Brain Computer Interface Using Detection of Movement Intention

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THESIS CONTAINS

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Dedicated to my parents.

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Last but not least I would like to thank GOD and always believed in the quote from Bhagavath Geetha "*Karmani ave adhikars te ma phalesu kadachana ma karmaphal hetur bhoo ma sangostu akramani*" – "you have the power to act only, you do not have the power to influence the result-therefore you must act without the anticipation of the result without succumbing to inaction"

Abstract

For the patient with extensive paralysis, developments in the emerging area of Brain Computer Interfaces (BCI) offer the prospect that some level of independent function can be regained by using signals recorded from the brain to control mobility aids or other forms of assistive technology. However, current BCI's are often slow and require extended user training. There is also a lack of multi-dimensional control and this places a limitation on the type of assistive technology that can be used with a BCI. The current study aims to investigate whether multi-dimensional control can be achieved from classification of brain activity recorded by surface electro-encephalogram (EEG) that precedes movement during motor tasks associated with rapid point-to-point movements of the wrist in different directions (or of the imagination of this task). The hypothesis is that because of the known properties of cortical neurones from the different areas of the cortex the electrical fields associated with this type of movement will be classifiable in relation to direction of movement of the wrist. Experiments were conducted with local ethical approval on normal subjects and EEG data from high density electrode montages were recorded. The study successfully identified the existence of statistical differences in the relative power of the EEG in the alpha, beta and gamma bands during the time preceding movement initiation related to movement in different directions. Classification of single pre-movement EEG epochs based on Euclidean Distance, K-nearest neighbour and binary decision tree techniques resulted in high success rates of upto 95%. These classification results support the hypothesis that the production or imagination of rapid wrist movements to different directions can be used for robust BCI systems that based on these results could achieved 4 separable command states. The construction of topographic maps of the success rates achieved in these classification results also reveal considerable variability in the electrode sites that produce the highest classification rates and this highlights the need for careful consideration of the number and location of EEG recording sites needed for multi-dimensional BCI systems. The work completed in this thesis has demonstrated that multi-dimensional control can be achieved by EEG based BCI devices that do not require computationally expensive algorithms for intention detection and classification.

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Abbreviation

EEG	Electroencephalogram
BCI	Brain Computer Interface
SCI	Spinal Cord Injury
EMG	Electromyogram
Pmd	Dorsal Premotor Cortex
MRCP	Motor Related Cortical Potentials
SMA	Supplementary Motor Area
PET	Positron Emission Tomography
MEG	Magnetoencephalogram
ERD	Event Related Desynchronization
ERS	Event Related Synchronization
MND	Motor Neurone Disease
ALS	Amytotrophic Lateral Sclerosis
PMA	Progressive Muscular Atrophy
PBP	Prgressive Bulbar Palsy
PLS	Primary Lateral Sclerosis
CVA	Cerebro-Vascular Accident
fMRI	Functional Magnetic Resonance Imaging
PSP	Post-Synaptic Potentials
CNS	Central Nervous System
ECoG	Electrocorticogram
SNR	Signal To Noise Ratio
PC	Personal Computer
KNN	K-Nearest Neighbours
ANOVA	Analysis of Variance
ERP	Event Related Potential
SCP	Slow Cortical Potentials

EOG	Electro-oculologram
SSVER	Steady State Visual Evoked Potential
LVQ	Learning Vector Quantization
LDA	Linear Discriminant Analysis
PCA	Principle Component Analysis
FFT	Fast Fourier Transforms
AAR	Adaptive Auto Regression
ERSP	Event Related Spectral Perturbation
FCR	Flexor Carpi Radialis
ECRL	Extensor Carpi Radialis Longus
ECRB	Extensor Carpi Radialis Brevis
ECU	Extensor Carpi Ulnaris
CAR	Common Average Reference

Contents

Chapter 1: Introduction

Johann Wolfgang once said "Thinking is easy, acting is difficult and to put one's thought into action is the most difficult thing in the world". This is particularly true for those who are affected by debilitating neuromuscular disorder brought on by condition like spinal cord injury (SCI), motor neurone disease or brain stem stroke.

In USA alone, SCI has an incidence rate of 40 injuries per million and this works to about 11,000 new cases per year. It has been reported that the most frequent neurologic category at discharge is incomplete tetraplegia(34.1%) followed by complete paraplegia(23%), complete tetraplegia(18.3%) and incomplete paraplegia(18.5). Table1.1 and 1.2 compare the average life expectancy of people with SCI at different levels. (http://www.spinalcord.uab.edu/show.asp?durki=21446)

Table 1.1. Life expectancy of persons who survive the first 24 hrs. (Referenced from http://www.spinalcord.uab.edu/show.asp?durki=21446)

Age at Injury	No SCI	Para	Low Tetra (C5-C8)	High Tetra (C1-C4)	Ventilator Dependent at any Level
20 yrs	58.2	45.3	40.2 Years	35.9 Years	16.4 Years
40 yrs	39.3	27.7	23.5 Years	20.0 Years	6.9 Years
60 yrs	22.0	12.8	10.0 Years	7.8 Years	1.4 Years

Table 1.2. Life expectancy of persons who survive at least one year post injury. (Referenced from http://www.spinalcord.uab.edu/show.asp?durki=21446)

Age at Injury	No SCl	Para	Low Tetra (C5-C8)	High Tetra (C1-C4)	Ventilator Dependent at any Level
20 yrs	58.2	45.9	41.4 Years	37.8 Years	23.1 Years
40 yrs	39.3	28.3	24.4 Years	21.5 Years	10.9 Years
60 yrs	22.0	13.3	10.6 Years	8.7 Years	3.0 Years

The study conducted by Westgren (Bret L. Hicken 2002) showed that individuals with spinal cord injury "enjoyed" a quality of life which was significantly lower than the normal population. Table 1.3 shows the measures of function and well being for both

groups. Each measure is scales from 0 to 100, 0 indicating worst health and 100 indicating best health.

Table 1.3. Quality of life after spinal cord injury (Modified from {Westgren, 1998 #27})

SubScale	Low Scores Indicate	SCI Group		Normal Group		p
Function						
Physical functioning	Limitation in physical activities	42.5	31.6	87.9	19.6	0.001
Role function, Physical	Problems with work/daily activities as a result of physical health	57.2	42.6	83.2	31.8	0.001
Role function, physical	Problems with work/daily activities as a result of emotional problems	70.4	40.4	85.7	29.2	0.001
Social functioning	Interference with normal social activities due to physical/emotional problems.	76.7	26.8	88.6	20.3	0.001
Bodily pain	Limiting pain	57.2	28.5	74.8	26.1	0.001
Well-Being						
Mental health	Feelings of nervousness and depression	74.8	20.4	80.9	18.9	0.001
Vitality	Feelings if fatigue	61.4	23.0	68.8	22.8	0.001
General health	Feelings of poor health, likely to get worse	63.9	23.8	75.8	22.0	0.001

Table 1.4 shows the average yearly care cost for the people with SCI. It is seen immediately that these expenses vary depending on the severity of the injury and are highest for persons which high tetraplegia.

Table 1.4 Average Yearly Expenses (in 2006 dollars US). Referenced from {Westgren, 1998 #27}.

Severity of Injury	First Year	Each Subsequent Year
High Tetraplegia (C1-C4)	$741,425	$132,807
Low Tetraplegia (C5-C8)	$478,782	$54,400
Paraplegia	$270,913	$27,568
Incomplete Motor Functional at any Level	$218,504	$15,313

Table 1 5. Estimated lifetime costs by Age at Injury (in dollars US). Referenced from {Westgren, 1998 #27}

Severity of Injury	25 years old	50 years old
High Tetraplegia (C1-C4)	$2,924,513	$1,721,677
Low Tetraplegia (C5-C8)	$1,653,607	$1,047,189
Paraplegia	$977,142	$666,473
Incomplete Motor Functional at any Level	$651,827	$472,392

Research (Francis et al. 1999; Hicken 2002; Foley et al. 2002; Sturm 2004) on stroke or and motor neurone disease patients also highlights the low quality of life and high cost of these highly dependent patients. The common finding for people with extensive

paralysis is that they lack the independence enjoyed by the normal population and depend on other for almost all functions and daily living.

Brain Computer Interface is a technological interface between the human brain and a computer; it is a prosthesis which augments the working of an impaired nervous system. The main purpose in developing motor neuroprosthetics is to be able to help restore independent control of the body and to enable control of assistive devices for individuals who are paralysed. Providing a controllable channel for higly dependent paralysed people may therefor lead to significant improvement in life quality and may assist in reducing care costs.

2. PROJECT OBJECTIVES

The Research at the neuro-physiology laboratory at the Bioengineering Unit, University of Strathclyde is primarily about movement and its control and a significant research effort has been directed to study the relationship between brain signals and motor output.We believe that it is theoretically poissible to extract information from the Electroencephalogram (EEG) which relates to different aspects of movement preparation(intention) and execution and the detection of signals related to movement in different directions can serve as multi-dimensional control for a brain computer interface.

The main objective of the project was to develop a Brain Computer Interface (BCI) based on Motor Related Cortical Potentials.

- The BCI should be able to recognize the user's intentions to move their wrist in different directions (actual or imagined) in order to provide multiple classifiable events for multiple commands.
- The classification of signals by the BCI should be reliable and consistent in its decision making.

The BCI should work real-time and should operate without any significant delays.

Chapter 2: Literature Review

The chapter below reviews the current literature on the control of movement relevant to this thesis. It discusses the different structures within the central nervous system which are involved in the control of movement. It then discusses how the different kinematic parameters like force, speed and direction may be controlled. It also examines the control of different movement types. Since brain computer interfaces are primarily to be used by people with severe motor paralysis the chapter compares activity within the brain during imagination of movement against actual movement. The section on "Paralysis and Loss of Voluntary Movement" discusses the various conditions which can lead to severe motor paralysis and thus could benefit from a brain computer interface. The last section in the chapter reviews current brain computer interface technologies highlighting the need for further work.

2.1 Neural Control Of Movement

An essential feature of being human is to be able to interact with ones surroundings by reacting to it, controlling it (to an extent) and to communicate with it. This involves the integration of both the sensory and motor systems of the body. The sensory systems provide an internal representation of the outside world. This allows for the extraction of essential information needed to inform motor systems that allow us to maintain posture and balance, control movement of our body, limbs, and eyes and to communicate through speech and gesture. The motor system thus transforms neural information into physical energy by issuing commands that are transmitted from the central nervous system to the skeletal muscles where these commands are translated into force.

The capabilities of our motor systems to plan, coordinated and execute movements are reflected in our agility and dexterity. Once trained our motor system executes a motor program for each skill with ease, almost automatically.

2.1.1 Classification of movement

At the simplest level movements can be considered to be either voluntary or reflex.

- Voluntary movement are considered complex because:
  - They are purposeful and initiated by conscious decision.
  - They are goal directed
  - They display learning where performance improves with practice.
  - Voluntary movements are initiated in higher brain centres and act on spinal circuits by descending pathways.
- Reflex responses are the simplest of movements and are normally evoked by sensory stimuli. They are rapid and mostly stereotyped. Reflexes can be evoked at a local level through short pathways within the spinal cord or via larger loops that influence cortical activity. (Eric et al. 1991).

All movements are caused by the contraction and relaxation of muscles at joints. Since individual muscles can only pull, coordination of many muscles is required in synergy to produce controlled motion. Each movement at a joint thus brings into play sets of muscles: some acting as agonists and the others acting as antagonists. By the combined action of these muscles helps generate control movements. (John et al. 1991)

The motor system needs to carry out three additional tasks in addition to simply controlling the contraction and relaxation of muscles (Melvill et al. 1991) and (John et al. 1991).

- It must transmit accurately timed commands to the many different muscle groups involved in the movement generation (synergy).
- The motor system must make adjustments to the posture/ distribution of body mass for the movement to be executed without leading to instability.
- Finally the motor system must take into account the motor plant: the mechanical arrangement of the muscles, bones and joints, and should make continuous adjustments in time and amplitude to motor drive to compensate for effects of

inertia of the limb and the mechanical arrangement of the muscles, bones, and joints being moved.

To be able to integrate these three features into voluntary and reflex movements the motor system relies on two different inter-related organizational features: the first is the continuous availability of sensory information of events in the environment, the position and orientation of the body and limbs, and the degree of the contraction of the muscles. The second is that the motor system is organized into a hierarchy of control levels and each is supported with sensory information that is relevant for its proper functioning hierarchy (John et al. 1991) and (Eric et al. 1991).The higher levels are concerned with the strategic issues such as the selection of a response appropriate to a specific goal and need not make continuous change for the moment-to-moment sensory information; this task is relegated to the lower levels of the motor system(John et al. 1991; Eric et al. 1991).

2.1.2 Transformation of Sensory Information into Motor Commands

Movement is one of the responses of the brain to environmental stimuli. Movements evolve both in space and time. Thus, for the proper functioning of the motor systems there is a need for the continuous flow of information about the environment. Firstly, vision, hearing and other receptors on the body provide information relating to the environment, the objects, their position and our position in space relative to the objects. Secondly, the sensory information also contains information regarding the position and orientation (angle of joints) of the limbs of the body. They also contain information regarding the length and tension in the muscles. (Shen and Alexander 1997, and Kalaska et al. 1997).

Need for sensory information is necessary to correct errors through feedback and feed forward mechanisms. (Eric et al. 1991). A high gain feedback loop can lead an undesirable state of oscillation. The sensory information is thus necessary for the following:

- To guide a goal oriented movement such as when reaching for an object. Here sensory feedback(actual movement direction) is compared with a reference signal (reference movement direction) by a controller (internal model) which compensates for error and issues corrective action.
- Feedback information can be used to help maintain or regulate a variable such as position or force. In this the reference signal is a constant.
- Sensory information can often control future motor actions by providing advance rather than feedback information. For example like that necessary to catch a ball. Here the information regarding the trajectory of the ball is predicted by the sensory feedback.

The control provided thus can be both feedback and feed-forward. The feedback is used to control posture and slow movements because of the long conduction delay involved. The feed-forward mechanisms are not affected by long-delays and operate more quickly. While with feedback the resulting state is continuously monitored and used to controls the movement from moment to moment, in feed-forward mechanisms the resulting state is evaluated only after the completion of the response of the muscles (Geoffrey et al. 1991; John et al. 1991; Pearson 2000).

2.1.3 Hierarchy of Motor Control

It takes a remarkably complex system to initiate, coordinate, and integrate the ongoing control of muscular contractions that result in human movement. Proper control of movement involves: the accurate timing and coordination of commands to multiple muscle groups, an on-going monitor of the current position of the body and distribution of body mass to allow for making necessary adjustments to body posture, and the consideration of factors imposed by the unique physical characteristics of the body and muscles (such as inertia, resistance, and muscle stiffness). All movement is controlled by multiple structures that compose a hierarchically arranged system. The feedback, feed-forward and adaptive mechanisms of control of movement are distributed anatomically

between 1) spinal cord, 2) the brain stem and basal ganglia, 3) primary motor cortex, and 4) associational cortex and higher centres. (Scott et al. 1997,Alexander 1990, John et al. 1991, and Eric et al. 1991).

The hierarchical structure means that higher centres can provide an execution command without having to specify the full requirements of the motion as lower centres (brain stem, spinal cord) have the capability to integrate the descending motor command with the complex spatiotemporal patterns of muscle activation required to generate purposeful movements yet not disrupt static or dynamic posture (see figure 2.1). It is believed that this combination of parallel and hierarchical mechanisms is important in the recovery of function after local lesions where reorganization and plasticity can aid in providing an alternative motor output channel to the damaged pathway. (Grasso, Ivanenko et al. 2004)

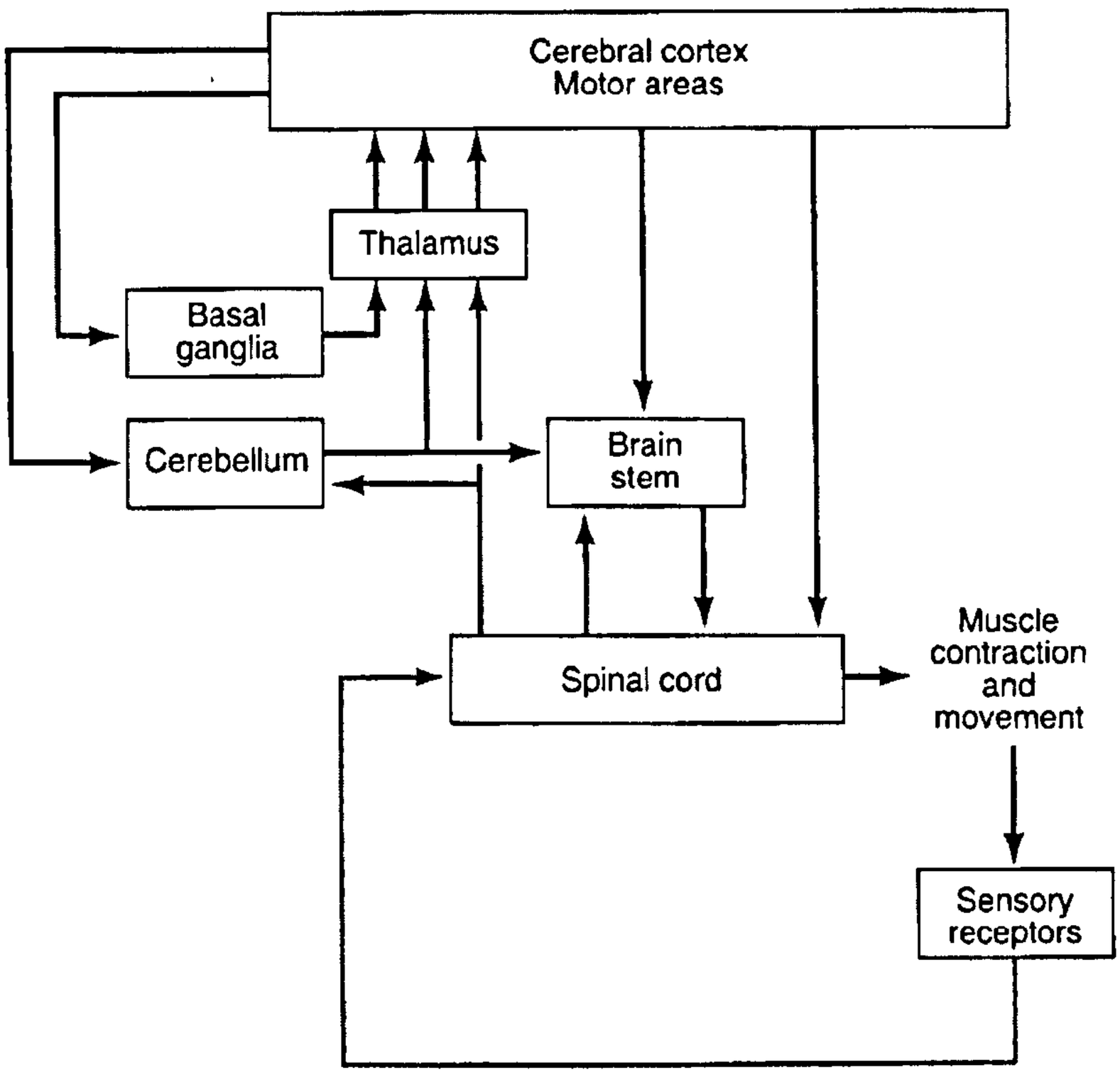


Figure 2.1 Shows the different systems involved in the production of muscle contraction and movement. Refered from http://www.fiu.edu/~condon/ksj35-3.gif

There are three features of the motor hierarchy that are important:

- First, each component of the motor system displays Somatotopic maps
- Second, each level receives information from the periphery so that the sensory input can modify the actions of the descending commands.
- Third, higher levels can control the amount of information that they receive by facilitating or suppressing the transmission of afferent input in the sensory relay nuclei.

The cortical hemisphere contains a number of distinct areas supporting different motor, sensory and cognitive functions. (Roland and Zilles 1996). Some of them will be reviewed here.

2.1.3.1 The Associational Cortex and Higher Centres

The associational cortex areas lie outside the primary, secondary and tertiary areas. They are involved to different degrees in the control of the three main brain functions: perception, movement and motivation and for this they integrate diverse information. (John et al. 1991, Scott et al. 1997 and Mikami et al. 1997).

The parietal-temporal-occipital association cortex occupies the interface between the three lobes for which it was named (see figure 2.2). It is believed to participate in forming complex perceptions by combining the primary sensory inputs of somatic sensation, hearing and vision.

The prefrontal association cortex, which occupies most of the rostral part of the frontal lobe (see figure 2.2), is concerned with the important function of planning voluntary movement. The limbic association cortex is located on the medial and inferior surfaces of the cerebral hemisphere (see figure 2.3) , in portions of the parietal, temporal and frontal lobes; and is devoted mainly to the motivation, emotion and memory.

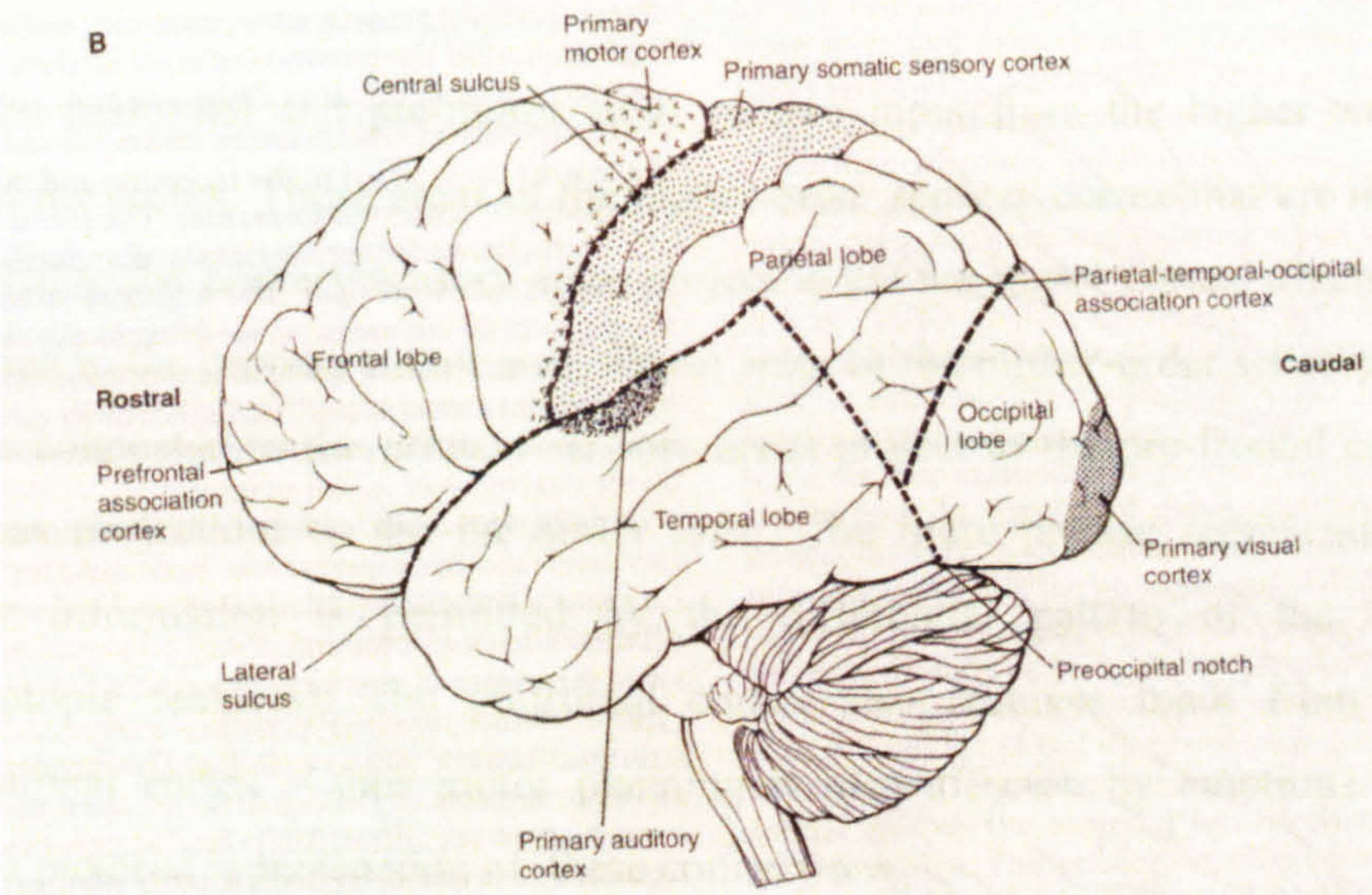


Figure2.2 shows the anatomic location of the different association cortex. [Referred from Pg 278, Principles Of Neural Science, Third Edition. Kandel et al 1991.]

