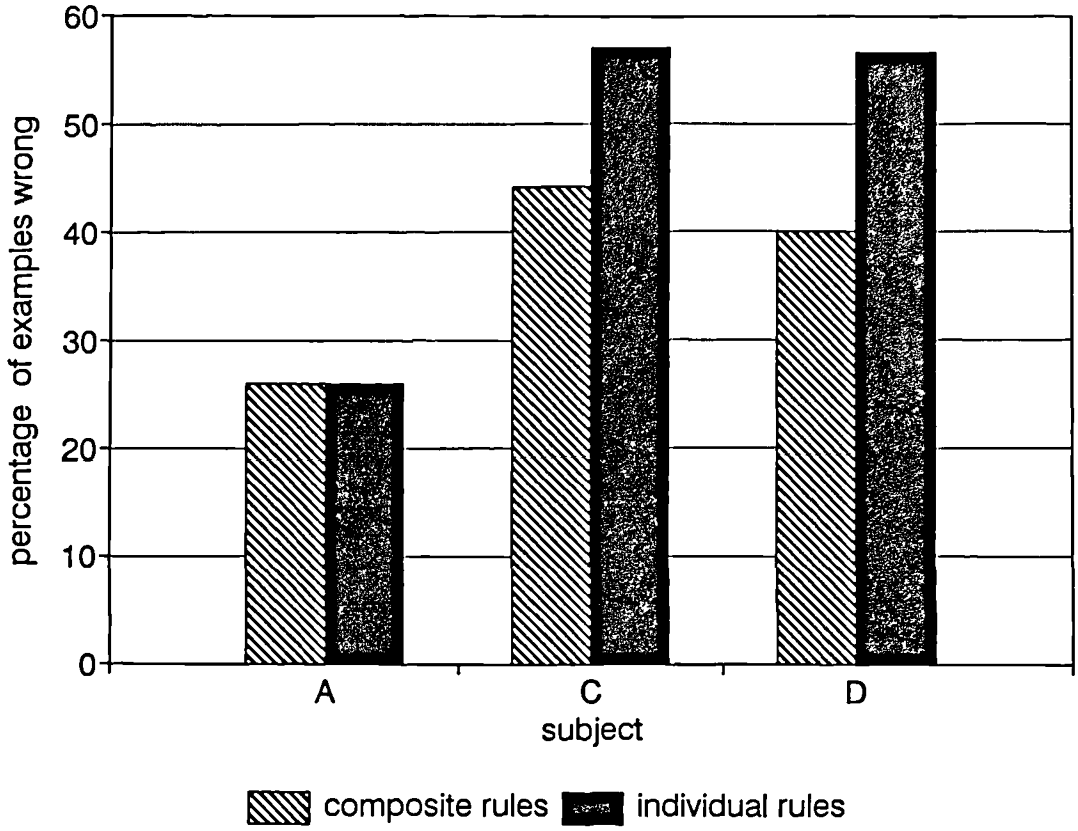
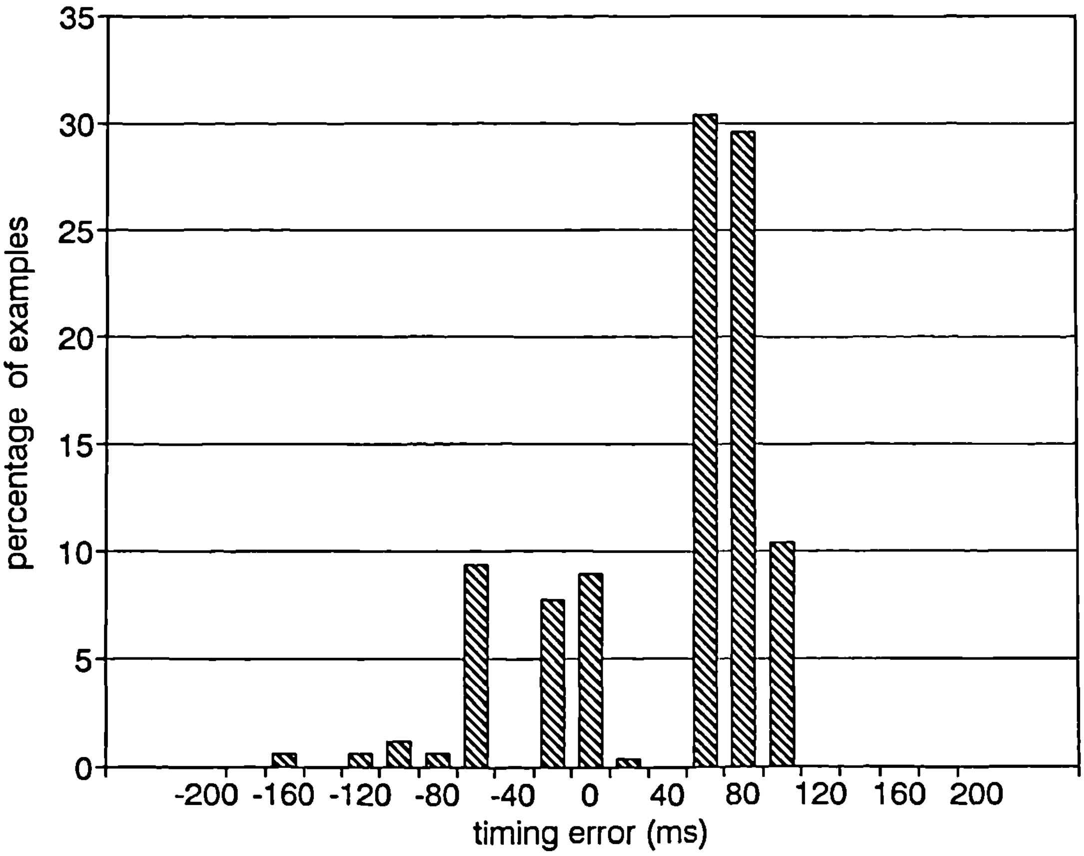


Figure 6.20 a *(Time is since the start of collection)*





Figures 6.22a and 6.24a *Generality of rules and spread of timing error*

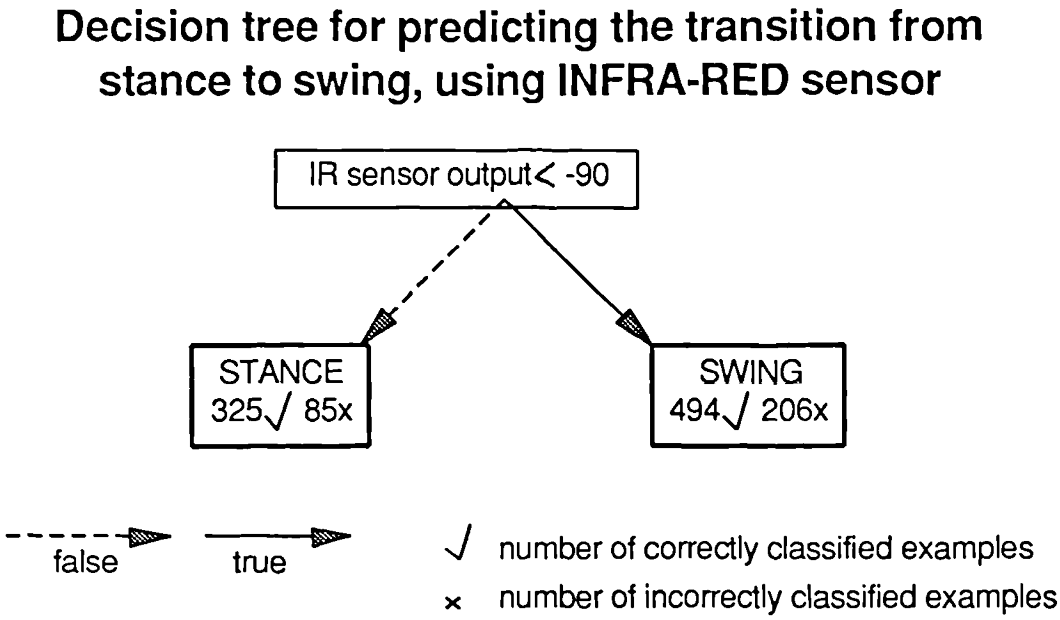


Figure 6.18 b

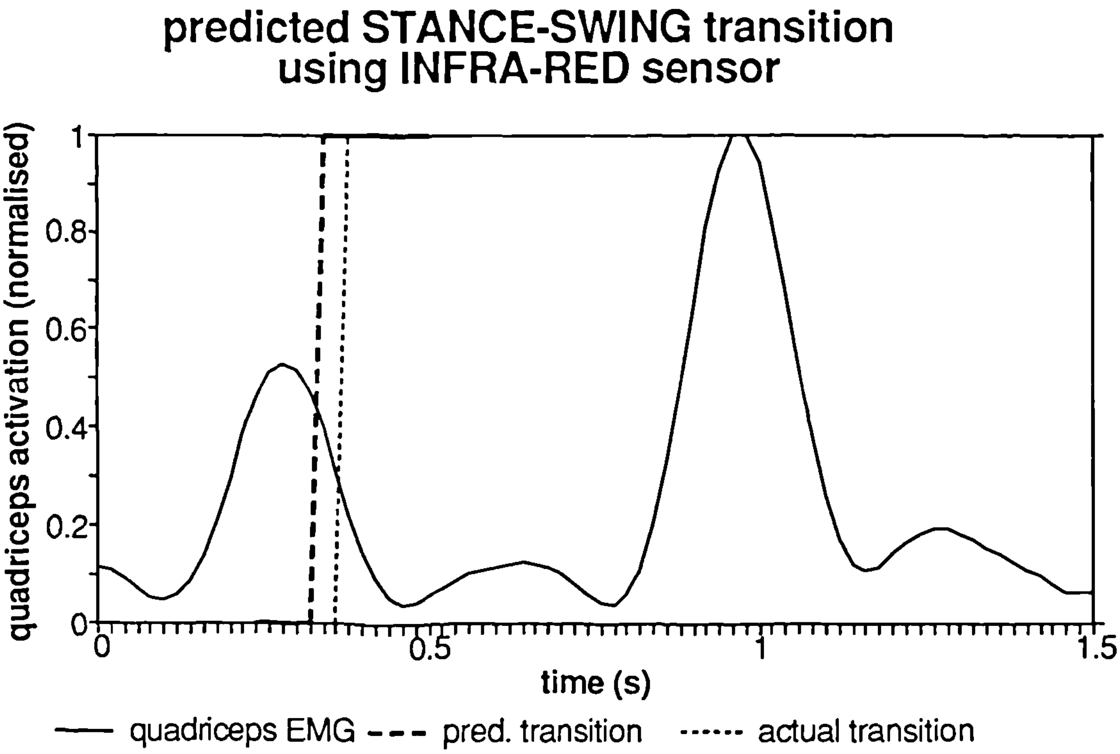
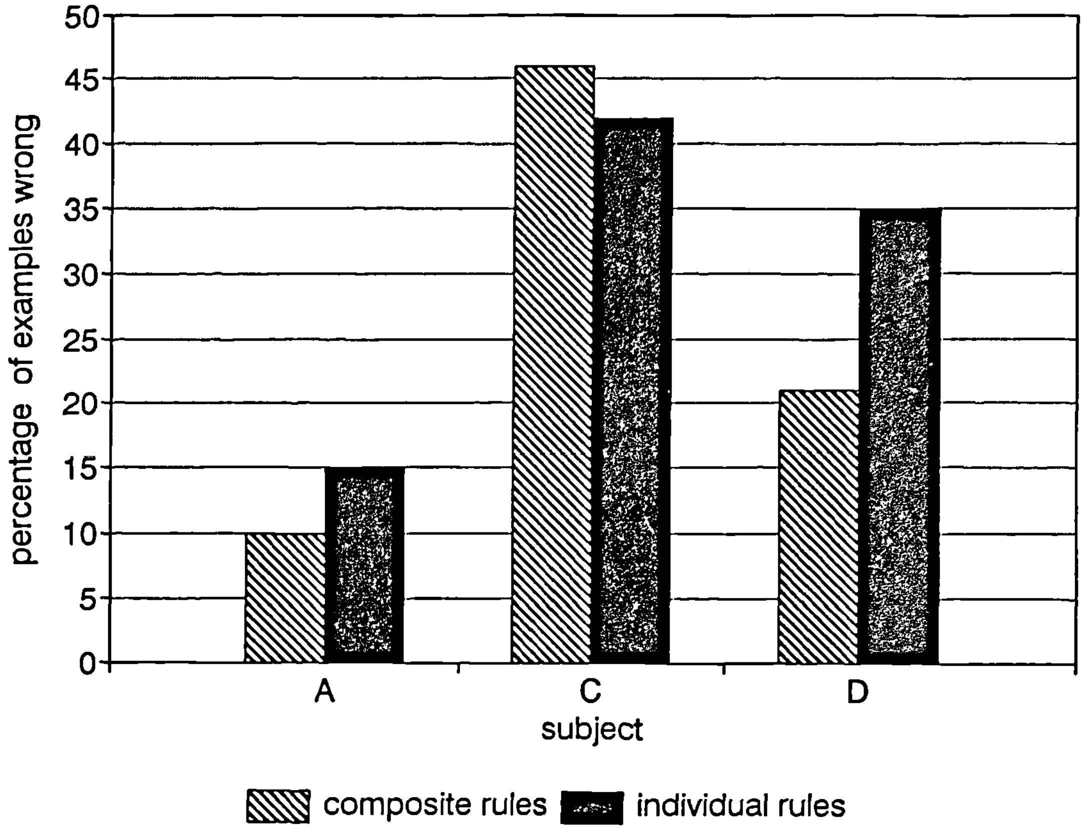
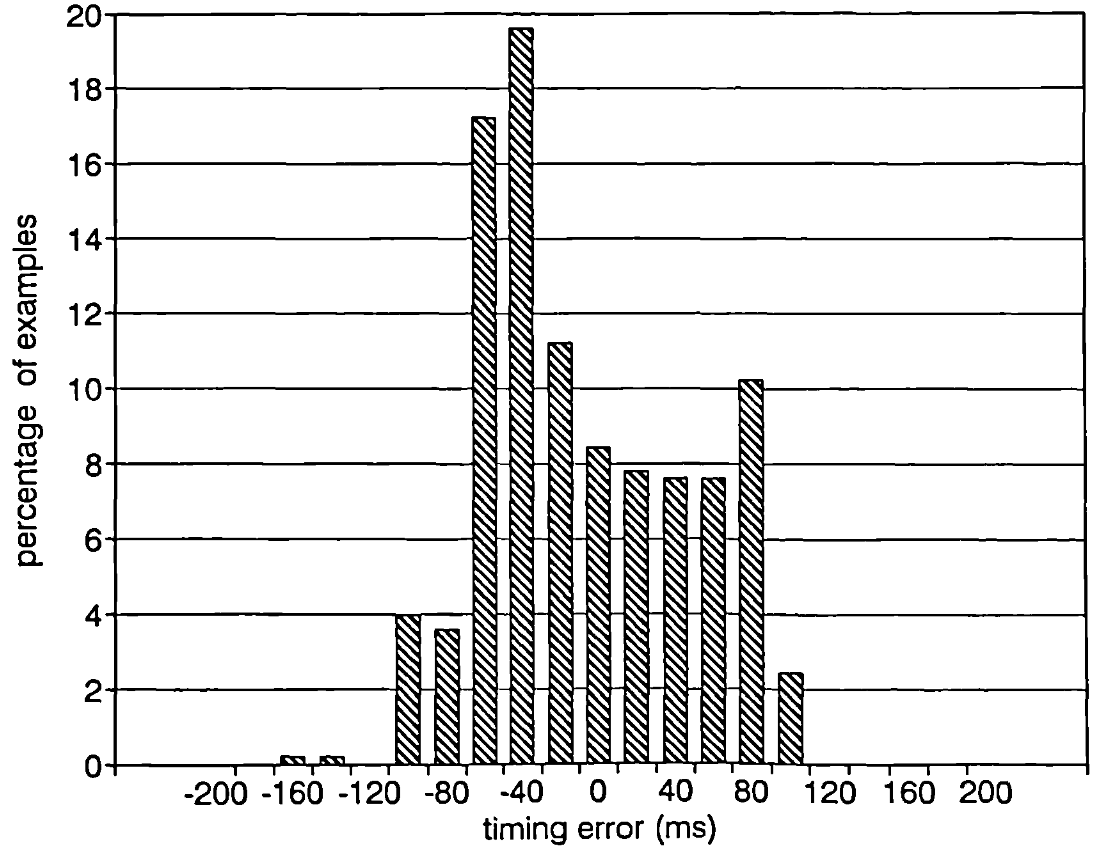


Figure 6.20 b *(Time is since the start of collection)*





Figures 6.22b and 6.24b *Generality of rules and spread of timing error*

Decision tree for predicting the transition from stance to swing, using CRUTCH INCLINATION

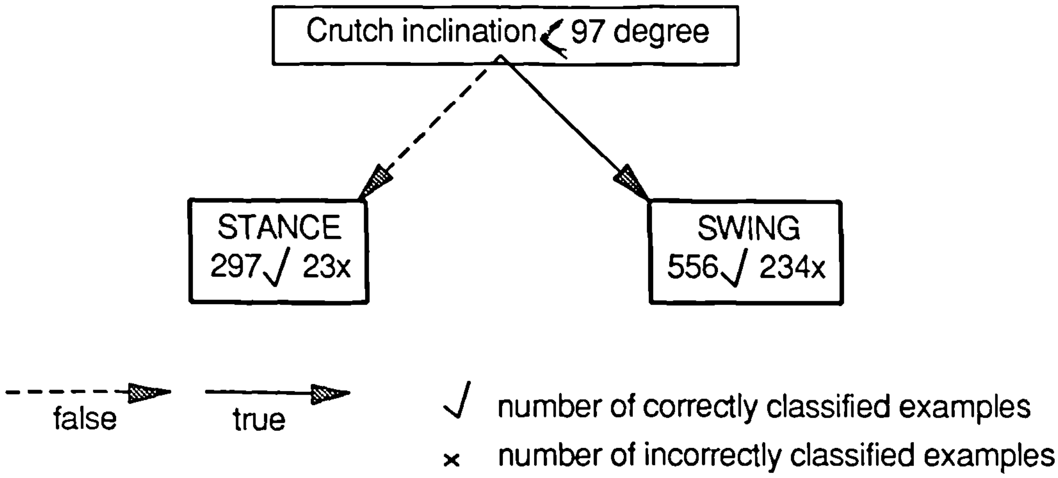


Figure 6.18 c

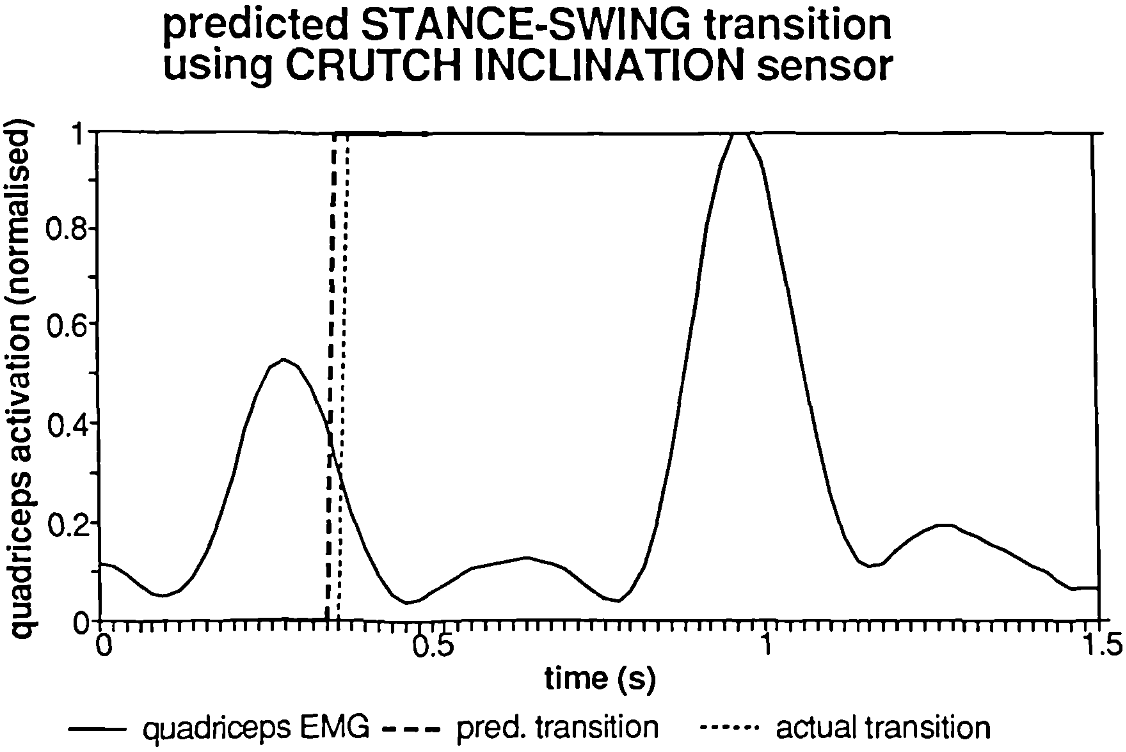
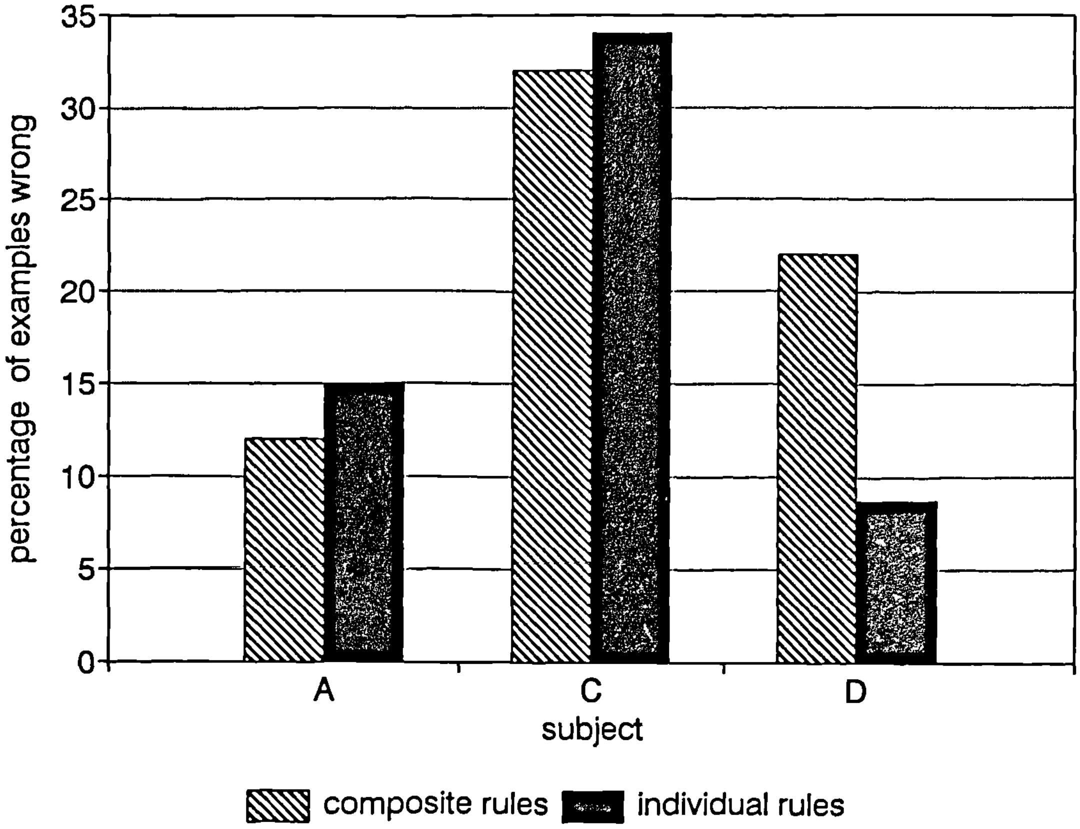
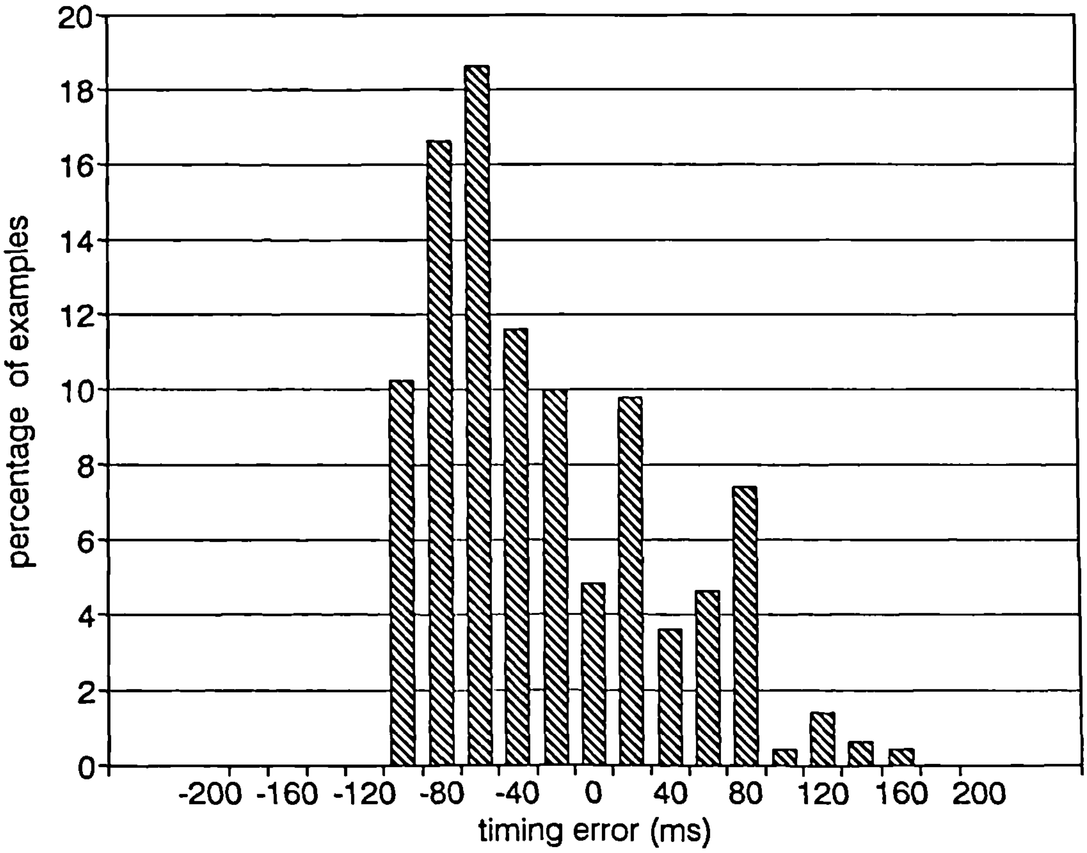


Figure 6.20 c *(Time is since the start of collection)*





Figures 6.22c and 6.24c *Generality of rules and spread of timing error*

Decision tree for predicting the transition from swing to stance, using INFRA RED SENSOR