The area of the frontal lobe that is anterior to the primary motor area has traditionally been divided into two regions: pre-motor areas (discussed later), and the prefrontal association cortex, which lies anterior to the pre-motor area (see figure 2.3). While the prefrontal cortex is important for the planning of movement the pre-motor area is important for the initiation of movement. (John et al. 1991).

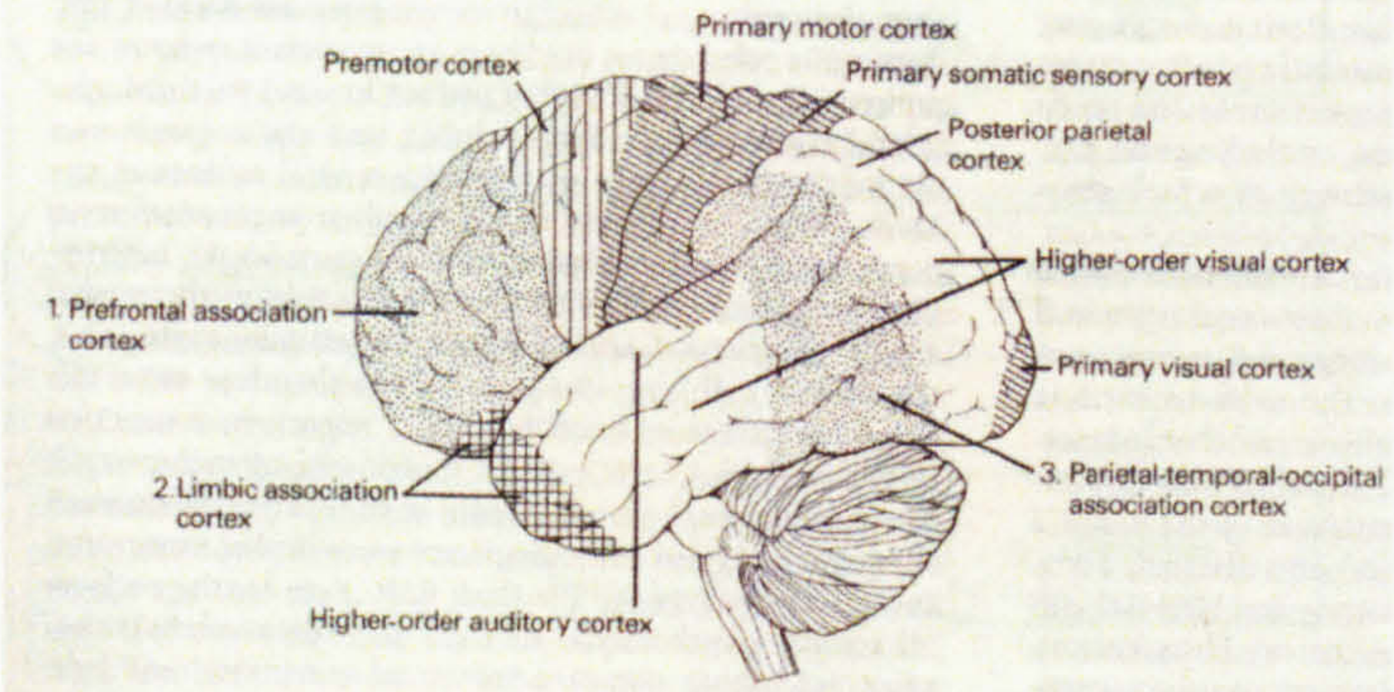


Figure2.3 shows the division of the frontal lobe into prefrontal association cortex and premotor cortex. Referred from Pg 825, Principles Of Neural Science, Third Edition. Kandel et al.

Both the prefrontal and pre-motor areas receive input from the higher-order sensory areas of the cortex. Those areas of the higher-order sensory cortex that are more closely connected to the primary sensory areas project to the pre-motor cortex which in-turn has projection to the primary motor area. Those areas of the higher-order sensory cortex that are less connected to the primary sensory areas project to the pre-frontal cortex which itself has projections to the pre-motor area.. The more precise representation of the sensory information is permitted by the differential pattern of the connections (somatotopic features). The prefrontal cortex also receives input from the limbic associational cortex – thus motor planning is also affected by emotions. Figure 2.4 shows a pictorial represenation of these connections

Surrounding the primary areas are the higher-order sensory and motor areas. The higher order sensory and motor areas process complex aspects of information related to motor function. While higher sensory areas integrate information coming from the primary sensory areas the higher-order motor areas send complex information required for the motor act to the primary motor cortex. (John et al. 1991, Kalaska, Scott et al. 1997)

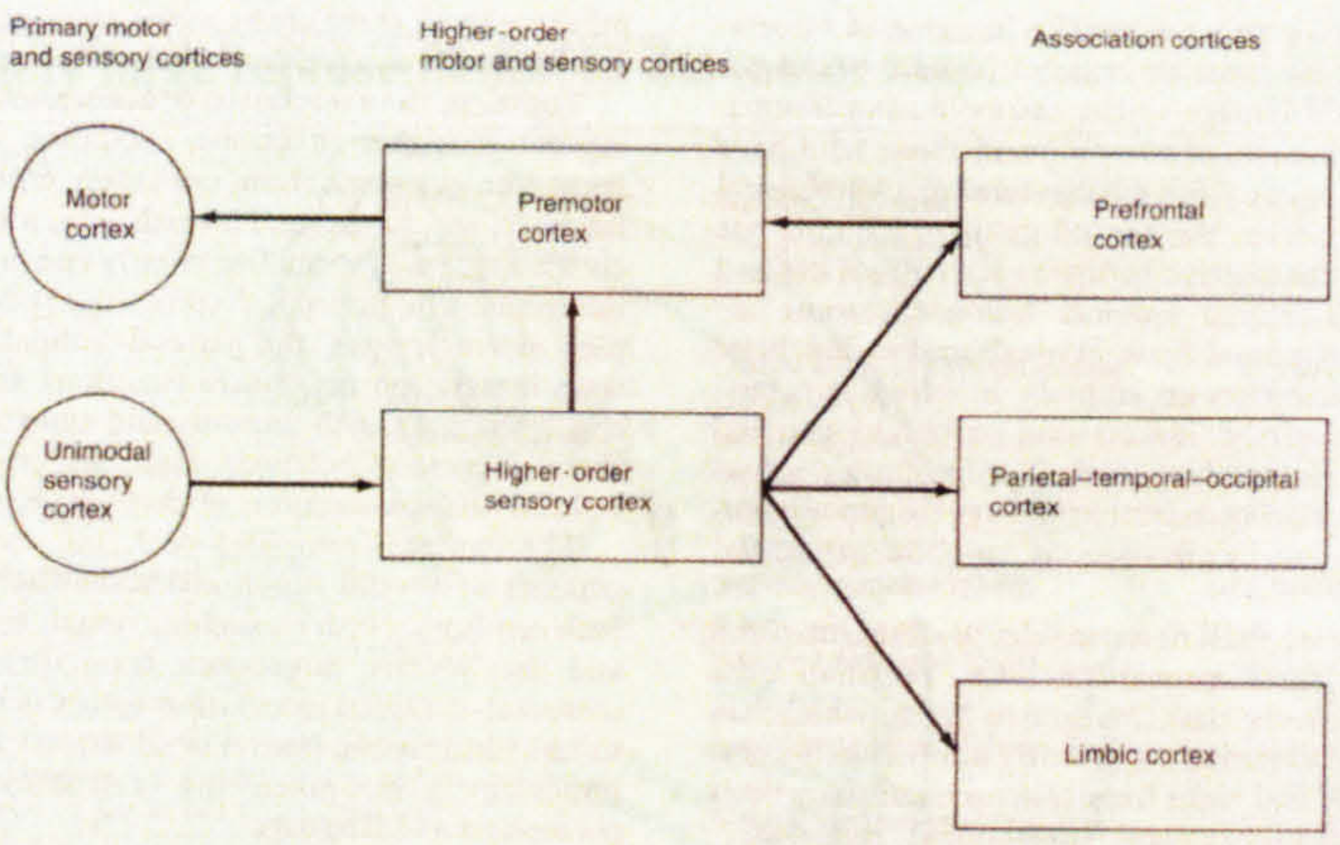


Figure2.4 shows the connection between the association cortex, the higher order motor centres and the higher order sensory cortex. From Kandel et al, Principles Of Neural Science, Third Edition. Pg 826.

In summary, the primary sensory areas of the cerebral cortex are devoted to the reception and initial cortical processing of sensory information. The primary areas project to the higher areas that further elaborate and process sensory input. The higher-order areas connect to the association areas; these provide the link between sensation and action by making connections with the higher order motor areas. The higher-order motor areas, in-turn, project to the primary cortex, which exerts direct control over motor neurons. (Deiber, Ibanez et al. 1996, Roland and Zilles 1996, Kalaska et al. 1997,Georgopoulos 2002 and Georgopoulos 2000).

2.1.3.2 Motor Areas of the Cerebral Cortex

In 1870 Gustav Fritsch and Eduard Hitzig provided the first direct evidence that the motor areas of the brain are organized somatotopically i.e. distinct areas of the brain control movement of different parts of the contralateral side of the body (John et al. 1991, Metman et al. 1993). Pioneering work on patients by Penfield and Woosely's work on monkeys using electrical stimulation of the cortex showed that the primary motor cortex contains a motor map of the body. They observed localised contraction of muscles resulting from the stimulation of the precentral gyrus. Not all body parts are represented equally in the motor map (see figure 2.5). Those parts of the body which are involved in tasks requiring precision and fine control, such as the face and hands, have a disproportionately large representation in the motor map.

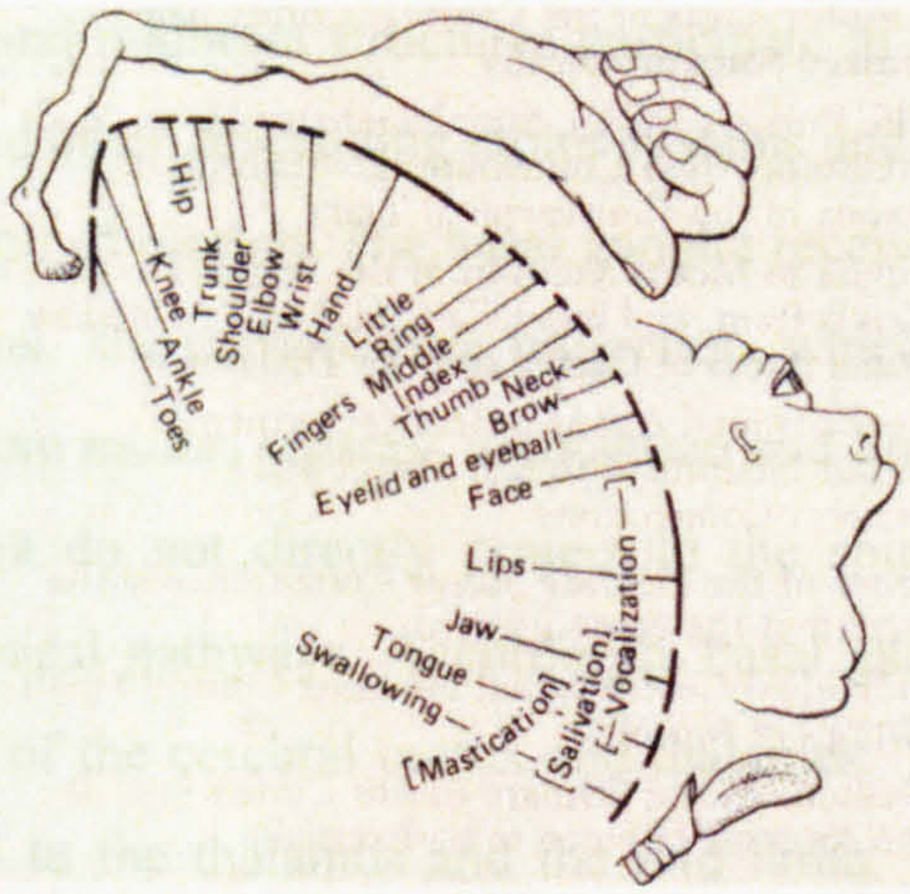


Figure 2.5.Shows the somatotopic organization of motor cortex. From Kandel et al, Principles Of Neural Science, Third Edition. Pg 610.

Stimulation of the area anterior to the primary motor cortex can also produce motor effects. These areas are called as the pre-motor areas. There are four main pre-motor areas the lateral ventral, the lateral dorsal, the supplementary and the cingulate motor areas. (John et al. 1991, Roland and Zilles 1996, Deiber 1991). Stimulation studies of the pre-motor areas show that complex movements involving multiple joints and bilateral movements are evoked as compared to the more localised connection seen with motor cortical stimulation. The four pre-motor areas project both into the primary motor cortex and the spinal cord. Each of the pre-motor areas receives sensory input from distinct locations within brodman areas 5, 7 and 46. While areas 5 and 7 provide sensory information, area 46 is associated with the working memory and for example stores information necessary for guiding a movement. Other than these connections there are extensive connections between the pre-motor areas themselves. It is thought that these allow the pre-motor areas to plan and coordinate complex movements by regulating the working of the primary motor cortex and the motor neurons in the spinal cord.

2.1.3.3 Basal Ganglia

The Caudate nucleus, Putamen, Pallidum, Subthalamic nucleus and Susbstatia nigra, are collectively called the basal ganglia (see figure 2.6). The basal ganglia and several associated sub-thalamic and midbrain structures participate in the control of movement along with cerebellum and other descending motor systems and play an important role in the extra-pyramidal control of motion. The basal ganglia receive massive input from the motor cortex and thalamus. The corticostriate projection, which arises from the cerebral cortex, contains fibres from motor, sensory, association and limbic areas of the cerebral cortex. The basal ganglia do not directly project to the spinal cord but form many parallel loops within cortical pathways. Accordingly basal ganglia are well placed for coordinating the activity of the cerebral cortex and thalamus. The major efferents from the basal ganglia project to the thalamus and the mid brain. The thalamic nuclei that receive projections from the basal ganglia also receive projections from the cerebellum.

These thalamic nuclei in-turn project onto the prefrontal cortex and the pre-central gyrus. Through these complex pathways the basal ganglia can influence the corticospinal and corticobulbar systems.

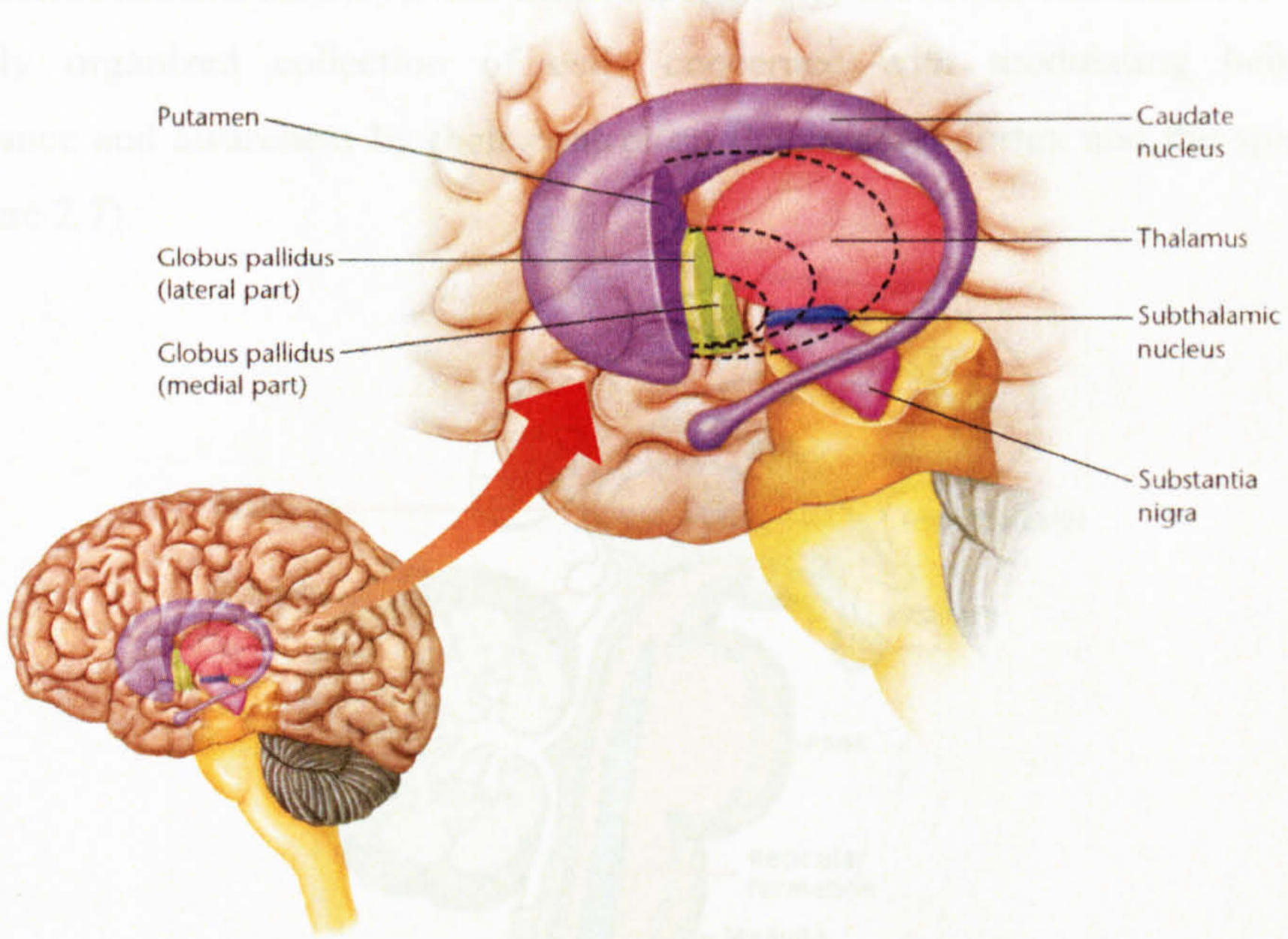


Figure 2.6 shows the anatomic location and substructures within the Basal Ganglia. Refered from http://cti.itc.virginia.edu/~psyc220/kalat/JK246.fig8.15.basal_ganglia.jpg

Studies by Bares et al (2001) have provided evidence that the basal ganglia play an important role in the intiation of movement. The study found that the activity of single neurons in different regions of monkey basal ganglia changes preceding the movement of a body part and before the firing of neurons of the motor cortex and cerebellum. (Grillner and Georgopoulos 1996, Georgopoulos 2000; Bares and Rektor 2001and Georgopoulos 2002). Diseases of the basal ganglia structures lead to many forms of movement disorders with symptoms including bradykinesis, poor and inappropriate co-contraction of muscle groups, and involuntary tremors.

2.1.3.4 Brain Stem

The brain stem is located in the small region between the start of the spinal cord and the diencephalon. The brain stem contains three types of structures: nuclear groups, long tracts (both motor and sensory), and the components of the reticular formation, which is a loosely organized collection of cells concerned with modulating behavioural performance and awareness by their control on the cerebral cortex and the spinal cord (see figure 2.7).

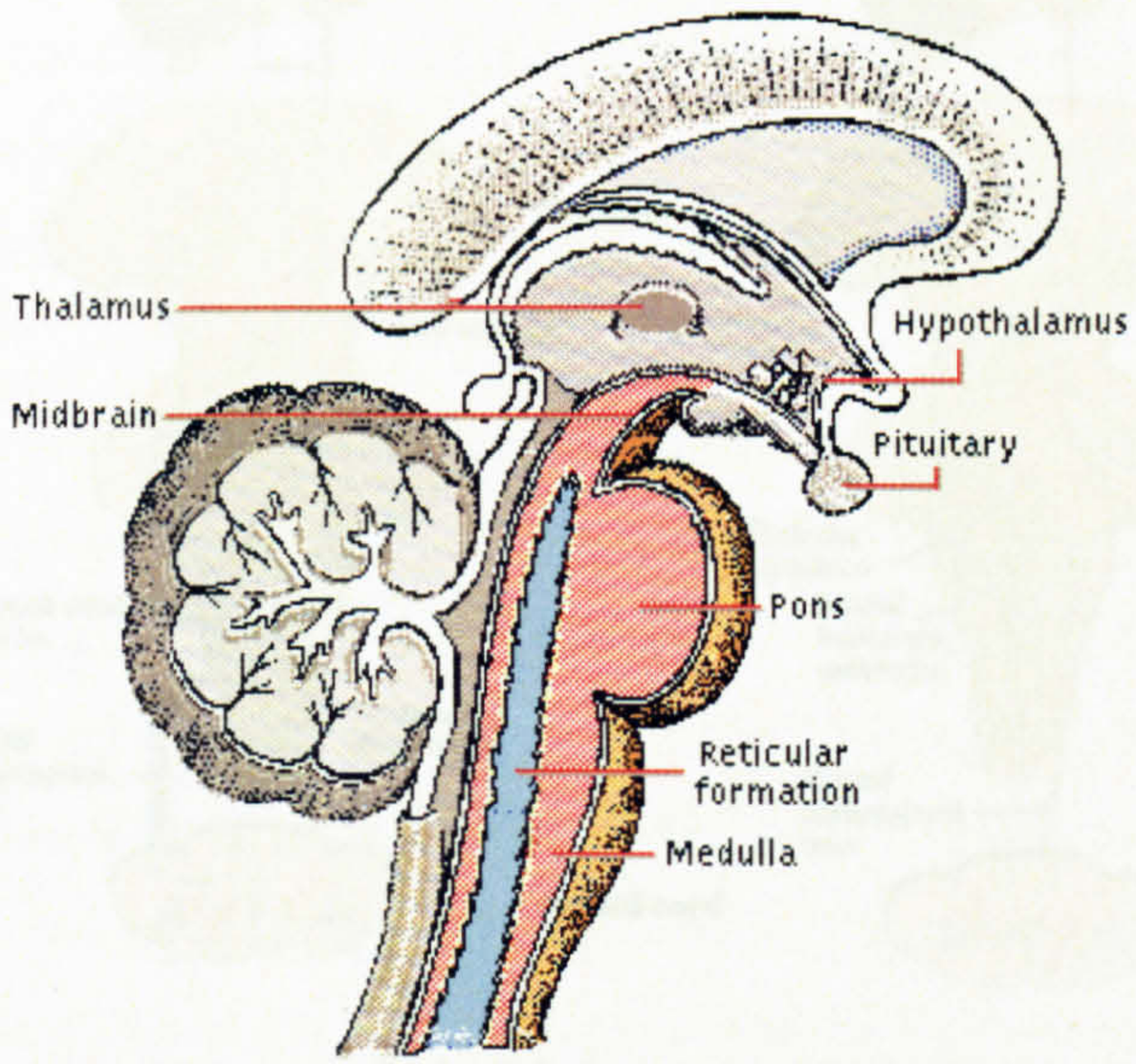


Figure 2.7 Shows the cross-section view of the brain stem. Refered from http://images.encarta.msn.com/xrefmedia/aencmed/targets/illus/ilt/T012864A.gif

There are many groups of neurons in the brain stem that project to the spinal grey matter, which based on their location have been classified into the medial and the lateral pathways, which will be described later.

2.1.3.5 The Various Descending Spinal Pathways

Pyramidal Pathway

A major output pathway for voluntary motor control is provided by the corticospinal tract system that originates from the pyramidal cells (upper motor neurones) of the primary motor cortex. The corticospinal pathway is notable because it forms a direct monosynaptic input to lower motor neurons in human and non-human primates giving a

fast and excitatory connection from the brain to muscle; it also works indirectly through the extra-pyramidal medial and lateral pathways (explained next) that it innervates. Corticospinal tract not only excites motoneurons but also activates interneurons within the spinal cord. Figure 2.8 shows the corticospinal pathways.