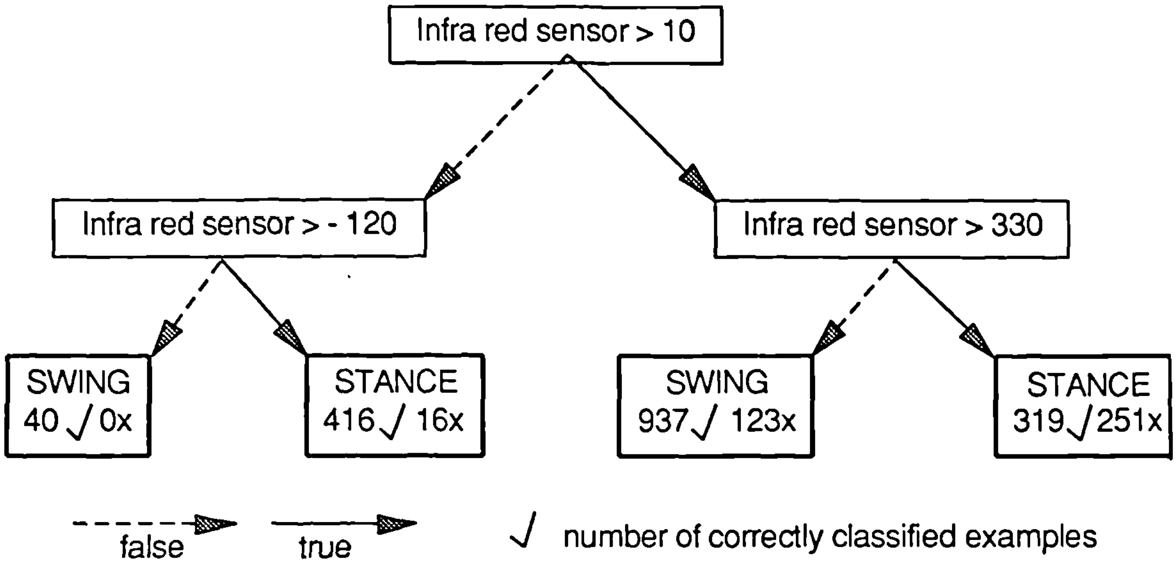


Figure 6.19 a

predicted SWING-STANCE transition using INFRA RED sensor

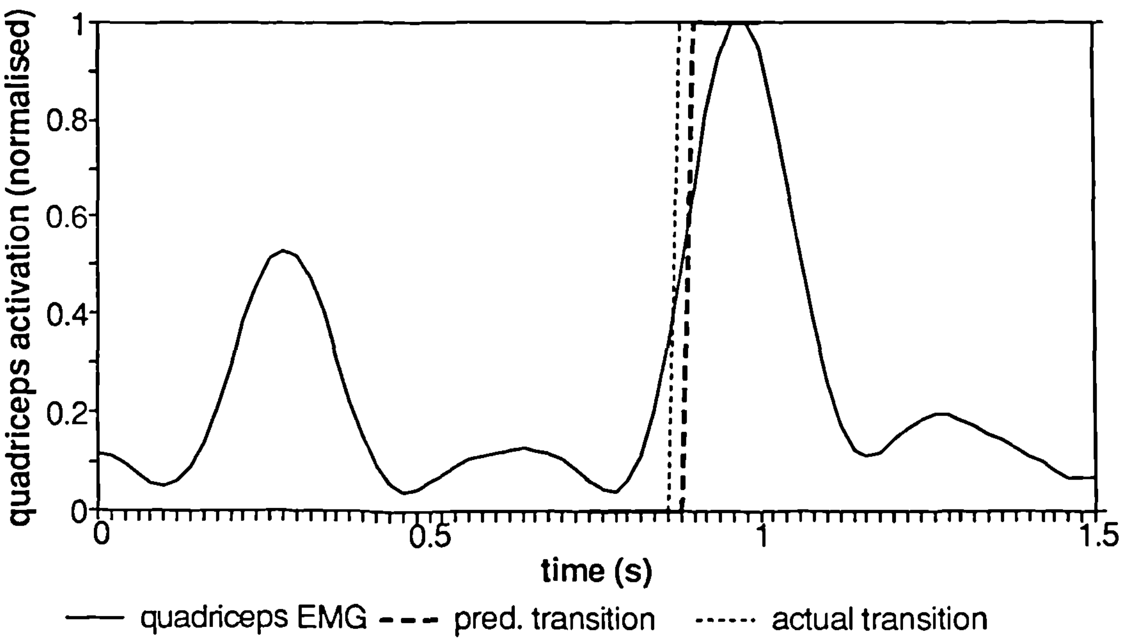
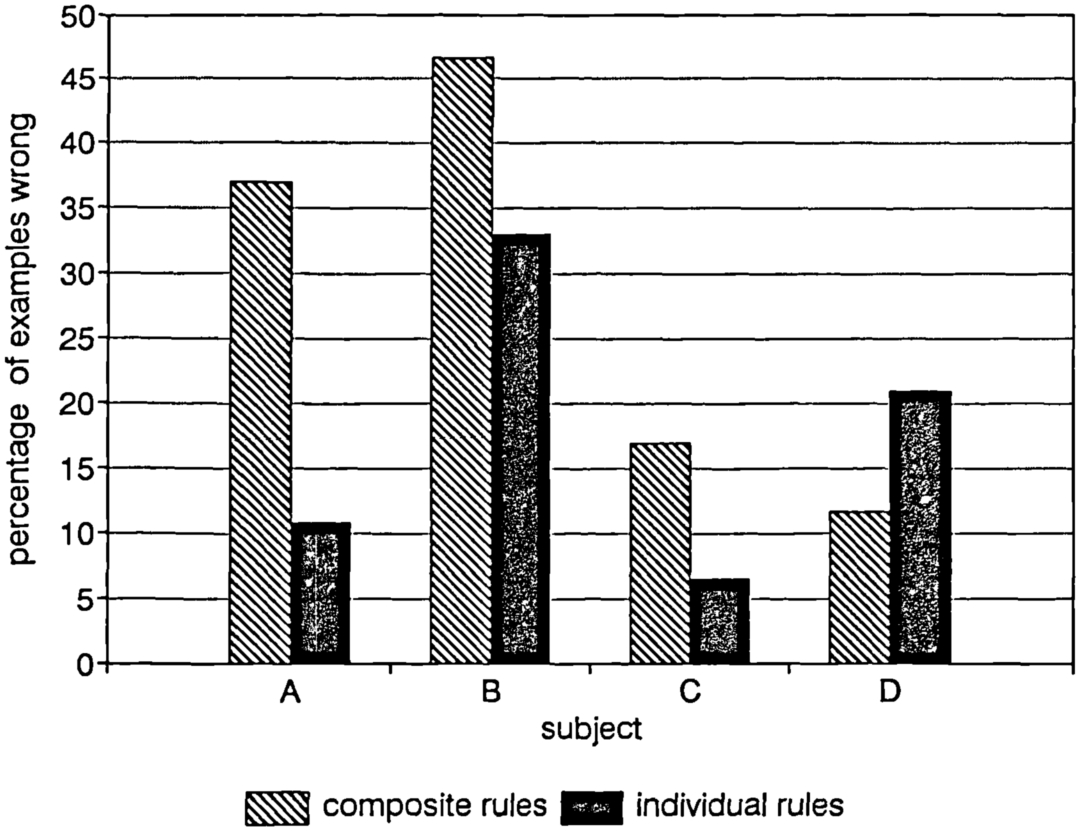
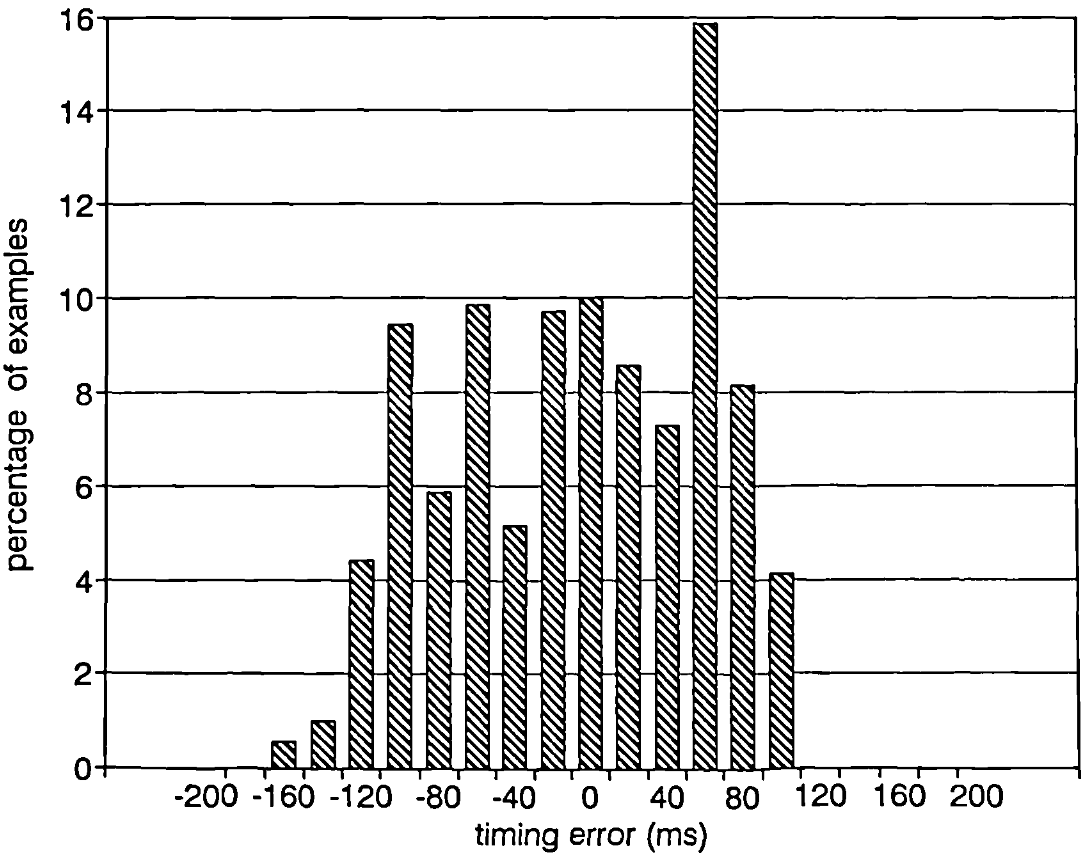


Figure 6.21 a *(Time is since the start of collection)*





Figures 6.23a and 6.25a *Generality of rules and spread of timing error*

Decision tree for predicting the transition from swing to stance, using CRUTCH and TORSO INCLINATIONS

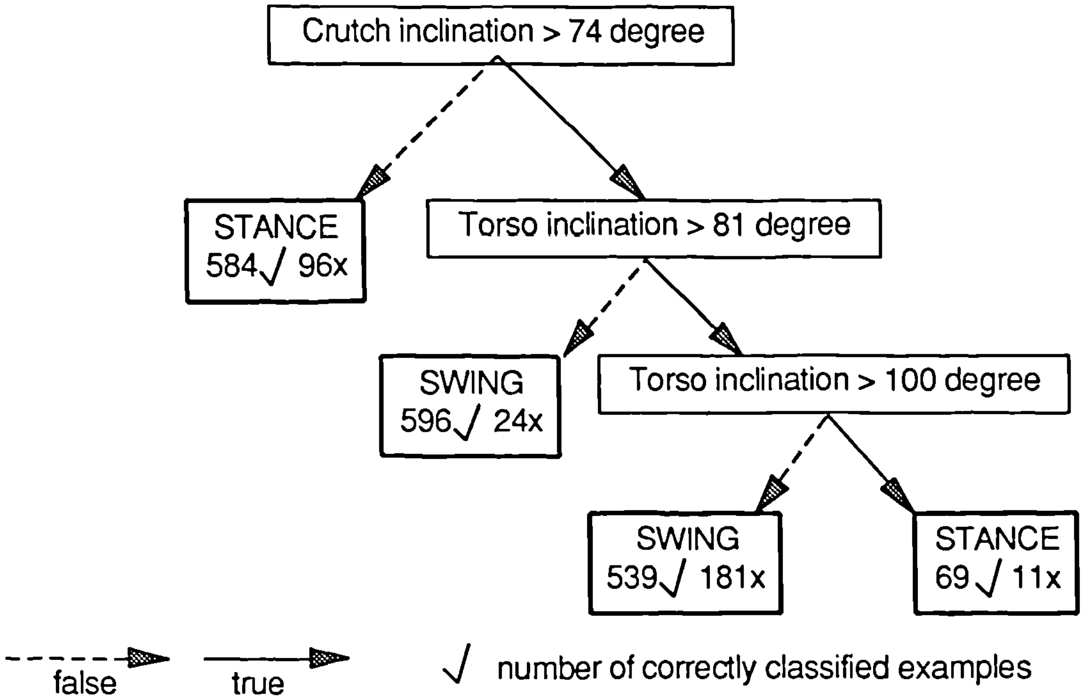


Figure 6.19 b

predicted SWING-STANCE transition using CRUTCH and TORSO INCLINATIONS

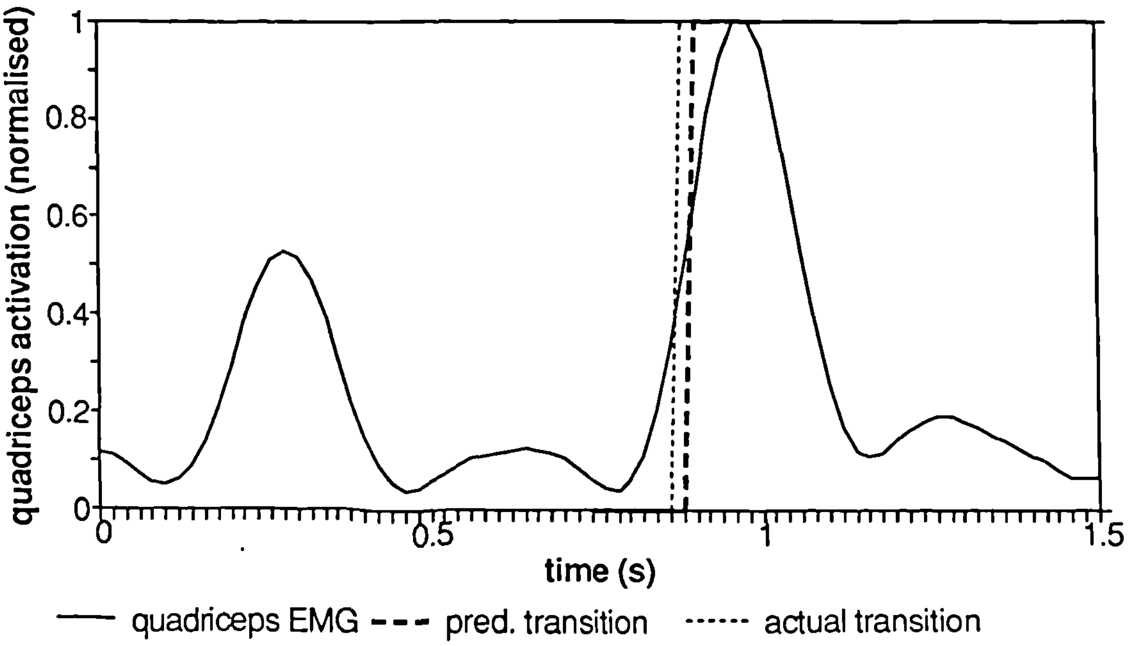
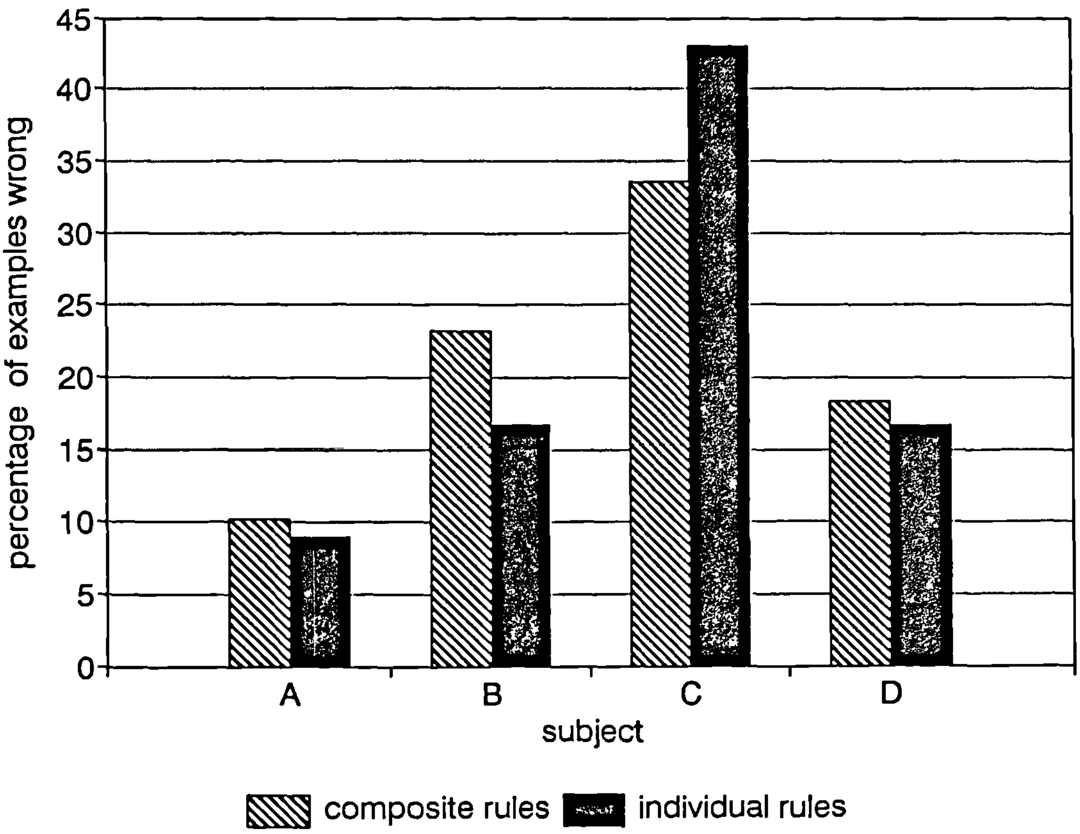
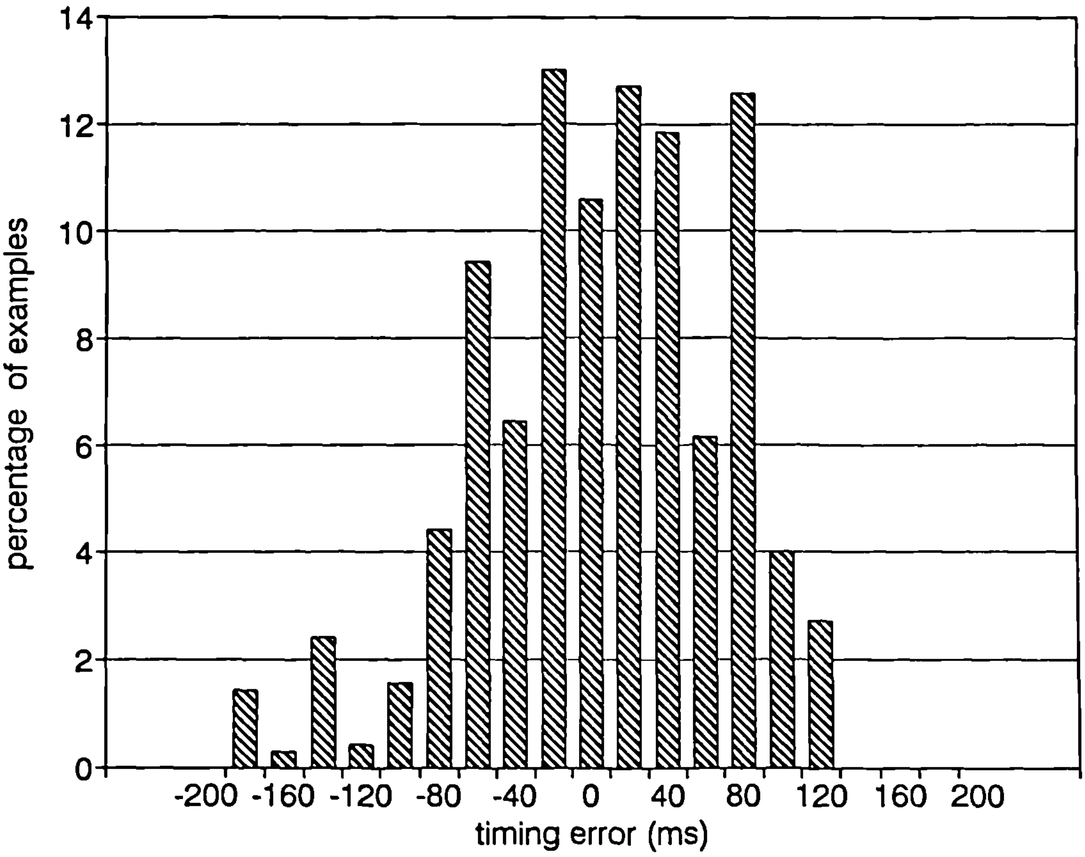