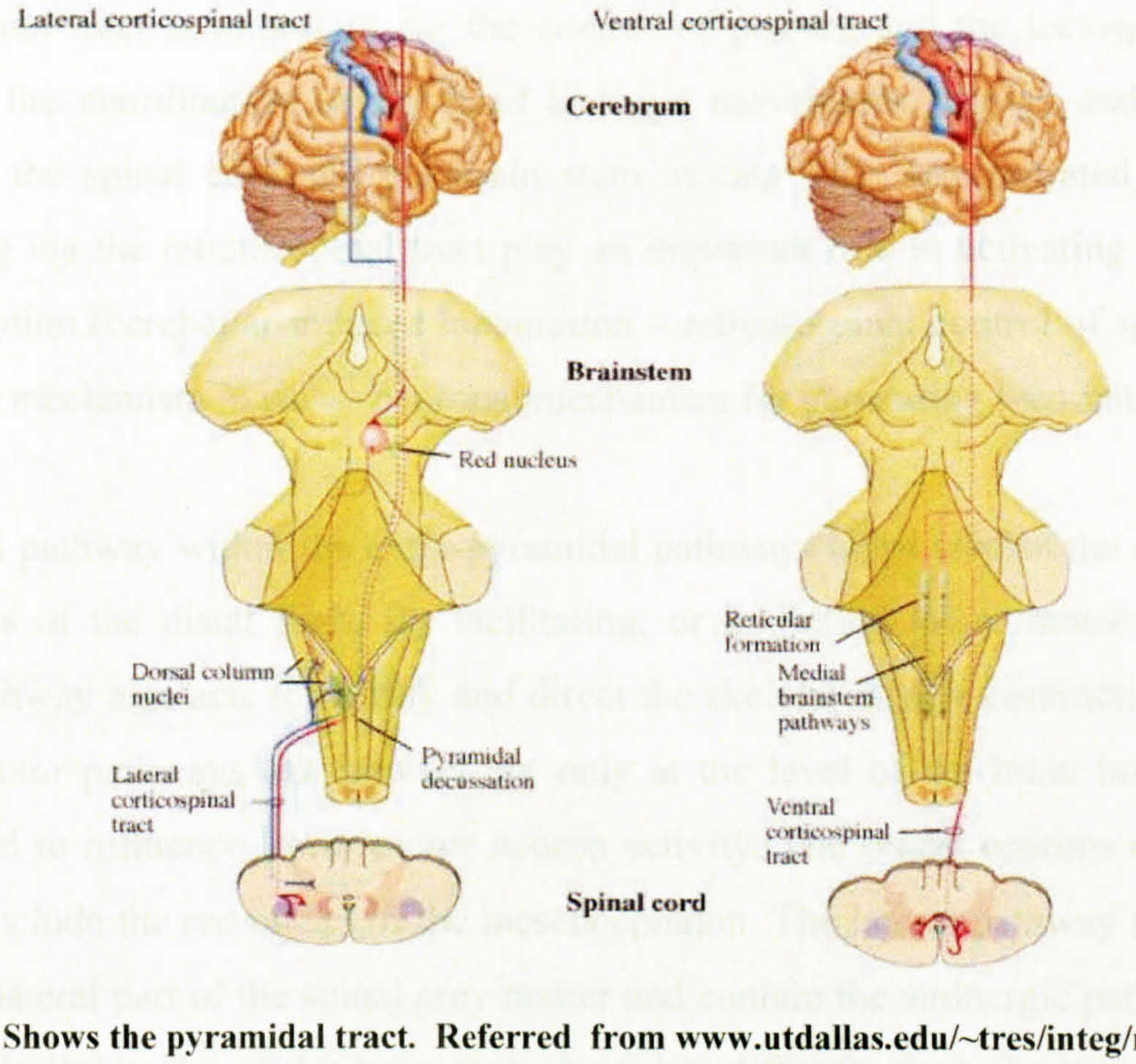


Figure 2.8. Shows the pyramidal tract. Referred from www.utdallas.edu/~tres/integ/mot2/2_12.jpg

Extra-pyramidal pathway

From an anatomical perspective a medial and lateral division of the extra-pyramidal system can be described. The medial pathway within the extra-pyramidal system helps control the gross movements of the trunk and proximal limb muscles. By acting to facilitate, or inhibit lower motor neurons the medial pathway can modify and direct the skeletal muscle contraction. Thus the various motor pathways can interact not only at the level of the brain but also at the level of the lower motor neuron. The medial pathway originates from – the vestibular nuclei, the superior and inferior calliculi and the reticular formation. The medial pathway influences the axial and proximal muscles and terminates in the ventro-medial part of the spinal grey matter.

The medial pathways shown in figure 2.9 and 2.10 have three major components – the vestibulospinal tract, the reticulospinal tract and the tectospinal tract. The vestibulospinal tract carries information for reflex control of balance and posture, the reticulospinal tract is important for the control of posture and the tectospinal tract is important the coordination of the head and eye movements. Lesion and stimulation studies of the spinal cord and the brain stem in cats have demonstrated that signals descending via the reticulospinal tract play an important role in activating mechanisms for locomotion (cerebellar-induced locomotion – reticulospinal control of spinal rhythm generating mechanism in cats – neuronal mechanism for generating locomotor activity).

The lateral pathway within the extra-pyramidal pathways helps control the more precise movements of the distal limb. By facilitating, or inhibiting lower motor neurons the medial pathway also acts to modify and direct the skeletal muscle contraction. Thus the various motor pathways can interact not only at the level of the brain but also at the spinal level to influence lower motor neuron activity. The origin neurons of the lateral pathway include the red nuclei of the mesencephalon. The lateral pathway terminates in the dorso-lateral part of the spinal grey matter and contain the aminergic pathway, which originates in the nuclei of the brain stem, branches diffusely throughout the spinal cord providing a neuromodulating action in spinal circuits by the release of monoamines such as noradrenalin and serotonin.

The rubrospinal tract originating from the red nucleus in the mid brain is the main lateral descending tract. These fibres descend to the spinal cord through the medulla and are involved in the control of distal muscles involved in a variety of fine movements. In humans this function is also largely assumed by the corticospinal system.

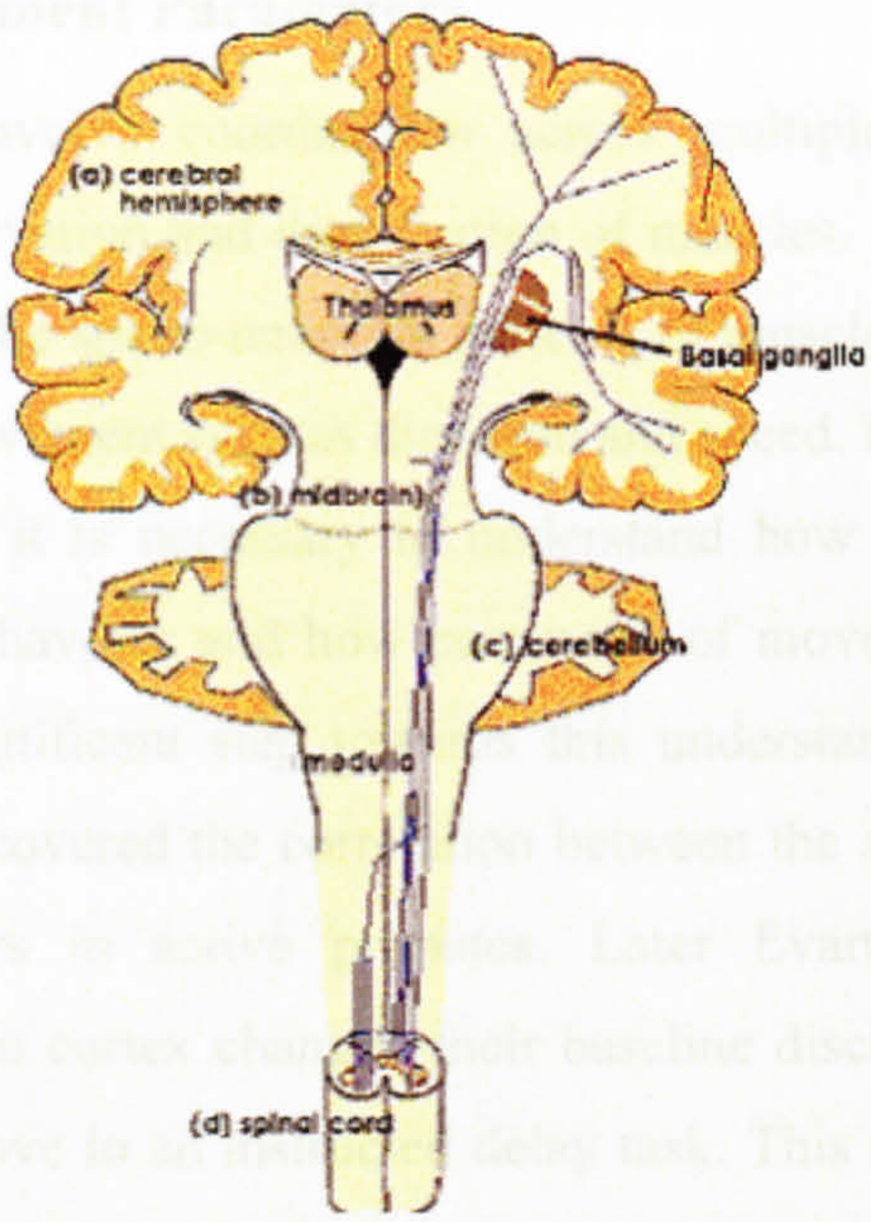


Figure 2.9. Shows the medial pathway of the extra-pyramidal system .Modified from http://web.lemoyne.edu/~hevern/psy340/graphics/tracts.ventromedial.2.jpg

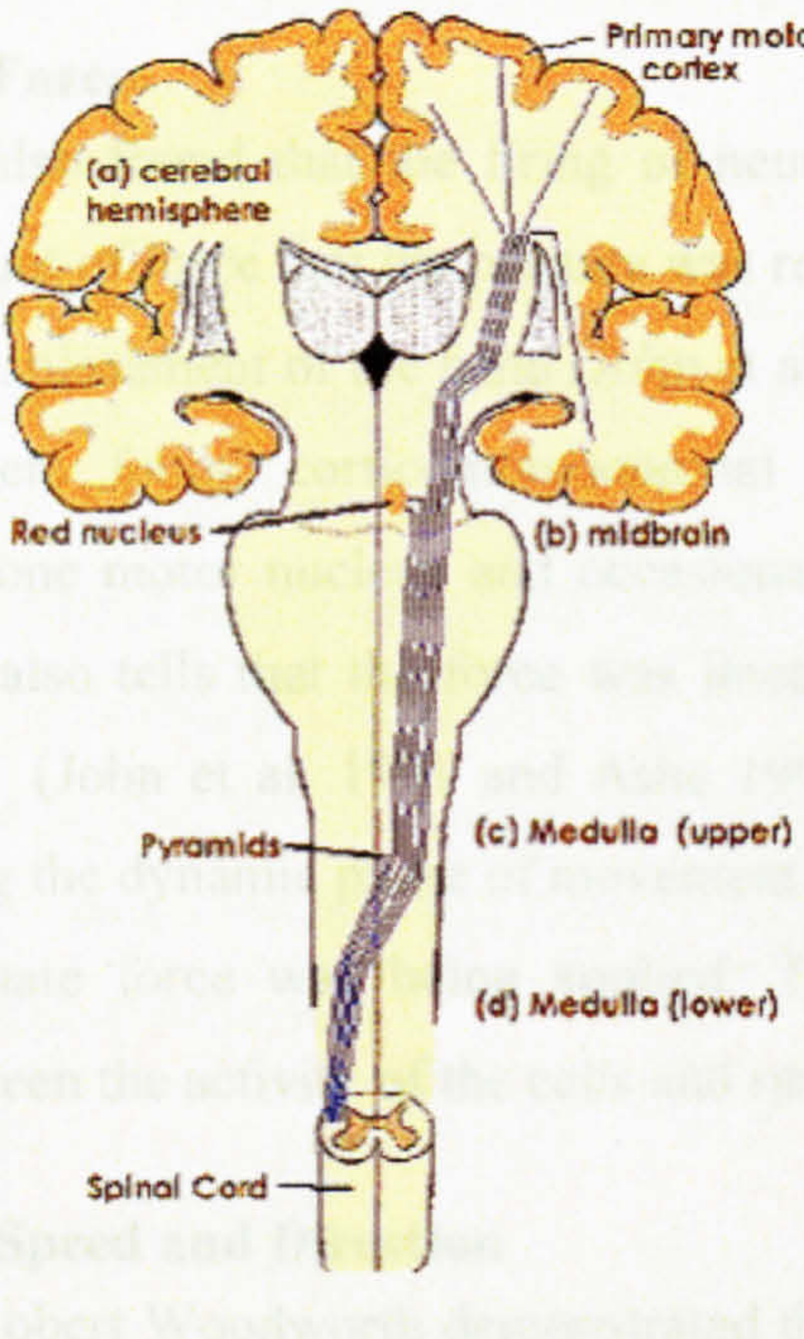


Figure 2.10. Shows the lateral pathway of the extra-pyramidal system .Modified from http://web.lemoyne.edu/~hevern/psy340/graphics/tracts.dorsolateral.2.jpg

2.1.4 Control of Movement Parameters

Movements generally involve coordination across multiple joints and also require precise timing in the activation and deactivation of muscles. Each voluntary movement thus can be defined by the spatio-temporal patterns of muscle drive but more simply by the global features of movement such as direction and speed. In order to understand how movement is controlled it is necessary to understand how individual neurons act to control natural motor behaviour and how parameter of movement may be encoded by neuronal systems. A significant step towards this understanding was taken in 1960s when Edward Evans discovered the correlation between the activities of single neurons with specific behaviours in active primates. Later Evarts and Jun Tanji (1976) demonstrated that cells in cortex changed their baseline discharge rate when a primate waited for a signal to move in an instructed delay task. This shows that the intention to move alters the firing of neurons in the primary motor cortex the source of the cortico-spinal tract. (Claude et al. 1991, Tanji and Evarts 1976).

2.1.4.1 Neural Control of Force

In his experiment Evarts also found that the firing of neurons in the primary motor cortex varied with the amount of force that the primate was required to generate to move its hand and not with the displacement of the hand (John et al. 1991). Later in the 1970s Fetz and his co-researchers found corticomotoneuronal cells that project mono-synaptically to more than one motor nucleus and occasionally to muscles that control different joints. Literature also tells that the force was linearly correlated to the firing rate in almost all neurons (John et al. 1991 and Ashe 1997). They found that these neurons fired briskly during the dynamic phase of movement and settled to a lower tonic firing rate when steady state force was being applied. They found that there was significant correlation between the activity of the cells and rate of change of force.

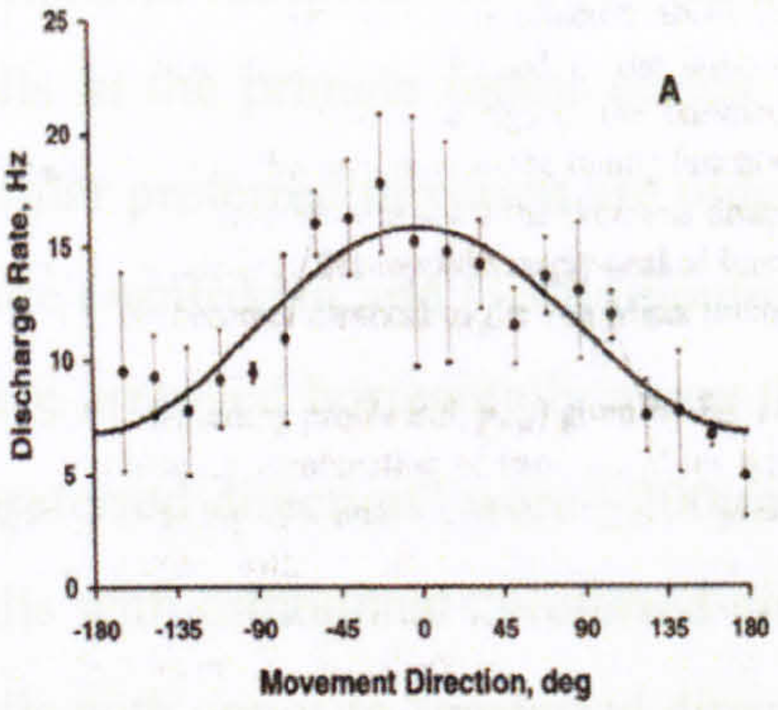
2.1.4.2 Neural Control of Speed and Direction

As far back as the 1890s Robert Woodworth demonstrated that fast movements are less accurate than slow movements (John et al. 1991). The principle reasons being that there is lack of time for correction and lack of visual feedback. The other reasons being

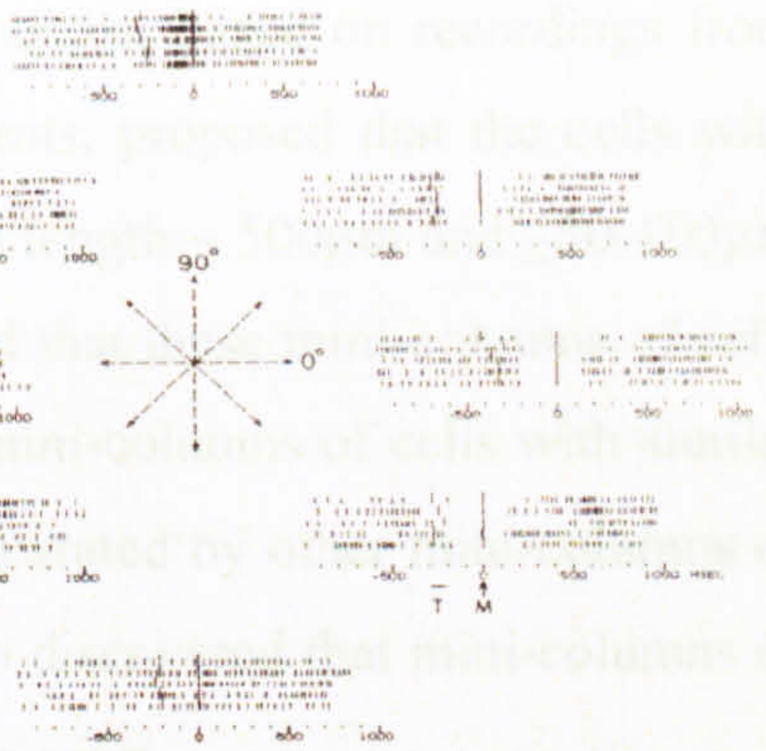
recruitment of addition motor neurons which have variable excitability. The variability can in part be explained by the fact the subject are seldom aware of the force and loads that will oppose the movement.

In 1982 Apostolos Georgopolous and his co-researchers proposed that movement in a particular direction is determine not by the activity of specific neurons but by the net activity in a whole population of neurons. They experimented on rhesus monkeys that were trained to move a manipulandum towards lighted targets. During these studies the activity of neurons in the arm area of the motor cortex was recorded. While analysing the data they found that the rate of discharge of the cells changed in an orderly fashion with direction (See figure2.11). They suggested that each cell has a preferred direction of movement and the rate of discharge is modulated as a cosine of the angle between this preferred direction of movement and the actual movement direction. By taking the contribution from all cells in a sample population and by deriving the population vector they found that the population vector closely matched the actual direction of movement (see figure 2.11). (Georgopoulos et al. 1982)

In their studies Kakei et al (Kakei et al. 2001) found that the cells in both the motor cortex and ventral premotor cortex were either tuned in an external fashion showing the same activity independent of the initial arm posture or were tuned in an internal fashion, that is their activity was dependent on the initial arm postures. They also found that there was greater portion of the "externally" tuned cells in the premotor cortex than in the motor cortex. They suggested that the intra-cortical processing between the premotor ventral cortex and the motor cortex results in a transformation of coordinates between the external and internal frame of reference.



(a)



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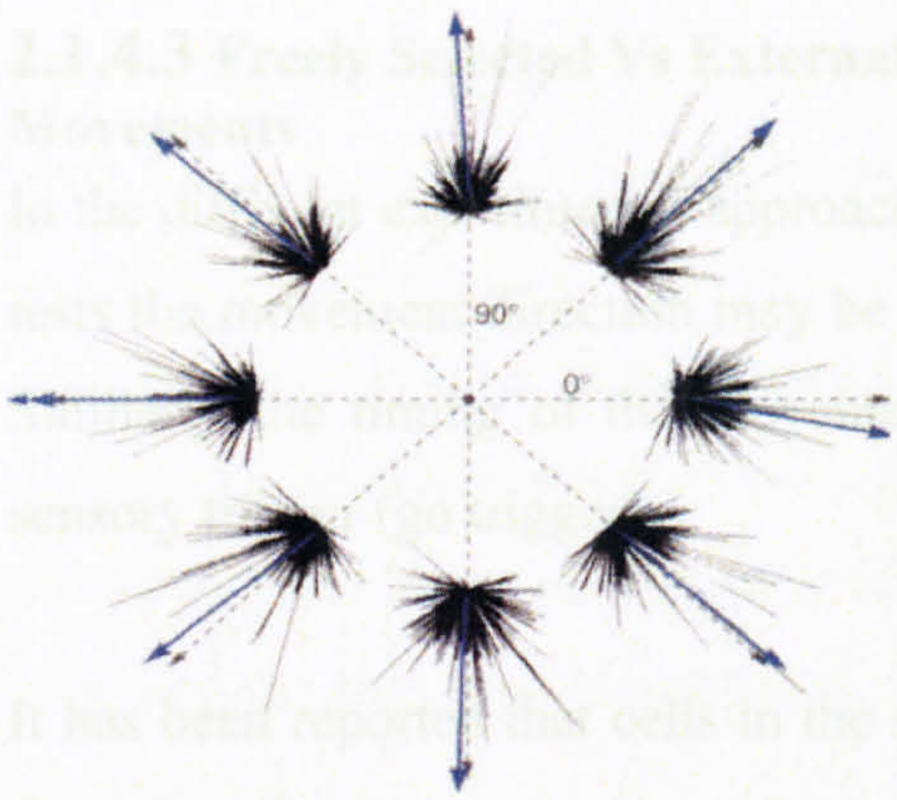
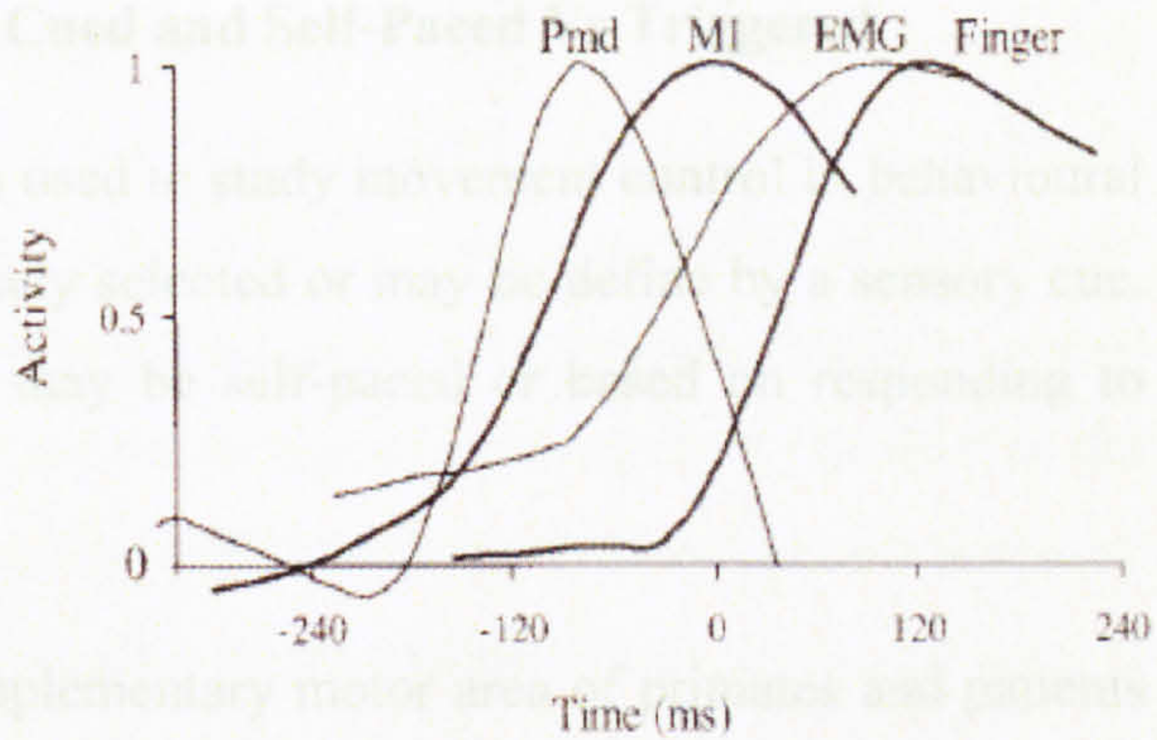


(c)



(d)

FIG 2.11. (a)The Figure shows the firing rate of a single neuron when movements were made at different angles with respect to its preferred direction. The figures (b) and (c) show the firing rate of the population group and the population vector that has been derived. It shows the population vector closely matches the actual movement. The figure (d) shows the non-directional components from the cortical cell and the EMG. Reference ((a) and (b) from Georgopolous et al 1982 , (c) and (d) from Moran et al 1999)

Morran and Schwartz (1999) demonstrated that the activity of cells in the motor cortex of primates which is modulated by the cells preferred direction is further modulated by the speed of the movement. They also showed that this activity clearly precedes the movement (Moran and Schwartz 1999).