Figure 6.21 b *(Time is since the start of collection)*





Figures 6.23b and 6.25b *Generality of rules and spread of timing error*

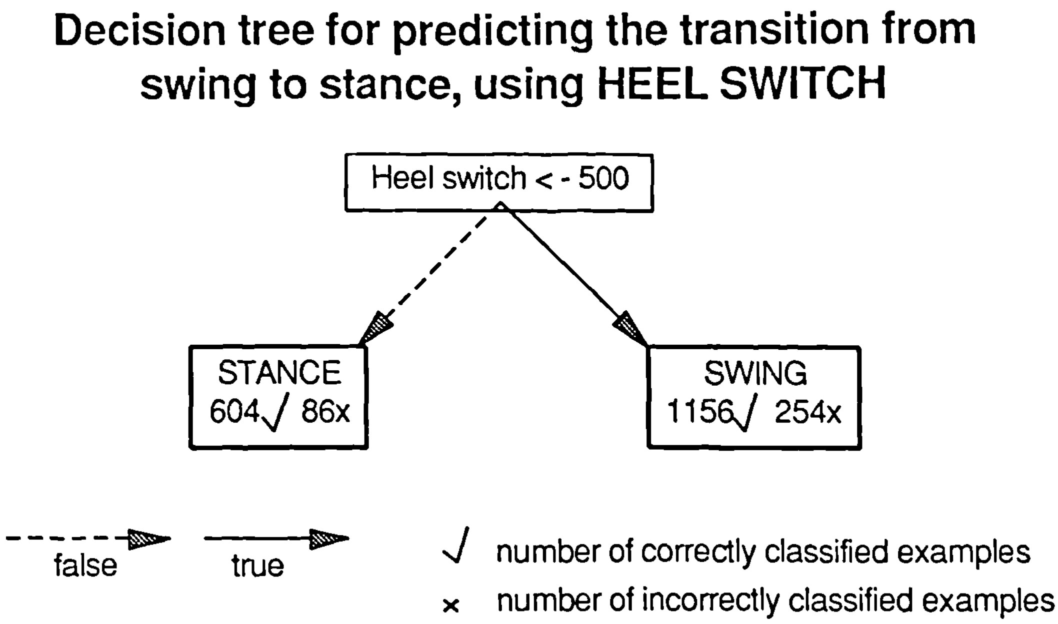


Figure 6.19 c

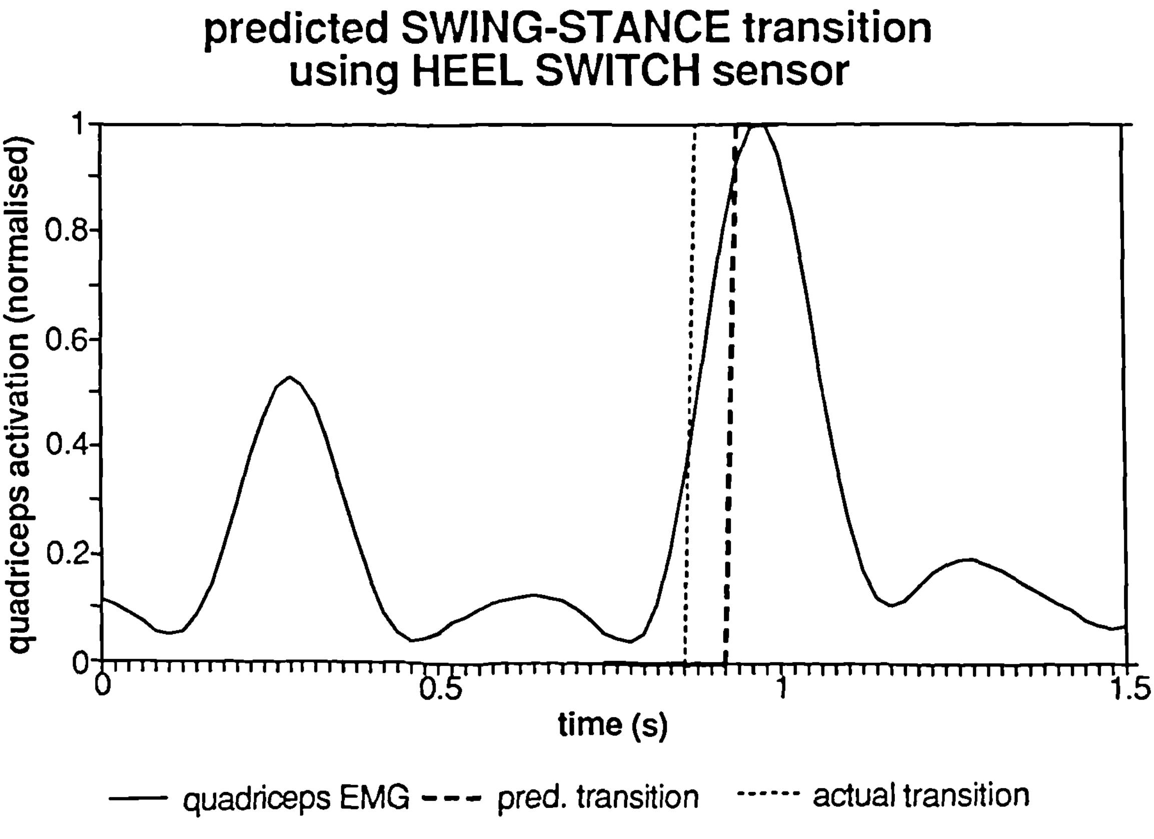
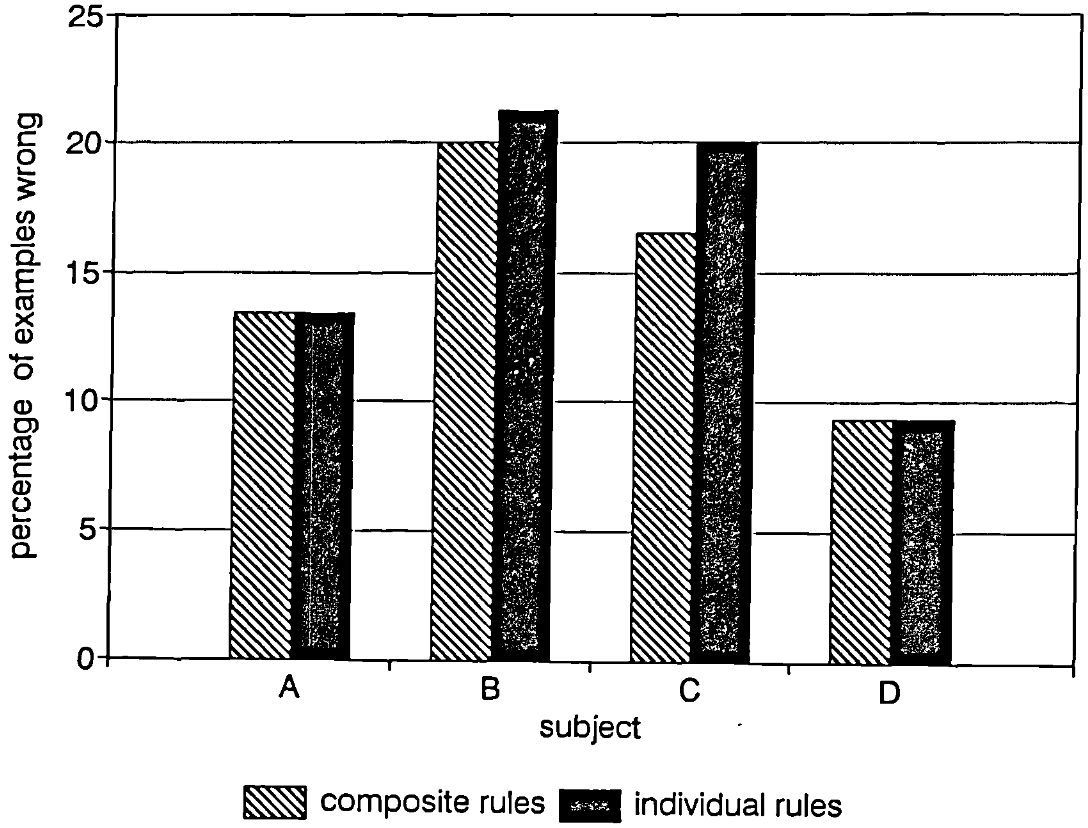
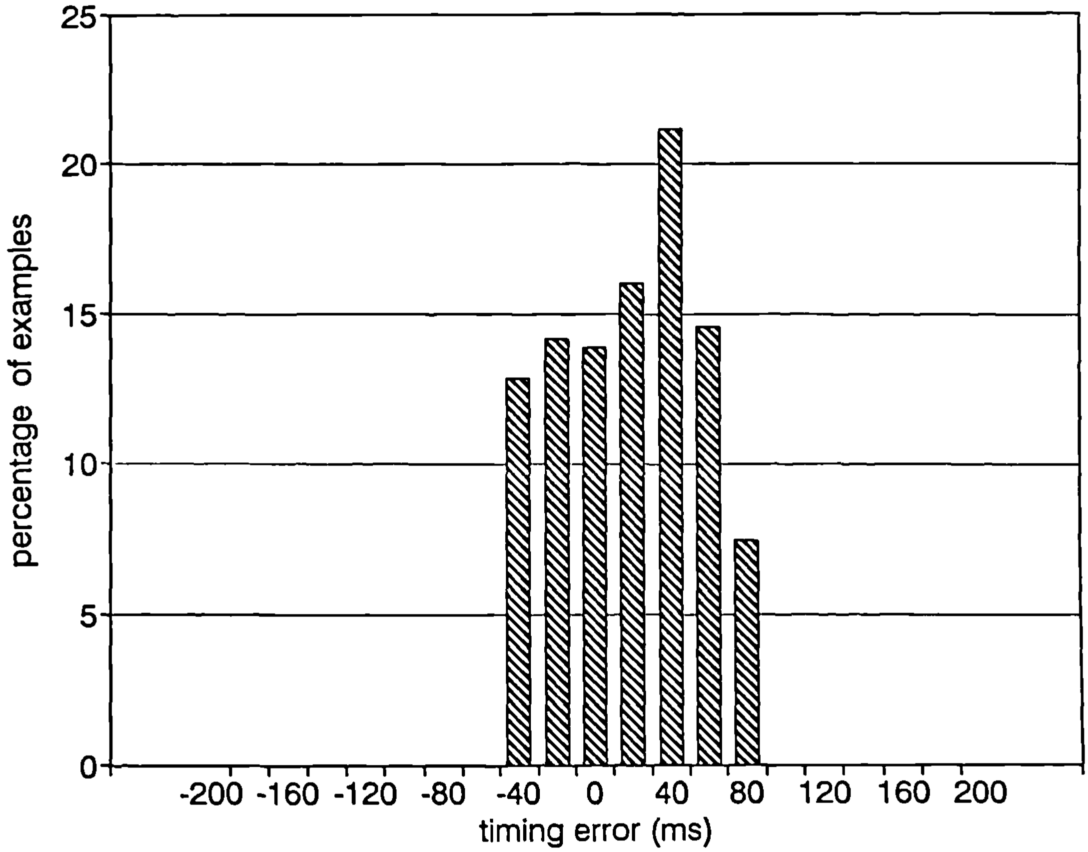


Figure 6.21 c *(Time is since the start of collection)*





Figures 6.23c and 6.25c *Generality of rules and spread of timing error*

Decision tree for predicting the transition from swing to stance, using CRUTCH FORCE

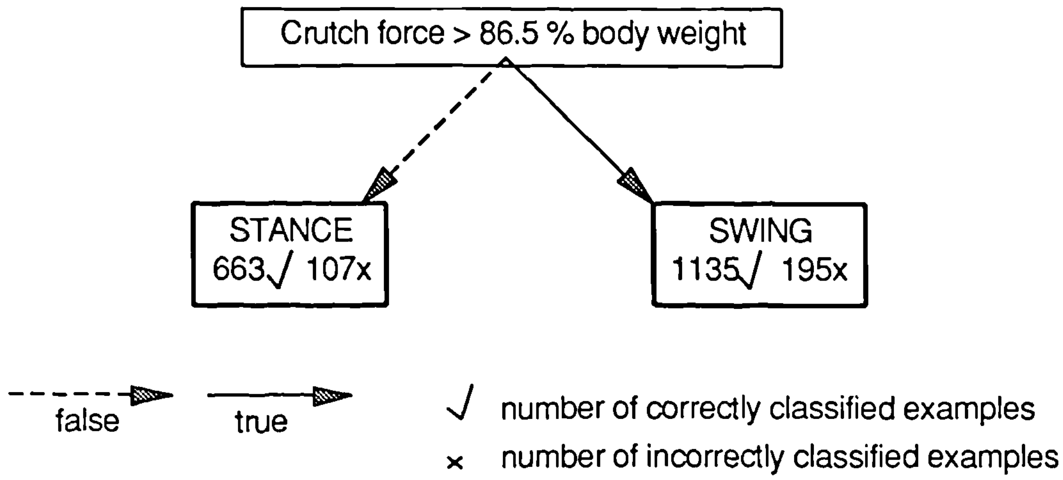


Figure 6.19 d

predicted SWING-STANCE transition using CRUTCH FORCE sensor

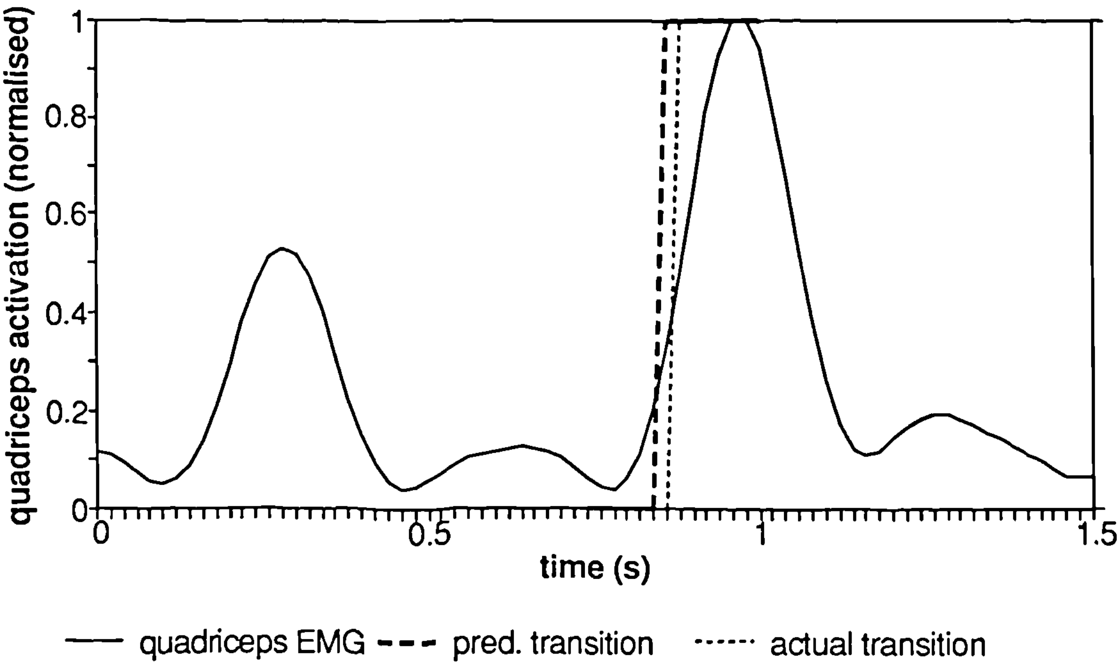
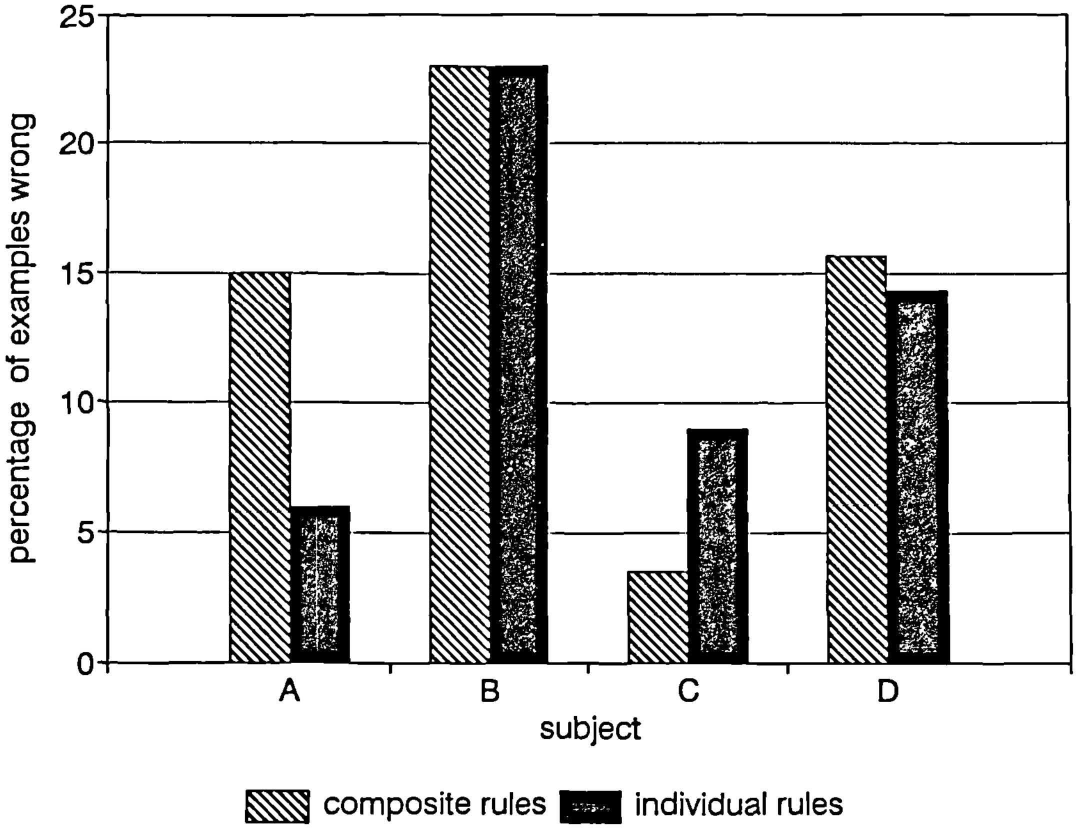
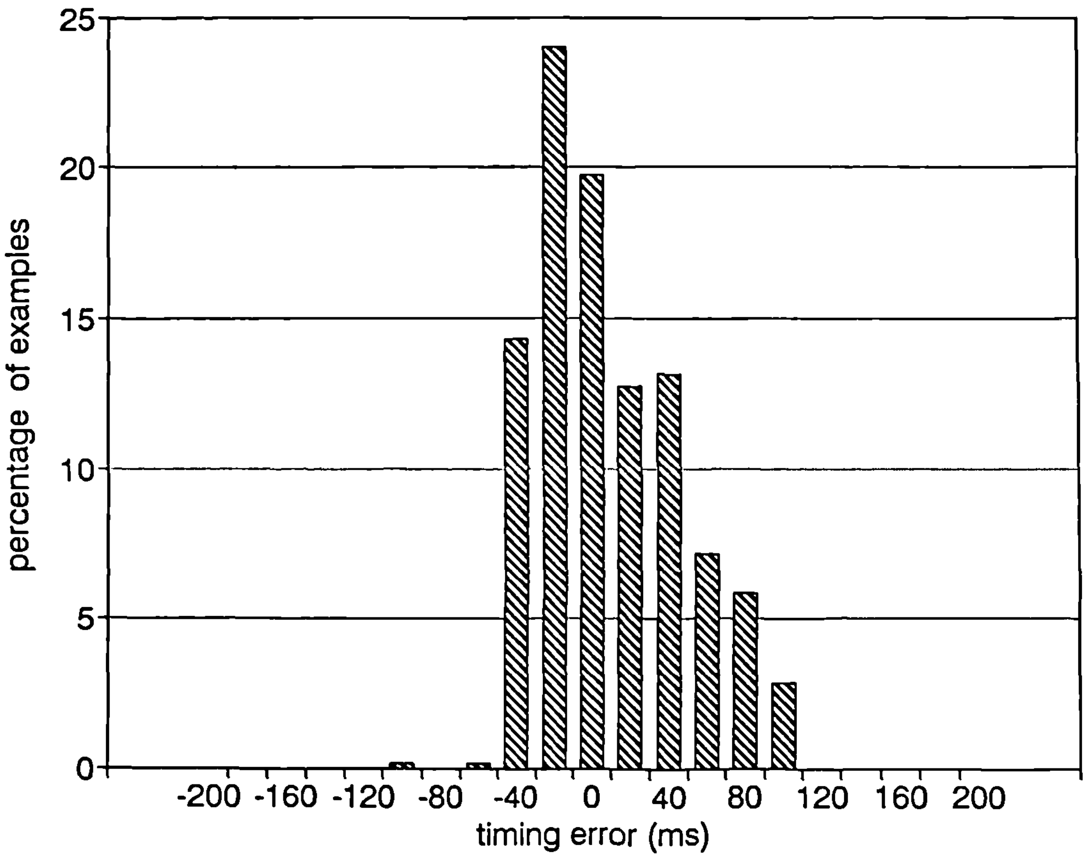


Figure 6.21 d *(Time is since the start of collection)*





Figures 6.23d and 6.25d *Generality of rules and spread of timing error*

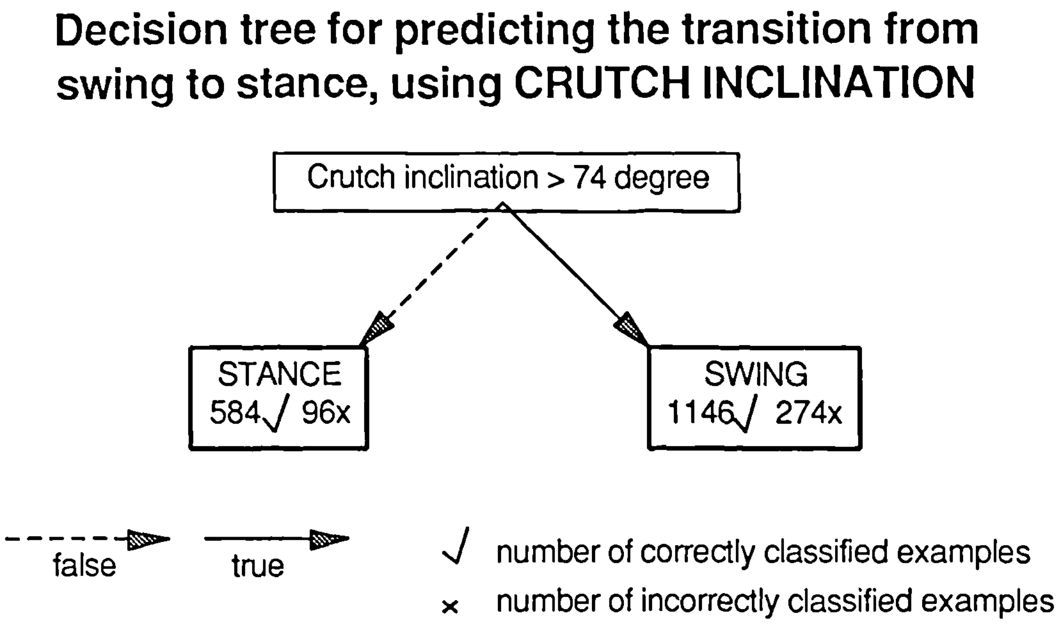


Figure 6.19 e

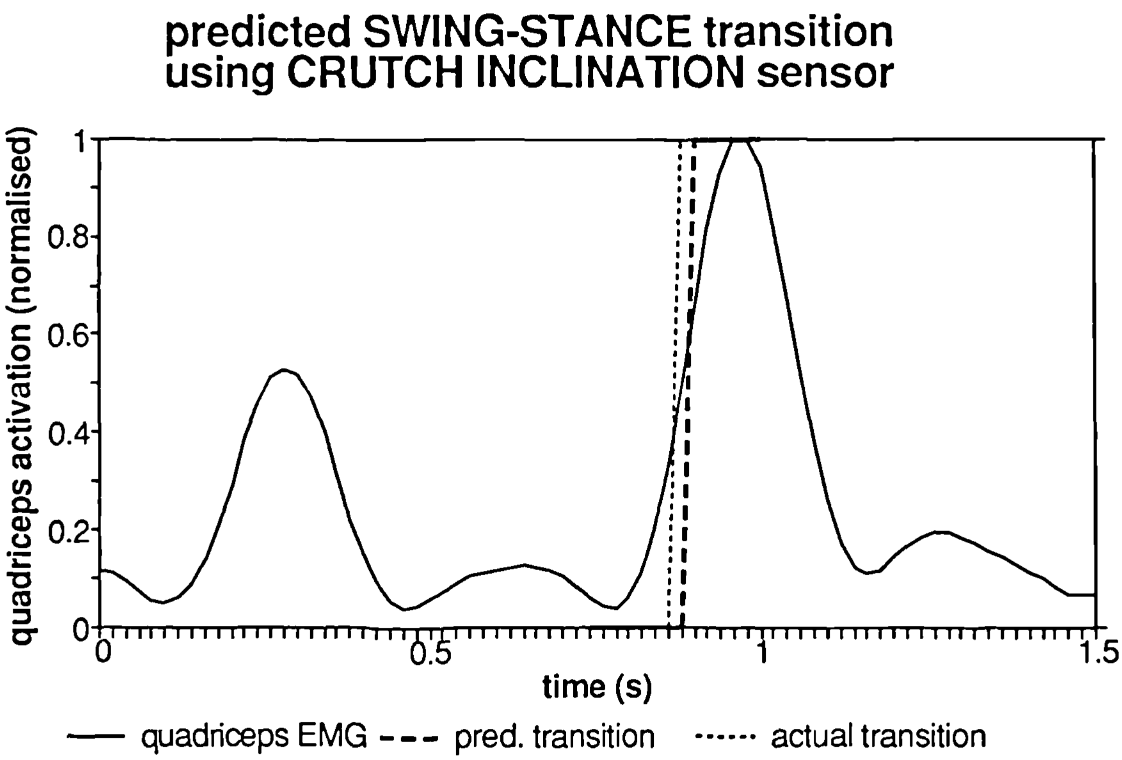
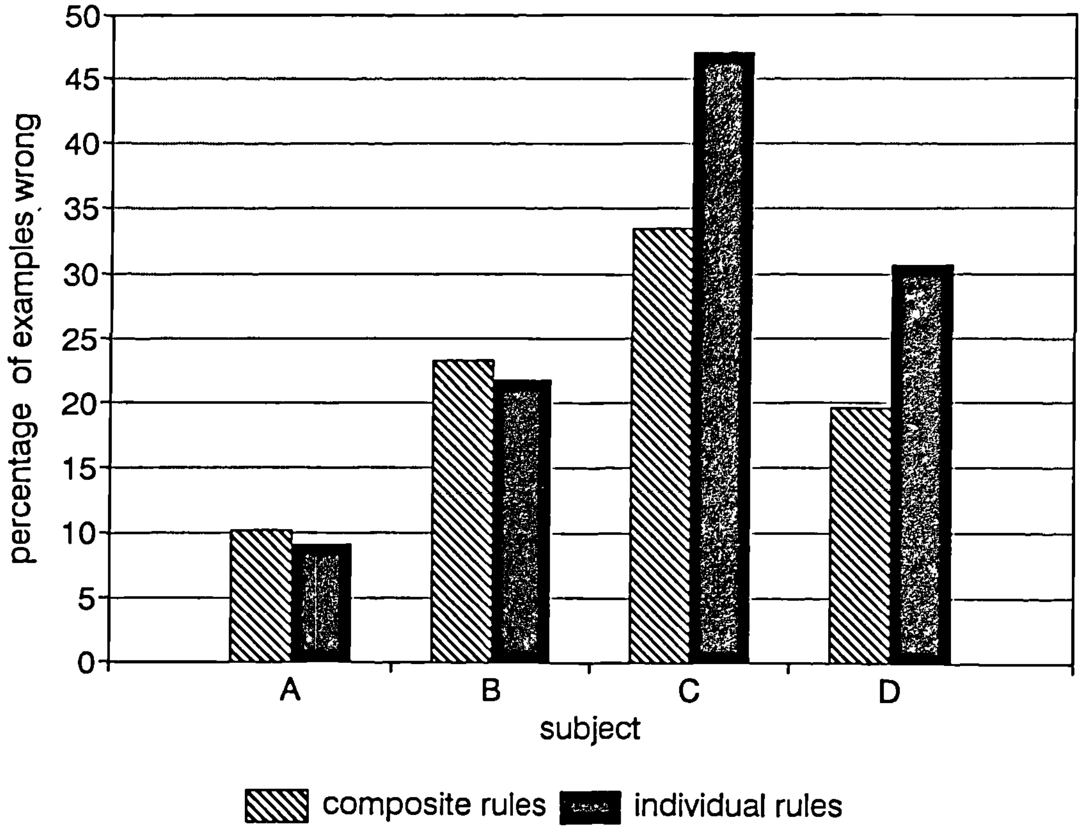
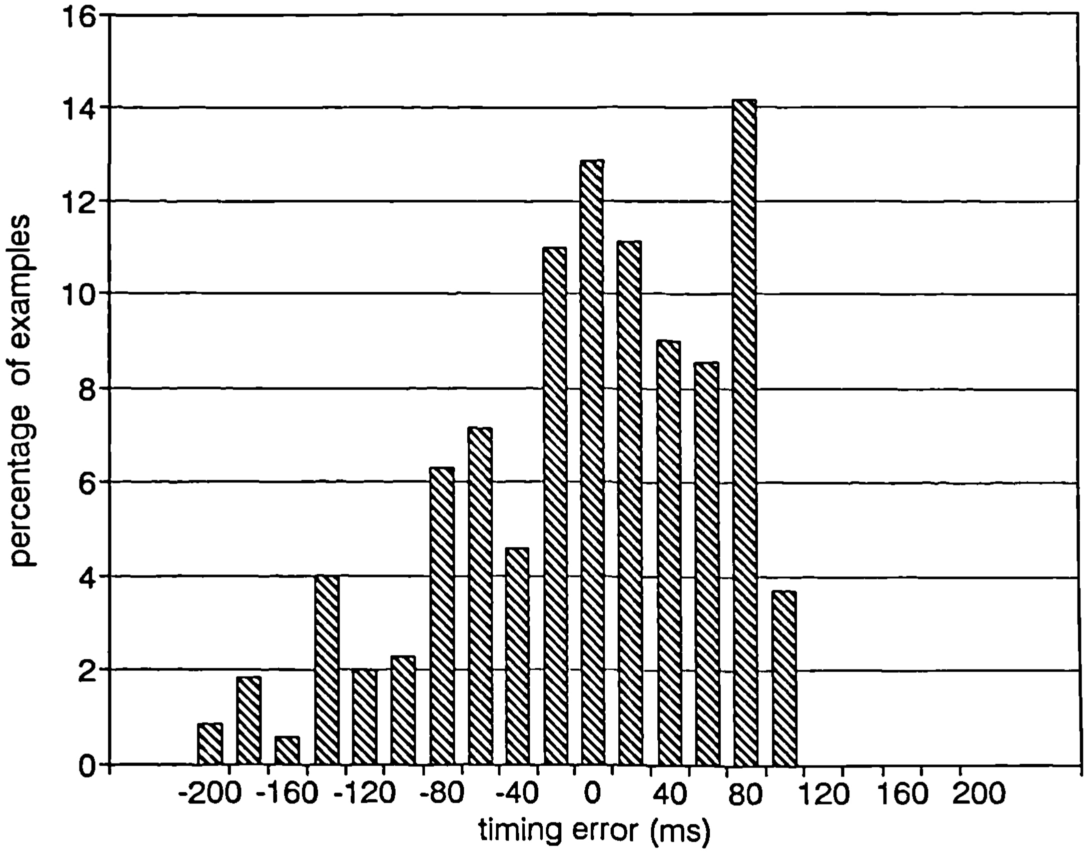


Figure 6.21 e *(Time is since the start of collection)*





Figures 6.25e and 6.25e *Generality of rules and spread of timing error*

Sensor	Empiric	A	B	C	D	E	mean
crutch inclination	1	6	4.5	2	3.5	6.5	4
infra-red sensor	2	6	8	7	7	8	8
toe switch	3	3	2	1	1	1	1
ankle transverse accn.	4	6	6	5	2	2	3
crutch force	5	1.5	1	3	6	4.5	2
torso inclination	6	6	4.5	7	3.5	6.5	7
ankle axial accn.	7	6	7	4	5	3	6
shoulder elevation	8	1.5	3	7	8	4.5	5
S		-7	-3	9	9	-2	2
maxS		17	27	25	27	26	28
τ		-0.41	-0.11	0.36	0.33	-0.08	0.07

Table 6.10 *Comparison of Empiric's ranking of sensor importance for SWING with that of five experts. τ is Kendall's coefficient: $\tau=1$ for identical rankings, $\tau=-1$ for opposite rankings.*

Sensor	Empiric	A	B	C	D	E	mean
crutch force	1	6	1	5.5	5	4.5	4
heel switch	2	6	6	1	3	1	2
crutch inclination	3	1	4	5.5	1.5	6.5	3
infra-red sensor	4	2	8	4	8	8	8
shoulder elevation	5	6	2.5	7.5	5	4.5	6
torso inclination	6	6	6	7.5	1.5	6.5	7
ankle transverse accn.	7	3	2.5	2	5	2	1
ankle axial accn.	8	6	6	3	7	3	5
S		2	4	0	4	-2	2
maxS		18	27	25	27	26	28
τ		0.11	0.15	0	0.15	-0.08	0.07

Table 6.11 *Comparison of Empiric's ranking of sensor importance for STANCE with that of five experts. τ is Kendall's coefficient: $\tau=1$ for identical rankings, $\tau=-1$ for opposite rankings.*

were applied to this data to predict the state transitions, and these are displayed, along with the original quadriceps EMG activation, in figures 6.20a to 6.20c (swing) and 6.21a to 6.21e (stance). The scatter of the timing error is displayed in figures 6.22a to 6.22c (swing) and 6.23a to 6.23e (stance). This was obtained by converting the percentage error for each testing set into a lead or lag time (using equation 4.19), and summing these for 100 rule-sets induced from randomly selected training sets and tested on randomly selected testing sets.

The mean performance of each subject's example files on rule-trees induced from a) his own data and b) data from the whole group are displayed in figures 6.24a to 6.24c (swing) and 6.25a to 6.25e (stance).

6.3.4.4. Comparison with experts ratings of sensor importance

Five replies to the questionnaire were received. The rankings are shown in tables 6.10 and 6.11, together with those produced by *Empiric*. The mean of the experts' rankings of each sensor was calculated, and these values were themselves ordered to form the mean rank. Following Kirkwood (1989), the Kendall coefficient τ was used to assess the degree of concordance between the rankings of each expert and that of *Empiric*. This statistic is defined as follows (Hettmansperger, 1984 p. 202):

$$\tau = \frac{S}{\max S}$$

$$S = P - Q$$

$$= \sum_{i<j}\sum \mathrm{sgn}(X_j - X_i)\,\mathrm{sgn}(Y_j - Y_i)$$

where P and Q are the number of concordant and discordant pairs respectively. Two sensors, i and j, form a *concordant pair* if the difference in their rankings is of the same sign for both sets of rankings, X and Y. The greatest value that S

can take is max$S$. If there are no ties then:

$$\max S = \frac{n(n-1)}{2}$$

If there are ties, then max$S$ will be reduced by:

$$\sum_{i=1}^{n} \frac{m(m-1)}{2}$$

Where m is the number of sensors sharing each score i.

The value of the Kendall coefficient can vary from 1 (identical rankings) to -1 (exactly opposite rankings); values around zero indicate no association.

These results are presented in table 6.10 for the initiation of swing and table 6.11 for the initiation of stance.

CHAPTER 7. DISCUSSION

7.1. DISCUSSION OF OXYGEN CONSUMPTION RESULTS

These results (table 6.1, figures 6.1, 6.2) demonstrate that swing through gait with free knees has a lower energy cost than swing-through gait with fixed knees. The mean of the ratios of the energy costs of free and fixed-knee swing-through gait for each subject is 0.63; i.e., on average for each subject, free-knee swing-through gait requires only 63% of the energy expenditure per metre of fixed-knee gait. These results support the findings of Wells (1979) that the **mechanical** energy costs of swing-through gait with fixed knees are higher than those with free knees. They suggest that the active flexion of a paraplegic subject's knees during FES swing-through gait may lead to a gait with a lower energy cost (and thus a higher range, or a higher speed for the same range).

7.2. DISCUSSION OF FES SWING-THROUGH GAIT RESULTS

7.2.1. Distance Trials

The speeds and distances attained during the distance walking tests (table 6.2) are lower than the values of 1.0-1.5 m/s for 150 m and 1.0 m/s for 2000 m suggested by Marsolais and Kobetic (1989) as being necessary for an acceptable gait, or the minimum speed of 0.5 m/s required for community walking (Symons *et al.*, 1986). However, they are probably adequate for a paraplegic who uses a wheelchair as her/his main form of locomotion, but occasionally needs to walk short distances when use of a wheelchair is inappropriate, or for exercise. The gait was clearly faster than the four-point FES gaits achieved by these subjects (0.11 m/s for subject A [T11 lesion] [Granat, 1990], and 0.06 m/s for subject B [T6 lesion] [Heller *et al.*, 1990]).

These maximum distances were obtained for continuous walking. If the subjects were to use 'hybrid' systems (Andrews and Bajd, 1984), incorporating floor reaction orthoses (FROs), they would be able to take regular rest-stops without needing stimulation (the FROs would passively extend the subject's knees, resting the quadriceps muscle group; the subjects hips could be maintained in extension by the adoption of a 'C' posture, resting gluteus maximus). In this way, the onset of both local muscular fatigue and systemic fatigue could be deferred (Andrews *et al.*, 1988). This would increase the range of the gait but decrease the average speed[1].

The mid-thoracic (T6) paraplegic walked for a shorter distance and at a lower speed than the low-thoracic subjects (although he walked for a slightly longer time than the other two). This may be because the subject's reduced control of his torso necessitated more use of his upper limbs for stabilisation, leading to a less confident and more tiring gait.

All three subjects achieved average stride lengths in excess of one metre.

7.2.2. Stride by Stride Analysis

7.2.2.1. Temporal parameters

More insight can be gained into the results of the previous section by examining the inter-stride variabilities of the temporal and kinematic parameters.

The speeds of subjects A and B performing FES swing through gait (table 6.3) were similar to, but slightly higher than, the speeds measured over the longer distance trials (table 6.2). Subject A (T11 lesion) performed swing-through gait both with KAFOs and with FES. She had a similar stride length for both gait modes, but a longer stride time (and hence a lower speed) for the KAFO gait. There were similar body-swing, crutch-swing and second double-support times for both gaits. The longer stride time in the KAFO gait was due to more time being spent in the first double support phase. This can be explained by comparing the subject's hip stability during the two gait modes: in the FES gait, hip extensors were stimulated during stance; there was no such stabilisation of the hip in the KAFO gait. This led to episodes of (hip) buckling in the latter gait. The extra time taken for the subject to right herself following buckling increased the duration of the first double support phase. The first double-support-time standard deviation is larger for the KAFO gait than for the FES gait, which indicates more inter-stride variability.

Subject B (T6 lesion) performed a swing-through gait with FES and a swing-to gait with KAFOs (he was not capable of performing KAFO swing-through gait). The speed for the swing-through gait was higher, owing to the longer stride length (despite the longer stride time). The subject had a similar

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1 Many activities of daily living require intermittent walking (e.g. visiting a supermarket)

stride length for FES swing-through gait to that of subject A, but a longer stride time, which led to a lower speed. This longer stride time was a result of the subject spending more time in both double support periods. This can be explained by the lower trunk stability of this subject compared to the T11 subject. What is particularly noticeable is that there was a long second double support time, followed by a short crutch swing time. The subject did not seem to 'trust' his body to move as a rigid single link pivoting about his feet. Instead, he paused in the second double support phase (losing forward momentum) to ensure that he was stable, then quickly threw himself forwards, bringing his crutches through and planting them as quickly as possible (see figure 6.3).

Part of the reason for the long second double support period may be that the subject's hip extensors were activated after a fixed timing delay, and were perhaps turned on too late (figure 4.5). A better control strategy might have activated them at a more appropriate time, providing hip stability immediately on heel-strike; this would have allowed a shorter second double support time (although it may have been at the price of reducing hip flexion during swing, and thus reducing stride length).

The first double stance period might also have been shortened by a better control strategy. The subject was required to explicitly press a switch to initiate the body-swing phase; if instead, the subjects' intention to initiate swing was detected from their posture and preparatory movements, then the timing and execution of the swing phase might have been improved. The generation of improved control strategies is discussed in section 7.3.4.7.

The non-impaired subject demonstrated higher speeds for the two gait modes than both of the paraplegics. This was due both to his longer stride length and to his shorter stride time. The shorter stride time resulted from a shorter period spent in both double support phases. What is noticeable about the non-impaired gait is the smaller inter-stride variability, indicating a higher degree of skill in crutch and foot positioning. This illustrates the great advantages of proprioception, sensation, and full muscular control in producing a consistent gait.

These results agree with those of Wells (1979) who also reported (for non- and artificially impaired subjects) a decrease in double support time with increasing speed, and an increase with increasing disablement.

The body-swing times were similar for all different swing-through gaits for all subjects; the crutch-swing (body-stance) times were also similar (with the exception of the T6 paraplegic discussed above). This reflects the pendular nature of both swing phases, and suggests that a decrease in stride time (and hence an increase in speed) should be achieved by minimising the double support times.

The double support phases do not contribute to forward progression, and extra time spent in them leads to loss of forward momentum and kinetic energy. Their duration may be reduced by training, providing extra-stability, providing 'artificial proprioception'[1] and improving control strategies. This may be the best way to increase the speed and reduce the energy cost of FES swing-through gait.

The fastest single strides give an indication of the potential speeds of the gait. As expected from the previous discussion, the increase in speed for each gait mode for both paraplegics corresponded to a reduction in double support ratio (there was also an increase in stride length for the swing-to gait). In the non-impaired subject, the (smaller) increase in speed was mainly due to longer strides, and corresponded to a slight increase in double support ratio.

7.2.2.2. Distance parameters

The mean stride length of the non-impaired subject was greater than that for the paraplegic ambulators. In particular, the distance that this subject's feet landed in front of the crutches was greater than that for the T11 paraplegic, which itself was greater than that for the T6 paraplegic. Sufficient kinetic energy is required at heel-strike to enable the body to pivot about the feet and pass through a vertical (maximum potential energy) position. The further the feet land in front of the crutches, the more energy, and hence the more speed, is required. If the body-stance phase is simply modelled as one link pivoting about the feet, then the height the centre of gravity needs to be raised from heel-strike to mid-stance (which is proportional to the potential energy required) is proportional to one minus the cosine of the angle the body makes with the vertical at heel-strike. If this angle is assumed small, so that first-order approximations for the angle and its cosine apply, the amount of potential energy required is found to be proportional to the square of the distance the feet land in front of the vertical projection of the centre of gravity.

1 This can be achieved by 'sensory feedback' - feeding back joint positions or contact forces to areas of the body with preserved sensation, by means of sound, vibration, vision or electrical stimulation (Andrews *et al*, 1988).

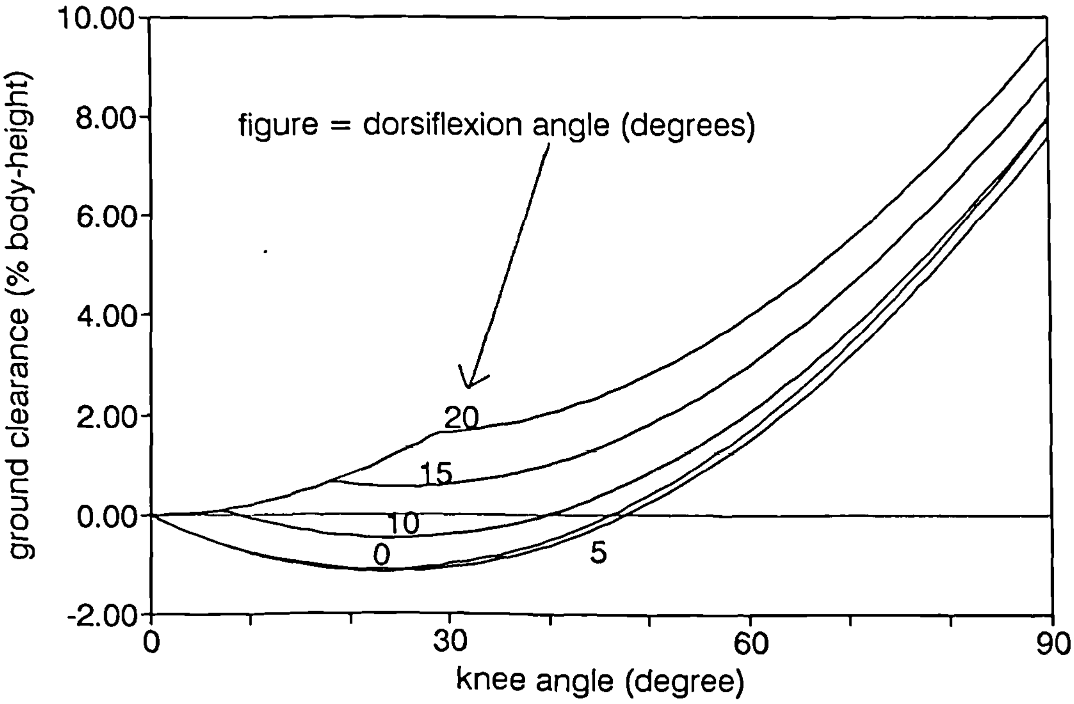


Figure 7.1 *Ground clearance vs. maximum knee flexion angle in the swing phase for specified ankle dorsi-flexion angles.*
The ratio (heel-ankle length / footlength) is assumed to be 0.2

Good trunk and hip extension are also required to ensure that the body acts as a rigid inverted pendulum and does not buckle at heel strike.

7.2.2.3. Angular parameters

The amount of ground clearance produced at different knee flexion angles is plotted in figure 7.1; this shows that the minimum angle of knee flexion required to obtain ground clearance during the swing phase of the gait is approximately 45 degrees. Details of the calculation of these values are given in Appendix F.

The mean, maximum angle of knee flexion occurring during swing for the T11 subject was only 10 degrees, despite simultaneous stimulation of hamstrings and flexor reflex. This angle was insufficient to produce any ground clearance in the swing phase of the gait, and in fact decreased the ground clearance by inclining the toe further downwards. Further observation showed that this subject displayed a strong reflex resistance to flexion of her leg when this immediately followed the termination of a period of quadriceps stimulation. The subject had discontinued taking an anti-spasmodic drug (*Baclofen*) approximately one year previously, and this may explain her heightened reflex activity. Solutions to this problem may involve re-administration of the drug, or preferably, using an alternative site of stimulation for the flexion reflex that will inhibit the unwanted knee-extensor activity[1].

The T6 paraplegic (who was taking an anti-spasmodic drug, *Baclofen*) demonstrated a larger knee flexion angle of 51 degrees. However, this is only slightly greater than the previously-quoted minimum value necessary to provide ground clearance, and so the extra clearance gained will be small (0.5 % of the subject's height[2], or less than 1 cm). In these circumstances, the benefits in ground clearance resulting from swing-phase knee flexion are small, and must be weighed against the reduced security of a gait without permanently extended knees. However, figure 7.1 shows that if the subject's AFOs are set in dorsi-flexion, more ground clearance will result from knee flexion; at 10 degrees of dorsi-flexion, the clearance would be 0.9% of the subject's height (1.4 cm

1 There is some evidence that inappropriate quadriceps contraction may be moderated by choosing different flexion-reflex stimulation sites (Drago Rudel, unpublished work at Ljubljana University and Rehabilitation Institute, Slovenia, and The Bioengineering Unit, Strathclyde University.)

2 Which was 1.60 m.

clearance); at 15 degrees it would be 1.9% (3 cm), and at 20 degrees it would be 2.9% (4.6 cm). Selection of an alternative site for application of the flexion-reflex stimulation may also improve this subject's angle of knee flexion.

The knee flexion angle produced by the non-impaired subject was higher than that of two paraplegic subjects. The mean of 65 degrees would produce ground clearance of over 2% of the subject's height (1.82 m), or approximately 4 cm.

A further benefit of active knee flexion during the swing phase of gait is that it will reduce the moment of inertia of the swinging leg, and thus reduce the required hip flexion moment (or more importantly for FES gait where producing hip flexion is difficult, increase the hip flexion angle resulting from a given hip flexing moment).

The maximum hip flexion angles of both paraplegic subjects performing FES gait were higher than for the (ballistic) flexion in the non-FES gaits, reflecting the active flexion caused by stimulation of the flexion reflex. The hip flexion angles were close to those of the non-impaired subject. Good hip flexion allows a longer stride to be taken, and can thus improve the speed of the gait.

7.2.3. Other Aspects of the Gait

It was apparent from early trials that the production of good body-stance-phase hip extension was vital for effective swing-through gait. This hip extension was successfully produced by bilateral stimulation of gluteus maximus; the placement of the electrodes also probably recruited some of the hamstrings group, which further helped hip extension. However, there were some problems associated with this stimulation site: firstly, electrode positioning was critical: a slightly misplaced electrode was either ineffective, or worse still, (in subject A) elicited a flexion response. Secondly, it was impossible for a paraplegic subject to apply gluteal electrodes independently, so s/he could not train these muscles at home. As a consequence, the muscle groups responsible for hip extension fatigued rapidly, and their endurance was the limiting factor in the duration of an experimental session.

The T6 paraplegic would probably also have benefited from some trunk stabilisation, which could have been provided by stimulation of the erector spinae group (however, this was precluded as all eight available channels of stimulation were already being utilised) or by the fitting of a lumbar brace.

The overhead support and harness were very important in raising the confidence of the subjects sufficiently for them to attempt this (initially precarious) gait. During the early training sessions they often fell, but these falls were always arrested by the support. The system did not seem to impede the gait in any way.

Finally, the opinions of the paraplegic subjects are pertinent. They accepted that the gait was faster than either KAFO or 4-point FES ambulation, but expressed the view that they would not use it for community walking, due to the unnatural gait style. This contrasts with the opinions of many commentators on gait in spinal cord injury, who report that (KAFO) swing-through gait is often the gait of choice (Bajd and Kralj, 1991; Bromley, 1985; Childs, 1964). The explanation for this disparity is probably that those paraplegics who can successfully perform KAFO swing-through gait have lower lesions, which allow them to produce a much faster gait (Rovick and Childress [1988] report a swing-through speed of 0.9 m/s in one paraplegic ambulator). These faster speeds make the gait a practical alternative to a wheelchair for community ambulation, and thus compensate for any lack of cosmesis. At the much lower speeds (and ranges) achieved in this study, any advantages over the use of a wheelchair are not sufficient to offset the unnaturalness of the gait and the time required to don the electrodes. It is hoped that use of a permanently implanted system would eliminate preparation time, and if this were combined with more advanced control strategies to speed up the gait, the cost/benefit balance for this form of gait would be improved sufficiently to make it practical.

7.3. DISCUSSION OF INDUCTIVE LEARNING RESULTS

7.3.1. Initial Evaluation of *Empiric*

The decision trees produced from the two artificial data sets of Kirkwood (1989) (figures 6.4 and 6.5) are both equivalent to the ones produced by his inductive learning program, *Disciple* (from which *Empiric* was developed). This indicates the correct operation of *Empiric* for simple data sets.

The rule-sets for the more complex artificial data set 3 (figure 6.6a), and for its variation (figure 6.6b), are both correct. This demonstrates the ability of

Empiric to handle a larger example set (1028 examples in this case[1]), requiring more rules to classify it.

7.3.2. Performance on a Noisy Data Set

The performance of the rule-set (which is a measure of its ability to generalise) is degraded as the level of noise contaminating the training set increases (figures 6.7a to e). The minimum number of rules required *a priori* to classify the uncontaminated data set is 23. For low levels of noise (below 128) the classification performance improves as the number of rules approaches this number; however, it **deteriorates** as the number of rules increases above it (figures 6.8a to e). The additional rules are **over-particularised** - they are attempting to classify the **noise** in the training set, rather than **general** features. For the highest noise level plotted (160), the deterioration occurs with increasing rule-set size **even before the minimum level required to represent the data is reached.** This demonstrates that larger noise levels can obscure the more subtle data features. The rule-sets with fuzzy weighting significantly[2] outperform both other weighting strategies 22 times out of a possible 40 (table 6.4). They are significantly outperformed by either of the other techniques 2 times (on both occasions by the quadratic weighting strategy).

For small error levels (32 and 64), the quadratic weighting function has a performance close to that of the fuzzy weighting function . At a noise level of 96, the performance of the quadratically weighted rule-set deteriorates to that of the un-weighted case. For noise levels beyond this, the quadratic function has the worst performance. This can be explained by considering the nature of the problem: each class band is 128 wide, due to the offset of 32 it requires one rule to classify the first 32 examples, one for the central 64, and one for the final 32. At low noise amplitudes, examples near the class boundaries are more likely to be misclassified than central examples. As noise amplitudes increase, the central examples begin to be affected. At noise levels at and above 128, all examples are equally likely to be misclassified (see Appendix E for a discussion of the probabilities of misclassification). The quadratic technique weights central examples stronger than outlying ones, thus it is immune to the effects of low levels of noise. However, when the central examples begin to be affected

1 The version of *Disciple* in Kirkwood (1989) can handle up to 50 examples.
2 For a significance level of 1%.

(noise levels above 64), the quadratic technique loses its advantage. As the quadratic technique is effectively ignoring outlying examples (which are as likely to be correct as central ones for noise amplitudes above 128), its performance is degraded to below that of the un-weighted rule-set for high noise levels.

The fuzzy weighting strategy treats examples that are moved by noise beyond the class boundary as both positive and counter-examples of both the correct and incorrect classes, thus diminishing the effects of noise. However, the fuzzy membership function of an example in a class only has a non-zero value if the example value is within 128 of the central class value. Once the noise levels become sufficiently high to displace most of the examples outside the fuzzy membership region, the advantages of using fuzzy weighting are lost. For the maximum noise level considered (256), the probability that an example will be moved outside the fuzzy region is 50%. As, on average, a total of 75% of examples will be misclassified, only 25% will be misclassified but remain in the fuzzy region. Thus there is only be a slight advantage in the use of fuzzy weighting for these very high noise levels[1].

7.3.3. Classification of EMG Data From Normal Gait, and Comparison With Neural Networks

The small rule-set (figure 6.9) was very simple: it relied on the timing information contained within the integrated foot contact signal to determine if the muscle was on or off; and on the angular acceleration at the knee to determine the magnitude of the activation. This is intuitively plausible, the muscle 'turns on' at a fixed time, the activation level it turns on to depends on the accelerations (which are largely determining the necessary torques). This is consistent with the results of Arendt-Nielsen *et al.* (1991), who found that the **shapes** (timings) of the EMG activation and knee kinematic patterns (normalised to the gait cycle period), remained similar for walking at different speeds, whereas the amplitudes varied.

There are no significant differences (at the 1% level of the Student *t*-test) between the performance of the small rule-set and that of the larger, more complex rule-set (tables 6.5a to c). This indicates that the additional rules of

1 In the presence of such noise levels, it would be un-realistic to expect to be able to induce rules that could discriminate so many classes. A better strategy would be to combine groups of adjacent classes, so that the noise levels remain smaller than the separation of class boundaries.

the larger rule-set are not contributing useful general information about the gait (they are over particularised).

There are also no significant differences between the performances of the two neural networks, and also between the performances of the inductive rule-sets and the neural networks.

The neural network technique produced continuous outputs, whereas the rule-based inductive learning technique produced discrete, five level outputs (figures 6.10a to 6.11d). This is unlikely to be important in practice, as the low-pass filtering characteristics of the muscle and the inertial dynamics of the limb will smooth out the sudden transitions in the quantised output.

The advantages of the rule-based inductive learning technique are:

1. The rules are explicit, comprehensible, and easily encoded into a knowledge base[1].
2. The algorithm is variable selective, only the 'best' (in terms of average mutual information gain) attribute threshold will be selected at any node on the tree; thus, it is possible to identify the most important attributes (sensors) in any rules that are produced.

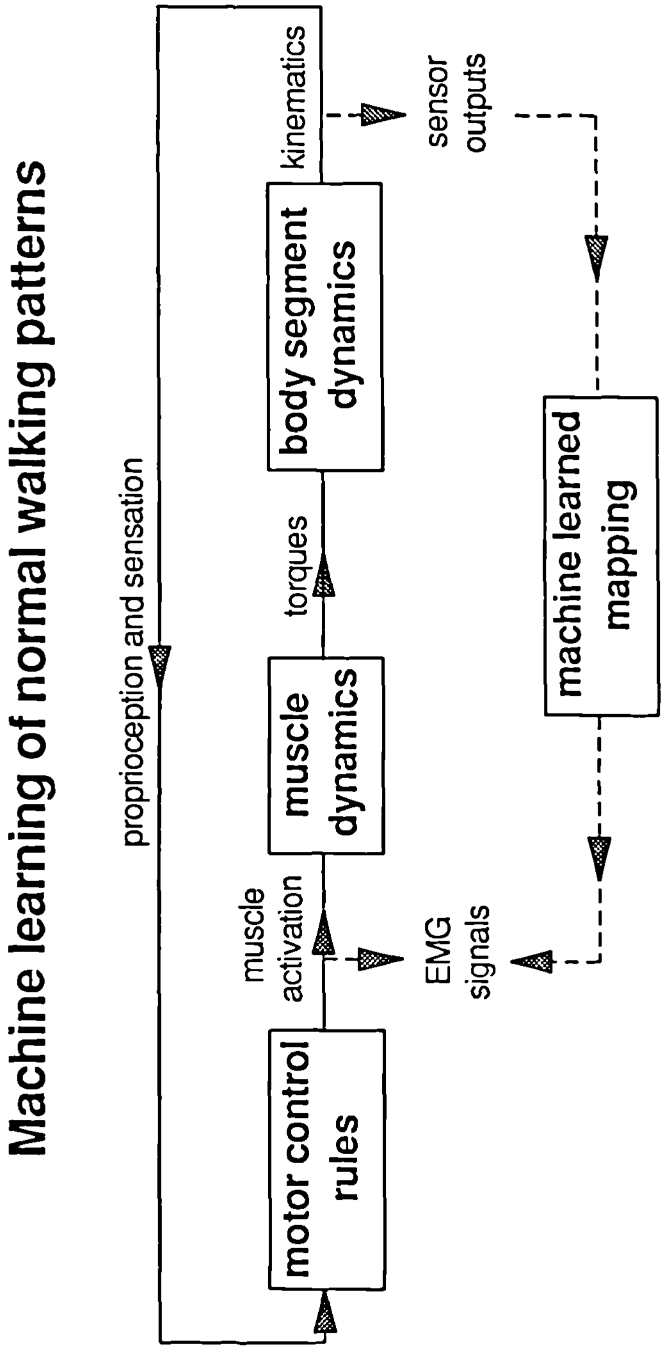
An advantage of the neural network technique was that one network was able to model the output of more than one muscle (Veltinck *et al.* 1990). The rule-based inductive learning technique required one independent decision tree per output.

The **timing** of the reconstructed patterns is important for the production of gait. The timing errors for all reconstructions are small (table 6.5a). Whilst it is impossible to state (without performing a detailed simulation) what error in timing is acceptable, the fact that the variations are small (maximum value 35 ms) is an indication of their validity.

The RMS error gives a general indication of the similarity of the reconstructions to the original patterns. There are no significant differences in the results for any of the techniques.

Given the relatively slow dynamics of the muscular-skeletal system, the impulse (time integral of muscle force) corresponding to each activation burst may be more important in determining the joint kinematics than the actual

1 Although dedicated neural-network hardware is being developed.



*The mapping of the relationship between the sensor outputs and the EMG signals can either be considered as an **indirect** model of the muscle and body segment dynamics, or a **direct** model of the (sub cognitive) rules relating proprioception and sensation to muscle activation.*

Figure 7.2 *Inverse and direct dynamical models* shape of the burst. The maximum average error is 25.5% (the large neural network/slow walking) which would produce an angular velocity that was similarly large.