Mountcastle proposed a scheme of functional organization in the motor cortical area based on his experiments on cats (Mountcastle 1997). He found vertical columns of neurons which extend from layer 2 to layer 4 which are activated by the same group of

peripheral receptors .In 2003 Amirikian and Georgopoulos, based on recordings from cells in the primate motor cortex during 3D movements, proposed that the cells with similar preferred direction are ordered into modules of length ≃ 500μm and ≃50-100μm wide (Amirikian and Georgopoulos 2003). They found that these mini-columns of cells were arranged horizontally along the cortical layers, mini-columns of cells with similar "preferred direction" were ≃200μm apart and were separated by other mini-columns of cells with orthogonal "preferred directions". They also discovered that mini-columns of cells with opposite "preferred directions" were ≃350μm apart.

2.1.4.3 Freely Selected Vs Externally Cued and Self-Paced Vs Triggered Movements

In the different experimental approaches used to study movement control in behavioural tests the movement direction may be freely selected or may be define by a sensory cue. Similarly the timing of the movement may be self-paced or based on responding to sensory trigger (go trigger).

It has been reported that cells in the supplementary motor area of primates and patients fire when the movements have been internally chosen and cells in the pre-motor cortex are more active in externally cued movements. (Passingham 1987 and Goldberg 1985). In human studies based on regional cerebral blood flow has confirmed that the supplementary motor area is significantly more active when movement direction is internally chosen than when the movement is based on external cues. (Deiber et al. 1991). This observation has been confirmed in studies on primates who were unable to perform arbitrary acts at their own pace when the supplementary motor area has been removed.

A study by Christian Gerloff (Gerloff et al. 1998) involving internally and externally paced finger movements found that in both cases there is significant "movement-related regional coupling" between the contralateral premotor and primary sensorimotor (primary motor and primary sensory) cortex of both sides and between the mesial premotor areas, probably including the SMA. However they also found that the main

difference observed was an increased functional coupling between the central motor areas during the internally paced finger movements (especially inter-hemisphereically between the left and right primary sensorimotor cortex) and between the primary sensorimotor cortex and the mesial premotor areas. Additional regional activation of the mesial premotor cortex was also observed during internally paced finger extension (Gerloff, Richard et al. 1998). They also reported an early negativity in the motor related cortical potentials (MRCP), which were prominent in the frontocentral midline electrodes (FCz extending into F3, FC3 and C3), during self paced finger extensions of the right hand. Moreover this negativity was measured at a latency of 168±49ms before EMG onset. In the same study they found that there was a spatial extension of task related power decrease towards electrodes Fz, FCz (and to a smaller extent Cz) during self paced finger movements compared to externally paced movements of the finger .The study concluded that because internal pacing is a more complex task the motor system increases both the regional activation of the mesial premotor areas (including the SMA) and also increases the information flow between the lateral and mesial premotor areas and the sensorimotor areas of both the sides of the cortex.

2.1.4.4 Motor Imagery Vs Actual Movement

Motor imagery or internal-simulation of movement can be defined as the dynamic mental activity during which the subject "feels" himself/herself performing a given actions.

Eric. Kandel (Eric 1991) examined studies based on PET scans of imagination of the alphabets and proposed that imagined visual images are generated by the same components of the visual system that produce real images produced by the external stimulus. He also discussed that many tasks that require visual imagery from memory cause very strong activation of the posterior parietal cortex, suggesting that in their imagination individuals reorient their body with respect to the imagined figure. The same reasoning that is used in visual imagery has been in used in motor imagery research, psychological studies using mental chronometry tasks suggest that there is a

remarkable parallelism between motor imagery and motor execution (Decety 1996). Results from studies by Decety also showed that the autonomic responses (cardiac and respiratory activity) of the subjects changed with the level of imagined exertion. They also discussed the importance of the supplementary motor area for internal programming and simulation of complex motor sequences. Studies by Gerardin (Gerardin et al. 2000) also found that the parietal, pre-motor cortex, the basal ganglia and the cerebellum were also active during internal simulation of movement.

In their paper Lang et al and Gerardin et al (Lang et al. 1996; Gerardin et al. 2000) based on EEG and MEG show that the primary motor cortex is active during internal simulation of movements (see figure 2.12). They also argue that their data does not support the idea that higher motor centres are disconnected from the lower motor centres. They argued further that though their data pointed to a possibility that the size and amount of activity of the motor cortex might be different between motor imagery and actual movement this might be because of internal simulation of movement may be less synchronized than actual movement. However it is clear that the final activation of the motor drive must be inhibited in some way. Romero et al (2000) using EEG showed that electro-cortical activity in the supplementary/pre-motor motor areas are similar between imaginary and executed movements as target force and rate of force development are varied. (Romero et al. 2000)

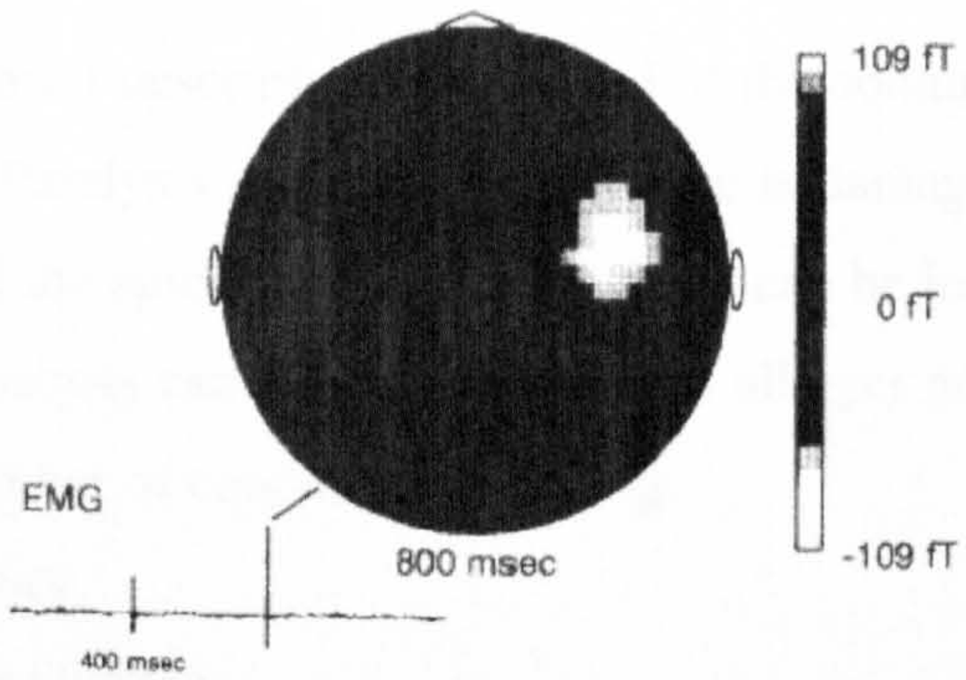


Figure 2.12 referenced from Lang et al 1996. The figure shows the activation of the primary motor cortex during internal simulation of finger movement.

Pfurtscheller et al (1997) have also reported that event related desynchronization(ERD) in the EEG recorded from the contra-lateral hemisphere of subjects instructed to imagine a movement of their left or right hand in response to visual stimuli. (Pfurtscheller 1997) (See figure 2.13). They reported ERD in the EEG recorded from the ipsi-lateral side of two out of three subjects. More recent studies have reported on the different patterns of event related synchronization and desynchronization after different types of motor imagery (Pfurtscheller et al. 2005).

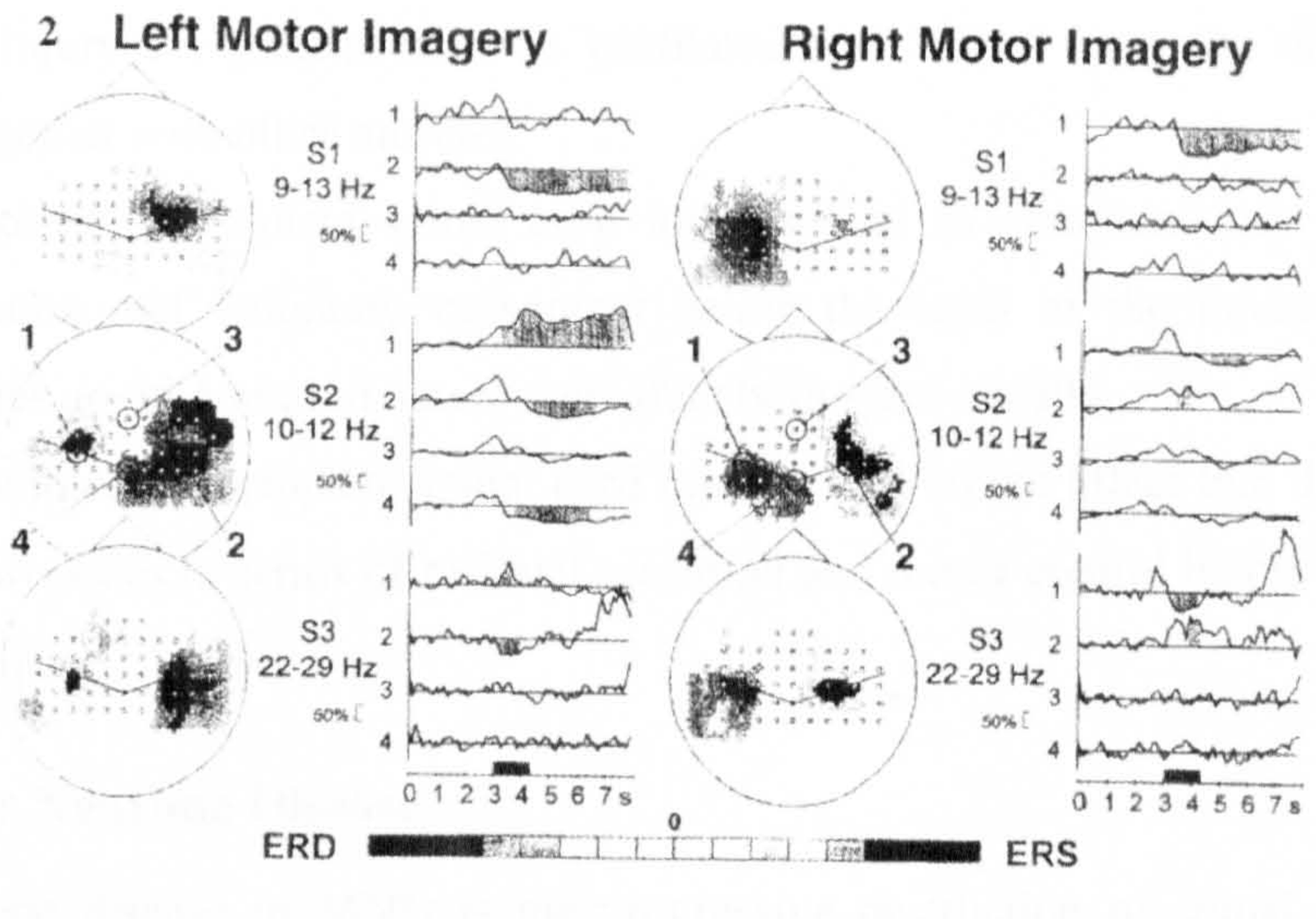


Figure 2.13. The figure shows the cortical maps and time course of ERD/ERS at four different electrode locations. From Pfurtscheller 1997

2.2 Paralysis and Loss of Voluntary Movement

In this section only a brief description is provided of the common causes for the loss of voluntary movement. Paralysis can result when there is damage to the motor pathways of the brain brain, and the spinal cord. The paralysis can be localised or be generalised to the whole body. Paralysis can affect people across all ages and population groups and it can result from a number of conditions including:

- Spinal cord injury.
- Motor Neurone Disease
- Brain Stem Stroke

2.2.1 Spinal Cord Injury

The spinal cord is the major neural route in the human body through which sensory information is transmitted to the brain and motor commands are sent from the brain. Spinal cord injury due to trauma or disease can lead to breakage of this information flow and cause loss of movement or sensation. The extent of loss of sensation and motor ability depends on the type and the level of injury (Hall, Cohen et al. 1999 and Burns and Ditunno 2001). The higher the lesion the greater the paralysis. In high (C1-C3) spinal cord injury the patient must be ventilated as in these cases the diaphragm is paralysed together with other muscles.

- Complete: Complete spinal cord injuries lead to complete loss of physical sensation and voluntary movement below the level of the injury. Complete injuries are bi-lateral in nature and affect both sides equally.
- In-complete: Incomplete spinal cord injuries vary in the affect that they have on the two sides in-terms of residual sensation and motor control below the level of the injury.

2.2.2 Motor Neurone Disease

Motor neurone disease or MND is the progressive destruction of spinal and bulbar. motor neurones. As these cells die the disease leads to progressive loss of voluntary control of muscles and loss of ability to walk, speak, swallow and breathe. Amyotrophic lateral sclerosis (ALS), progressive muscular atrophy (PMA), spinal muscular atrophy (SMA), progressive bulbar palsy or pseudobulbar palsy (PBP) and primary lateral sclerosis (PLS) are all forms of motor neurone disease. (Hughes 2005 and Francis 1999).

2.2.3 Brain Stem Stroke

Stroke or Cerebro-vascular accident (CVA) is caused by the lack of blood supply to parts of the brain causing cell death due to lack of oxygen and nutrients. (Foley et al. 2002 and Sturm 2004) . The brain stem connects the brain to the spinal cord and because it regulates body functions such as breathing, heart rate, temperature control, balance, and eye movement a stroke affecting the brain stem can lead to loss of

- Ability to communicate because of weakened mouth, tongue and throat muscles
- Movement because of weakness or paralysis of one or more limbs, and poor eye coordination.
- Vision and sensation of touch.
- Ability to swallow
- Ability to breath

There are several health and fitness issues specific to people with mobility-related disabilities due to paralysis, limitations in performing activities of daily living, respiratory issues, dysreflexia, spasticity, pain, bowel care, bladder management and skin care. In addition to the primary problems there are secondary conditions such as depression and obesity due to the loss of mobility and independence. The individuals and the families often face substantial costs associated with the treatment of both the priamary and secondary issues, need for assistive technology and obtaining caregive services. (Sturm et al. 2004, Westgren and Levi 1998 and Francis, Bach et al. 1999) . Health and quality of life are affected by mutliple environmental barriers such as acessibility to buildings. While advances in healthcare, technology and law have made it increasingly possible for many with disabilities to lead an healthy, productive and active life there is a clear indication that these individuals still experience a lower quality of life and the cost of care is still very high. (Westgren and Levi 1998; Francis, Bach et al. 1999; Bret L. Hicken 2002; Sturm 2004 and Donnan et al. 2004). The main purpose in developing brain computer interface for these individuals is to increase their independence and reduce their reliance on care staff in a hope to increase their quality of life and reduce cost of care.

2.3 Brain Computer Interfaces

A wide variety of neuromuscular disorders can disrupt the channels through which the brain normally communicates with and controls its external environment. In the absence of means of repairing this damage there are three options. The first is to augment the current capabilities of the remaining pathways – this includes use of muscles that require

voluntary control to substitutes for the paralyzed muscle. The second option is to bypass the points of damage along the original information path – example functional electrical stimulation. The third option is to provide the brain with a whole new communication and control pathway. (Lebedev and Nicolelis 2006 and Wolpaw et al. 2002).

The development of new communication and control pathway independent of the normal output channels of the brain is dependent on the design of a brain computer interface. However, this approach assumes that voluntary command signals can be extracted from recording of brain activity in a robust and stable way that allows a persons intention to be detected despite the presence of a disrupted flow of information to and from the brain.

Currently there are a variety of methods available that help monitor brain function and its relation to behaviour. Functional brain mapping (such as EEG, MEG, FMRI) helps to describe local neural activity associated with sensory, motor and cognitive processes. To be effective a brain mapping modality needs both precision in localizing a region of activation and temporal precision for characterizing changes in patterns of activation over time. (Nicolelis 2001 and Wolpaw et al. 2002).

Though the Electroencephalogram (EEG) has a poor spatial resolution compared to techniques like fMRI that makes it possible to interpret underlying neural functionality at the level of cortical lobes it is well suited to study how synchronization in systems corelate with mental activity. EEG has a temporal resolution as fine as the analog to digital sampling rate used to record it. These features and the fact that it can recorded from ambulatory (or mobile) subjects in their natural environment makes it ideally suited for BCIs (Wolpaw et al. 2002 and Fisch 1999).

2.3.1 Generation Of EEG

EEG is generated by synaptic current flow either into or out of a population of neurons. The EEG recorded at the scalp is largely attributed to synchronized post synaptic

potentials (PSPs) of cell body and large dendrites of vertically oriented pyramidal cells in cortical layers 3 to 5. These synaptic potentials are of lower voltage but last much longer than action potentials and the extracellular currents produced by their generation have relatively wide distribution. The columnar structure of the cerebral cortex facilitates a large degree of electrical summation rather than electrical cancellation. Though most of the signals recorded at the scalp are presumed to originate at cortical regions near the electrode site relatively large signals from the more distal areas also might make a significant contribution. Relatively small signals generated sub-cortically can be resolved by signal averaging techniques. (Fisch 1999)

2.3.2 EEG AND Brain Ccomputer Interfaces

The brain computer interface uses voluntary control of spontaneous or evoked electroencephalographic (EEG) or single neuron activity. The computer based detection and interpretation of this activity is then used for communication and control. (Nicolelis 2001 and Wolpaw et al. 2002).

EEG activity includes a variety of different rhythms that are identifiable by their frequency, location, and association with the various aspects of brain function that can be used for BCI. EEG activity also includes a variety of evoked potentials generated by sensory stimuli and motor related potentials associated with actual or imagined movements, and these too can be used for BCI-based communication and control. Researchers have used different approaches to detect user-initiated or evoked changes in the EEG signals or in cortical single neuron activity.

2.3.3 Classification Of Brain Computer Interfaces

BCIs can basically be classified into two categories (Wolpaw et al. 2002): dependent and independent. A dependent BCI does not make use of the brain's normal output pathways for conveying the messages; however activity in these pathways is essential to

generate the necessary brain activity that does carry the messages. On the other-hand the independent BCI does not depend on the brain's normal output pathways or peripheral nerves or muscles. The dependent BCI is essentially an alternative method of detecting messages carried in the brains normal output pathways and despite the fact that it does not provide a new communication channel it is useful. The independent BCI on the other hand provides the brain with a wholly new output pathway. The independent BCI is deemed to be more useful because it can be used for individuals who may lack all normal output channels.

2.3.4 Major Components Of A Brain Compute Interface System

Like most control systems, the BCI system has an input, an output and an intermediate signal processing element (which includes feature extraction, translation and operating protocol) that translates the input to commands that control some assistive device. (Wolpaw et al. 2002, Nicolelis 2001 and Mason and Birch 2003).

The location size, and function of the cortical areas generating a feature in the form of a rhythm or an evoked potential can dictate how the signal should be recorded, how users might best learn how to control it , and how to recognize and eliminate the effects of non-CNS artifacts. (Wolpaw et al. 2002).

trials accurately. From figure 5.32(c) it can be seen that for movement to target 9 the electrodes FC3 and FC1 classify over 85% of the trials accurately. The results shown in figure 5.32(d) are from classification exploring the subjects intention to move towards direction 6 and it shows that EEG from electrodes FC1,FCz and CP1 classifies close to 75% of the trials accurately.

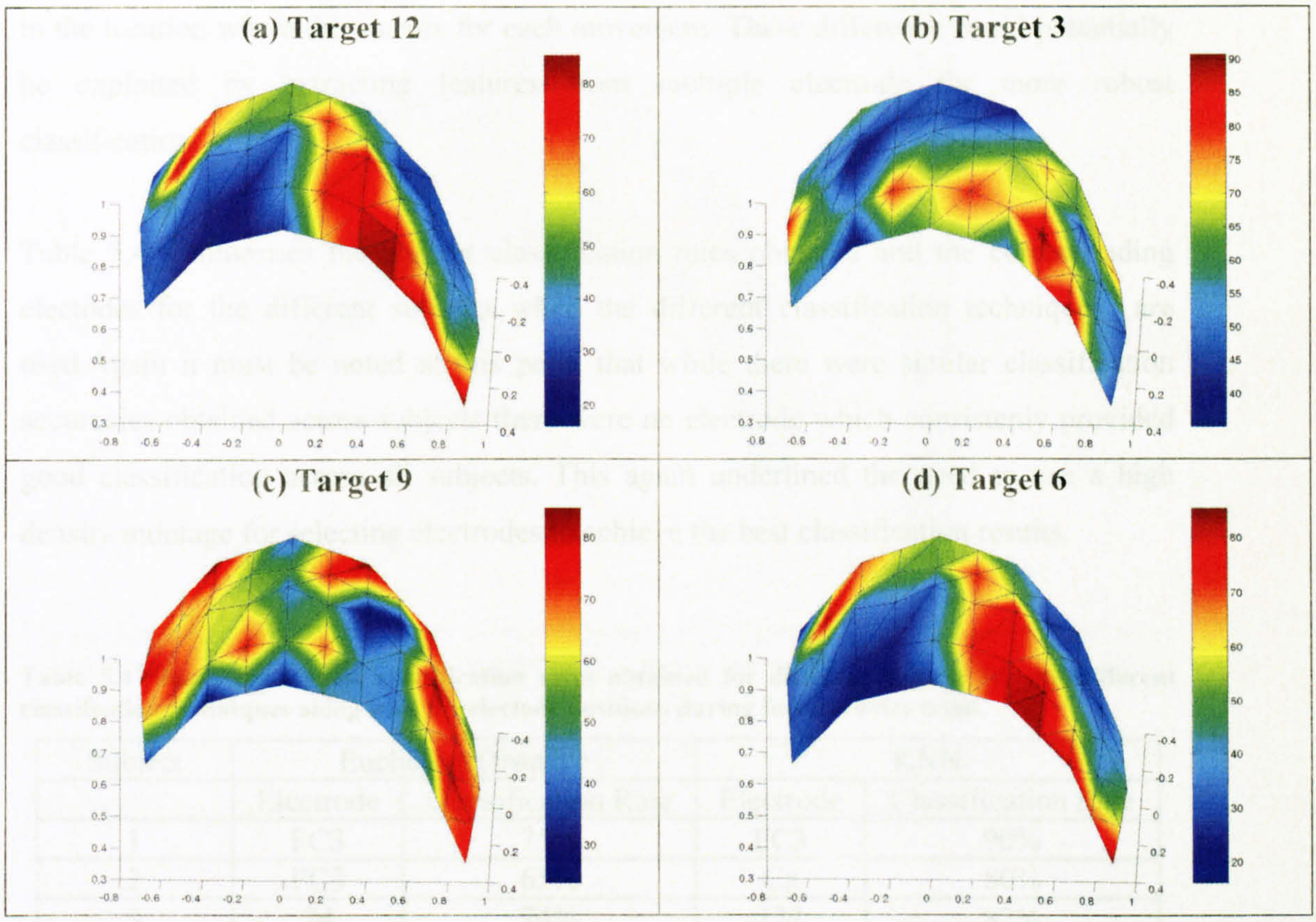


Figure 5.33 shows the results from classifcation of intention to move in different directions during externally cued two choice movement trials. Featreus Extraction: PCA. Classifier: Eucliedean Distance. (Subject 1).

Figure 5.33 is generated by using KNN for classification of the same trials recorded from subject1 . Figure 5.33(a) shows that the electrodes FC1, 78 and C1 classify 85 % of the trials accurately while trying to predict the intention to mvoe towards direction 12. Figure 5.33(b) shows that the best result for predicting intention to move towards direction 3 is obtained from electrode 74 which classifies 90% of the trials accurately.

Invasive systems are based on recording electrical activity of single neurons or by measuring the electrocorticogram (ECoG).