An advantage of the use of these techniques over explicit inverse muscular skeletal models is that they generate the EMG activation level **with no time delay**. An explicit model's estimation of muscular activation must always lag by a time equal to the delay between electrical activation and mechanical torque generation (of the order of 100 ms [Barnett, 1990]). As there is no such lag for the inductive learning techniques, they must incorporate anticipatory knowledge of the movements to be performed. This is solely due to the repetitive nature of walking.

The induced rules (or weights for the neural networks) link the kinematic variables to the muscle activation levels. They can be considered as providing either a **direct** model ('cloning') of the cognitive and neurological rules and mechanisms that relate sensory inputs to motor outputs, or an **inverse** model of the muscular-skeletal dynamics (see figure 7.2). Although these two descriptions seem contradictory, they are both equally valid and both equally limited. Whereas a deductive model will be valid (within the limits of its assumptions) for all movement patterns, the induced models will only be valid over a range of movements that are similar to ones contained within their training sets. They will not be able to predict movements that are very different to ones they have encountered before. In particular, the predictive nature of the models means that they will only be valid for **cyclic** movement patterns.

7.3.4. Application to Swing-Through Data

7.3.4.1. Optimal attribute sets for training data

The error levels fall as the number of attributes increases up to 4; beyond this number the improvement stops and the error levels actually increase for larger numbers of attributes (figures 6.12 and 6.13). This increase is unexpected, and is probably due to some attributes having high mutual information values, which leads the tree to split on them, when the global error would have been reduced if a different attribute and/or threshold had been chosen. This reflects the nature of the algorithm, which can only be guaranteed to find a **local** optimum decision tree[1].

Larger rule-sets give lower error-rates, but it should be remembered that these are error-rates on the **training** set, where increased rule-set complexity models the **noise** in the data, rather than underlying general patterns. Optimal rule-set sizes will be discussed further in section 7.3.4.2.

7.3.4.2 Optimal rule-set size and attribute set for testing data

These results (figures 6.14 and 6.15) demonstrate the unreliability of gauging classification accuracy on training set performance. For all graphs, the **training** set accuracy increases with increasing rule-set size, whereas the **testing** set accuracy generally **falls** (error-rate increases) for rule-sets with more than two rules (an exception to this is the performance of the infra-red sensor in predicting the onset of stance, which has minimum error for 4 rules).

Initiation of stance

The following sensors gave the best performance:

- crutch force (11.5% [37 ms][2] testing-set error)
- heel switch (12.6% [40 ms] testing-set error)

All combinations with multiple attributes had inferior performances to those with a single attributes. The performance of all 9 attributes was worse still (15.9%). These results are unexpected and demonstrate the advantage of assessing all combinations of sensors, rather than assuming that the inductive algorithm will be able to select the optimal set. The heel switch and crutch force sensors are included in all the rule-sets with low error-rates; the best attribute combinations that do **not** involve either of these sensors are:

- crutch tilt (17.5% [56 ms] testing-set error)
- torso and crutch tilts (17.0% [54 ms] testing-set error)
- infra-red sensor (22.4% [72 ms] testing-set error)

1 For a decision tree with only one node, the local optimum decision tree is also the global optimum.

2 Using equation 4.19

Initiation of swing

The following sensor combinations give the best performance:

- crutch tilt (23.7% [62 ms] testing-set error)
- infra-red sensor (25.0% [65 ms] testing-set error)
- toe switch (27.4% [71 ms] testing-set error)

These are higher error-rates, with a further deterioration in performance for rule-sets with more than one attribute. The performance of the rule-set using all 9 sensors is worse than for the restricted sensor sets. A possible reason for this higher variation is that the timing of quadriceps activation at the end of the swing phase is more critical than the timing of its relaxation at the start of swing. Thus there is more room for intra-and inter subject timing variation in the 'swing' data-sets.

The complex nature of the gait suggests that it would require multiple attributes to describe it. However, these results indicate that any general patterns in the data are best modelled by the use of only one attribute. Possible reasons for this are:

- If all the gait runs were similar, they could be adequately modelled by a single sensor, even if there was no genuine link between the sensor output and the actual gait event. This is possible, as the artificial nature of walking in a gait laboratory, (straight-line, no obstacles, no distractions) may lead to unrealistically homogeneous gait runs. However, if this was the case, it should have been possible to model such a repeatable gait using any of the attributes; in fact, only a limited number were shown to be useful.

- The single selected attributes may, in fact, be genuinely sufficient at predicting the state transitions. Attributes such as crutch force and inclination are directly influenced by the subject, and may reflect her/his intention to initiate stance or swing.

The fact that the residual errors from the single sensors could not be reduced by using more sensors can be explained as follows:

- The data from five different subjects were combined to form the training set. Inter-subject variation in EMG activation patterns is to be expected (Winter and Yack, 1987) and these will lead to un-reducible errors[1].

- The attributes used may not have sufficiently described the situation, leading to modelling error (section 2.5.2); i.e., there was insufficient information to form an adequate model of the gait. For example, the knee and hip angular variables, which were not used to induce the rule tree, may have been important. However, the remaining attributes were fairly comprehensive and should have adequately described the gait.

- There may have been genuine random intra-subject variations in the timing of the EMG activations (system variability - section 2.5.2). Human experts are not benign teachers, their performance may be degraded by random error, slow reaction times and inattention. Higgins and Spaeth (1972) demonstrated that the kinematics of apparently identical movements are not exactly alike, even when performed under identical environmental conditions. Glencross (1980) showed that EMG records of movements also demonstrated variations (of insufficient magnitudes to disrupt performance). Thus the rule-set may, in fact, demonstrate a 'better' performance than the experts used to train and test it - Michie's 'clean-up' effect (Michie *et al.*,1990).

The best mean-magnitude-of-timing-error, T_{av}, was 37 ms for the (initiation of) stance and 62 ms for the (initiation of) swing. However, the scatter of these errors is important (figures 6.22a-c and 6.23a-e). Whereas some sensors (e.g. crutch force and heel switch used to predict the initiation of the

1 In an early comprehensive studies of human gait, Eberhart *et al.* found variations in the timings ('spread') of the quadriceps activation pattern of 10 unimpaired subjects, relative to heel-strike. They, however, suggested that the discrepancy was more likely to reflect variation in the detection of heel-strike, rather than a dissimilarity between individuals.

stance phase) have a narrow spread of errors, others have a much larger spread (e.g. crutch inclination and crutch and torso inclinations used to predict the initiation of the stance phase). It is not possible to state what magnitude of timing errors will compromise the stability of the gait without performing a detailed simulation, but a rule of thumb is that using the common stimulation frequency of 20 Hz only allows pulses to be output at 50 ms intervals, which limits the timing precision which can be attained. If one accepts one missed stimulation pulse then a maximum error of 100 ms is acceptable. Some of the rule-trees produce errors beyond this limit, which would indicate caution in using them for such time-critical applications. A corroborative strategy (e.g. majority voting between a number of different rule-trees) may reduce the outlying errors.

The technique of explicitly considering all combinations of sensors, rather than relying on the inductive learning algorithm to select the best set, produces lower error-rates (in figures 6.14 and 6.15, the error-rates for the restricted attribute combinations are lower than those when all attributes were available). However, the improvement in error-rate may not justify the large increase in computer processing required to obtain the decision trees for all the combinations. The major advantage of the technique is that it allows all alternative combinations of attributes to be assessed. Unlike artificial situations (such as in this thesis) where the data is already collected and sensors are 'cost-free', the development of a rule-based controller for FES gait requires the selection of appropriate sensors. There is a cost penalty associated with each sensor, which must consider aspects such as power consumption, bulk, weight, disruption to the gait, cosmesis, safety, robustness, and financial cost. A rule-set based on 'cheap' sensors might be preferred to one using 'expensive' sensors, even if its performance was slightly inferior. Thus, the explicit consideration of all attribute combinations allows the selection of the most appropriate sensor set using wider criteria than simply discrimination power.

7.3.4.3. Sample rule-sets

Stance to swing transition (figures 6.18a to c)

a. Toe switch: the transition occurs when the processed toe-switch output becomes less than -460: this occurs when the toe-switch opens (output goes to -1000). So this rule associates the transition from stance to swing with 'toe-off'.

b. Infra-red sensor: swing begins once the processed sensor output becomes less than -90. The infra-red sensor counts (down) the time in milliseconds following crutch loading, thus -90 represents a transition occurring 90 milliseconds after the crutches are initially loaded.

c. Crutch inclination: the transition occurs when the crutch angle to the forward horizontal becomes less than 97 degrees; i.e., when the crutches are tilted less than 7 degrees backwards. This corresponds to a subject leaning forwards on the crutches as she/he moves from stance to swing.

Swing to stance transition (figures 6.19a to e)

a. Infra-red sensor: this is the only sensor that demonstrates markedly improved performance as the number of rules increases; the reason for this is apparent from the decision tree (figure 6.19e) and the sample sensor output (figure B.1f). The set of examples which fulfill the first rule (IR < 10) consist of those for which the crutches are unloaded (definitely stance, IR = 0) and those for which the crutches are loaded and the knees have not yet passed through them (definitely swing, IR < 0). The rule:

IF *IR* < -120 THEN *swing* ELSE *stance*

separates these two classes. If the first rule is not met then IR is positive and the crutches must be loaded, the value of IR representing the time since the knees passed through the crutches. The rule

IF *IR* > 330 THEN *stance* ELSE *swing*

states that stance will begin 0.33 seconds after the knees have passed through the crutches, even if the crutches are still loaded.

b. Crutch and torso inclinations: a similar rule-set to (c), with the additional qualification that even if the crutch inclination is more than 74 degrees, the transition will still occur if the torso inclination is greater than 100 degrees (i.e. the subject leans backwards beyond 10 degrees). This is understood if one considers that if the crutches do not progress much beyond the vertical, the body will swing further and thus incline further backwards.

c. Heel switch: the transition occurs when the value of the processed heel switch output rises above -500. When the switch is open, the output is -1000; immediately it closes, the output becomes zero. The output then rises every 20 ms until the switch opens again. Thus, a value of -500 for the transition implies it will occur immediately the switch is closed (heel strike).

d. Crutch force sensor: the transition occurs when the crutch load becomes less than 86.5% of body weight; i.e., in the early stages of weight transfer from the crutches to the subject's feet.

e. Crutch inclination: the transition occurs as the angle of the crutches to the forwards horizontal falls below 74 degrees (i.e. 16 degrees forwards of vertical). This forward inclination corresponds to the late phase of swing.

7.3.4.4 Generality of the rules

The error rates obtained on composite rule-sets induced from the whole group are similar to those induced from the specific individual. Sometimes the whole-group error rates are superior, which would perhaps indicate an intra-subject variation which is 'smoothed out' by the group - the 'clean-up' effect (Michie *et al.*, 1990).

The inter/intra subject performances are closest for the toe-switch and infra-red sensor rule-trees used to predict the initiation of swing, and the heel switch, crutch tilt and crutch tilt and torso tilt sensors used to predict the initiation of stance. This may indicate that there is little scope for individual variations of strategy with regard to these sensors. There are larger variations for subjects A and C for the infra-red rule-tree used to predict the initiation of stance, for subject A for the crutch-force rule-tree for the initiation of stance, and for subject D for the crutch inclination rule-tree used to predict the initiation of swing. These subjects may be using stategies that differ from those of the rest of the group with regard to these sensors.

It is apparent that subject A's intra-subject error rates are regularly amongst the lowest. This indicates that the subject is adopting quite consistent control strategies. It may be worth concentrating on rules induced from this subject for further induction of control rules for swing-through gait.

7.3.4.5. Comparison with experts' rating of sensors

It can be seen from the values of τ in tables 6.10 and 6.11 that there is very little association between any of the experts' rankings of sensors and those produced by *Empiric*. The value of τ for the mean rankings is also very close to zero (no correlation). These results indicate that despite being knowledgeable in the field, it is was not easy for the respondents to select the appropriate sensors to control this complex gait. This corresponds with the results of Kirkwood (1989) for reciprocal gait.

This provides an argument for the use of the swing-through model (the trained, unimpaired subjects) to investigate the selection of appropriate sensors. It is possible that the 'experts' would have produced closer rankings to those of *Empiric* if they too had seen the data collected from the unimpaired subjects.

7.3.4.6. Sensor substitution

The inductive learning technique allows exploration of the use of alternative, possibly non-obvious, sensors and sensor combinations (see previous section). The ability to form a decision tree from any sensor or sensor combination permits an undesirable sensor (e.g. one that is unrobust or that impedes gait) to be replaced by a more appropriate one. For example, in section 7.3.4.3, rules based on foot-switches were generated both for the swing and the stance transitions; foot-switches are renowned for being unreliable. However, in both cases, alternative rule-sets were generated that had similar performances, but used crutch-mounted sensors instead of foot switches; these sensors may be mounted inside the crutches, increasing their robustness and cosmesis. Thus, the inductive technique provides the designer of FES control systems with a mechanism for writing controllers that use the most **appropriate** sensors, rather than the most **obvious** ones.

7.3.4.7. Generation of rule-based controllers

Intention detection

Those spinal cord injured subjects who perform FES gait often have unimpaired upper limb proprioception, sensation and motor control; consequently, they have both full knowledge and full control of crutch position and crutch force. Any movement will correspond to changes in crutch force and/or position; thus those induced rule-sets that involve crutch force or crutch inclination may be considered as detecting the subject's movement intentions (see section 2.4.1.4). In contrast, the rule-sets involving heel and toe switches can be considered as providing a more automatic type of control (although by raising or lowering her/his body the subject does have some influence over the activation of these switches).

Controller implementation

There are three approaches for integrating rules induced from non-impaired subjects into a practical FES controller for a spinal cord injured subject:

1. Use the induced rules only to suggest which sensors, or combinations of sensors, may be useful for forming controllers.

2. Use the induced rules to determine the **form** of a controller (i.e. the rule-set contains the same sequence of attribute tests as the original), but tailor the actual **thresholds** used by means of intuition and/or trial-and-error and/or formal modelling.

3. Assume that if the rules are induced from a population similar (size, weight, joint ranges of motion) to the SCI subject, then they may be used verbatim.

Unless the viability of approach 3 can be demonstrated by means of simulations or risk-free tests, a more cautious approach (1 or 2) should be adopted.

As the induced rules can only be **guaranteed** to be valid for situations identical to the training sets, it is likely that any practical controller will contain hand-modified rules; i.e., ones combining the specific induced knowledge about the gait with the rehabilitation professional's more general knowledge.

CHAPTER 8. CONCLUSIONS AND RECOMMENDATIONS FOR FURTHER WORK

8.1. CONCLUSIONS

Swing-through gait with free knees has a lower energy cost (mean 63 %) than fixed-knee gait.

It has been demonstrated (for the first time) that FES free-knee swing-through gait is possible in subjects with thoracic level lesions using surface stimulation techniques.

FES swing-through gait with active knee-flexion during the body-swing phase provides a faster form of locomotion than both KAFO swing-through gait and FES reciprocal gait for SCI subjects with mid to low thoracic lesions.

The study of the gait using motion analysis techniques allows it to be assessed, and identifies specific areas that can be improved.

It is possible to induce rules that describe human movements by using machine learning techniques to find invariants in movement patterns.

The study of trained and appropriately braced unimpaired subjects performing swing-through gait allows the induction of rules that describe this gait; these rules can then be used to automatically form controllers for FES gait.

The use of the inductive learning technique, together with appropriate sensors, allows the detection of a subject's intention to move. The technique also permits identification of substitute sensors for those which may be intuitively obvious, but otherwise undesirable.

The application of 'fuzzy' example weighting to a set of training examples allows the induction of more robust rule-sets.

8.2. RECOMMENDATIONS FOR FURTHER WORK

In order to make FES swing-through gait practical for use outside the laboratory, its speed, range, safety and convenience must be improved. This requires the following areas to be addressed:

Trunk and hip stability are important for a fast, safe gait; they may be improved by the stimulation of other muscles (such as adductor magnus or the erector spinae group) in addition to gluteus maximus. Due to the difficulty of applying surface electrodes to stimulate the appropriate motor points, it may be advantageous to use percutaneous or fully implanted electrodes. An appropriate training regime may then improve the strength and fatigue-resistance of these muscles. An alternative solution is to use mechanical bracing of the hip, or a hybrid system combining mechanical bracing with electrical stimulation.

A logical progression from this work is the assessment of the 'cloned' controllers, and their comparison with controllers derived intuitively, or through formal modelling. For a 'risk-free' assessment, a customised computer simulation should be developed, the performance indicators being stability, speed, minimum local and whole body fatigue and minimal contact forces.

The reduction in cognitive burden associated with using rules which allow the detection of movement intention, rather than rules which require explicit manual switching, may be assessed using the techniques of Mulder and Guerts (1991).

The particular states, and their associations with EMG levels, were determined from *a priori* assumptions about the gait (i.e. that the major phases roughly correspond to foot-fall patterns). It may be possible to obtain more robust controllers by automatically determining invariant states from the training data by means of clustering techniques, and then relating these to (not necessarily simultaneous) changes in stimulation state.

The technique has been used to induce 'coordinating', mid level rules (transitions between major states), it could also be used to induce low level, execution rules (control of continuous variables within a state). This could be achieved by mapping EMG activations to joint angles. In this way a comprehensive rule-based controller could be formed inductively.

Any use of the system outside the laboratory would require the development of robust sensors and a lightweight 'stand-alone' stimulator capable of running complex control programs. The robustness of the rule-based controller in a noisy domain may be improved by including a number of alternative rules to predict the state transitions, and allowing some degree of corroboration between them. This corroboration may be implemented by a simple majority voting stratagem, or may be based on fuzzy or Bayesian weightings of each rule output[1]. If the rules are formed from a number of

1 At present there is no degree of probability or fuzziness associated with the output of the decision rule, but this may be easily introduced by examining the performance of the rules on testing data.

different sensors, the controller can be given a degree of fault **tolerance** in the event of sensor failure. Further, fault **diagnosis** can be provided by simulating various sensor failure states in the training data, and inducing decision trees to recognise these.

The controller should be able to improve (adapt) its rules during operation; such incremental learning has been demonstrated in rule-tree induction (Utgoff, 1988). The difficulty is to determine new training examples in the absence of external control inputs; one possibility is the use of a 'quality supervisor', which would assess the quality of each stride, and use model-based or heuristic reasoning to retrospectively infer when the appropriate state transition should have occurred. This data would be used to adapt the controller rule-base.

The 'fuzzy' weighting technique should be further investigated. In particular, the choice and application of the triangular weighting function (although straightforward and common) was an arbitrary decision, and was not based on a formal analysis of the characteristics of the noise in the training data. Other possible membership functions are the sigmoid (which will allow many examples to have low values of membership), or a quantised function (the shape being entirely determined by the data characteristics).

The 'IF *input* > *threshold* THEN *output*' nature of the rules used in the inductive learning algorithm are restrictive, being entirely dependent on concepts supplied by the user. Constructive induction (Rendell, 1988) may allow the modelling of more complex knowledge by introducing new concepts (functions of attributes). Alternative forms of machine learning may also be explored. For example, the neural networks technique has been shown to be promising.

Wider applications of the technique are mentioned by Michie *et al.* (1990): these include 'skill grafting' to produce autopilots that can operate in situations where the control problems are beyond conventional automatic control systems, yet the environment precludes the use of human pilots[1].

1 For example, signals from earth may travel too slowly to control an unmanned lander on another planet.

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APPENDIX A. ALGORITHM FOR INDUCTIVE LEARNING PROGRAMME 'EMPIRIC'

This algorithm is an implementation of the hierarchical mutual information classifier of Sethi and Sarvarayudu (1982). It performs a hierarchical partitioning of the attribute space (which is n-dimensional for n attributes) using hyper-planes perpendicular to the attribute axes. Thus the n-dimensional attribute space is sectioned into hyper-cuboids, each of which is designed to contain members of only one class. The choice of partition involves the calculation of the information quantity *average mutual information gain.* The information theory underlying this is discussed in the main body of this work.

The present implementation, *Empiric*, is a development of the program *Disciple* (Kirkwood, 1989; Kirkwood *et al.*, 1989). It has been redesigned by the author to improve processing efficiency and to add certain extra features, particularly the inclusion of weighted and 'fuzzy' weighted examples (see the main text for a discussion of these concepts).

This appendix will describe the use of the program, the required data format, and the operation of the major procedures.

A.1. PROGRAM USE

The program operates on IBM *PC* compatible computers. It can be run by typing **[path] empiric** at the DOS prompt, where [path] represents the location of the code.

The program is menu driven; the following options are available:

1. 'read in example files'
2. 'construct decision tree'
3. 'classify a file from disc'
4. 'display decision tree'
5. 'eliminate an attribute'
6. 'output rules to file'
7. 'load rules from file'
8. 'directory'
9. 'help'

D. 'DOS shell'

B. 'batch process a group of files'

X. 'exit'

These options will now be discussed in detail.

Option 1. 'read in example files'

Reads in a file containing training data from disc. The file must be in the *Empiric* data format (specified in this appendix). If required, a directory of files is provided.

Option 2. 'construct decision tree'

The user is prompted for the required error-rate (from 0 [no errors] to 1 [100% misclassification acceptable]). A decision tree is then formed for the training file that has been previously loaded into memory (with option 1). For large training files (several hundred examples or more) this may take some time to perform. During the calculations, a count is displayed showing the number of nodes that have been formed, and the present level of mutual information.

Option 3. 'classify a file from disc'

Once a decision tree has been formed (or loaded from disc), it can be tested on example files with known classifications. The example file can either be a new file loaded from disc, or the existing file in memory that was used to form the decision tree. The former option allows the performance of the rule-set to be tested on independent testing data. The latter allows the performance to be assessed on the training set.

Option 4. 'display decision tree'

The decision tree in memory is displayed either on screen, or saved to a file in ASCII format. The latter option allows it to be printed, or loaded into an expert-system shell or controller rule-base.

Option 5. 'eliminate an attribute'

This option is used to prevent a particular attribute being used to form the decision tree. The status of an attribute is toggled each time it is selected: i.e. the first time it is eliminated, the second time it is restored, etc.

Option 6. 'output rules to file'

The induced rules are saved to disc (in a non-ASCII format).

Option 7. 'load rules from file'

Allows the restoration of rules saved with option 6.

Option 8. 'directory'

Prompts for a path-name and then displays its directory.

Option 9. 'help'

Displays basic information about the use of the program

Option D. 'DOS shell'

Allows the user to perform DOS operations, this option is useful for modifying files without leaving the program. Typing **exit** returns to the program.

Option B. 'batch process a group of files'

This routine allows the assessment of different attribute combinations. It begins by prompting the user for the name of a file in 'batch-format'[1]; this file contains a list of example files which will be used to form testing and training sets. The routine loads this file, then requests the maximum number of rules R_{max}, the minimum number of attributes A_{min}, the maximum number of attributes A_{max}, and the number of repetitions N. The user is given the option of excluding any attributes, then prompted for the name of the file to which the results will be stored.

This routine then generates all the attribute combinations that contain at least A_{min} and at most A_{max} attributes. For each combination N training sets are formed, each containing half the example files (assigned at random). For each training set $\log_2(R_{max})$ decision trees are constructed, containing from 1 to R_{max} rules, and the performance of each one is determined on a testing set consisting of the remaining examples files. The mean and standard deviations of the classification performances for the N training and testing sets are calculated and saved to the file in ASCII format.

---

1 Described later in this appendix.

Option X. 'exit'

This ends the program and returns control to DOS.

A.2. FILE FORMATS

A.2.1. Training and Testing Data

The example files containing testing or training data are stored as ASCII files with the DOS extension name **.emp**. They have the format listed below:

- Description of the data
- The number of attributes
- List of attribute names
- The number of classes
- List of class names
- The data
- End marker

All entries are on consecutive lines. Each is described in detail below.

Description of the data: Up to 255 characters on one line.

The number of attributes: An integer from 1 to 16 (in this implementation).

List of attribute names: Each on a separate line, there must be the same number as specified above. Each attribute name can have up to 20 characters; spaces are allowed.

The number of classes: An integer from 1 to 15.

List of class names: Each on a separate line, there must be the same number as specified above. Each class name can have up to 20 characters; spaces are allowed.

The data: Each line represents one example. The first parameter is the class number (from 1 to the maximum class); if the examples have a 'fuzzy' weighting then the second class is included as follows:

$$class = firstClass + 16 \cdot secondClass$$

The program automatically detects fuzzy weighting if any of the class values are greater than 15.

The second value represents the weight of the example. If no weighting is being applied (i.e. all examples have equal weight) then this should be set to 1; otherwise, this parameter can take any integer value from 1 to 255. If fuzzy weighting is being used then the first four bits represent the degree of membership of the example in the first class, and the second four bits represent the degree of membership in the second class. Thus, the weight is calculated as follows:

$$weight = wt_{class1} + wt_{class2} \cdot 16$$

where wt_{class1} and wt_{class2} are integers from 0 to 15.

The list of attribute values follows, each value is a signed 16 bit integer, thus the range is -32k to 32k-1.

All data associated with one example is on the same line; each item is separated by at least one space.

End marker: The word 'END' on a separate line.

A.2.2. Batch Control Files

These files contain a list of example-file names that can be combined to form training and testing sets. They are used in the 'batch process' option.

Batch control files are stored as ASCII files with the DOS extension name **.emp**. They have the format listed below:

- Description of the data
- The number of attributes
- List of attribute names
- The number of classes
- List of class names
- Batch marker
- List of batch file names

Each entry is similar to those described in the previous section, apart from 'batch marker', which is the word 'BATCH'; and 'list of batch files', which is a list of all the individual batch files used to form training and testing sets. Each filename must contain the full path, and is on a separate line.

A.2.3. Batch Files

These are the files loaded by the batch control files. They contain only training/testing example data in the format given in section A.2.

A.3. PROGRAM OPERATION

A.3.1. Variables

The most relevant variables are listed below:

NodeList (global)

An array of records, each of which contains the following information about the node:

Its parent node; its left and right child nodes (if any); whether it is active (i.e.it is neither a terminal node, nor has any offspring); whether it is terminal; if terminal, the class associated with it, what threshold it uses on what attribute to partition the training set, and the information level associated with that threshold.

ExamplesList (global)

An array of records containing the following information about each example:

Its class, the membership weight in that class, and the node it is currently associated with (all examples are initially associated with the root node; as the tree grows, they are allocated to right child nodes if they are above the threshold, or left child nodes if they are below/equal to the threshold.

Attributes (global)

A two-dimensional array that is used to store the values on each attribute for each example. It is implemented using pointers to maximise available memory space.

Fuzzy (global)

A switch that indicates if 'fuzzy' example weighting is being used. It is set automatically from the input data.

AttributeDeleted (global)

An array of switches that indicate which attributes can be used to induce the decision tree.

ExamplesAtThisNode (local)

A two-dimensional array that is used to temporarily store the subset of examples associated with the right and left offspring of the current node. This allows faster access than if the entire example-set (stored in **ExamplesList**) was searched.