The spontaneous EEG is a sensitive and useful measure of task related changes in cortical activity. However it is necessary to pay careful attention to experimental design and to include appropriate control conditions to ensure that observed changes in the composition of the EEG are actually related to the experimental process of interest and not some extraneous variable. Even when such factors are controlled it is difficult to deduce the characteristics, like order, time of onset and duration, of the component operations with absolute certainty. This situation can be improved by analyzing procedures using shorter data sample time locked to an event. The montage (location of electrodes on the scalp) and the referencing can have a profound effect of what is being recorded. (Teplan 2002 and Marc R. Nuwera 1998).

The electrical response of the brain in response to a specific event or stimulus is called an evoked potential. Such stimulus related potentials are difficult to identify because of their relatively low amplitude in comparison with the background EEG activity. With the use computer averaging techniques the signal to noise ratio can be increased so that the evoked potential is more clearly defined.

2.3.4.2 Signal Processing:

After digitization the signal is conditioned by one or more signal processing algorithms. The two basic stages to which the signal is fed are: feature extraction and the translation algorithm.

Feature extraction: In this stage the main aim is to obtain from the signal features that encode the messages or commands from the user. Initially the signal is processed to maximize the signal to noise ratio (SNR). To achieve this it is necessary to take into account the major sources of noise: neural (features of EEG not being used) and non-neural (mains, eye movement). Noise elimination can be become difficult when both

signal and noise have common frequencies. Non-neural noise under user control can also be a potential problem since it can disguise it self as actual EEG control (Wolpaw 2000 and Lebedev and Nicolelis 2006)

The signal is then subjected to one or more stages of feature extraction such as spatial filtering, spectral analysis, voltage amplitude measurement. The features extracted can be in the time domain, frequency domain or the BCI might utilize feature in both time and frequency domain.

Translation Algorithm: The next phase of signal processing stage is the translation algorithm which translates the signal feature into device control commands that carry out the user's intent. Both linear and non-linear methods can be used by the translation algorithm.

Algorithms in the BCI can currently adjust to the user at three levels. BCIs in the first level use non-adaptive classification that are set at for the first time of usage and do not alter with changes in the user's signal features. BCI that possess the second level of adaptation would not only adapt to the user's signal feature on first use but would also adapt to the short term variation is user's signal caused by the affects of other physiological variations, stress and fatigue, illness and other factors. The third level of adaptation while accommodating the first two levels would also engage the adaptive capabilities of the brain. This means that the BCI would be able to accommodate for changes in the BCI's input features that change as a result of it output operations (since execution of the user's intent would have its effect on signal features through feedback).

2.3.5 Review Current Brain Computer Interfaces

There are several ways in which BCI can be classified. The most basic classification which has already been discussed is based on whether the system is invasive or non-invasive. While invasive systems are based on recording of brain activity using direct-cortical recordings, non-invasive systems are based on using brain activity recorded at

the scalp of the user. Leuthardt et al (Leuthardt et al. 2004) recently reported a partially invasive systems which makes use of electro-corticograms which have been recorded from electrodes placed beneath the dura-mater. While non-invasive systems have less risk of infection associated with them they suffer from poorer spatial resolution and signal quality (compared to invasive and partially invasive systems). Moreover the signals can be easily corrupted by signals of non-cortical origin.

BCIs can also be classified based on whether their input is spontaneous or evoked. Since in evoked response systems the EEG features are time locked to an external cue most evoked response systems depend on a synchronous protocol. Asynchronous protocols are developed for BCIs using spontaneous activity. Asynchronous BCIs are flexible, easier to use and have shorter response time.

The BCIs being designed and developed are a combination of invasive/non-invasive systems with spontaneous/evoked inputs. In view of the fact that there are many different types of BCIs it is necessary to match the capability of the user with the BCIs input features. The next section contains a brief review of some of the BCI being developed in different laboratories around the world.

2.3.5.1 A Brain Computer Interface Based on Cortical neuronal action potentials

Implanted micro-electrodes have been used since the 1960s to record the action potentials of single neurons in the cerebral cortex of awake animals during movement. (Hern, Phillips et al. 1962; Kernell and Chien-Ping 1967) . Most of these studies however were focused on relationship between neuronal activity and sensorimotor performance. After the work during the mid and late 1970s (Fetz and Finocchio 1975, Burchiel et al. 1980 and Rockstroh et al. 1984) came the realization that with operant conditioning methods humans could learn to control the discharge of neurons in the motor cortex. With this came the realization that it could be possible to use these features of neural activation for communication and to control neuroprosthesis.

The intra-cortical electrode described by Kennedy in 1989 helped over come the limitation of the conventional implanted electrodes, whose recording deteriorates over time. This new electrode consisted of a hollow glass cone containing the recording wires. The glass cone also contained neurotrophic factors which induced the growth of neural processes into the cone. This allowed better adhesion, better recording of the action potentials and it also ensured stable neuronal recordings over long periods of time. Donoghue (Donoghue 2002) reported on the developement of a silicon based intra-cortical electrode array and a polyamide based bioactive electrode array for recording neural signals from human motor cortex.

The experiments by Kennedy et al (2000 & 2004) have shown that it is possible to obtain stable signals from implanted electrodes for periods up to 16 months (or more data not available). They also demonstrated that it is possible for subjects to develop control over these signals so as to drive a cursor across a computer screen. The rate of movement or speed of the cursor is controlled by the firing rate.

In these experiments spikes in the recorded signal are converted into a TTL pulse train by a first computer. Three such pulse outputs were then routed as the mouse input to second computer – one signal controlling the X movement, second controlling the Y movement of the and the third signal is used to trigger the mouse click. They simplified the operation of the system to respond only to increase in firing rate – so that speed of the cursor now depended on the rate at which the firing rate increased and the cursor was reset at the upper left hand corner of the screen immediately after a 'mouse click'. While the movement of the cursor on the screen provided the visual feedback, a distinct tone produced for each pulse served as the auditory feedback.

To train the 'locked in' patient to use the system they developed three models. The first two models use Talk assist (software that uses icons for common phrases) and the third one uses a visual keyboard.

In the first training pattern the mouse is moved left-right using one control signal and up-down using a second control signal. The selection of a particular icon (usually the nearest) is triggered if the mouse pointer hovers over it for over a specified time interval. In the second training method the user is encouraged to increase the accuracy and speed of the cursor movement. In the third training pattern a visual key board is displayed to the user and the patient is encouraged to spell words (usually his own name).

The BCI described by Levine et al in 2000 (Simon P. Levine, Jane E. Huggins et al. 2000) used cross-correlation of the trigger averaged EEG segments with continuous EEG segments to detect the ERPs related to specific movement. The investigators chose cross-correlation because of its previous success in detecting sensory evoked potentials and because it is simple, well understood, and can be implemented with real time computation.

During the study researchers used seventeen subjects from two epilepsy surgery programs. The subjects had 16-126 sub-dural electrode arrays implanted as a part of their surgical evaluation. The cortical locations of these electrodes were solely determined by the clinical conditions. The electrodes that were implanted were of 4mm diameter and of platinum or stainless steel arranged either in stripes or grids with a centre to centre distance of 1cm.

Signals were recorded from the subjects while they performed one to four repetitions of upto six actions. Each repetition had 50 trials separated by three seconds. The actions performed include movement of face, tongue, hand, foot and also verbalization of sound or word. An appropriate transducer helped record the time of occurrence of each trial in the trigger channel. The EEG and the trigger signal were sampled at 200Hz using Cadwell Spectrum 32 or a Nicolet BMSI 5000. The signals were then digitally bandpassed from 0.05Hz to 100Hz.

The first half of each EEG segment was then processed to produce a trigger averaged EEG segment for a period of 6 seconds centred on the trigger point. This trigger averaged EEG segment was used as a template on the second half of each recording to evaluate the accuracy of the ERP detection method which was based on the cross-correlation technique.

Cross-correlation is the moving summation of the point by point multiplication of template averages and the continuous EEG signal (See Figure 2.15). The set of points at which the cross-correlation values exceeds an experimentally determined threshold is defined as detection points. This is compared with the triggers in the trigger channel to determine hits or false positive. To emphasize the importance of detecting the action before the movement trigger a criterion is set which registers any detection between one second before and a quarter second after the trigger as a hit.

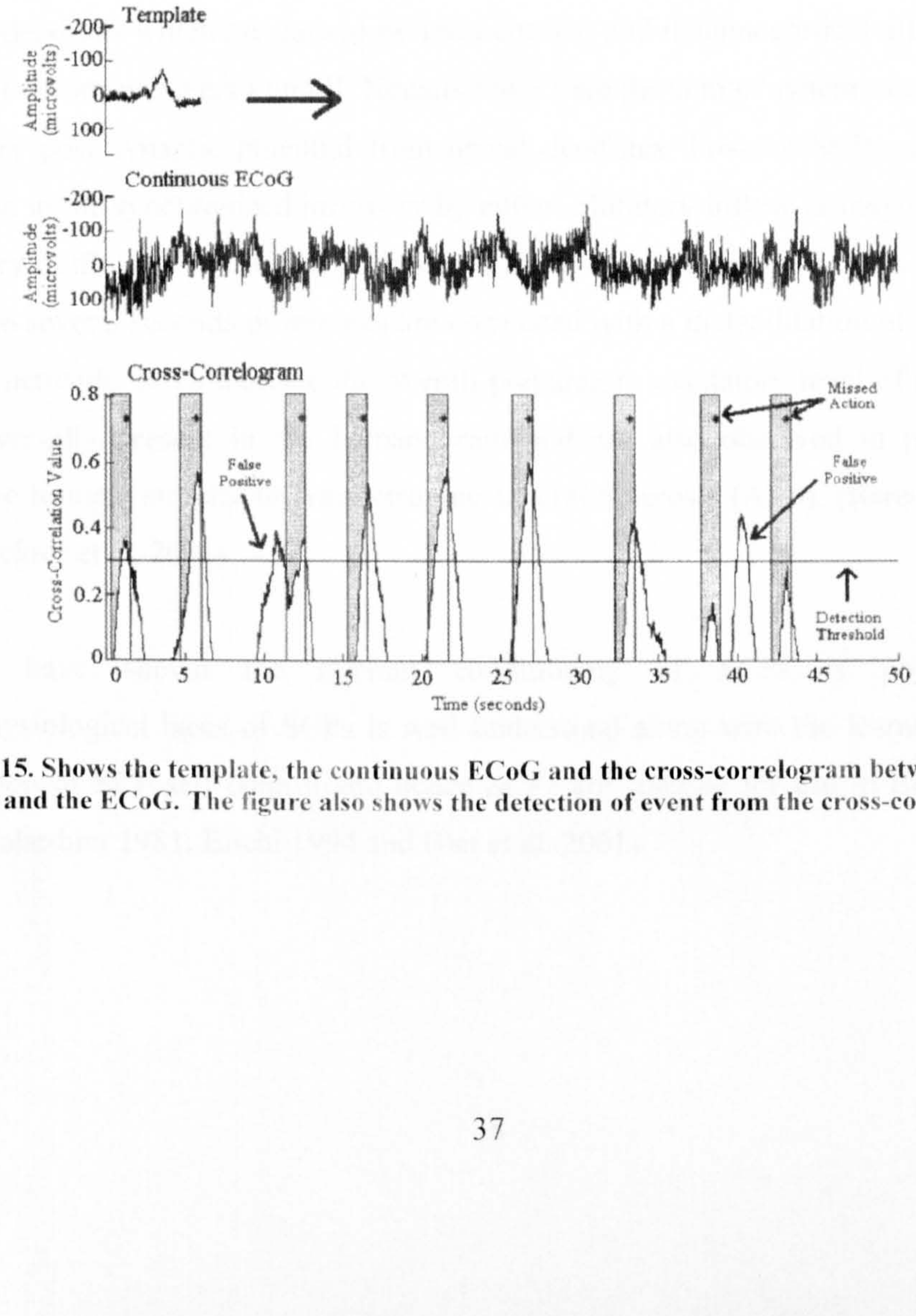


Figure 2.15. Shows the template, the continuous ECoG and the cross-correlogram between the template and the ECoG. The figure also shows the detection of event from the cross-correlogram.

The hit percentage and the false hit percentage are the two statistics used to describe the effectiveness of the detection methods. Different detection methods were compared by comparing the differences between hit percentage and the false hit percentage.

Differences greater than 90% were found for 5 of the 17 subjects, greater than 75% for 10 of the 17 subjects and greater than 50% for 15 of the 17 subjects.

Using a different approach Donoghue (Donoghue et al. 2006) reported on a BCI system which achieved success rates between 73-95% in the control of a computer by a tetraplegic human using an implanted 96 microelectrode array to predict imagined limb movement.

2.3.5.2 Slow Cortical Potentials and Brain Computer Interfaces

Slow Cortical Potentials (SCPs) are shifts in the depolarization levels of the upper cortical dendrites which are caused by intra-cortical and thalamocortical afferent inflow into the neocortical layers I and II. Negative SCPs are the sum of synchronized ultraslow excitatory post synaptic potential from apical dendrites. Positive SCPs result from a reduction in the synchronized inflow or by either inhibitory inflow or may be caused by excitatory outflow from the cell bodies in layers IV and V. Positive SCPs lasting from 300ms to several seconds or minutes are correlated with a disfacilitation of the involved cortical network. SCPs indicate the overall preparatory excitatory level of a cortex and are universally present in the human brain and are also observed in patients with extensive lesions, atrophy or Amytotrophic Lateral Sclerosis (ALS). (Bares and Rektor 2001; Rektor et al. 2001)

Studies have shown the operant conditioning of SCPs is possible. The neurophysiological basis of SCPs is well understood along with the learning rules for acquisition of SCP self control and hence SCPs are suitable for use in BCIs. (Perdok 1980; Zuberbier 1981; Eiichi 1994 and Bler et al. 2001).

In the BCI discussed by Birbaumer et al in 2000 Ag/AgCl electrodes were attached to the scalp using collodium to give low impedances (below 5KΩ) for recording EEG. An eight channel EEG data acquisition system was used. The signals were sampled at a rate of 256Hz and processed online for removing eye movement artefacts.

Visual feedback was provided through an EEG display which was updated every 63ms after an initial 2 second baseline period. The EEG was averaged over a window of 500ms moving in steps of 63ms. Audio feedback was provided by a high pitched tone during the baseline period and the feedback period is indicated by a low pitched tone.

A target box was displayed either above or below the EEG trace. When displayed above, a negative SCP had to be produced and when displayed below a positive SCP had to be produced.

If the subject achieved the required amplitude change reinforcement was provided by a smiling face being shown to the subject. The response criterion was gradually increased from 5 to 8 μV. The subject was trained with 6-12 sessions a day, each session lasting 5-10 minutes and with 70-100 trials per session. When the subject achieved 75% accuracy the subject was moved into a language support platform.

In these trials the alphabet set was divided into two groups, each displayed at the bottom of the screen. The patients selected a group by generating a SCP. The selected group is then re-divided into two groups. This went on till the subject had to make a selection of a single letter. A return function allowed deleting of characters.

In these experiments the average number of trials per selection averaged between 8 and 80 the median lying at 28. In terms of speed this meant that the subject took 2 minutes to select a single letter.

These speeds were clearly not sufficient to allow participation in normal human communication. It has been suggested the communication speed can be improved by presenting entire words, word prediction and pictograms.

2.3.5.3 P300 And Brain Computer Interfaces

The P300 is a commonly used Event Related Potential (ERP) used in psychological cognitive experiments. It is an event related potential that is elicited in response to external or internal event. Event related potentials have both endogenous and exogenous components. While the exogenous components are obligatory responses to the presentation of a stimulus, endogenous components are results of the processing activities. An important feature of the P300 is its generation when an infrequent stimulus is interspersed with frequent stimulation. This oddball paradigm results in a positive peak and is observed in the EEG recorded over the parietal cortex at a latency of 300 ms. (Friedman 1984; Farwell and Donchin 1988).

The P300 wave which is most commonly elicited in this oddball paradigm is observed if the subject is actively engaged in the task of detecting the targets. The parameters of the observed P300 depend on a number of variables. The subjects mental state, the task that has to be accomplished, the significance of the stimulus and the degree of attention all seem to affect the P300 wave observed .The amplitude of the P300 varies with the improbability of the targets – the more improbable the higher the amplitude. The typical latency of the P300 in a young adult is 300ms however the latency can vary depending on the difficulty of discriminating the target stimuli from the standard stimuli. (Farwell and Donchin 1988).

Though the intracerebral origin of the P300 wave and its significance in cognition is not known it has been suggested that P300 may have multiple sources with generators in the hippocampus and associational areas of the neocortex. It has also been suggested that the P300 may represent the transfer of information to consciousness which may involve different regions of the brain and that its latency provides an indirect indication of the

duration of the process involved in stimulus discrimination and its amplitude can give an indication as to the intensity of the energetic arousal involved. (Friedman 1984; Rektor et al. 2001).

The P300 obtained by the oddball paradigm is made use of in the BCI described by Farwell in 1998 and Donchin in 2000. (Farwell and Donchin 1988; Donchin et al. 2000). In this paradigm the subject was presented with a sequence of events that had to be classified into two categories. Generally one of the events in one of the categories was rarely presented. Under these situations events in the rare category elicit an ERP characterized by a P300 wave. Lesser the probability of the event larger is the amplitude of P300 generated.

In the approach described by Donchin (Donchin et al. 2000),the BCI system was designed to use P300 evoked in a subject to identify and select one character in a 6x6 matrix of characters that a subject wanted to select. By successively and randomly intensifying either a row or a column of the 6x6 matrix an oddball paradigm was setup. In each trial the subject is asked to focus of the letter that has to be selected. The two categories are – the 16.7% of the intensification that include the desired cell and the remaining intensification of the rows and columns that do not include the desired cell. The communication task is thus reduced to detecting the P300 wave generated when the desired cell is intensified.

In this experiment the EEG was recorded by means of an electrode cap using tin electrodes. Signals from the Fz, Cz, Pz, O1, O2 and the right mastoid sites were recorded referenced to the left mastoid. The EEG was amplified, band-limited to 0.01 to 100Hz and then digitized at 200Hz. Vertical and horizontal EOG artifacts were removed using the eye movement correction method.

The subjects (6 able bodied, 3 with complete paraplegia and one with incomplete paraplegia) viewed a matrix of characters (see figure 2.16). The characters were

presented as white on a black background. Each of the 6 rows and 6 columns were then intensified in a random sequence. Each intensification lasted for 100ms with an inter-stimulus interval of 125ms. The subject who sat 50cm from the display was instructed to count the number of times the row or column containing the desired letter was intensified.

Figure 2.16. Shows the matrix of character viewed by the subjects participating in the experiments. From (Donchin et al. 2000)

The BCI was implemented using two computers – one for data acquisition and the second for controlling the display. Single trial EEG epochs were then derived for each intensification in a trial – starting 300ms prior to each intensification and lasting 1100ms. In this way 12 epochs were obtained for each trial. The data submitted to the detection algorithm was obtained by averaging each combination of row and column – this 36 such epochs were generated for each trial.

Since the ERP was substantially smaller than the ongoing EEG activity there was a need for a method to extract the ERP signal from the EEG noise. While taking the grand average of the EEG over 40 trials may be a solution the investigators have pointed out that it could not be relied upon as a practical solution because it severely limits the communication speed (1 minute per character). Hence the authors tried to develop techniques that use of fewer trials. A method suggested was bootstrap analysis.

2.3.5.4 Brain Computer Interfaces Using Steady State Visual Evoked Potential

Middendorf et al (2000) reported of a BCI that used Steady State Visual Evoked Response (SSVER) as an effective communication medium for BCIs. (Middendorf et al. 2000).

SSVER was elicited using a visual stimulus that was modulated at a fixed frequency. The SSVER was characterized as an increase in EEG evoked activity at the stimulus frequency. Typically the stimulus was generated by using white fluorescent tubes that were luminance modulated at 13.5Hz and mounted behind a translucent diffusing panel.

The researchers took two approaches

- Self Regulation of SSVER
- Naturally Occurring SSVER

While in the first approach the subjects were trained to control the strength of their SSVER the second required no training since the system took advantage of the naturally occurring responses where attention to a stimulus augmented the evoked response.

Self Regulation Of SSVER

EEG was recorded over the whole scalp during these studies and this showed that there was inter-hemispheric shifts of the SSVER activity relating to enhance and suppress conditions .The subjects (3 able bodied subjects) in these studies were not instructed on how to accomplish the self-regulation (but they were told to keep their eyes open) and they were monitored by EOG and video cameras. These studies revealed a wide variety of eye movement and cognitive based strategies.

A differential signal has obtained from the occipital sites O1 and O2. This differential signal was then amplified, filtered and processed by a lock in the amplifier that provided a measure of the SSVER amplitude. This information was then sampled by a computer for control and feedback. The control logic then transforms the signal into smooth and stable control. The control logic was based threshold and duration requirements, each

being modified to suit the subject and the intended application. Two threshold levels were applied. Raising the SSVER strength to above the upper threshold results in one control action and lower it to below the lower threshold resulted in a second control action.

Mechanism of Control

The control signal that was derived as the differential signal between O1 and O2 and could be modified by the subject by changing the:

- amplitude at O1 relative to O2
- relative timing of the SSVER activity
- or both

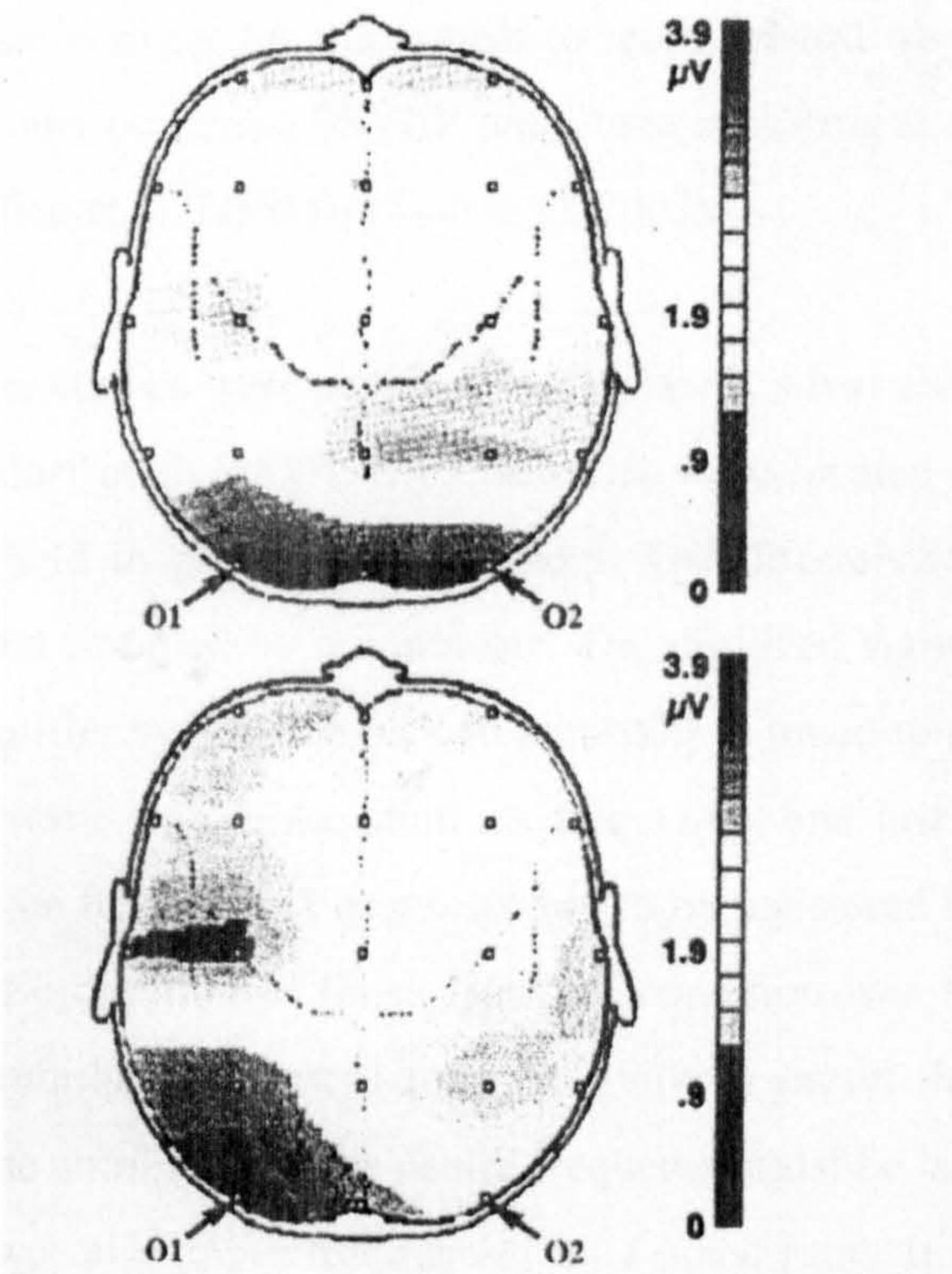


Figure 2.17. Shows the topographic map of the 13.5 activity during task related enhancement and suppression of SSVER. The top figure shows the activity during suppression and the bottom figure the activity during enhancement. (Middendorf et al. 2000).