A.3.2. Procedure

The main flow of the algorithm is described in the following numbered events.

1. Calculate the required information level for the given error rate P_e, and number of classes N_c, using the formula:

   $$I_{min} = \log_2(N_c) + P_e*\log_2(P_e) + (1-P_e)*\log_2(1-P_e) - P_e*\log_2(N_c-1)$$

2. Form two new nodes, left and right (if this is the first time around the loop, then only form one node - the root node)

3. Search through **ExamplesList** to find those examples associated with the two nodes, store them in **ExamplesAtThisNode.**

4. Start with the left node.

5. Start with the first undeleted attribute.

6. Sort all the examples at the present node into ascending order on the present attribute values.

7. Search through the sorted list to find a change of class.

8. Find the attribute value (threshold) at which the class change occurred.

9. Calculate the average mutual information gain at that threshold. The formula is:

$$I_{gain} = \sum_{1}^{N_c} \frac{I_{class}}{N_{total}}$$

$$I_{class} = \frac{C_{below}}{N_{node}} \log_2 \frac{C_{below} N_{node}}{N_{below} C_{node}} + \frac{C_{above}}{N_{node}} \log_2 \frac{C_{above} N_{node}}{N_{above} C_{node}}$$

where:

C_{node} is the total weighted number of examples of one class present at the node
C_{above} is the total weighted number of examples of one class above the threshold
C_{below} is the total weighted number of examples of one class below the threshold
I_{class} is the increase in mutual information at the threshold for one class
I_{gain} is the total increase in mutual information over all classes at the threshold
N_{total} is the weighted total number of examples in the entire training set
N_{node} is the weighted total number of examples present at the node
N_{above} is the weighted total number of examples above the threshold

N_{below} is the weighted total number of examples below the threshold

If *fuzzy* is true, then each example is considered as two separate examples, one in the primary class and one in the secondary class.

10. Find the next change of class.

11. Repeat 7-9 until the threshold with the maximum information gain on the present attribute has been found.

12. Select the next attribute.

13. Repeat 6-12 until the threshold with the highest information gain on all attributes has been found.

14. If no threshold has been found the node is terminal, set it to inactive.

15. Repeat 5-14 for the right node.

16. Select the node with the maximum information gain from all nodes that are presently active; this node is now the current node. Set it to inactive.

17. Increment the total information level, if it is both below the value established in 1 and there are still active nodes then repeat 2-16.

18. A decision tree with the required accuracy, or one which cannot be split any further, has been formed. If any remaining nodes are active then make them terminal and set them to the weighted majority class present at the node.

An example is classified by starting at the root node, then selecting the right or left offspring according to the attribute test at the node, until a terminal node is reached. The predicted class of the example is the class associated with the terminal node.

The rules can be extracted from this decision tree by searching through **NodeList**, taking each terminal node in turn and chaining back through its ancestors until the root node is reached.

The *Turbo Pascal* source code for this program is contained on a floppy disc accompanying this thesis.

APPENDIX B. PROGRAM 'ALIGN'

This program processes the raw kinematic, kinetic and EMG data obtained from the study of non-impaired subjects performing swing through gait. It synthesises various sensor outputs and generates training and testing files in *Empiric* compatible format. It is included on a floppy disc accompanying this thesis.

B.1. PROGRAM USE

The program operates on IBM *PC* compatible computers. It can be run by typing **[path] align** at the DOS prompt, where [path] represents the location of the code.

The program is graphics-based; the user is initially prompted to select an appropriate graphics driver. The program switches to graphics mode and there is a delay whilst the filter coefficients are calculated.

A description filename is then requested; this is a file which contains general information about the subject performing the test. The information includes zero and scale factors for each analogue signal, zero angles for the hip and knee, the subject's weight and the physical location of the centre of the force-plate.

The program then prompts for the data base-filename, all files for each run have slight modifications of the same base-filename, which allow them to be loaded automatically. The data files are:

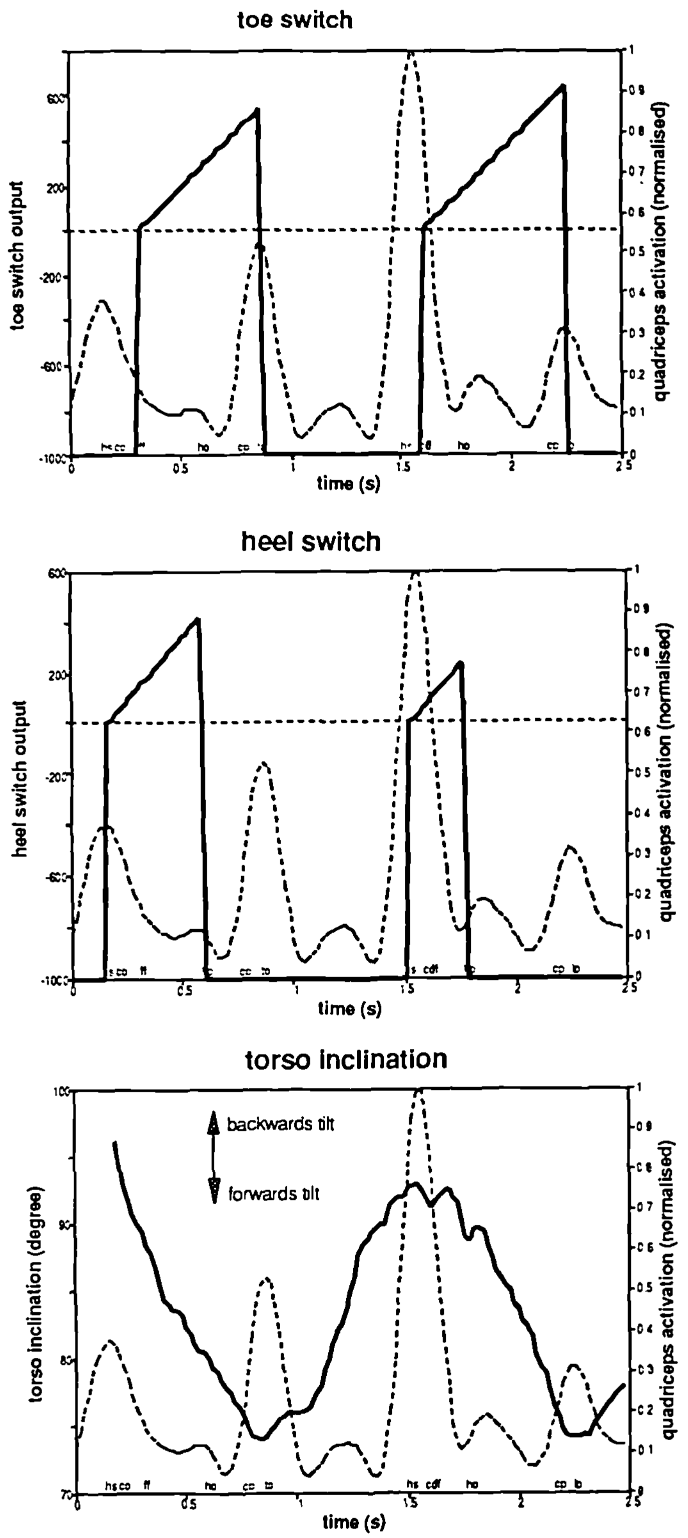
1-3. ASCII files for the x,y, and z kinematic coordinates. The filename is basename + ['x', 'y' or 'z'] + '.dat'. These files are generated by the *VICON* graphics program.

4. An ASCII file containing the force-plate, crutch-force readings and the synchronisation switch. The filename is:

   basename + 'fp' + ' dat'.

   This file is also generated by the *VICON* graphics program.

5. A file containing EMG samples, in the format produced by the program *Acquire* (GF Phillips, 1988). The filename is basename + '.dat'. This file also contains the synchronisation switch output.



Figures B.1 a,b,c *Sensor outputs with sample EMG traces*

Having loaded in the movement data, the program aligns EMG and movement data by using the synchronisation switch channels, then calculates the synthesised sensor values and processes the EMG data (see appendix G). A menu is then presented which allows sensors to be selected for graphical display. When the processed quadriceps EMG activation is displayed, the region to be output to *Empiric* is selected by the user. The 'Empiric' option is then selected and an *Empiric* compatible file is generated.

B.2. CALCULATION OF SIMULATED SENSORS

The following section details the calculation of each of the simulated sensors, from the kinematic and kinetic data obtained from the *VICON* system, the instrumented crutches and the force-plates. Sample outputs of all sensors for one gait run are given in figures B.1a to B.1q.

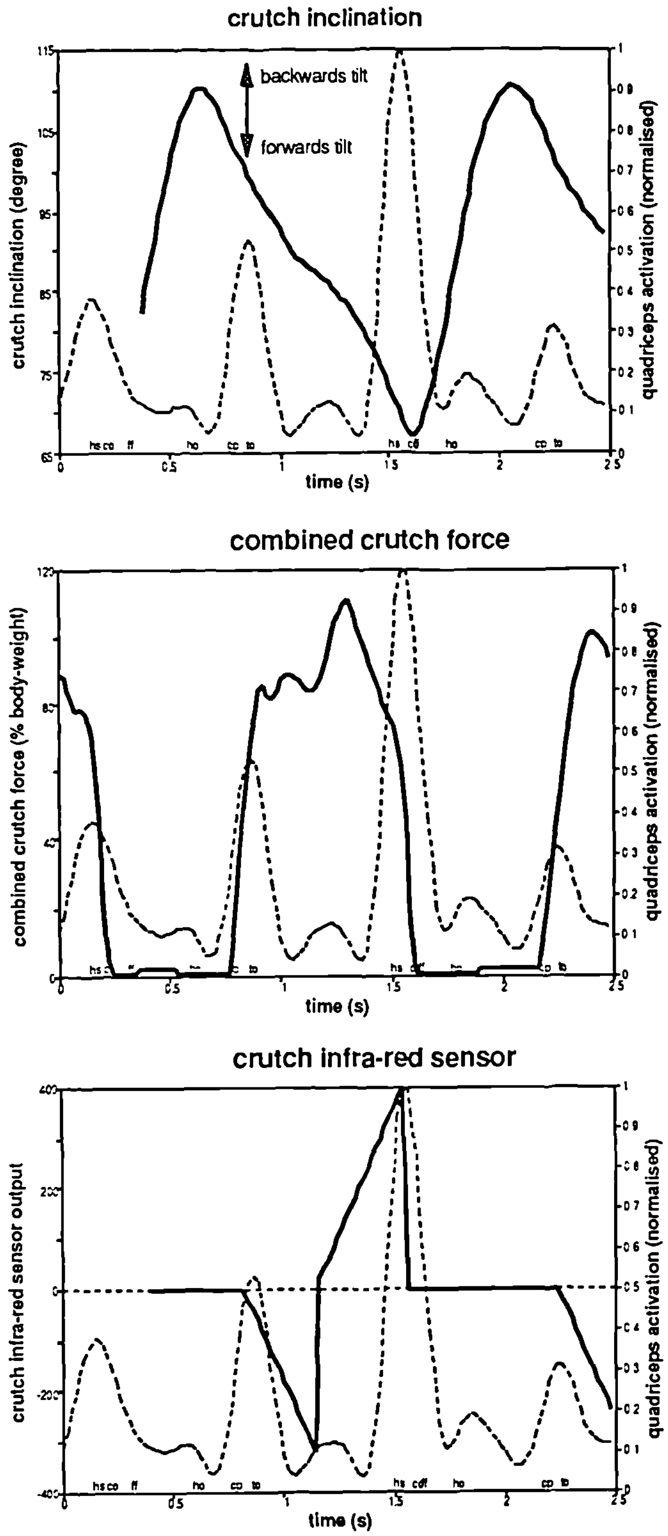
NotFound is a constant that indicates that the sensor output could not be calculated; its value is -32767.

B.2.1. Toe switch

A simple switch placed under the anterior foot. This sensor is processed to give timing information about the stance phase (see figures 4.7 and B.1a).

ToeSwitchPressed = TRUE IF (height of toe marker < 10 mm)
FALSE otherwise

1. WHILE **ToeSwitchPressed** is TRUE step through the samples, setting **ToeSwitch** to be **NotFound**.
2. WHILE **ToeSwitchPressed** is FALSE step through the samples, setting **ToeSwitch** to be -5000.
3. Set **ToeSwitch** to be 0.
4. WHILE **ToeSwitchPressed** is TRUE step through the samples, incrementing **ToeSwitch** by 20 for each sample.
5. Repeat 2-4 until the last sample is reached.



Figures B.1 d,e,f *Sensor outputs with sample EMG traces*

B.2.2. Heel switch

A similar switch to the toe switch, placed under the posterior foot. This sensor is processed to give timing information about the stance phase . Its value is calculated in the same manner as B.2.1, with the height of the heel marker being used to determine if the switch is pressed (see figure B.1b).

B.2.3. Torso inclination sensor

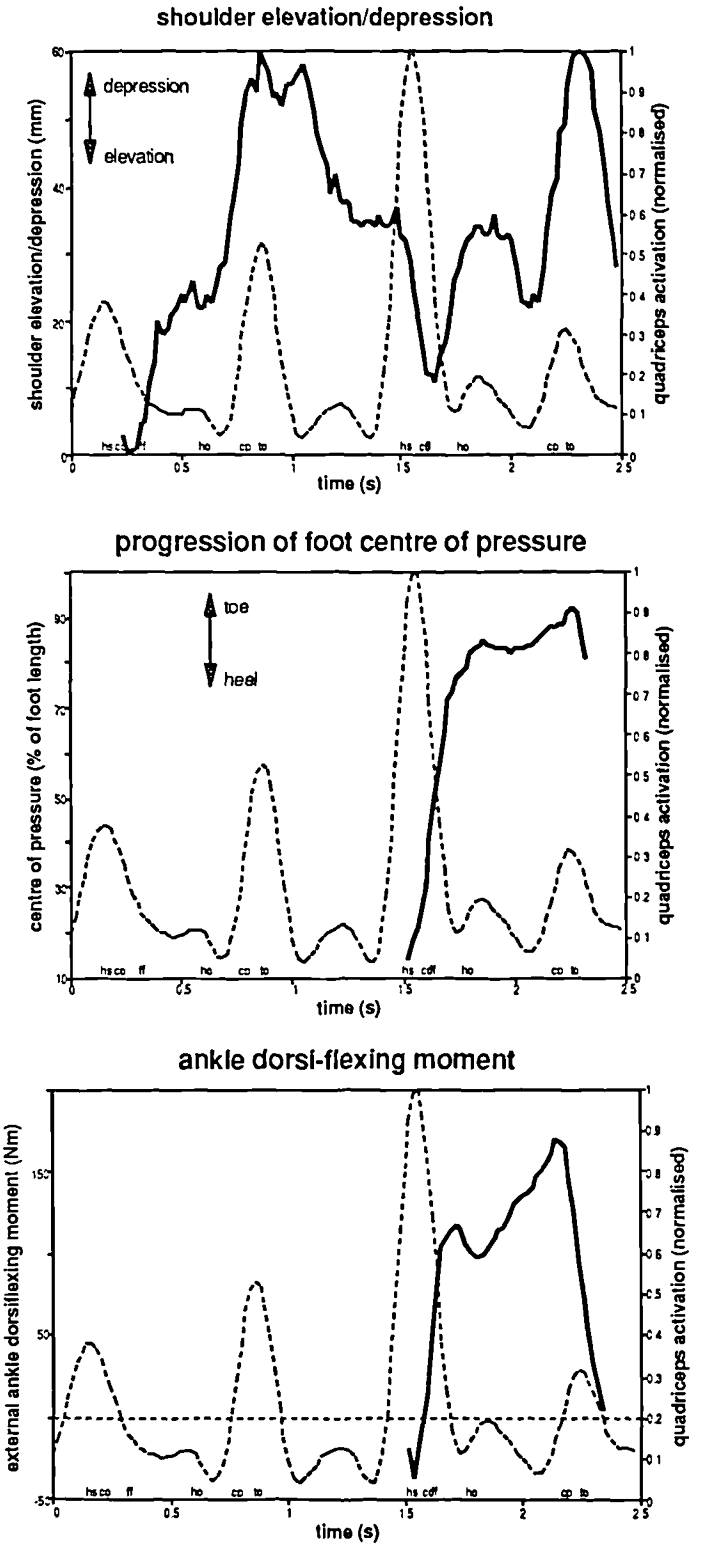
An inclinometer, possibly located in a stimulator or a power-pack on the subject's back or chest. Its value is the angle between the projection of the hip-to-shoulder vector on to the sagittal plane, and the forwards horizontal (x axis). The units are tenths of degrees (see figure B.1c).

B.2.4. Crutch inclination sensor

Either an inclinometer located on one crutch, or a potentiometer connected to a crutch rocker bottom (the latter would only give valid readings when the crutch was in contact with the ground). Its value is the angle between the projection of the hand-to-crutch-tip vector on to the sagittal plane, and the forwards horizontal (x axis). The units are tenths of degrees (see figure B.1d).

B.2.5. Crutch axial force sensor

A set of strain gauges and corresponding amplifiers connected to one crutch to measure axial force (as the gait is symmetrical, the force in both crutches is assumed to be equal). The output of this sensor is calculated by averaging the force in both crutches and dividing by bodyweight. The units are percent-of-bodyweight (see figure B.1e).



Figures B.1 g,h,i *Sensor outputs with sample EMG traces*

B.2.6. Crutch infra-red sensor

A sensor consisting of an infra-red transmitter/receiver pair mounted one on each crutch. When the crutches are loaded (see B.2.5), and the beam is broken, this indicates that the legs are passing between the crutches during the body-swing phase of the gait. This signal is processed to give timing information about the swing phase (see figure B.1f). This sensor had not been previously constructed: the simulation technique allowed its performance to be evaluated before construction.

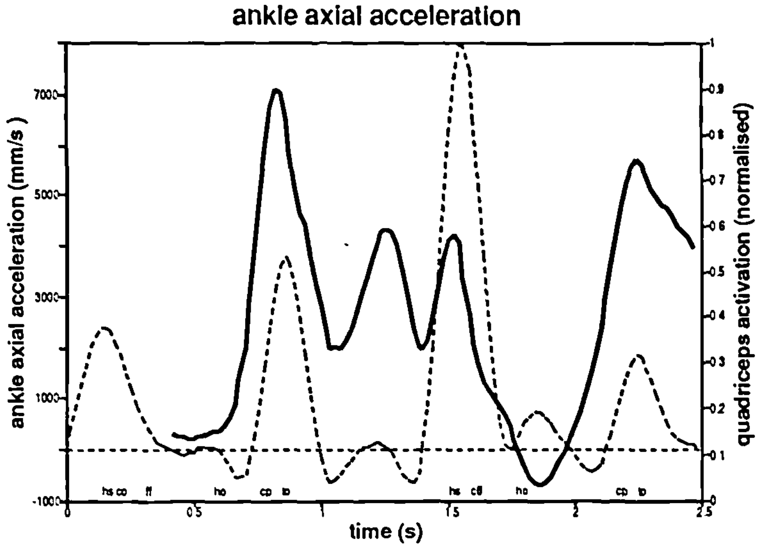
CrutchesLoaded = TRUE IF (crutch force > 50 [% bodyweight])
FALSE otherwise

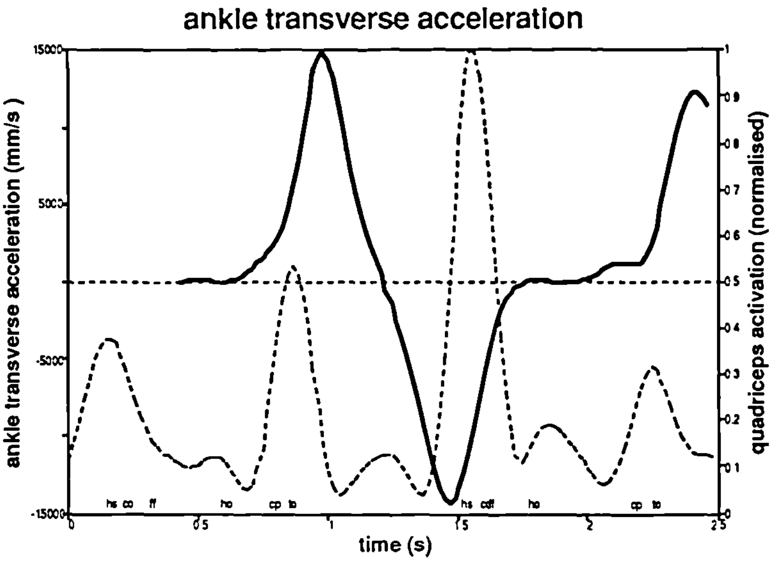
KneesInFront = TRUE IF (knee x-coordinate >
(crutch-tip x-coordinate + hand x-coordinate) / 2)
FALSE otherwise

1. Step through the sample until (**CrutchesLoaded** is FALSE) OR (**KneesInFront** changes from FALSE to TRUE), setting **IRsensor** to be **NotFound.**
2. WHILE **CrutchesLoaded** is FALSE, step through the samples, setting **IRsensor** to be 0.
3. WHILE (**CrutchesLoaded** is TRUE) and (**KneesInFront** is FALSE), step through the samples, incrementing **IRsensor** by 20 for each sample.
4. WHILE (**CrutchesLoaded** is TRUE) and (**KneesInFront** is TRUE), set **IRsensor** to be zero, then step through the samples, decrementing **IRsensor** by 20 for each sample.
5. Repeat 2-4 until the last sample is reached.

B.2.7. Shoulder elevation

A sensor that detects elevation or depression of the shoulders, possibly by means of a sprung linear potentiometer fixed to the mid back, and attached to a strap passing over the shoulder(s). The value of the output of this sensor is found by calculating the length of the projection of the forehead-to-shoulder vector on to the sagittal plane. The units are mm (see figure B.1g).





Figures B.1 j,k *Sensor outputs with sample EMG traces*

B.2.8. Centre of pressure insole

A sensor that measures the position of the centre of pressure acting through it, mounted either under the shoe, or inside it. Possibly consisting of a matrix of small force sensitive switches. The value of its output is calculated from the force-plate output as follows:

$$\textbf{COP} = 100 * | X_{cop} - X_{heel} | / footLength$$

$$X_{cop} = X_{FP} + (M_z - F_x * Y_{FP}) / F_y$$

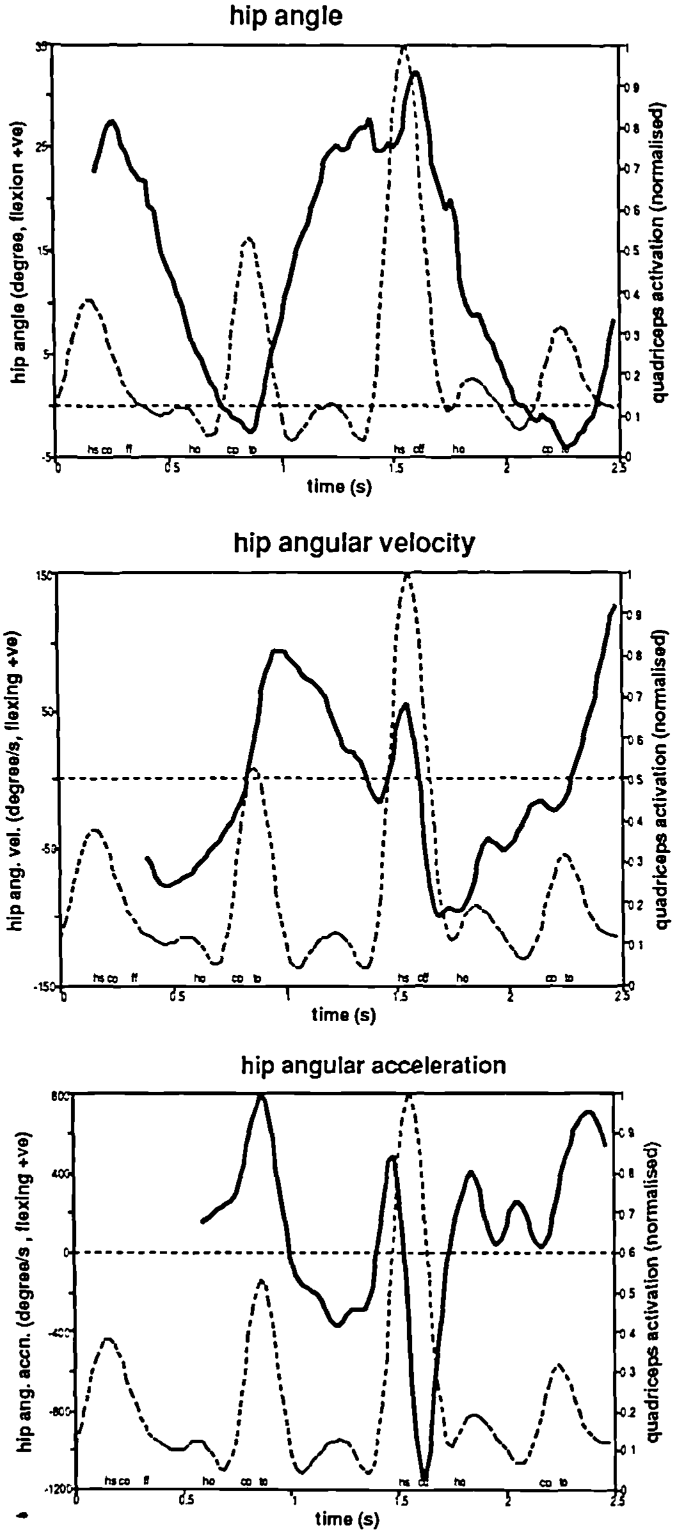
where:

X_{cop} is the x-coordinate of the centre of pressure,
X_{heel} is the x-coordinate of the subject's heel,
X_{FP} is the x-coordinate of the centre of the force-plate,
Y_{FP} is the y-coordinate of the effective centre of the force-plate,
F_x is the force in the x-direction obtained from the force-plate,
F_y is the force in the y-direction obtained from the force-plate,
M_z is the moment about the z-axis obtained from the force-plate,
footLength is the length of the subject's foot.

The result is the distance that the centre-of-pressure is in front of the heel, expressed as a percentage of the foot-length (see figure B.1h). The modulus operation permits the formula to work whether the subject is walking in the direction of increasing or decreasing x. The result is only valid whilst the subject is standing completely on the force-plate.

B.2.9. Ankle moment sensor

A sensor that detects the bending moment at the subject's ankle. It can be implemented by strain-gauges attached to the subject's ankle-foot orthosis



Figures B.1 l,m,n *Sensor outputs with sample EMG traces*

(AFO). The output of the sensor is calculated as follows:

$$\textbf{AnkleMom} = F_y*(X_{FP}-X_{ankle}) + F_x*(Y_{ankle}-Y_{FP}) + M_z$$

where all symbols are as previously defined, and:
X_{ankle} is the x-coordinate of the subject's ankle,
Y_{ankle} is the y-coordinate of the subject's ankle.

The result is the dorsi-flexing moment at the subject's ankle, in Nm (see figure B.1i). The result is only valid whilst the subject is standing completely on the force-plate.

B.2.10. Ankle axial acceleration

An accelerometer placed near the subject's ankle (probably on the AFO), aligned parallel to the shank - assumed to be unaffected by inclination[1] (see figure B.1j). Its signal is calculated as follows:

$$\textbf{AAaccn} = \ddot{y}_{ankle}*\cos\theta - \ddot{x}_{ankle}*\sin\theta$$

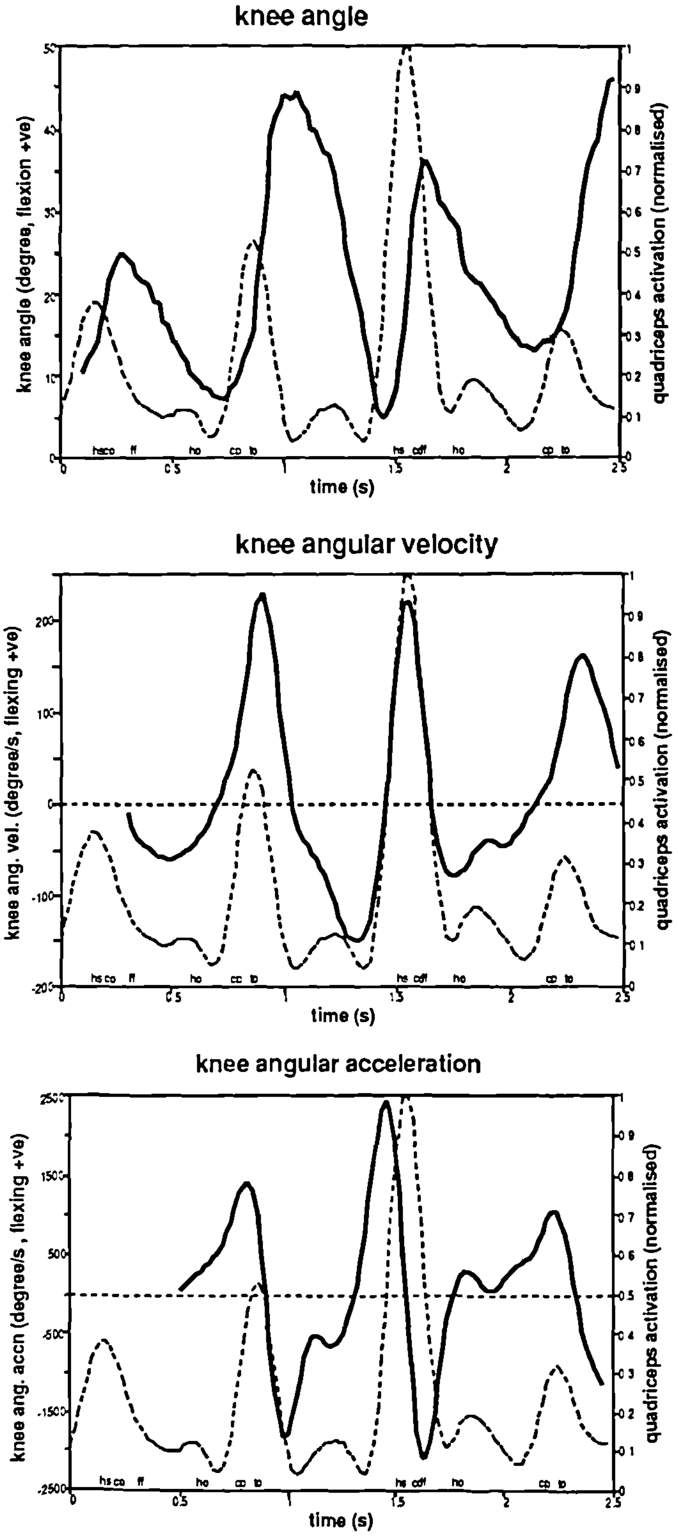
where:

$\ddot{x}_{ankle}$ is the acceleration of the ankle marker in the positive x direction, calculated by passing a 10 point FIR differentiating filter over the data twice.

$\ddot{y}_{ankle}$ is the acceleration of the ankle marker in the positive y direction,

θ is the angle between the ankle-knee vector and the positive y axis (the angle of the shank to the vertical).

1 A real accelerometer will give a signal that is dependent both on the acceleration and its angle to the earths gravitational field. However, if the inclination is known (e.g. by using a non-inertial inclinometer) then the gravitational component can be subtracted out.



Figures B.1 o,p,q *Sensor outputs with sample EMG traces*

B.2.11. Ankle transverse acceleration

A similar accelerometer, aligned perpendicular to the first, and in the plane formed by the shank and the foot (see figure B.1k). Its signal is calculated as follows:

$$\textbf{ATaccn} = \ddot{x}_{ankle}*\cos\theta + \ddot{y}_{ankle}*\sin\theta$$

where the symbols have the same meanings as above.

B.2.12. Hip goniometer

A goniometer mounted at the hip to detect flexion/extension. It is formed by calculating the angle between the projections of the knee-hip vector and the hip-shoulder vector on to a sagittal plane (see figure B.1l).

B.2.13. First and second time derivatives

Either tachometers and acceleration sensors, or hardware/software derivatives of the angle sensor. Formed by passing a 10 point FIR differentiating filter over the data twice (see figures B.1m and B.1n).

B.2.14. Knee goniometer and first and second time derivatives

Similar to the hip goniometer sensors (see figures B.1o, B.1p and B.1q).

APPENDIX C. FINITE-STATE FES CONTROL PROGRAM 'GAIT'

This appendix describes the program *Gait* which is used to control the production of FES swing-through and reciprocal gait. This program was jointly written (in *Turbo Pascal* [Borland Ltd]) with Dr. Malcolm Granat of the Bioengineering Unit, University of Strathclyde. It is designed to run on an IBM *AT* compatible computer. It drives a 'Strathclyde' 8 channel stimulator (Phillips, 1989; Phillips *et al.*, 1989) via a specially modified 8 bit input/output card (*PC14-A*, Amplicon Ltd); the modifications are detailed in Phillips (1989). This program is included on a floppy disc accompanying this thesis.

C.1. PROGRAM USE

The program can be run by typing 'gait' from DOS. The user initially sees the following menu:

P to change stimulator parameters
D to change defaults
O to change options
C to calibrate
G to initiate gait
E to exit program

Each option will be described in the following sections:

C.1.1. Option P, Change Parameters

On selecting this option, the user is presented with a list of the eight stimulation channels and their settings (pulse-width and inter-pulse interval). Any channel can be selected by moving the highlighting bar over it and pressing <RETURN>; new parameters for that channel may then be entered. The main menu can be regained by selecting 'continue' or by pressing <ESC>.

C.1.2. Option D, Change Defaults

The following menu of default values is displayed:

SWING-THROUGH
Latency
Gluts off/peroneal on
Peroneal off/quads on
Quads on/gluts on
Heel-strike delay

RECIPROCAL
Recip. latency
Swing-phase time
Knee-extn time

Bodyweight
eXit

Each option can be selected by moving the highlighting bar to it, or by pressing the capitalised letter in its name. All options except 'bodyweight' alter timing delays which may or may not affect the gait (depending on the particular gait mode selected). 'Bodyweight' requires the subject's body-weight (in force-plate units) to be entered, so that the strain-gauged crutch outputs can be expressed as a proportion of body-weight.

C.1.3. Option O, Change Options

The following menu of default values is displayed:

Fro controller
Crutch switches
Switch type
gen Lock
Gait type
Top channels
eXit

Each option can be selected by moving the highlighting bar to it, or by pressing the capitalised letter in its name. They have the following functions:

Fro controller: toggles the FRO controller on and off. This controller only stimulates quadriceps when knee-buckling is about to occur, thus reducing fatigue. It requires an instrumented orthosis that can detect changes in knee angle or knee moment (see e.g. Andrews and Baxendale [1986]).

Crutch switches: when this is set, the forces measured through the instrumented crutches are used to automatically certain trigger phases in the gait cycle, otherwise they are manually triggered by pressing switches.

Switch type: selects either force-sensitive resistors (FSRs, Interlink Ltd.) as switches (which produce an analogue signal proportional to the force they are loaded with, the switch is deemed to change if this signal crosses a pre-defined threshold) or standard switches.

Gen Lock: this toggles the gen-lock display (Vine Micros Ltd). When it is enabled, the computer display (giving information about the state of the sensors and stimulation channels) is superimposed on to the video recording of the subject walking.

Gait type: selects between different gait modes (such as reciprocal, swing-through, swing-through with fixed knees, etc.).

Top channels: determines if the two highest channels of stimulation are to be used to stimulate the erector-spinae group or the hamstrings group.

Exit: quits the menu.

C.1.4. Option C, Calibrate

Begins calibration of the sensors. The user chooses whether to calibrate the FSR switches or the instrumented crutches, and is then directed through the appropriate procedure.

C.1.5. Option G, Initiate Gait

The user is prompted to press <RETURN> for the subject to stand. The quadriceps stimulation level is then ramped-up (stand-up) to the pre-defined maximum, the stance state. The quadriceps stimulation level may now be adjusted. When a second <RETURN> is pressed, the gait sequence is initiated. It can be interrupted at any time by pressing the <ESCAPE> key, which forces the program to return to the stance state. From the stance state, gait can be re-initiated, or quadriceps stimulation can be ramped-down (sit-down). Once quadriceps stimulation has reached zero, the program returns to the main menu.

C.2. PROGRAM STRUCTURE

The program is written in a hierarchical structure. The initial options are selected from a procedure **INSTRUCTIONS**. When 'gait' is selected, the procedure **GAIT** calls the appropriate routines for the designated locomotion mode. A typical routine is listed below:

```
PROCEDURE Reciprocating;
BEGIN
        REPEAT
                IF NOT exitFlag THEN DoubleSupportState;
                IF NOT exitFlag THEN InitialSwingState;
                IF NOT exitFlag THEN MidSwingState;
                IF NOT exitFlag THEN FinalSwingState;
        UNTIL exitFlag;
END {Reciprocating};
```

The sub-procedures (such as **DoubleSupportState**) called from these gait-mode procedures implement the states within the gait. A typical example is listed below:

```
PROCEDURE HeelStrikeState;
BEGIN
        SetUpTime (0, 0);
        Peroneal (OFF, OFF);
        Quads (ON, ON);
        Gastroc (OFF, OFF);
        Glutei (ON, ON);
        FlushKbd;
        REPEAT
                IF KEYPRESSED THEN
                        IF READKEY = Esc THEN
                                exitFlag:= TRUE;
                IF GenLockFlag THEN UpdateDisplay
        UNTIL (GetUpTime(0) > HeelStrikeDelay) OR exitFlag;
END; {HeelStrikeState}
```

This procedure sets stimulation channels on and off with the procedures **Peroneal,Quads**, etc. It then waits in a loop, checking to see if the escape-key has been pressed and updating the information superimposed on the video picture (if the 'gen-lock') option has been selected. The loop finishes after the pre-defined time 'HeelStrikeDelay' has elapsed, or if <ESCAPE> is pressed.

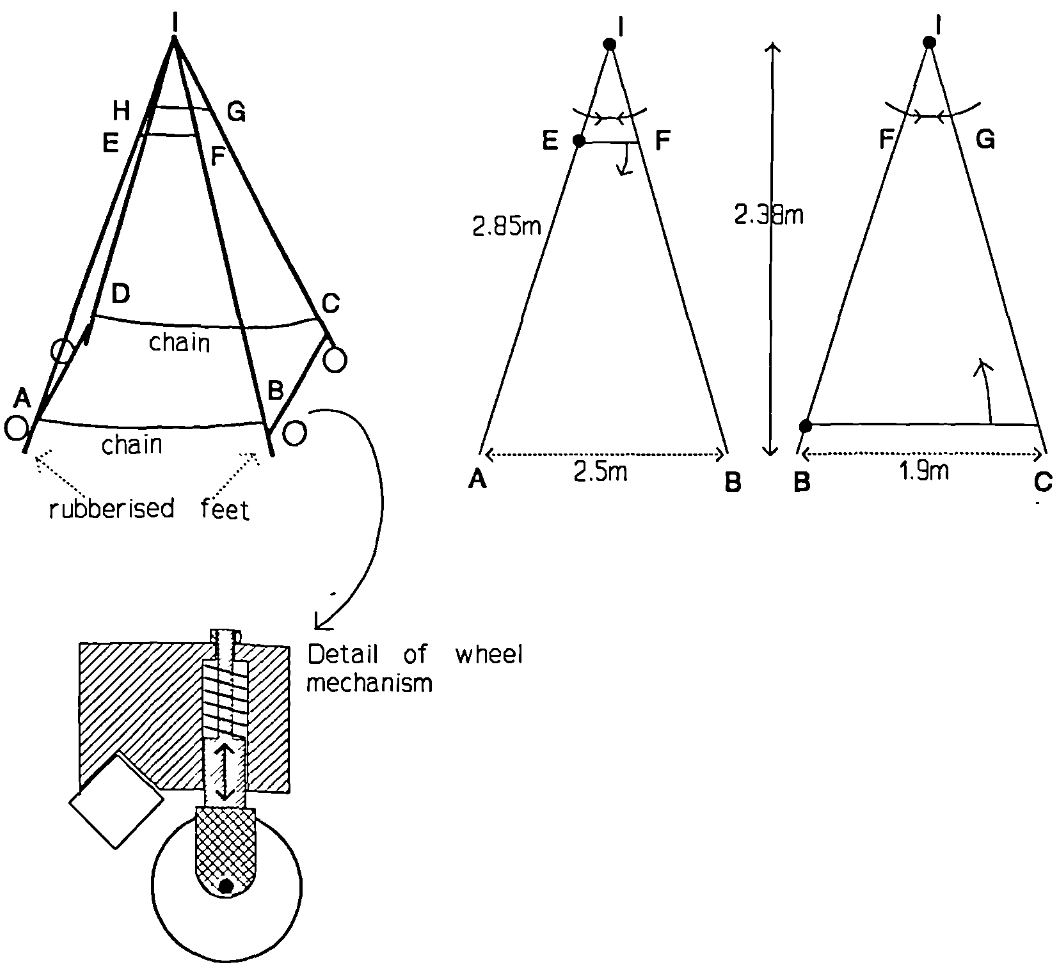


Figure D.1 *Design of the mobile overhead support*

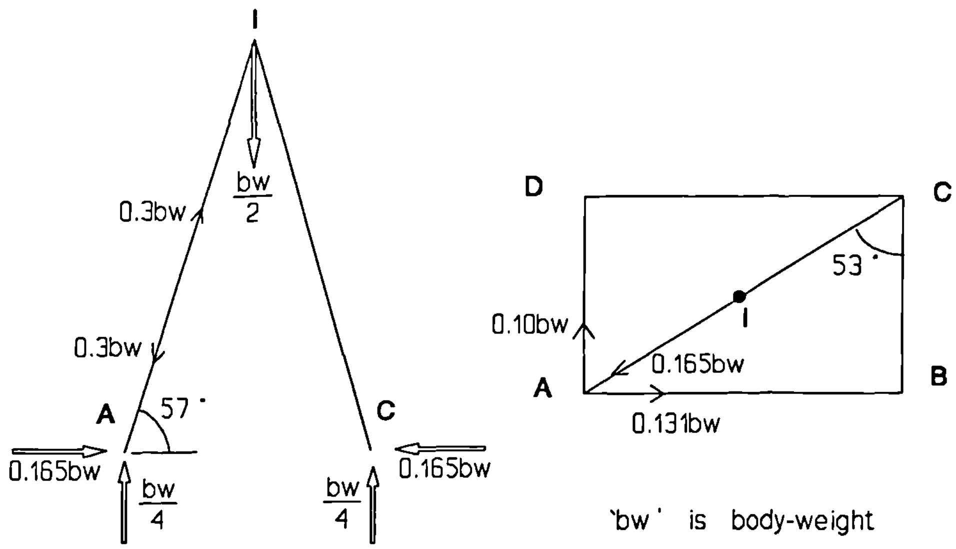


Figure D.2 *Forces acting on the members of the frame*

APPENDIX D. DESIGN OF OVERHEAD SUPPORT

This appendix describes the construction of the mobile overhead safety support. This device is used to prevent falls during the conduct of FES walking trials with spinal cord injured subjects. The operation of the support during the conduct of tests is discussed in the main body of this thesis; more details can be found in Andrews, Granat and Heller - *Proposal for the use of the Overhead Safety Harness* (Bioengineering Unit, University of Strathclyde Safety Committee application A9, November 1990).

D.1. DESIGN CONSIDERATIONS

The requirements of the device were:

1. It must be guaranteed to prevent a paraplegic subject falling to the floor during a gait trial.
2. It must not, itself, present a safety hazard to subjects or investigators.
3. It must provide minimum, preferably no, interference with crutch-aided swing-through gait.
4. It can be easily stored.
5. It can be used in a number of locations (including one a number of miles away from the Bioengineering Unit).

Requirements 4 and 5 determined that a lightweight, mobile support must be used, and that it must be small enough (or capable of being easily collapsed) for storage and to fit in a minibus. Requirement 3 constrained the minimum dimensions of the device.

The solution that was adopted is shown in figure D.1. It is a pyramidal structure, hinged at its apex, to allow it to be easily folded by folding down bars EF and GH. If it is to be transported, bolts at A and B are removed, allowing bars BC and AD to be folded and bars IB and IC, and IA and ID to fold together. The use of chains for the tension members AB and DC allows the design to be lighter, and permits the frame to be easily folded, whilst maintaining its strength when it is loaded. The chains can be unclipped to allow easy wheelchair entry to the frame; THEY MUST BE FASTENED BEFORE

THE DEVICE IS USED, MEMBERS EF AND GH ARE NOT DESIGNED TO TAKE TENSION.

Members IA, IB, IC, ID, AD and AC are constructed from 25 mm plastic-coated square-section tubing, with 1.2 mm wall thickness. AB and DC are mild-steel chain, with a maximum rated load of 800 N.

In use, the subject wears a harness which is attached by mountaineering rope and karabiners to the apex I. The frame is mounted on wheels and can be easily pushed or pulled (bars EF and GH prevent the frame folding if it is pushed). If the subject should fall, load is transferred, via the rope, to the apex of the pyramid, then to the ground via IA, IB, IC, ID. Sides ADI and CIB are prevented from rotating outwards by the chains AB and DC. As an additional safety feature, the specially designed sprung castors allow the frame to drop slightly when it is loaded, bringing the rubber tips of bars IA, IB, IC, ID in contact with the ground, and preventing the frame moving until it is unloaded.

D.2. LOADS

The static loads taken by the members of the structure are shown in figure d.2. These calculations are based on the assumption of a pin-jointed structure (i.e. the joints transmit forces but not moments); this assumption is justified by the use of bolts to assemble the frame, which allow some rotation and thus resemble pin-joints.

D.2.1. Failure by Buckling in IA, etc,

Members IA, etc., must take the greatest load (30% of body weight). Using Euler's formula the buckling load is:

$$\frac{\pi^2 EI}{L^2} = 2.9 \text{ kN}$$

where:

- E is Youngs modulus for mildsteel, 210×10^9 Nm^{-2}
- I is the second moment of area of the square tubing about its neutral axis of bending, $0.67D^3t$, where D is the average diameter of the bar and t is its thickness $= 1.13 \times 10^{-8}$ m^4.
- L is the length of the bar = 2.85 m.

From figure D.2, this corresponds to a weight of 2.9/0.3 = 9.6 kN.

D.2.2. Failure of Chains AB, CD in Tension

Maximum specified load for the chains is 800 N. From figure D.2 this corresponds to a weight of 800/0.131 = 6.1 kN[1].

1 This is a conservative estimate as some of this load will be taken through the floor, due to the friction of the rubberised feet against the floor.

D.2.3. Failure of Bars BC, AD in Tension

The tensile strength for mild steel is 430 MN m^{-2}, the cross-section area of the member is $4 \times 25.4 \times 10^{-3} \times 1.2 \times 10^{-3} \approx 1.2 \times 10^{-4}$ m^2, thus the maximum tension in the member is $430 \times 10^6 \times 1.2 \times 10^{-4} = 52$ kN. From figure D.2 this corresponds to a weight of $52/0.1 = 520$ kN.

D.2.4. Rope failure

The maximum quoted load for the rope is 15 kN; the rope is used doubled, so this corresponds to a weight of 30 kN.

D.2.5. Summary

Failure of the chains is the most likely mode of failure, occuring at a load of 6.1 kN. Allowing for a safety-margin of 5, the weight of the heaviest subject that can use the device is 1220 N.

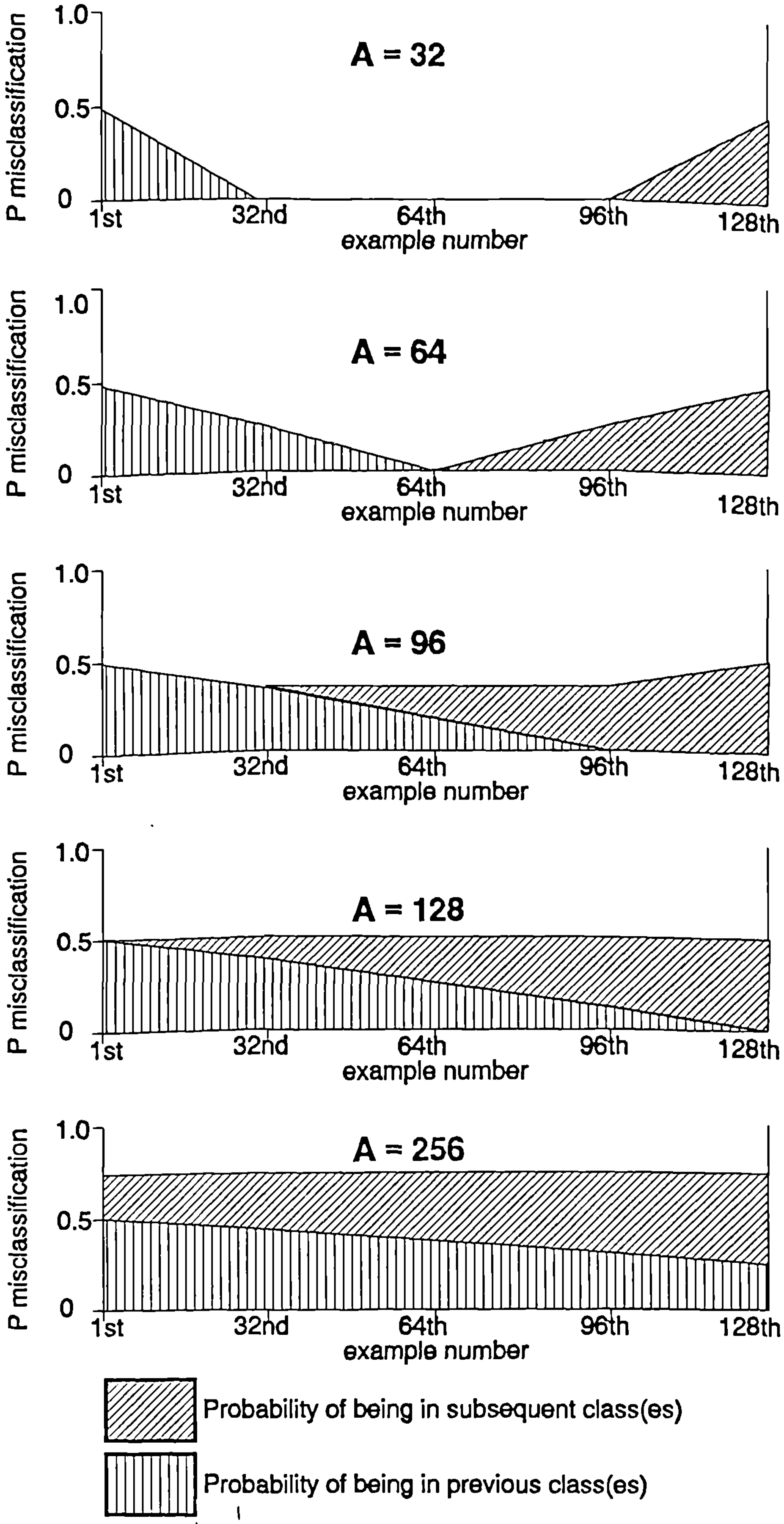


Figure E.1 *Probability of misclassification for various amplitudes of error A*

APPENDIX E. EFFECT OF NOISE

This appendix examines the relationship between noise level and the likelihood of an example being mis-classified for the noisy, artificial data set described in chapter 5.

This set was formed from the set of natural numbers 0 to 1023 by adding a pseudo-random number of magnitude a (with a uniform probability distribution between $-A$ and $+A$) to each number x, thus forming a new number y; y was assigned to a class c (from a set of 8 classes C $\{c=1 \text{ to } 8\}$) according to the following rule:

$$C(y) \rightarrow c \text{ if } y \geq t(c\text{-}1) \text{ and } y < t(c)$$
$$C(y) \rightarrow C(y+1024) \text{ if } y < t(0)$$
$$C(y) \rightarrow C(y\text{-}1024) \text{ if } y \geq t(8)$$

where $t(c)$ is upper threshold of class c and $t(0)$ is the lower threshold of class 1.

P_{mis}, the probability of misclassification $[C(y) \neq C(x)]$, is a function of x and A for $A < 128$, and a function of A for $A \geq 128$.

E.1 Case One, $A < 128$

Examples nearest the class boundaries are most likely to be misclassified. The first example in a class will be classified into the previous class if $a < 0$, the second if $a < -1$, etc. Example numbers beyond A-1 cannot be classified into the previous class. The 128th (last) example will be classified into the subsequent class if $a > 0$, the 127th (penultimate) if $a > 1$, etc. Example numbers lower than 129-A cannot be classified into the subsequent class. If $A > 64$ then the central examples can be classified to both the previous and the subsequent class. The probability of misclassification for various values of A and x is shown in figure E.1.