In a switch selection experiment the subjects were instructed to select a switch. To begin cycling through the switches the subjects had to increase the SSVER amplitude above the upper threshold and to make a selection they had to reduce the SSVER amplitude below the lower threshold. During the experiment the subject was seated in front of a screen (covering 83°) with a light source behind it. The intensity of the stimulus was highest in the centre and reduced towards the edges. During these studies participants used subtle eye movements to shift their gaze away from the centre of the screen to enhance their SSVER amplitude.

Naturally Occurring SSVER

Unlike the previous system this form of BCI is passive in the sense that the subjects do not have to participate actively for the system to 'comprehend' their 'wishes' since the system uses the naturally occurring SSVER amplitude occurring at different frequencies. (Middendorf, McMillan et al. 2000 and Gao et al. 2003)

The EEG during these studies were acquired using plastic, silver chloride coated, surface electrodes. (Middendorf et al. 2000). The electrodes were located over O1, O2 and Oz (ground) and were held in place by a headband. The differential (O1-O2) EEG was filtered, amplified and sampled by a computer. The digitized signal was then analyzed by three lock-in amplifier systems (a lock in amplifier is tuned to a specific frequency) implemented in software- one at the stimulus frequency, one just above and the other just below the stimulus frequency. For a selection to be registered two criteria had to be satisfied for a specific duration of time. The first condition was that amplitude of the centre frequency (stimulus frequency) must be above a preset threshold. The second condition was that the amplitude of the centre frequency must be larger than the average amplitude of the lower and upper frequencies by a fixed ratio. If these two conditions were satisfied for a period of 0.3s then a selection was registered.

During the studies two virtual buttons (2.9x3.8 cm) were displayed on the left and right side of a monitor (separated by 10.3 cm) and whose intensities were modulated at 23.42 and 17.56Hz. The screen was at a distance of 71cm hence the visual angles were 3 degree vertically and 2.3degrees horizontally. The task during the experiment was to select the virtual button highlighted with yellow colour. Eight subjects participated in these experiments and averaged 92% correct selection.

2.3.5.5 Brain Computer Interfaces Using Motor Related Potentials

Different studies have confirmed that both movement and imagination of movement produces significant changes in the EEG patterns and these changes can be used as a control signal in a BCI. (Pfurtscheller and Neuper 1997; Guger et al. 2001; Cincotti et al. 2003; Deng et al. 2005; Pfurtscheller et al. 2006).

Two other types of EEG signals that can be used for controlling a BCI are the mu- and beta-rhythms. Beta-rhythm is one of the fastest normal EEG rhythms with a frequency of 13-30Hz. It can occur naturally when awake or during light sleep. Per definition, alpha rhythms occur in the region of the visual cortex, whereas the mu rhythm originates above the motor cortex. (Wolpaw 2000).

The mu-rhythm consists of a variety of different rhythms with frequencies between 8-12Hz. They can be distinguished by location and by their relationship to sensory input or motor activity. The faster beta-rhythms are either associated with the mu-rhythm as "harmonics" or can be separated from them as completely independent EEG features. (Wolpaw et al. 2002).

Theoretically, mu- and beta-rhythms are ideal for controlling a neuroprosthesis as the signals are - due to their origin in the motor cortex - as close as possible to the structures the brain normally uses for movement decisions. Mu-rhythm varies with activity, especially on the side of the brain which lies opposite to the limb movement. For

example Conway et al 1995 provided the first direct evidence that β rhythmic cortical activity during tonic contraction is coherent with the EMG of the contracting muscles, thus demonstrating the β rhythm relationship to motor behavior. (Conway et al. 1995). Similarly mu rhythms have been associated with active contractions. (Conway, Reid et al. 2004). Furthermore, these variations also occur when movement is only imagined, making mu-based BCIs promising for patients who lost their ability to move but have sustained no cortical impairment (eg spinal cord injury). (Pfurtscheller 2006).

Mu- and beta-rhythms are suitable for BCIs, because people can learn to control their amplitude by movement or thinking of movement, which, as with SCP-based BCIs, can be used to drive a cursor up and down. Algorithms translate the differences in rhythm amplitude into cursor movement. As with SCPs and unlike p300-BCIs, this needs training, but the effort seems to be smaller than with SCPs due to the relationship to tasks that are easier to visualise. (Wolpaw et al. 2000)

Pineda et al in 2000 (Pineda et al. 2000) conducted a study in which subjects participated in four conditions:-

- Rest
- Self-generated movement
- Observation
- Imagination

EEG signals were recorded from 6 sites on an electrode cap placed over frontal (F3,F4) central (C3,C4), and occipital (O1,O2) areas according to the standard 10-20 International electrode placement system. After being amplifier by Grass Model 7D polygraph using 7P5B preamplifiers with a pass band of 1-35 Hz the signals were sampled at 256Hz for two minutes during each of the conditions.

The power spectrum was calculated for each second of the EEG and the mean power spectrum was calculated within the mu range. This data was then subjected to repeated

analysis of variance with factors of the different conditions and electrode sites. This showed that there was statistically significant difference in the power level in the 8-13 Hz frequency range during the various conditions. Pairwise comparisons showed that the most significant difference was during the condition of self-generated movement (see figure 2.18). The results also showed that the mu power also decreased at the frontal sites but remained unaffected at the central and occipital sites during the condition of imagined movements.

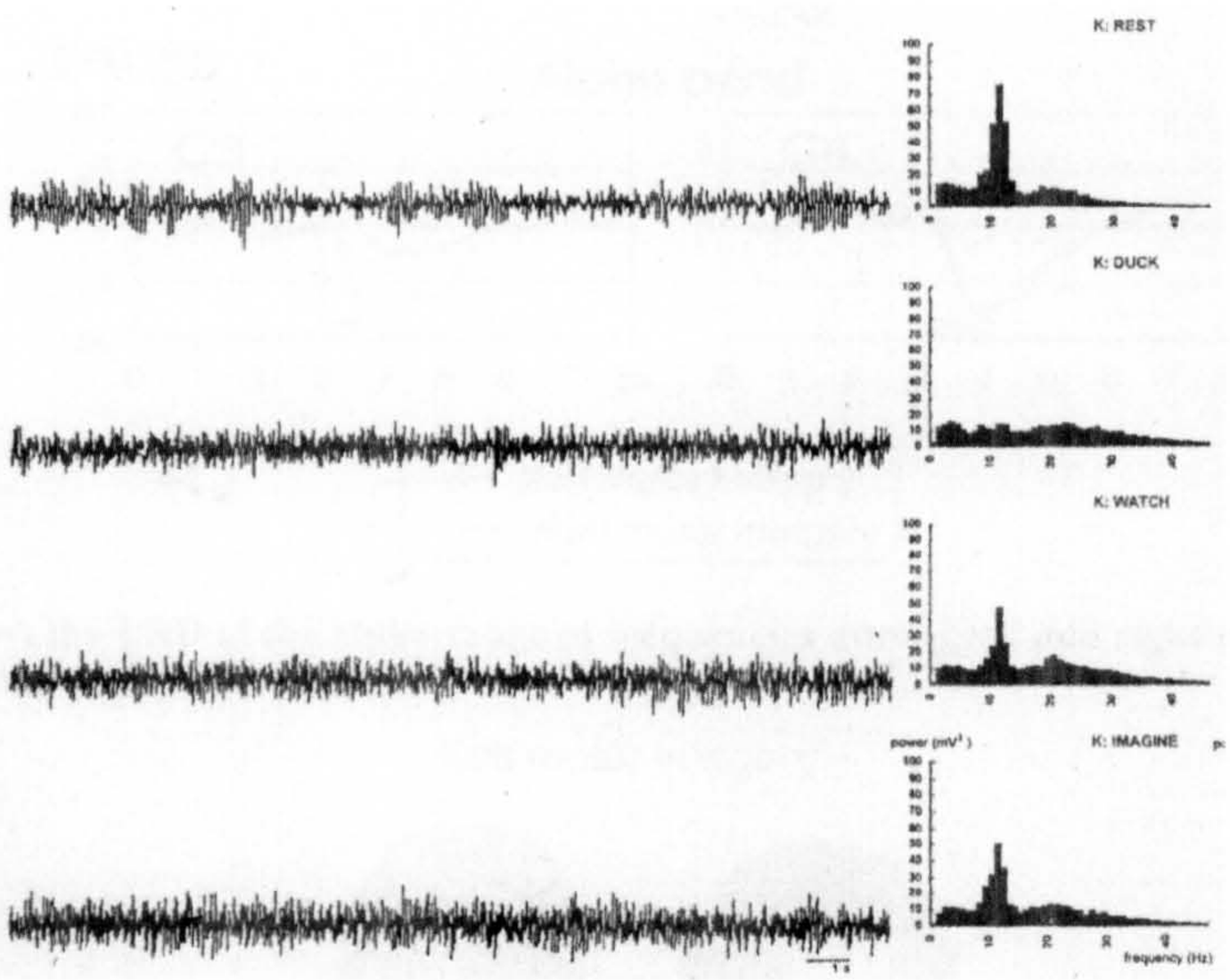


Figure 2.18 Shows the EEG (left panel), the integrated power for the entire time duration recorded when the subject participated in 4 different experiements: rest, duck movements of the middle and thumb finger, imagination and observation top to bottom. [Referred from Pineda et al. 2000]

The Graz BCI described by Pfurtscheller et al (2000) used oscillatory EEG signals recorded during specific mental activity as the control signal. Initially signals during wilful movement of the left or right lower or upper limb were used for the classification of the signals. The classification accuracy was improved by optimizing the input features such as electrode position, and frequency bands to suit each subject. Later it was shown that not only movement but also imagination of the movement caused event related de-synchronization on the contralateral hemisphere and event related synchronization on the ipsilateral hemisphere of the sensorimotor areas.

The investigators looked at the following pre-processing methods to obtain a control signal:

- Calculation of band power in pre-defined subject specific bands in intervals of 250ms or 500ms.
- Adaptive autoregressive parameters estimated for each iteration with the recursive least square algorithm.
- Calculation of common spatial filters.

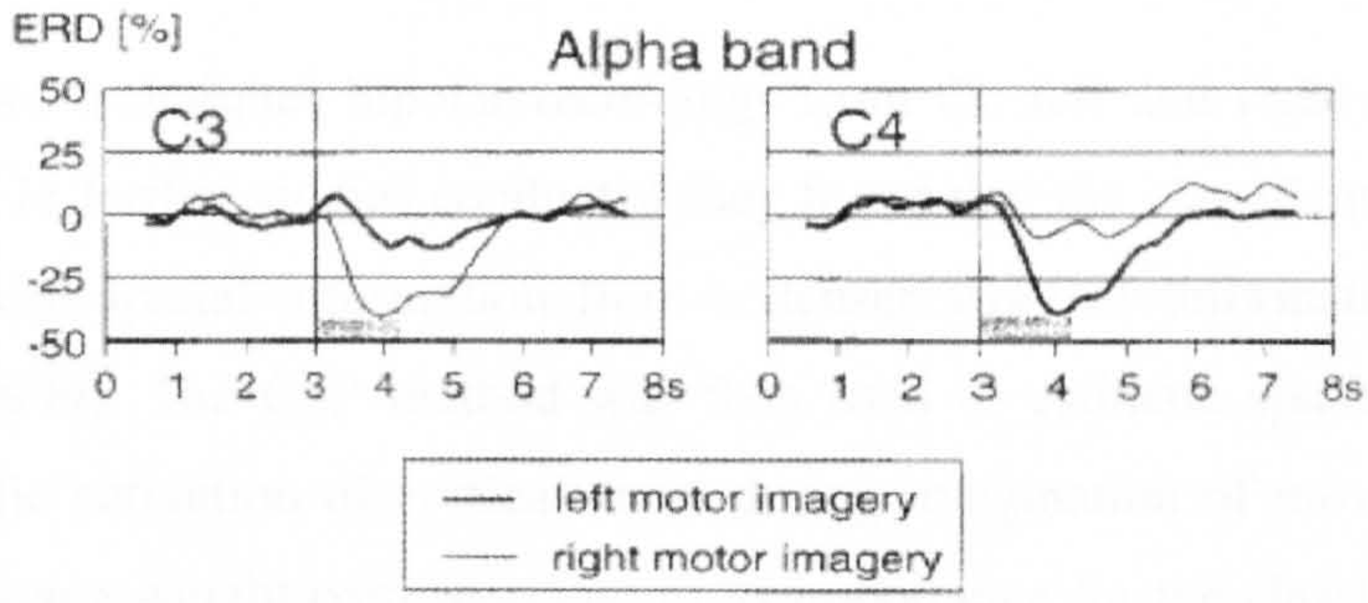


Figure 2.19. Shows the ERD of the alpha range of frequencies during left and right motor imager. Modified from (Pfurtscheller G 2000).

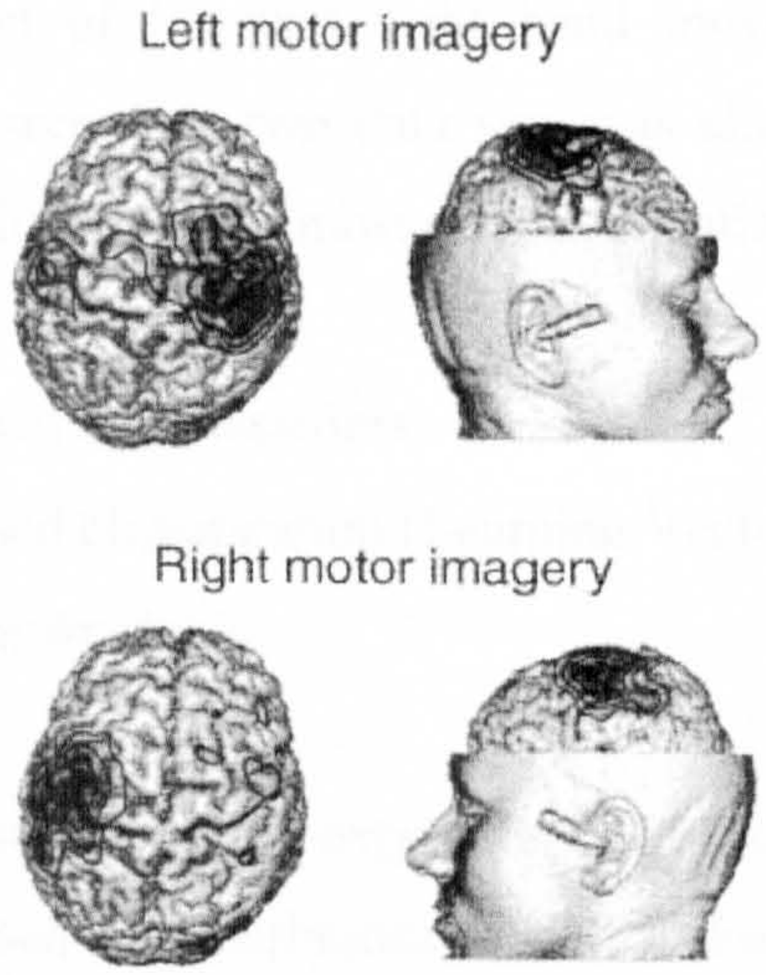


Figure 2.20. Shows the ERD maps during left and right motor imagery. Modified from (Pfurtscheller G 2000).

For the first method the reactive frequency band for each subject was first selected by applying a distinction sensitive learning vector quantization on the spectral components of the EEG signal. This gave the weighted values of each frequency according to their

relevance for the classification task. The band power was calculated by digitally bandpassing the signal, squaring each sample and then averaging over several samples.

In the adaptive autoregressive technique parameters were estimated from the whole EEG signal (limited only by the cut-off frequency set by the sampling frequency). This technique had the advantage that it made no assumptions of the information in the different frequency bands.

For the above two techniques bipolar recordings from the left and right sensorimotor cortex was used. In further studies conducted they found that the classification accuracy was improved with spatial information from a denser array of information. (Muller-Gerking et al. 1999). The CSP method was then used to estimate spatial filters that reflect the specific activation of cortical areas during imagination of movement. Each electrode was given a weight corresponding to its importance for the classification. The EEG data was then split into spatial patterns that were extracted from two data sets – EEG data during imagination of left and right hand movement. The pattern that maximized the difference between the two data sets was chosen. Thus during online operation the EEG data was filtered by the most effective spatial pattern.

The researchers also investigated two classifiers:

- Neural network based classification (Learning Vector Quantization or LVQ)
- Linear Discriminant Analysis.

While LQV was mainly applied to online experiments with delayed feedback a linear Discriminant classifier was used for continuous feedback. For the LQV technique the input features were extracted from a 1 second segment of the EEG recorded during motor imagery. The 1 second was further split into 4 250ms segments. The band power during each of these quarters were then estimated, this was then used as the input to the LQV which derived a classification and a measure of the certainty of the classification which was then feedback to the subject.

The linear discriminant analysis was used along with AAR and CSPs for online analysis. The feedback was provided by a continuously moving feedback bar.

Each trial began with fixation cross appearing at the centre of the screen. A warning tone after 2 seconds informed the subject to get ready for the next stimulus which was an arrow pointing with right or left which was presented for 1.25 seconds and indicated the target side of the trial. The subject imagines movement of the appropriate limb in response to seeing the arrow. Each experimental session had 4 runs of 40 trials each.

In delayed feedback experiments the classification of the result was provided at the end of the trial i.e., after 6 seconds after the trial began. In continuous feedback a feedback bar moves right or left (for a period of 4 seconds) depending on whether the subject was imagining the movement of his right or left limb.

Once feedback was provided the EEG patterns normally change. Hence the classifier was updated after a few sessions with feedback.

With long term testing using the techniques of LQV and bandpower the minimum online classification errors obtained were between 10%-17% with four different subjects. The online classification errors were between 1.5%-12.5% when CSP and LDA were used and the errors were between 5% and 9% when AAR and LDA was used.

It was immediately apparent that instantaneous feedback improved the left-right differentiation of EEG pattern.

The investigators were also able to implement remote control via the internet. This means that the patients BCI system could be remotely controlled and the classifier updated if necessary. Currently the Graz system consists of a two channel amplifier and

a notebook computer, the system being installed in the subjects home and being controlled from the lab situated 50Km away. (Pfurtscheller et al. 2003)

The BCI research at the Wadsworth centre for Alloway New York has focused its research in the past on using 8-12 Hz (Mu) and 13-38 Hz (beta) rhythms in the EEG recorded from the scalp for communication and control. (Wolpaw et al. 2000).

As discussed earlier these rhythms are evident in the sensorimotor cortex and associated areas. They were chosen by these researchers because they are directly related to movement and because previous research has shown that it possible for people to control the amplitude of these rhythms.

During the course of the project subjects with and without motor disabilities were used. The subjects learnt to control the amplitude of their Mu or Beta rhythms over a series of sessions. New users were advised that various kinds of motor imagery are usually helpful to acquire control. With more and more training the users often reported that they used the motor imagery less frequently indicative of the brain control being achieved in the BCI.

A linear equation was used translate the amplitude of the rhythms into cursor movement 10 times per second. There were three different control modes (see figure 2.21). The most basic was the one dimensional mode in which the target was either at top or bottom (or left or right) edge of the screen and the cursor was in between. The cursor was then moved vertically (or horizontally) by the subject by exercising control over his EEG. The second was the two-dimensional mode. In this mode the target was displayed at one of the four corners of the screen and the subject has to move the cursor to the appropriate corner. This was accomplished by moving the cursor both vertically and horizontally. The third mode was the graded one dimensional mode in which the target was one of a series of boxes. The cursor was initially placed at the centre of the screen and the subject

had to move the cursor to the appropriate box and had to maintain the cursor in the box for a predefined time to select it.

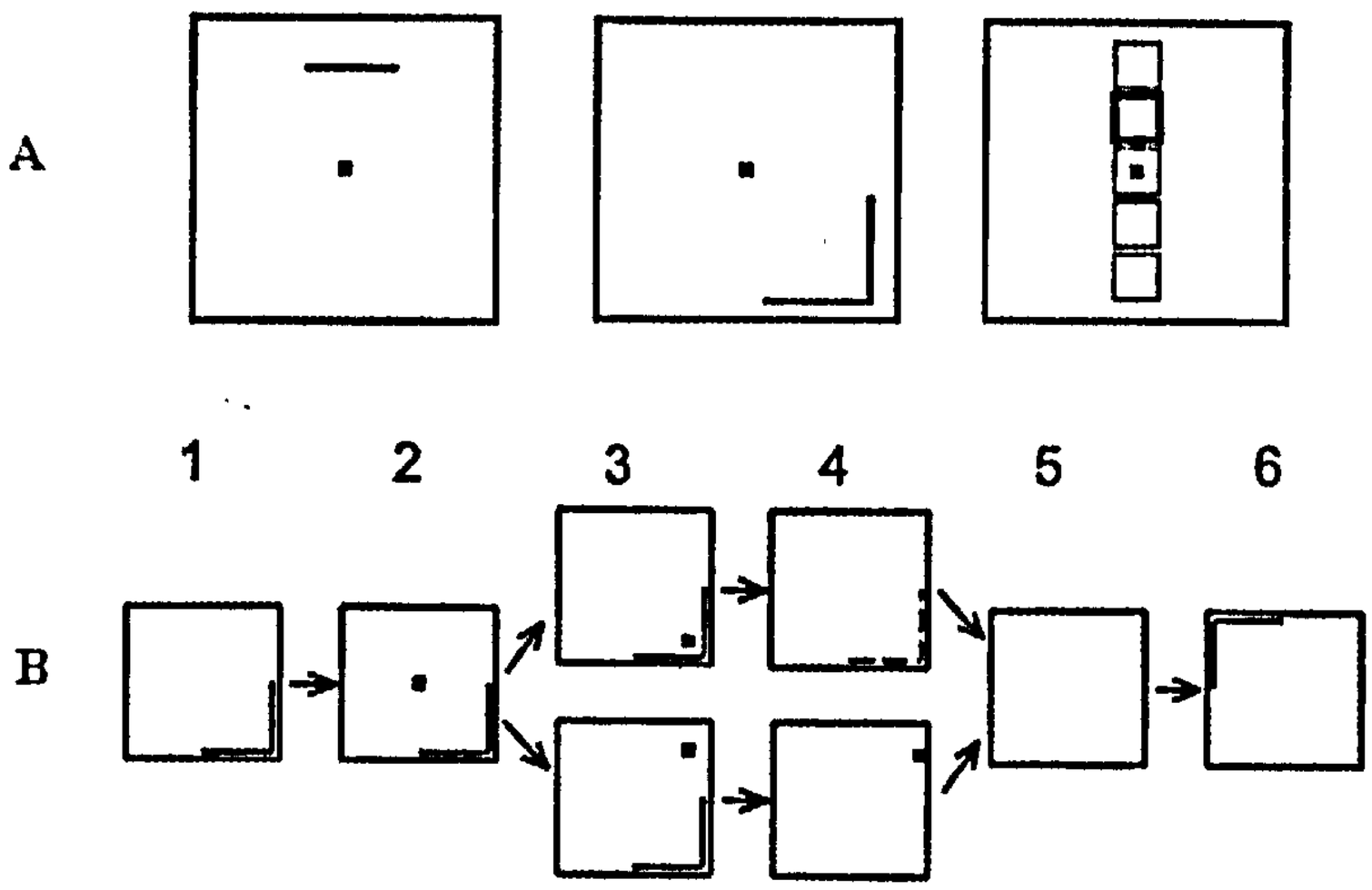


Figure 2.21. Shows the control modes used during the experiments at Wadsworth. (A)The figures show the different control modes. (B) Shows the time line of the two dimensional control mode.

Figure 2.21 B shows the sequence of events in the two dimensional control mode:

1. At t = 0s target appears at the edge or corner.
2. At t = 1s cursor appears in the centre. The time lag allows the subject to note the position of the target.
3. Cursor is moved by the subject by controlling the amplitude of the EEG rhythms
4. If the cursor reaches the target – the cursor disappears and the target flashes for 1 second. If cursor reaches elsewhere the target disappears but the cursor remains.
5. The screen is blanked for 1 second.
6. The next target appears.

There has been significant work in the past 6-10 years exploring the use of EEG changes during movement or imagination of movement as control signals for BCI. Table 2.1 summarizes and presents the classification rates obtained by a few of BCI reported.

Table 2.1 Presents the BCI based on movement (imagination of movement) related potentials developed by different groups , the tasks and the classification results of the BCIs.

Group	Tasks	Feature Extraction and Classifiier	Results
Haselsteiner 2000 (Haselsteiner and Pfurtscheller 2000)	Imagined Left and right hand movement	Linear Discriminant Analysis, Neural Networks	85%
Ramoser 2000 (Ramoser, Muller-Gerking et al. 2000)	Imagined Left and right hand movement	Spatial Filters	90%
Guger 2001 (Guger, Schlogl et al. 2001)	Imagined Left and right hand movement	Adaptive Auto-Regression, Linear Discriminant Analysis	95%
Pfurtscheller 2003 (Pfurtscheller, Neuper et al. 2003)	Left and right hand motor imagery	Oscillatory EEG Components, Hidden Markov Models	90-100%
Sajda 2003 (Sajda, Gerson et al. 2003)	Left and right button press	Neural Network	96%
Sajda 2003 (Sajda, Gerson et al. 2003)	Imagined left and right button press	Neural Network	76%
Mason 2003 (Mason and Birch 2003)	Thumb movement	Low Frequency Asychronous Detector, Learning Vector Quantization	94%
Cincotti 2003 (Cincotti, Mattia et al. 2003)	Imagination of right and left middle finger	Linear and Quadratic Classifiers	75-95%
Leuthhardt 2004 (Leuthardt, Schalk et al. 2004)	Action and imagination of left and right hand, tongue movement and vocalisation.	Localised cortical rhythms.	74-100%
Wang 2004 (Wang et al 2004)	Imagination of right and left middle finger	Principal Component Analysis, Linear Discriminant Analysis, Linear Classifiers	77%
Pfurtscheller 2006 (Pfurtscheller, Brunner et al. 2006)	Left and right hand motor imagery	Linear Discriminant Analysis, Neural Networks	85%

In 2006 Santhanam et al (Santhanam et al. 2006) reported on the development of an interface between the brain of a monkey and a computer. Table 2.2 which summarizes the results of this study shows that they were able to predict the direction of movement of the monkey's arm towards upto 16 different targets in instructed delay tasks .

Table 2.2 Shows the results of the BCI developed by (Santhanam et al. 2006) using invasive electrodes

Monkey	Number of Target	Accuracy	Trials Per Second	Bits Per Second (ITR)
H	2	94.3	3.5	2.4
H	4	94.5	2.8	4.7
H	8	68.9	3.5	6.5
H	16	51.1	2.9	6.4
G	2	84.2	3.6	1.3
G	4	93	2.5	3.8
G	8	76.8	2.5	5.3
G	16	26.4	2.2	3.1

While the investigators were exploring the various designs and implementation and practical applications that are benefited by EEG based communication and control there is always a need to improve the performance of the system. The performance of the system can be enhanced by improving the feature extraction and translation algorithms that are responsible for transforming the EEG control into device control commands. The next section briefly describes the analytical techniques used in the current study for identifying and extracting features that can be used for classification.

2.4 Analytical Techniques

The main aim of the current study was to study and extract features from the EEG for the optimal classification. The initial analysis of the EEG signals recorded during the study involved studying the group averages in the time and frequency domain and then using statistical techniques to identify features which were consistent and robust and

could be used for the classification. This was then followed by the section which described the techniques used for classification of the EEG on a single trial basis. A review of the literature on BCI systems (see Table 2.1) shows that both linear and non-linear techniques have been used for feature extraction and classification with no significant differences in performance. In the present study only linear techniques were used for feature extraction and classification stages because the algorithms are simple to implement.

2.4.1 Event Related Potentials

Much of the analysis performed was based on quantifying evoked changes in EEG in response to a stimulus or event. Event-related potentials (ERP) are voltage changes recorded from the human scalp that are time-locked to a sensory, motor, or cognitive process and therefore provide an electrophysiological window onto brain function during task perception and execution.

The electrical response of the brain that accompanies motor planning and action is referred to as a Movement Related Cortical Potential (MRCP) .Such potentials are difficult to identify because of their relatively low amplitude in comparison with the background EEG activity. With the use computer averaging techniques the signal to noise ratio can be increased so that the pre and post movement potential is more clearly defined. The basic assumption is that while the event related potential is time locked to the stimulus the ongoing EEG is just additive noise. Before averaging it is necessary to reject trials which have been corrupted by obvious artifacts due to blinking, swallowing, coughing, etc.

MRCP can be computed for both monopolar EEG signals and for signals derived from two or more monopolar signals. The morphology and topography of MRCPs are of interest and most studies of these potentials use simple time domain analysis.

2.4.2 Event Related Synchronization/Desynchronization

While the average ERP is a time locked response of the neural structures to an event the Event Related Synchronizaton/Desynchronization (ERSD) is a frequency domain measure that can contain both phase locked and non-phase locked activity (Pfurtscheller 1997, Pfurtscheller and Lopes da Silva 1999). While ERP is a time domain measure ERSD provides a description of the relative changes in EEG power evoked by a stimulus in relation to a reference EEG signal. Thus ERSD is a frequency analysis technique that is used to extract changes that may not be obvious from the time domain measure of ERP. ERSD can be simply defined as increases or decreases of power within specific frequency bands relative to reference level. This can further be interpreted as increased or decreased synchronization within the underlying neural populations. If there is an increase in synchronization between the neural populations brought about by the event then it is called Event Related Synchronization (ERS) on the other hand if the event causes desynchronization between the neural populations then it is called Event Related Desynchronization (ERD). Cortical areas involved in the production of motor action or in cognitive and sensory production exhibit ERD. In the deactivated state, coherent activity of cell assemblies spread over several square centimetres produce ERS.

2.4.3 Event Related Spectral Perturbation (ERSP).

Averaging of trials in time domain is the most preferred analysis tool in most studies involving evoked potentials however the averaging of trials time-locked to an event causes rhythmic or quasi-rhythmic brain activity not synchronized to the event to dissolve out because of phase cancellation. As described previously ERD/ERS is only a measure of event-related shifts within a predetermined frequency band, but to get a complete picture it is helpful to have information of the event related shifts at all frequencies of interests and specifically in the α, β and γ bands. The event related spectral perturbation (ERSP) is a generalization of the ERD/ERS computation but graphically visualizes the entire spectrum as in the form of a spectrogram. (Makeig et al. 2004).

To compute the ERSP each epoch is divided into a number of overlapping windows and spectral power is calculated for each window. The spectrogram calculated is then normalized by dividing by the baseline spectra calculated from the EEG immediately before each event. By averaging the normalized spectra over all the trials we get the Event Related Spectral Perturbation (ERSP), which is plotted as spectral log amplitude on a time vs. frequency graph. (Delorme and Makeig 2004).

2.4.4 Statistical Comparison of ERSP

For the BCI to be a robust and reliable system it is necessary to use features that are robust and consistent for classification. There is thus a need to measure statistically the significance of the difference between features that seem to distinguish the different groups. ANOVA has been used to measure the test-retest reliability of spectral parameters of EEG [Krause 2001, Makeig 1993] and has been applied in this study. The different groups were compared by performing the ANOVA for the ERSP values at each time and frequency points across the different groups. The p values were then presented as a contour plot thereby allowing zones of statistical differences to be easily mapped in time and frequency.

2.4.5 Feature Extraction

It is computationally expensive to try and treat each data point in a signal with the same importance. Feature extraction helps to identify the information which is more useful for computation (classification). It is difficult to decide where feature extraction ends and pattern classification starts because an ideal feature extractor would map the data into the respective class labels. Dimensional reduction, mapping of data to a lower dimension, is one of the usual steps involved in feature extraction.

2.4.5.1 Power Spectrum

Spectral analysis helps decompose a complex signal into a sum of sinusoidal signals of different frequencies. This can then be represented in plots which show the magnitudes of the sinusoidal signals, and the phase relationships between the signals. When the power of these individual components is plotted we get the power spectrum of the

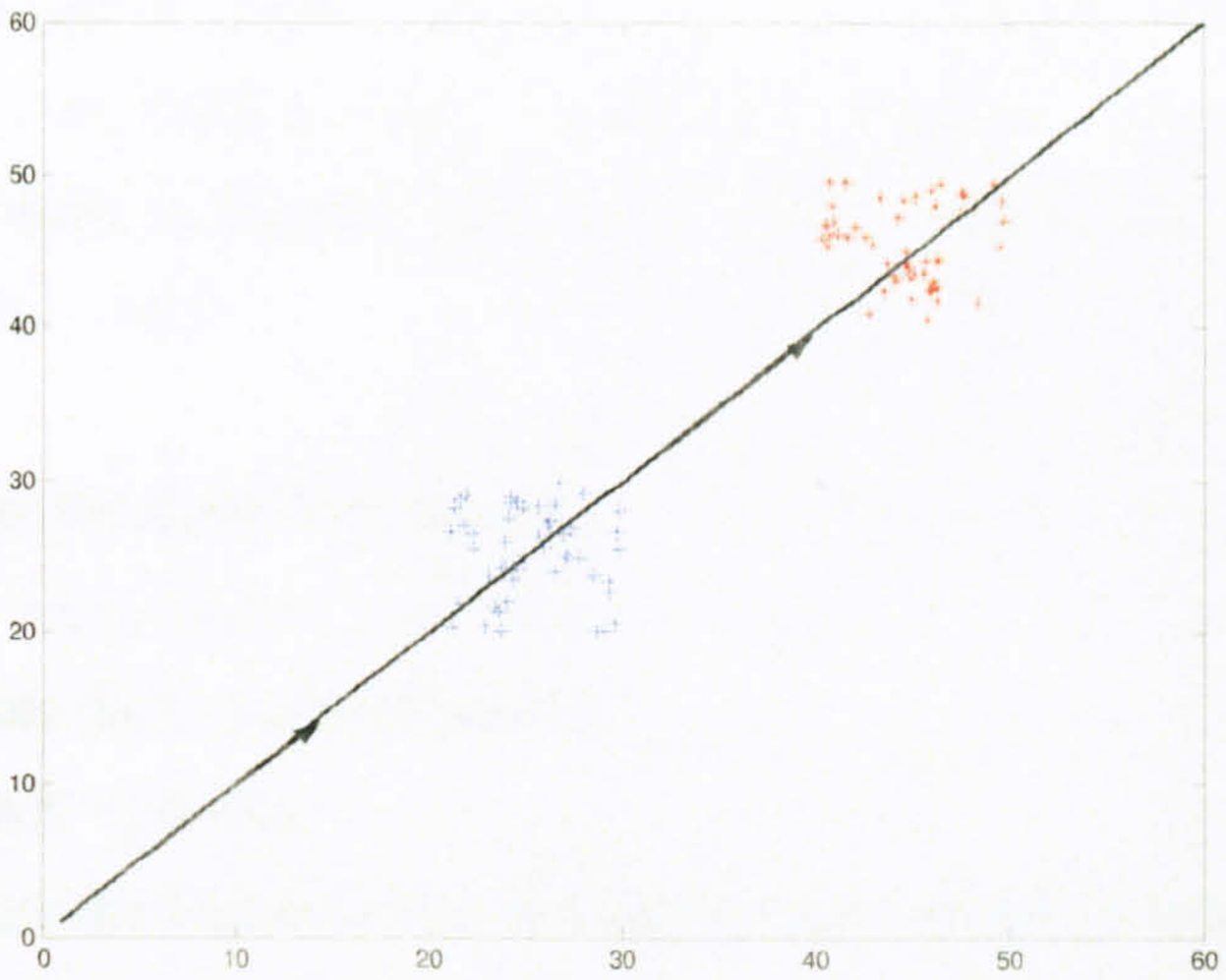
original signal. Fourier transforms give the coefficient of the component sinusoidal functions. Fast Fourier transform is an efficient and popular technique for frequency analysis. While performing spectral analysis of a time domain signals the longer the length or duration of the signal in time domain the finer is the frequency resolution in the frequency domain. However, taking a longer window reduces the time resolution of events. There is thus a trade-off selecting the length of the window. In order to reduce the end effects while taking Fourier transforms it is necessary to multiply the original windowed signal with a window function. (Proakis and Manolakis 1996).

By repeatedly taking Fourier transforms of a signal with a moving window it is possible to study the changes in the frequency spectrum with time. This technique is called short-time Fourier transform. (Proakis and Manolakis 1996).

Analysis of the power spectrum of the EEG helps us study the behaviour of different frequency ranges (alpha, beta and gamma) of interest as the participant responds to a stimulus. This would also help us choose statistically significant features which are consistent.

2.4.5.2 Principal Component Analysis (PCA)

PCA computes new variables, which are uncorrelated, but preserve most of the variation present in the original variables. PCA is mainly used to reduce the dimensionality of the data set while retaining as much information. (Smith 2002). Figure 2.22a shows a scatter plot of the two data sets in blue '+' and red '*'. The figure also shows the first principal component after performing a PCA. Figure 2.22.b shows the plot of the two datasets when only the first principal component is plotted.



(a)

(b)

Figure 2.22 (a) Shows the scatter plot of two datasets + and *. It also shows first principal component. (b) Shows the transformed dataset when only the first principal component is plotted.

The standard mathematical technique, which is used to compute the principal components, is described below:

Suppose you have a set X of n data vectors $X_1 \ldots\ldots X_n$ of *d* dimensions each

i.e., $X_1 = (x_1^1 \ldots\ldots\ldots x_1^d)$ and $X_n = (x_n^1 \ldots\ldots\ldots x_n^d)$

Now calulate the mean of the data $X_m = (x_m^1 \ldots\ldots x_m^d)$ such that $x_m^1 = \text{mean}(x_1^1 \ldots . x_n^1)$

and $x_m d = \text{mean}(x_m^1 \ldots . x_m^d)$.

1. Subtract the mean from the data

   $X_1' = (x_1^1 - x_m^1, \ldots\ldots, x_1^d - x_m^d)$

2. Calculate the Covariance matrix.

   $\text{CovX} = \text{cov}(X)$

3. Calculate the Eigen-vectors and Eigen-values of the Covariance Matrix.

   $\text{CovX} * \gamma_{\lambda 1} = \lambda_1 . \gamma_{\lambda 1}$ where $\gamma_{\lambda 1}$ is the eigen-vector and λ_1 is the corresponding eigen-value.

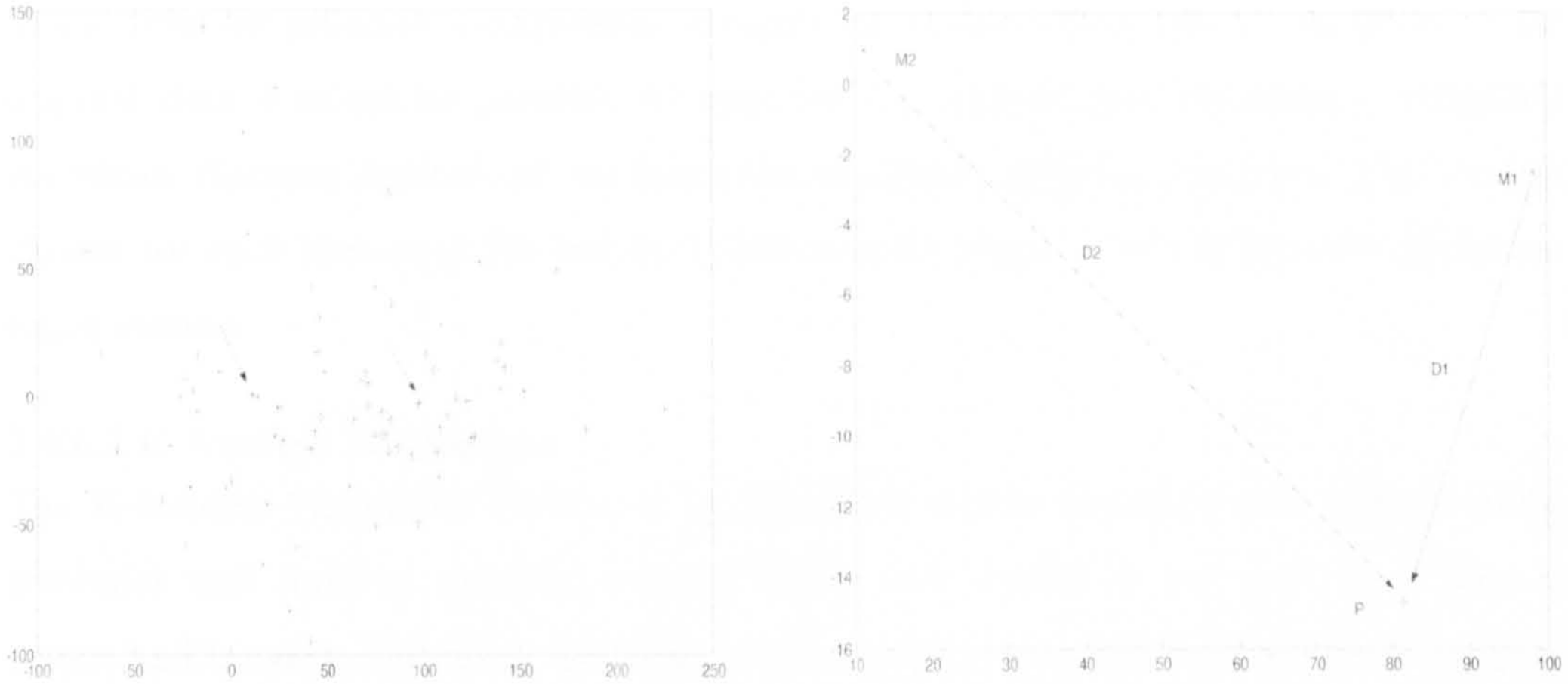
4. Arrange the Eigen-vectors in descending order of the Eigen-vectors to get the different principal components.

2.4.6 Pattern Classification

Pattern classification or recognition is the operation of acquiring raw data and taking an action depending on the class to which the data belongs. The classification being made is based on priori knowledge and/or statistical information derived from the data. The classification is usually based on data sets (training data sets) that have already been ordered.

2.4.6.1 Euclidean Distance

Given a set of points in a Euclidean space, and a partitioning of this (training set) into two or more subsets, the process of classification of a new point into one of these two classes can be done by determining the distance between the new point and the mean of each group from the training dataset. (Beale and Jackson 1990)



(a) (b)

Figure 2.23 (a) Shows an example computation of the means of two groups in a euclidean space. (b) Shows the computation of euclidean distance between a new trial and the two groups means M1 and M2. The new trials is classified to group M1.

In N dimensions, the Euclidean distance between two points p and q is

$$\sqrt{\sum_{i}^{n}(p_i - q_i)^2} \quad \text{.....Eq.2.1}$$

where p_i (or q_i) is the coordinate of p (or q) in dimension i.

The class to which the new point is closest to will be the class to which the new data point will be assigned.

The code for a Euclidean Distance based classifier was implemented in Matlab[8](The MathWorks, Inc. Natick, United States). Using the new feature vectors that were obtained after PCA group means were computed for each group in the training dataset. The 20 feature vector for the trial from the testing dataset is classified by computing the euclidean distance between this new trial and each of the group means. The new trial was then assigned to the class that it was closest to.

Since different principle components account for different amounts of variance in the original data it might be possible to improve the classification by using a weighted euclidean distance instead of an isometric euclidean distance measure. The weight chosen for each feature in the feature vector was the eigen values of the corresponding eigen vectors.

2.4.6.2 K-Nearest Neighbours

The K-Nearest Neighbour (KNN) is an algorithm which classifies new objects using attributes and training samples without fitting any model to the data. It is thus a supervised learning algorithm which uses its memory of the training samples to classify a new trial. In very simple terms the KNN technique finds the 'K' nearest neighbours from the training data set for the new unclassified trial and classifies to the group which has the highest majority among the K nearest neighbours.

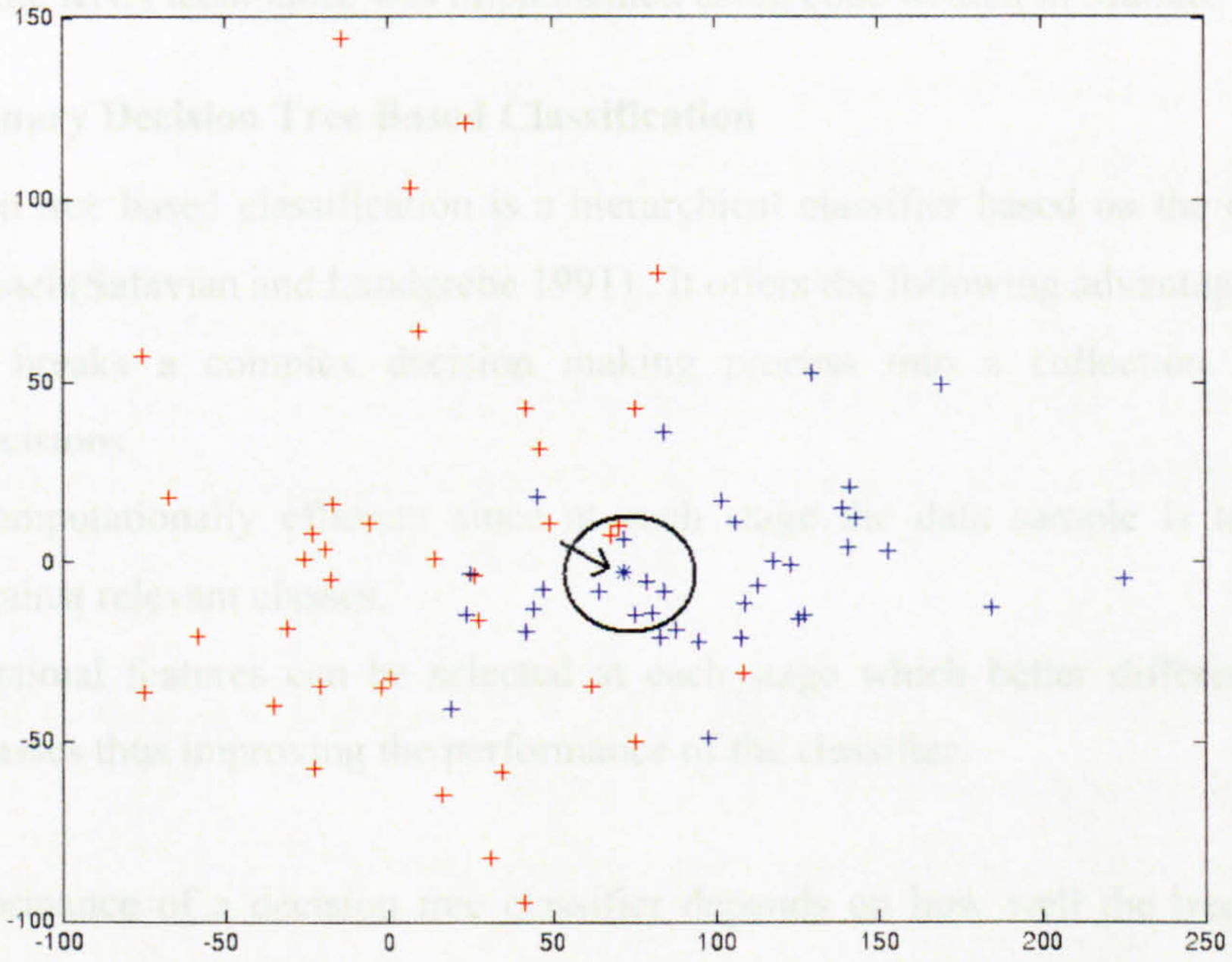


Figure2.24. The figure shows a simple example of the KNN classification technique. In this, the new trial '*' is classified to the group '+' because among the 8 nearest neighbours 6 of them belong to group '+' and only 2 belong to group '+'.

The K nearest neighbours for a new trial is computed after transforming the trials using the eigen vectors obtained from PCA. The new trial is then classified to the group which has a majority among the K nearest neighbours.