The **average** probability of misclassifying an example is found by summing the probabilities of misclassifying individual examples, and dividing by the number of examples. The probability of an example being put into a previous class is given by:

$$P_{mis}(1) = \frac{A}{2A+1},\ P_{mis}(2) = \frac{A\text{-}1}{2A+1} \dots P_{mis}(A) = \frac{1}{2A+1}$$

The sum of these probabilities for the first A terms in a class is $\frac{A(A+1)}{2(2A+1)}$

By a similar argument, the sum of the probabilities of an example being put into a subsequent class is the same, thus the total sum of the probabilities of being mis-classed is:

$\frac{A(A+1)}{2A+1}$, the average probability is thus $\frac{A(A+1)}{128(2A+1)}$

Thus the following average probabilities are obtained:

A	P_{mis}
32	12.7%
64	25.2%
96	37.7%

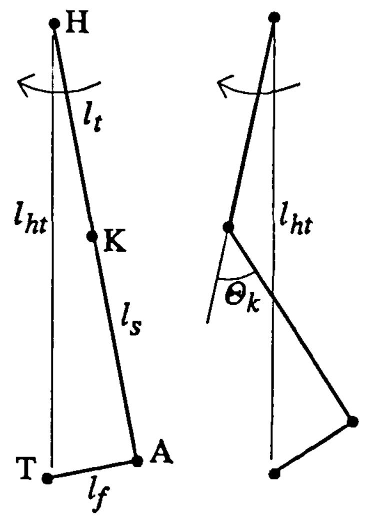
E.2 Case Two, $A \geq 128$

All examples may now be misclassified into both subsequent and previous classes. The probability of **not** being misclassified is constant for all x, and is equal to the size of each class (128) divided by the range of possible random offsets (-A to +A). Thus

$$P_{mis} = 1 - \frac{128}{2A+1} = \frac{2A\text{-}127}{2A+1}$$

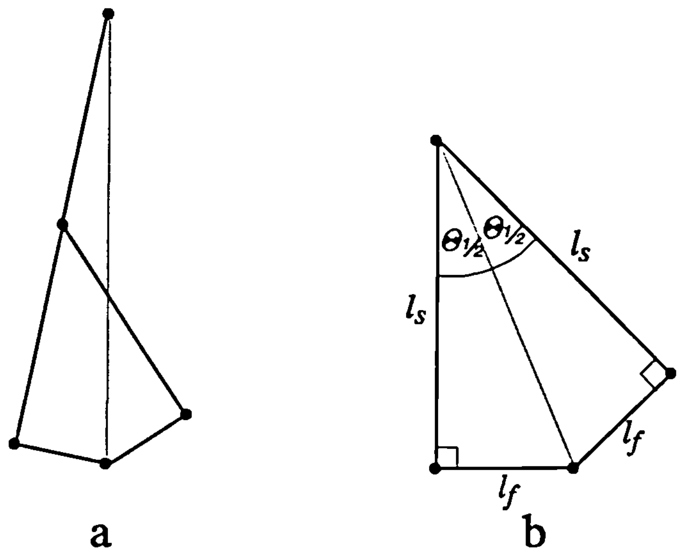
Thus the following average probabilities are obtained:

A	P_{mis}
128	50.2%
160	60.1%
192	66.8%
224	71.5%
256	87.7%



H is the hip joint
K is the knee joint
A is the ankle joint
T is the end of foot (toe)
l_t is the thigh-length, 0.245 *BH*
l_s is the shank-length, 0.285 *BH*
l_f is the foot-length (from ankle to toe, the projection of the heel behind the ankle is assumed negligible), 0.122 *BH*
l_{ht} is the hip to toe distance
Θ_k is the knee flexion angle
BH is total body height

Figure F1 *Model of ground clearance during body-swing phase*



The minimum knee-flexion angle for increased ground-clearance, Θ_{min} occurs when the flexed hip-toe length is the same as that when the knee is extended. This occurs in the situation shown in diagram (a). The minimum angle can thus be found by considering the knee-ankle-toe triangle and its reflection shown in diagram (b), where Θ½ is half of the minimum knee angle.

It is clear from this diagram that:

$$\tan \Theta_{1/2} = \frac{l_f}{l_s} \quad \text{thus} \quad \Theta_{min} = 2 \, . \, \tan^{-1}\left(\frac{l_f}{l_s}\right) = 46.2^{\circ}$$

Figure F.2 *Calculation of the minimum knee-flexion angle for increased ground clearance*

APPENDIX F. CALCULATION OF FOOT CLEARANCE

This appendix describes the relationship between the knee flexion angle produced during the body-swing phase of swing-through gait, and the corresponding increase in foot-clearance. This is important as the production of foot-clearance in this manner minimises the distance that the body needs to be lifted by the arms, thus reducing upper-body fatigue.

Figure F.1 is assumed to be a representative model of the gait. To reduce the degrees-of-freedom to one, swing-movement is assumed to take place about the hip. Thus, the 'critical point' in the swing-phase, when foot-clearance is a minimum, occurs when the sagittal-plane projection of the hip-toe vector is vertical. In reality, swing-movement will take place about the hip and shoulder, modifying the results slightly. Other assumptions are that the projection of the heel behind the ankle can be ignored, that the knee, hip and ankle act as perfect planar-hinges and that shoe dimensions negligible. These assumptions suggest that the results should be taken to indicate general trends, rather than providing definitive values.

The mean values of shank length, and thigh length are from Contini (1972). Contini gives a figure for foot-length, but not for the anterior-posterior location of the ankle centre on the foot; this location was estimated to be at a distance of 20% of the total foot-length from the heel[1]. Thus the value of l_f used was 80% of the foot-length quoted by Contini. The effect of any error in this figure is explored in a subsequent calculation.

F.1. Minimum Knee-Flexion Angle for Increased Clearance

As the knee is flexed, the distance from the hip to the toe initially increases, reaches a maximum, then decreases. The knee-flexion angle θ_k at which the hip to toe distance $l_{ht}(\theta)$ is the same as that for zero knee-flexion $l_{ht}(0)$ represents the minimum angle necessary for increased ground clearance. Greater knee-flexion results in shortening of the hip-toe distance, leading to improved ground clearance. The calculations to obtain this minimum knee flexion angle are detailed in figure F.2 The effect on this angle of varying the heel-ankle distance (as a ratio of the total foot-length) is shown in figure F.3.

1 Obtained from approximate measurements made on a small number of subjects.

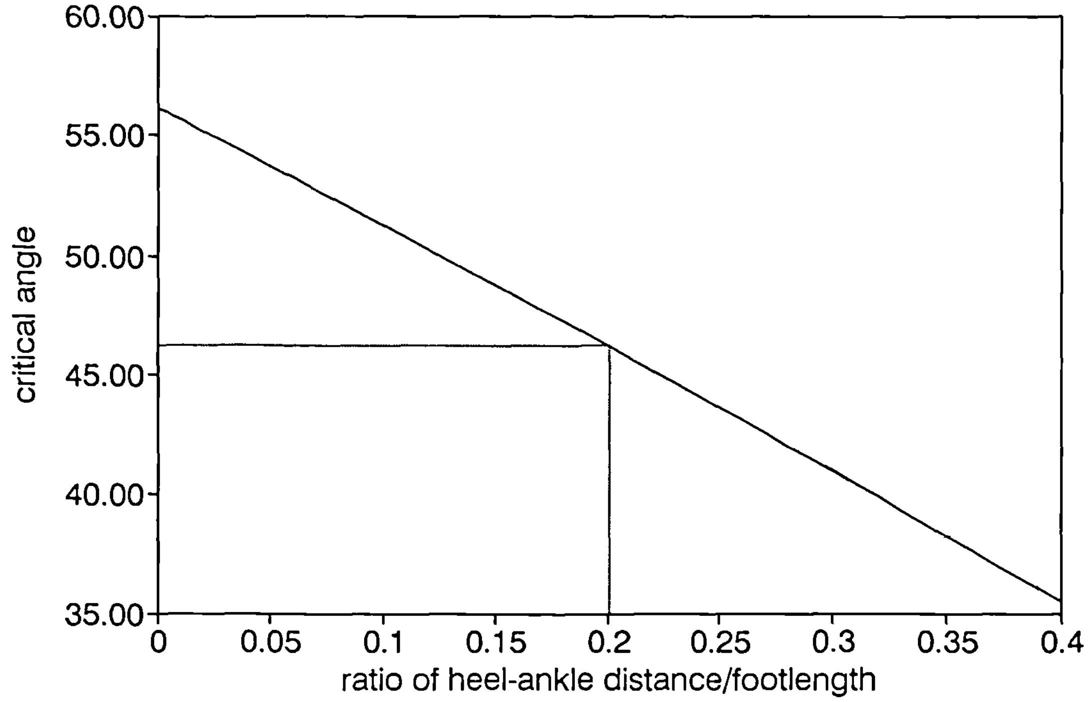
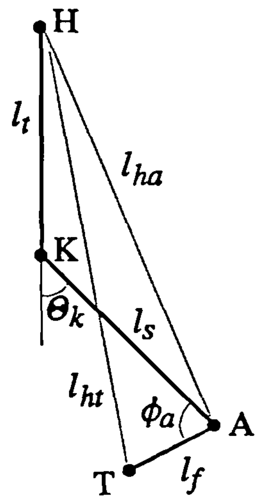


Figure F.3 *Angle beyond which there is increased ground clearance vs. ratio of heel-ankle length / footlength*



By the cosine rule, the length from hip to ankle is:

$$l_{ha}^2 = l_t^2 + l_s^2 + 2 l_s l_t \cos\Theta_k$$

By Pythagoras' theorem:

$$l_{ht}^2 = \{l_t + l_s \cos\Theta_k - l_f \cos(\Theta_k + \phi_a)\}^2 + \{l_s \sin\Theta_k - l_f \sin(\phi_a + \Theta_k)\}^2$$

The increase in ground-clearance due to knee flexion is:
whichever is larger out of $l_{ht}(0)$ and $l_{ha}(0)$ minus whichever is larger out of $l_{ht}(\Theta_k)$ and $l_{ha}(\Theta_k)$.

By considering the isosceles triangle formed by H, A and T when $l_{ht}(0)$ is equal to $l_{ha}(0)$, it is seen that the condition for $l_{ha}(0)$ to be larger than $l_{ht}(0)$ is:

$$\cos\phi_a = \frac{l_f}{2(l_t+l_s)} \text{ i.e. } \phi_a = \cos^{-1}\left(\frac{l_f}{2(l_t+l_s)}\right) = 6.6\,°$$

Figure F.4 *The effect of dorsi-flexion*

F.2. Effect of Dorsi-flexed AFO

If the ankle angle of the AFO is set in dorsi-flexion, this will limit the reduction in ground clearance caused by the toe. The calculations to obtain the ground-clearance for a knee angle θ_k with an ankle angle ϕ_a are given in figure F.4. The variations of ground clearance with θ_k for various ϕ_a are shown in figure 7.1.

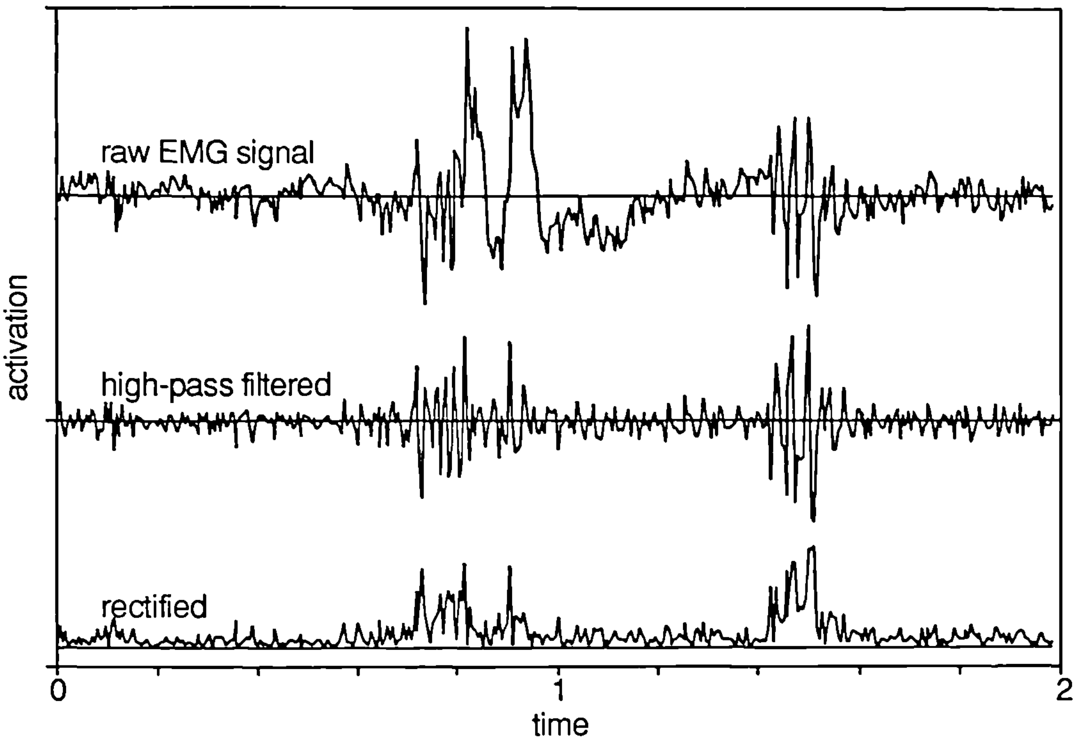


Figure G.1 *High-pass filtering and rectification of raw EMG*

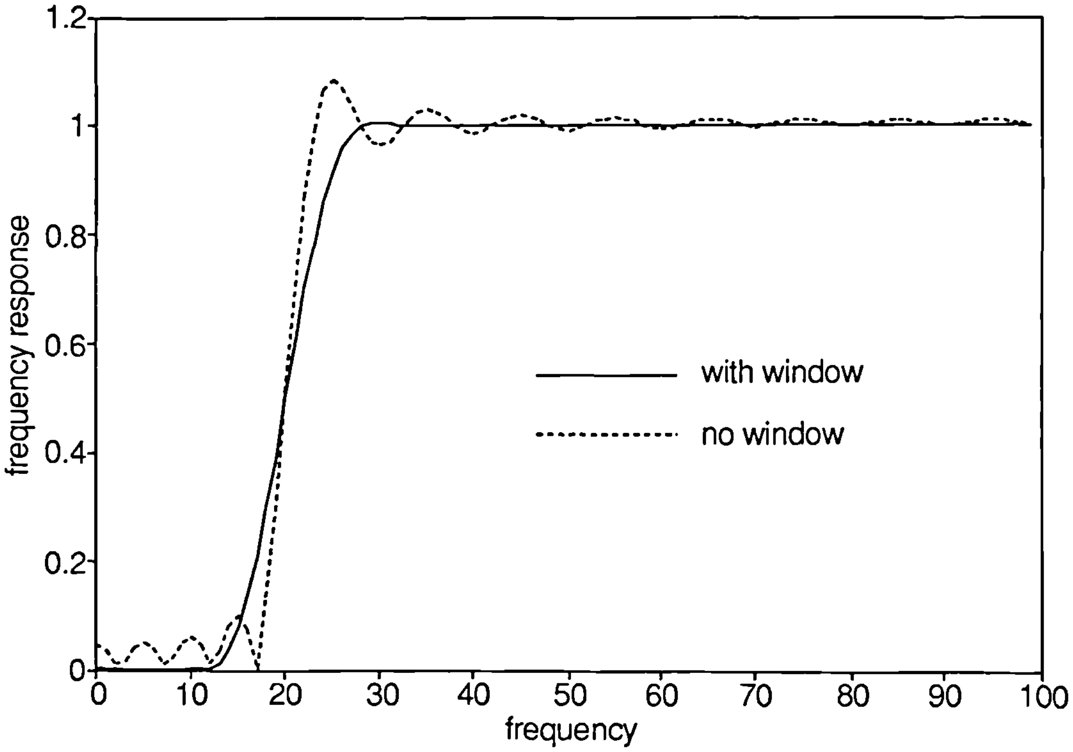


Figure G.2 *20 Hz high-pass filter transfer function*

APPENDIX G. EMG PROCESSING

This appendix describes the processing of the raw EMG signal to produce the muscle activation level.

G.1. Raw EMG Signal

The raw EMG signal $e(t)$ can be described as follows:

$$e(t) = I(t) \cdot \underline{n}(t) + A(t)$$

Where $I(t)$ is the time varying EMG activation level (the desired signal to be extracted), $\underline{n}(t)$ is a stationary stochastic process with zero mean and unit variance (a noise signal with unit intensity and with the characteristics of the EMG signal) (Hof, 1984), and $A(t)$ is a low-frequency noise signal caused by electrode and movement artifacts. A typical raw signal obtained from the quadriceps muscle group during swing-through gait is shown in figure G.1.

G.2. Processing

The following steps allow the extraction of the activation levels from the raw signal:

1. **High-pass filtering:** The electrode and movement artifacts $A(t)$ are low-frequency signals; they can thus be removed by a high-pass filter, which only passes the (higher frequency) EMG signals. The lower 3 dB frequency of the surface EMG signal is approximately 20 Hz (Winter, 1979), thus a high-pass filter with a low cut-off frequency of 20 Hz was chosen. The filter used was a 39 term symmetrical (19 terms on either side of the central point) finite impulse response (FIR) high-pass filter (Ludeman, 1986). A raised-cosine-bell (Hanning) window was applied. The frequency response of this filter (with and without the window) is given in figure G.2. The effect of the filter on the typical raw EMG signal is shown in figure G.1.

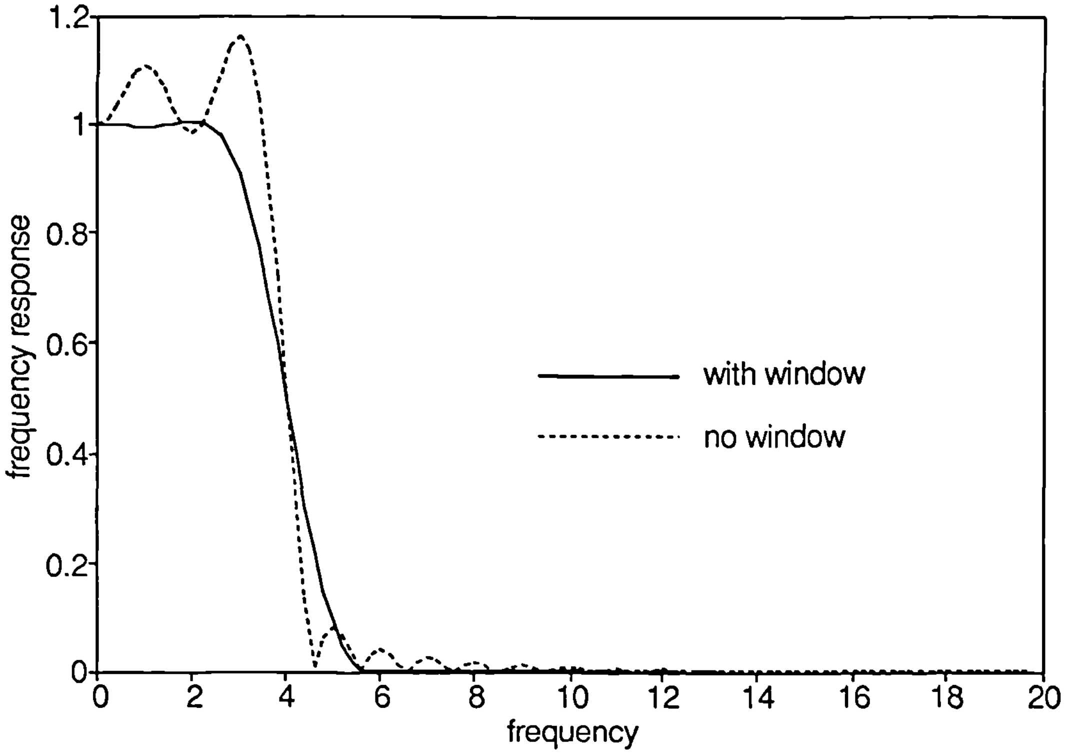


Figure G.3 *4 Hz low-pass filter transfer function*

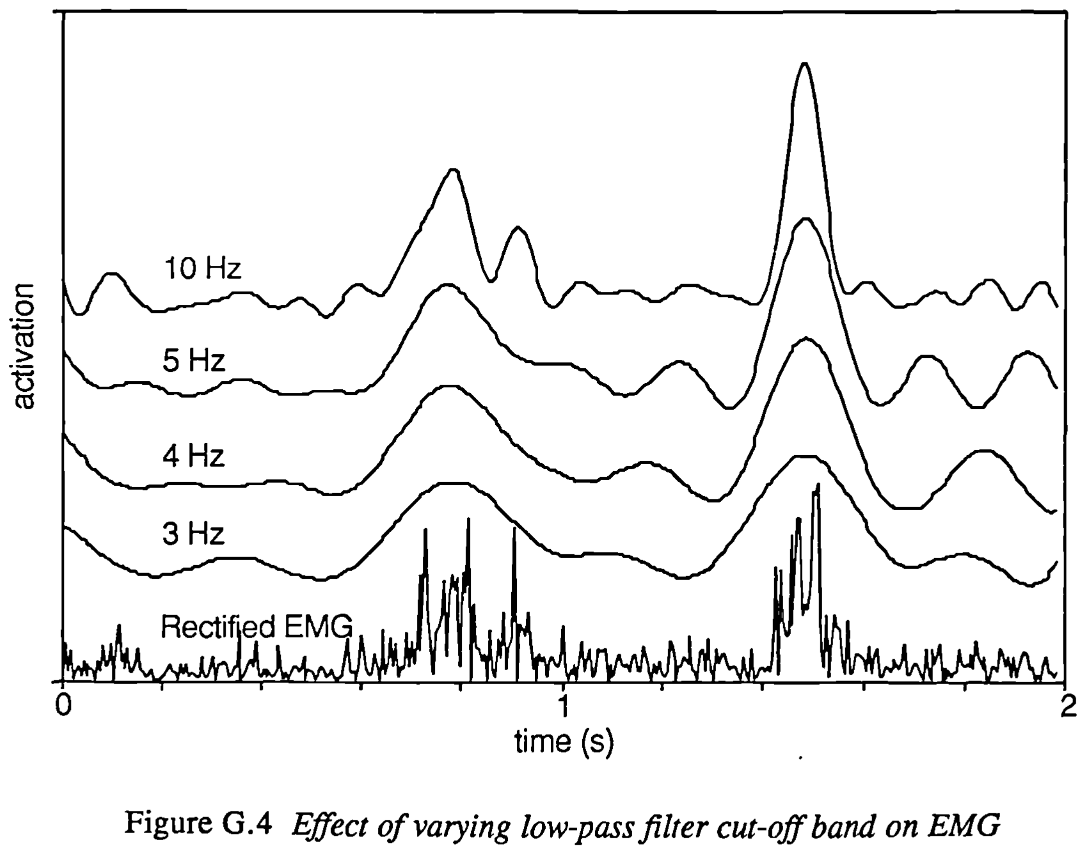


Figure G.4 *Effect of varying low-pass filter cut-off band on EMG*

2. **Rectification:** This is the next stage of processing. Full wave, digital rectification was performed. The effect of rectification on the typical raw EMG signal is shown in figure G.1.

3. **Low-pass filtering:** The linear-envelope of the EMG signal can be obtained by low-pass filtering the rectified signal. As was discussed in the main text, the choice of cut-off frequency is critical. To obtain a sharp transition band, a 199 term symmetrical FIR filter was used. This provided an acceptable trade-off between sharpness, and the lengthy processing time and loss of endpoint data associated with large-span filters. A Hanning window was used on this filter, which reduced the sharpness of the transition band, but prevented 'ringing'. The filter transfer-function is shown in figure G3. The effect of using filters with cut-off frequencies of 3, 4, 5 and 10 Hz is demonstrated in figure G.4. A cut-off frequency of 4 Hz was chosen as providing the best tradeoff between maximising information about the movement and minimising the random fluctuations due to $\underline{n}(t)$. This choice was made by comparing the traces for different cut-off frequencies with the expected activation of the quadriceps group.

The routines to perform the filtering were incorporated in the program *Align*, which is contained on a floppy disc accompanying this thesis.

APPENDIX H. QUESTIONNAIRE

This appendix reproduces the questionnaire that was distributed to the 'experts' in swing-through gait, asking them to rate the efficacy of various sensors.

As part of my PhD project, I am examining the use of machine learning techniques to automatically derive a rule-based controller for FES walking (in mid-thoracic paraplegics). I am particularly focussing on swing-through gait with free knees, in which both feet move simultaneously, followed by both crutches.

I have conducted a thorough motion analysis on five trained normal men performing swing-through gait (with ankle-foot orthoses to lock their ankles) involving measuring the following quantities: angles between body segments, crutch forces, foot-floor contact forces and 8 channels of surface EMG. I have used the kinetic and kinematic information to synthesise various sensors, which I am attempting to use to identify two important state transitions: that between late stance and the initiation of swing (roughly corresponding to toe off); and between late swing and early stance (roughly corresponding to heel strike). I am defining these transitions as occurring at certain singularities in the EMG traces, in this way I hope to be able to mimic ('clone') the control rules used by the trained subjects. The machine learning program I am using allows me to determine which sensors and sensor combinations are best (contain the most mutual information) in determining these transitions.

I would like to evaluate the performance of these machine recommended sensors against those suggested by human experts in the motion analysis / biomechanics field, which is why I would like your help. The following instructions may sound complex, but should only take about fifteen minutes to follow (although it may help to carefully consider the problem first).

There follows a short description of each sensor, and the definition of the two state-transition events I am trying to predict, then instructions as to what to do.

STATE TRANSITIONS

SWING: the minimum activation of the quadriceps group as the knee begins to flex is used to determine the initiation of the swing state.

STANCE: similarly, the peak in quadriceps EMG level as the leg is braced prior to heel strike defines the initiation of the stance state

SENSORS

a. toe switch: A simple switch placed near the metatarsal heads, which may be constructed from a force-sensing resistor. When this switch closes (i.e. the distal end of the shoe first contacts the floor) it initiates a timer which is incremented every 20 ms whilst the switch remains closed, and which is then reset on toe-off. This gives timing information about the stance phase.
b. heel switch: a similar switch to above, which is placed under the posterior foot. This sensor is similarly processed to give timing information about the stance phase
c. torso inclination sensor: An inclinometer mounted on the anterior or posterior chest wall.
d. crutch inclination sensor: Either an inclinometer located on one crutch, or a potentiometer connected to a crutch rocker bottom (the latter would only give valid readings when the crutch was in contact with the ground, but ignore this).
e. crutch axial force sensor: Strain gauges and corresponding amplifiers connected to one crutch to measure axial force.

f. crutch infra-red beam: A sensor consisting of an infra-red transmitter/receiver pair mounted one on each crutch. When the crutches are first loaded (see e. above) a timer begins counting upwards in a similar manner to a. When the beam is then broken (indicating that the legs are passing between the crutches during the swing phase) the timer is reset to zero, then counts DOWN until the crutches become unloaded. This gives timing information about the swing phase.

g. shoulder elevation: A sensor that detects elevation or depression of the shoulders, possibly by means of a sprung linear potentiometer, fixed to the mid back, and attached to a strap passing over the shoulder(s).

h. ankle axial acceleration: an accelerometer placed near the subject's ankle (probably on the AFO), aligned to detect accelerations that are parallel to the shank (but not sensitive to inclination).

i. ankle tangential acceleration: a similar accelerometer, aligned perpendicular to the first, and in the plane formed by the shank and the foot.

WHAT TO DO

I would like you to rank how well you think each sensor would do BY ITSELF (ie. as the only sensor used) in predicting the event. Please type them on separate lines, with the MOST USEFUL SENSOR AT THE TOP. If you think that two sensors are of equal importance please put them on the same line.

e.g. if I thought that the torso inclinometer was the most important sensor in predicting the start of swing, with the ankle transverse and axial accelerometers equal second I would type

SWING
c
h i
.
.
etc.

and similarly for the start of stance.

The second thing I would like you to do is to suggest sensor PAIRS: for each sensor I would like you to suggest the best sensor it should be combined with to predict each event (i.e information from both sensors would be available). Please pick the best three pairs (or more if you cannot destinguish them) and rate them in order of importance.

e.g. if I thought that the best sensor to combine with the toe switch (a) to predict the start of swing was the heel switch (b), the second best was the crutch infra-red beam (f) and the third best was the ankle axial acceleration (h) I would type

SWING
a) 1=b, 2=f, 3=h.
b) similarly
. "
. "
i) "

and similarly for the start of stance.

Finally, please write approximately the number of years that you have been working in the biomechanics field, and your background (e.g. engineer, physical therapist, etc.).