In a simple implementation of KNN classification which involved classifying a new trial into one of the two groups only the first three nearest neighbours need to found. In a more general case it is necessary to select an odd number of k nearest neighbours since number of neighbours of one group will have to be greater than the number of neighbours of the second group by at least '1'. In an implementation of KNN classification in which a new trial has to be classified into one of the 'n' group (n >2) a more complicated implementation is required to get a majority since there is possible that number of neighbours for two or more groups might tie. The code for classification based on the KNN techniques was implemented using code written in Matlab.

2.4.6.3 Binary Decision Tree Based Classification

A decision tree based classification is a hierarchical classifier based on the divide and rule approach(Safavian and Landgrebe 1991) . It offers the following advantages

- It breaks a complex decision making process into a collection of simple decisions.
- Computationally efficient since at each stage the data sample is tested only against relevant classes.
- Optimal features can be selected at each stage which better differentiates the classes thus improving the performance of the classifier.

The performance of a decision tree classifier depends on how well the tree has been designed. The major draw back of the decision tree based classifier is that an error made at a higher level is transmitted though the following lower levels. (Safavian and Landgrebe 1991)

2.4.7 Information Transfer Rate – A Measure of BCI Performance

An important measure of the performance of a BCI is its information transfer rate. The information transfer rate of a BCI depends on both the information transferred per trial and the length of time per trial. It can thus be defined as the information transferred per unit time. Information transfer rate of BCI depends not only on the accuracy of the system but also on the dimensionality of the control signal that can be extracted. (Dornhege 2006)

The earliest definition of information transfer rate was proposed by Farwell and Donchin in 1988 considered only the number of targets (N) or the dimensionality of the control signal that can be extracted. The definition shown in equation below did not take into account the accuracy of the system. (Farwell and Donchin 1988).

$$Rate = Log_2(N) \quad \text{.....Eq. 2.2}$$

Where Rate is the information transfer rate per trial

N is the number of targets or the dimensionality of the control signal

In their paper McFarland et al (Dennis J. McFarland 2003) had proposed new a definition to calculate the bit rate of a BCI based on Shannon's channel theory. This new definition shown in the equation below accounted not only for the number of targets but also of the accuracy of the classification system.

$$Rate = Log_2(N) + P \times Log_2(P) + (1-P) \times Log_2((1-P)/(N-1)) \quad \text{.....Eq. 2.3}$$

Where Rate is the information transfer rate per trial

N is the number of targets or the dimensionality of the control signal

P is the accuracy of the system.

The figure below shows the effect of change in accuracy and the dimensionality of the control signal on the bits transmitted per trial. (Dennis J. McFarland 2003).

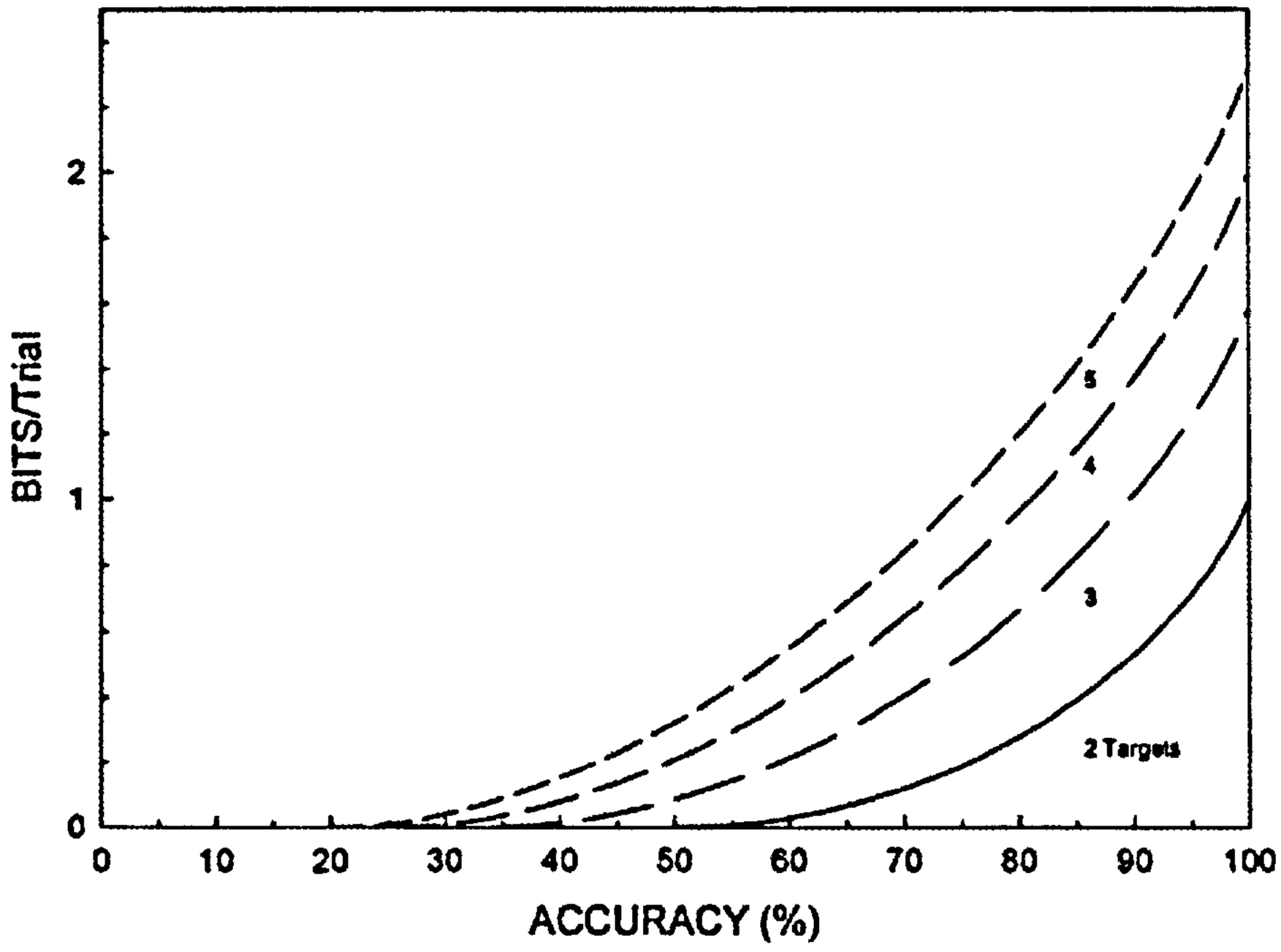


Figure 2.25. Shows the effect of accuracy and dimensionality of the classification on the information tranfer rate of the BCI (Wolpaw, Birbaumer et al. 2002).

2.5 Limitation of Current Studies and Future Work

A major performance measure of a BCI is its information transfer rate. It can be decided as the number of bits (a decision of yes/no) that can be transferred in a minute. The information transfer rate of a system can be improved by increasing the number of output control signals or channels. The investigators are thus trying to enhance the system performance by using topographically distinct rhythms that can be controlled independently which would allow several independent control channels and thereby increasing the dimensionality of the control signal. Most of the BCI reported in literature (Table 2.1) have been designed to have only two states (two dimensional control signal yes/no) and there has been no significant report on the ability to extract a multi-dimensional control signal from a single channel of EEG.

Most of current experimental protocols (Ramoser et al. 2000; Cincotti et al. 2003; Mason and Birch 2003; Pfurtscheller et al. 2003; Sajda et al. 2003; Pfurtscheller et al.

2006) are based on movement or imagination of movement of anatomically different areas. In the current study it is proposed that it is possible to extract features from the EEG which can be used to differentiate the movement (or imagination of movement) of wrist in different directions. The main reason in concentrating on the wrist is due to the larger representation of the wrist in the motor somatotopic map. The movements performed in the present study are fast burst movement which primarily involve direct activation of the wrist from the motor cortex through the pyramidal system. (Hoffman and Strick 1999).

While a few of studies involving invasive BCIs utilizing microelectrode arrays have successfully extracted multi-dimensional control signal, the current study proposes that it is possible to extract a multi-dimensional control signal from the non-invasive EEG recorded from scalp. (Hochberg et al. 2006 and Santhanam et al. 2006).

A review of movement control has revealed that there are multiple areas involved in the planning and execution of a movement (and motor imagery) most of BCI based on movement and imagination of movement use EEG recorded directly over the motor cortex. There has been no significant work on using EEG recorded at multiple sites over the scalp for deriving control signals for BCIs and on the selection of the best electrode sites which provide robust and consistent features for classification.

Chapter 3: Methodology

The main aim of this project was to explore the potential for developing multi-dimensional control for a BCI based on scalp EEG signal related to the intention to move the wrist in different directions. During the course of this project it was hoped that by studying EEG data features associated with the pre-movement period in instructed, self-paced and imagined wrist movements that the utility of movement related cortical potentials (MRCP) could be demonstrated for BCI purposes in a group of normal subjects. With this view in mind the following experiments based on a centre-out wrist movement were performed:-

- Externally cued movement trials(subjects moved to displayed targets)
- Forced choice based movement trials (subjects moved to one of two displayed targets)
- Self-paced and self-determined movement trials(free choice of target directions)
- Imagination of movement trials (as in externally cued tasks but no movement made)
- Visual Stimulus Presentation (as in externally cued tasks but subject must ignore target)

Table 3.6 Subject Log detailing the different experiments each participant completed.

Subject	Externally Cued	Forced Choice	Self paced and Self Determined	Imagination	Only Visual Stimulus
1	Participated	Participated	Participated	Participated	Participated
2	Participated	Participated	Participated	Participated	Participated
3	Participated	Participated	Participated	Participated	
4	Participated				
5	Participated			Participated	Participated
6	Participated				
7	Participated				
8	Participated		Participated		
9			Participated		
10	Participated	Participated	Participated		

The Ethical approval for the experiments was provided through the Department of Bioengineering Ethical Committee. The subjects (N = 10, 4 Female, 6 Male, Average age 29.3) who participated in some or all of these experiments were provided with information regarding the experiment and were asked to sign an informed consent form before they participated in the experiment. Table 3.1 shows the participants and the experiments that they participated in.

3.1 Experimental Protocols

For all experiments a common experimental setup was adopted. The experimental protocols required the subject to either move or imagine movement of their right wrist. These movements included flexion and extension of the wrist and ulnar and radial deviation of the wrist starting from a neutral position. This was therefore a centre out movement task in which the subject could be instructed to move in one of four directions. For the period of the experiment the subject was seated in front of a PC monitor and was asked to hold a manipulandum (an instrument used to measure the degree of wrist rotation in the X-horizontal and Y-vertical planes). Figure 3.1 shows the experimental setup in which the subject was seated at distance of approximately 1m from a computer screen on an ergonomic chair to which the manipulandum is attached. The position of the manipulandum was adjusted for each subject so that X and Y axes passed close to the centre of rotation of the wrist. The X and Y planes correspond to flexion/extension and radial/ulnar deviation respectively. Movement of the wrist generates a signal from the potentiometer measuring angular displacement of the manipulandum in the X and Y planes and this drove in real time a computer cursor displayed to the subject. Flexion generates cursor movement to the left, extension generates cursor movement to the right, wrist ulnar and radial deviation resulted in vertical up and down cursor motion. During the experiment sufficient trials for each direction had to be recorded for statistical reasons. For each experiment each subject took part in 10 movement and/or 10 movement imagination sessions. In each session there were 40 trials where a trial was a wrist movement to one of the four target positions. During the whole experiment 400 trials were recorded (movement or

imagined) and this provided around 100 trials for each direction of movement. Each trial of the externally cued, forced choice and imagination experiments was triggered by the appearance of a visual target (multiple targets for forced choice experiments) to which the subject responded to by moving the cursor for the movement trials or by imagining the wrist movement towards the target. During the self-paced and self–determined movement experiments the subject had free choice to initiate the movement along any one of the four directions.

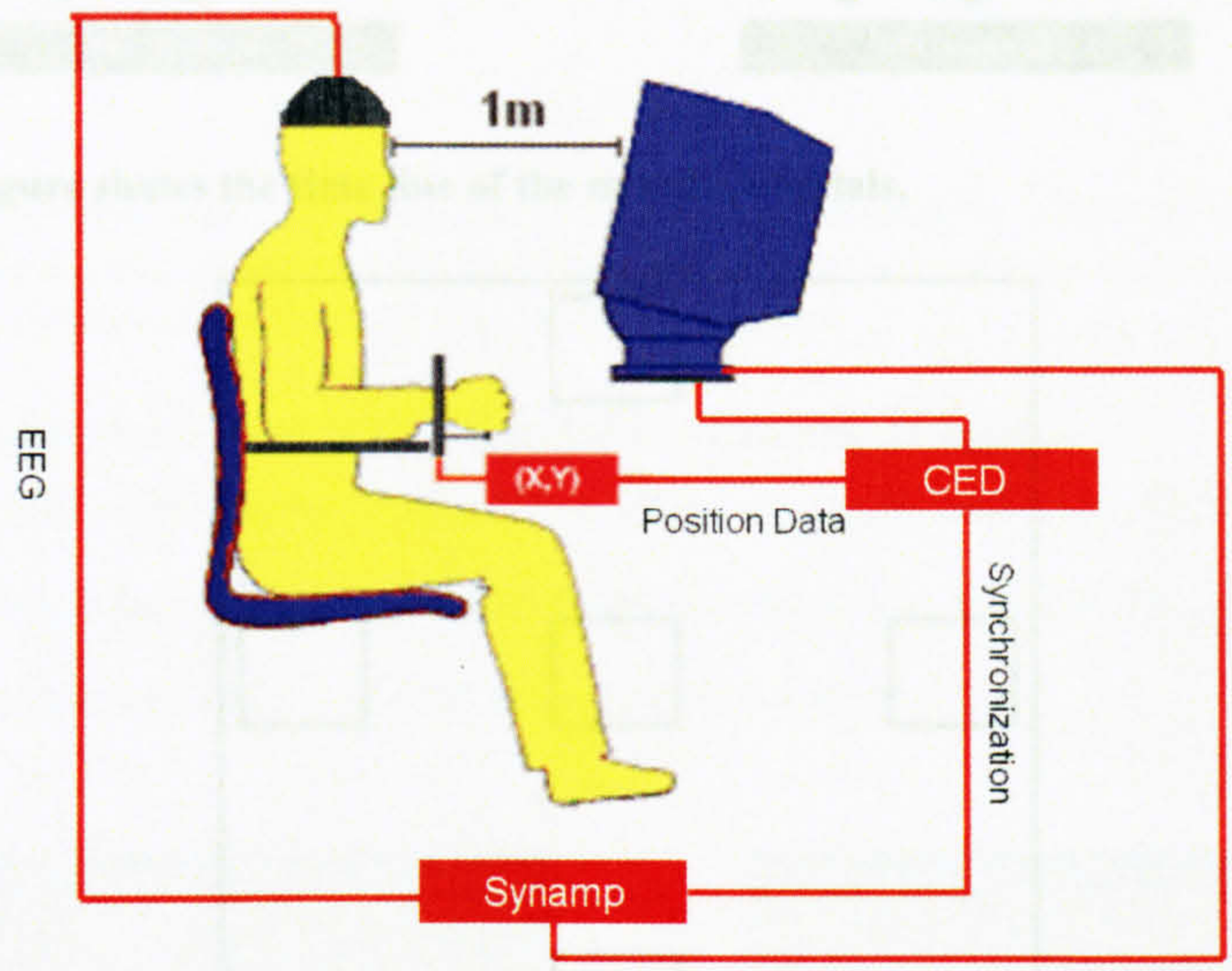


Figure 3.1 Experimental Arrangement. This Figure shows the manipulandum attached to an ergonomic chair on which the subject is seated at distance of ~ 1m from the computer screen.

3.1.1 Externally Cued Movement Trials

During these trials the subject was instructed to hold the manipulandum and to move the cursor from the neutral position to the target box (normally 15° of displacement) as soon as it was displayed on the monitor. This was the standard centre out movement task. On seeing a target the subjects were asked to move the cursor as fast as they could to the target (burst movements). On reaching the target the subject would hold the cursor at the target position for as long as the target remained visible; when the target disappeared the subject repositioned the cursor back to the neutral position. A new target was then

presented at 10s intervals. Figure 3.2 shows the time line of the experiment while figure 3.3 illustrates a schematic of the display shown to the subject.

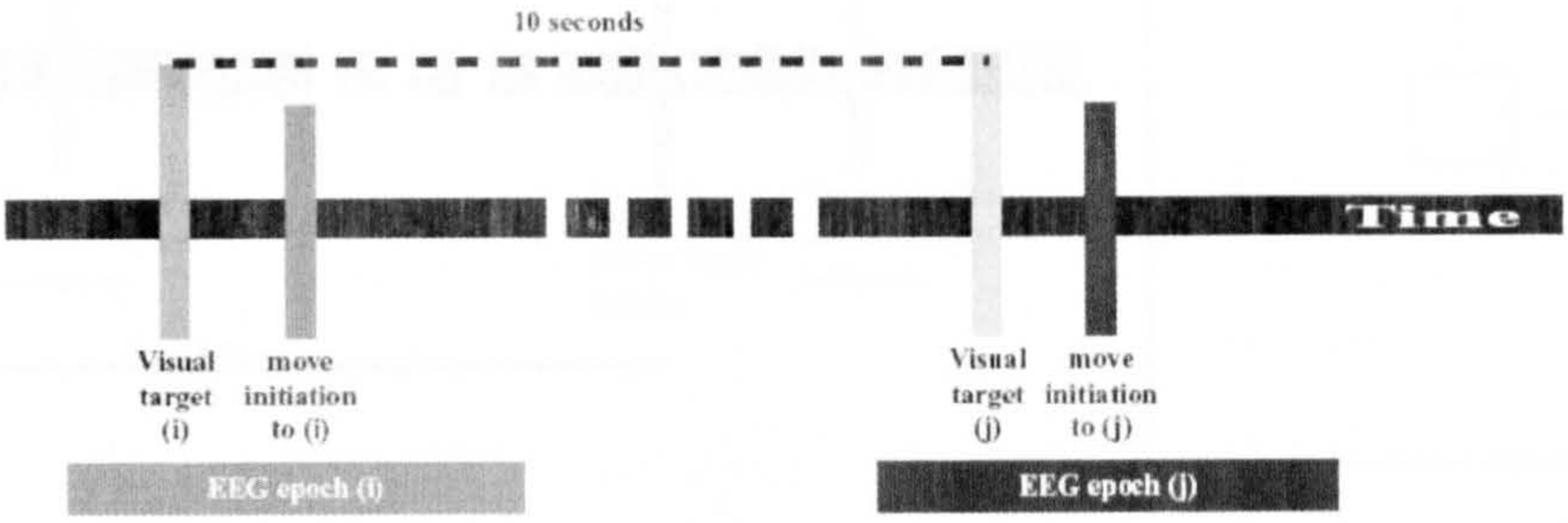


Figure 3.2. The figure shows the time line of the movement trials.

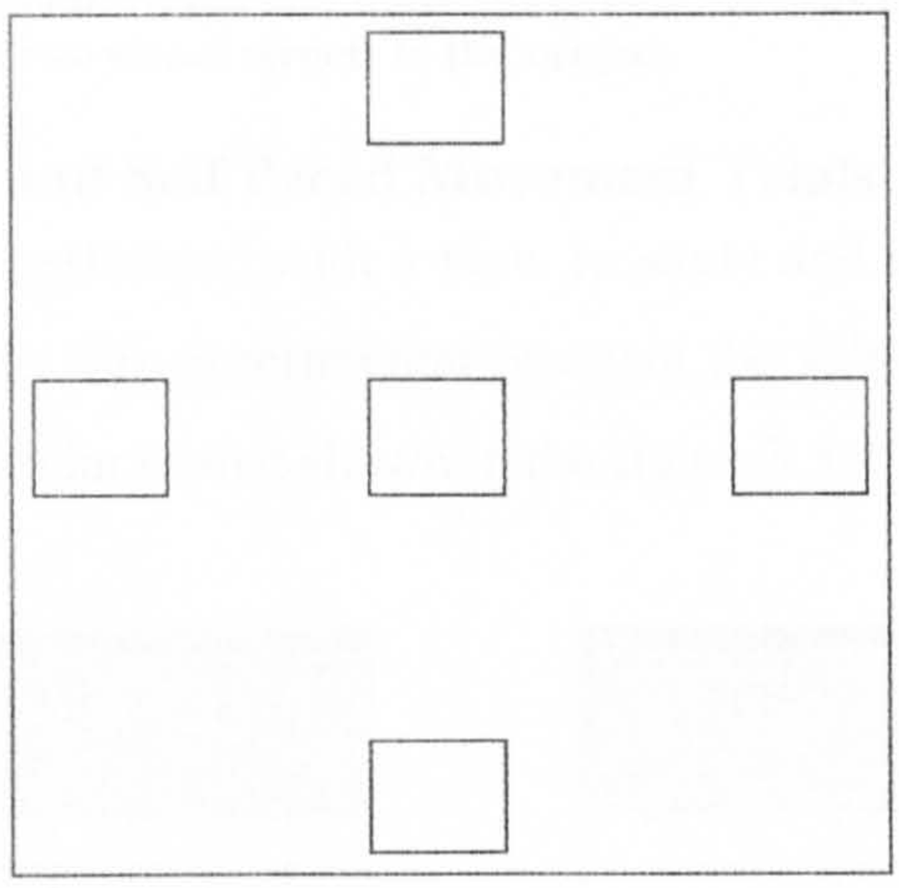
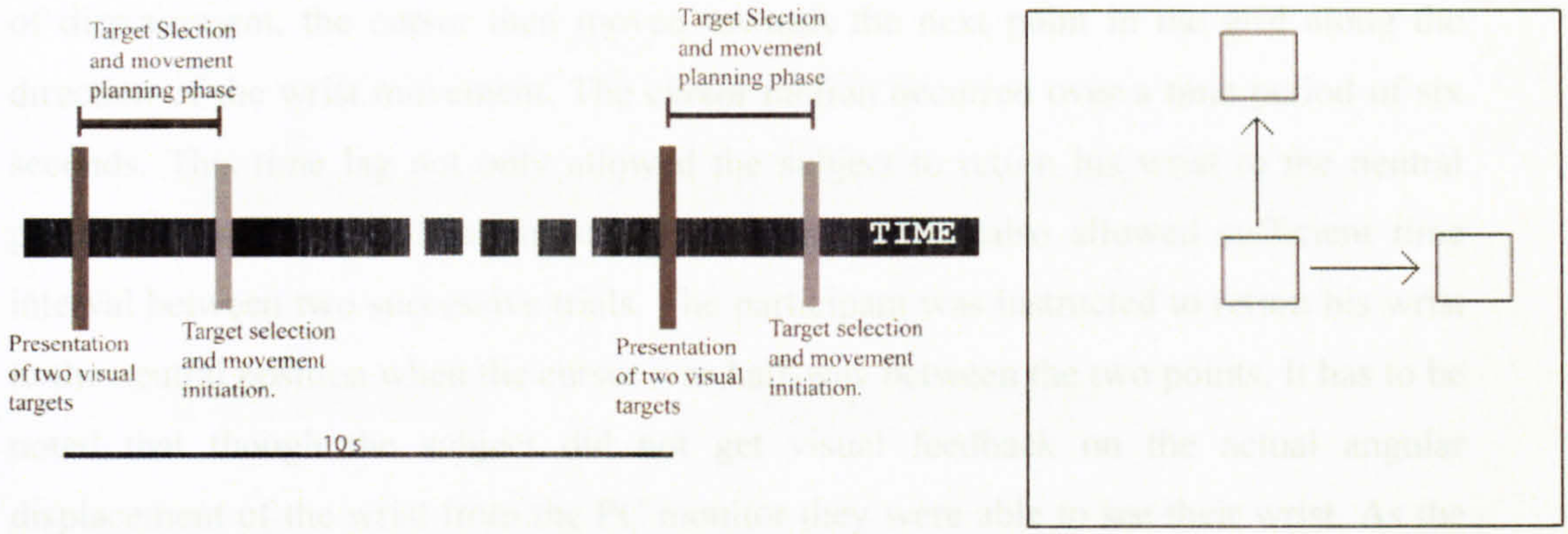


Figure 3.3. The figure shows each target position. During an experiment the presentation of a single target is randomized.

3.1.2 Forced Choice Movement Trials

In this experimental protocol any two of the potential four visual targets were simultaneously presented to the participant. The subject was then asked to select one of them and then to move the cursor to the selected target of choice. The subject was required to move as fast as possible and therefore had to quickly select one of the targets. Figure 3.4 shows the timeline of the experiment and an example of the simultaneous presentation of the two visual targets.

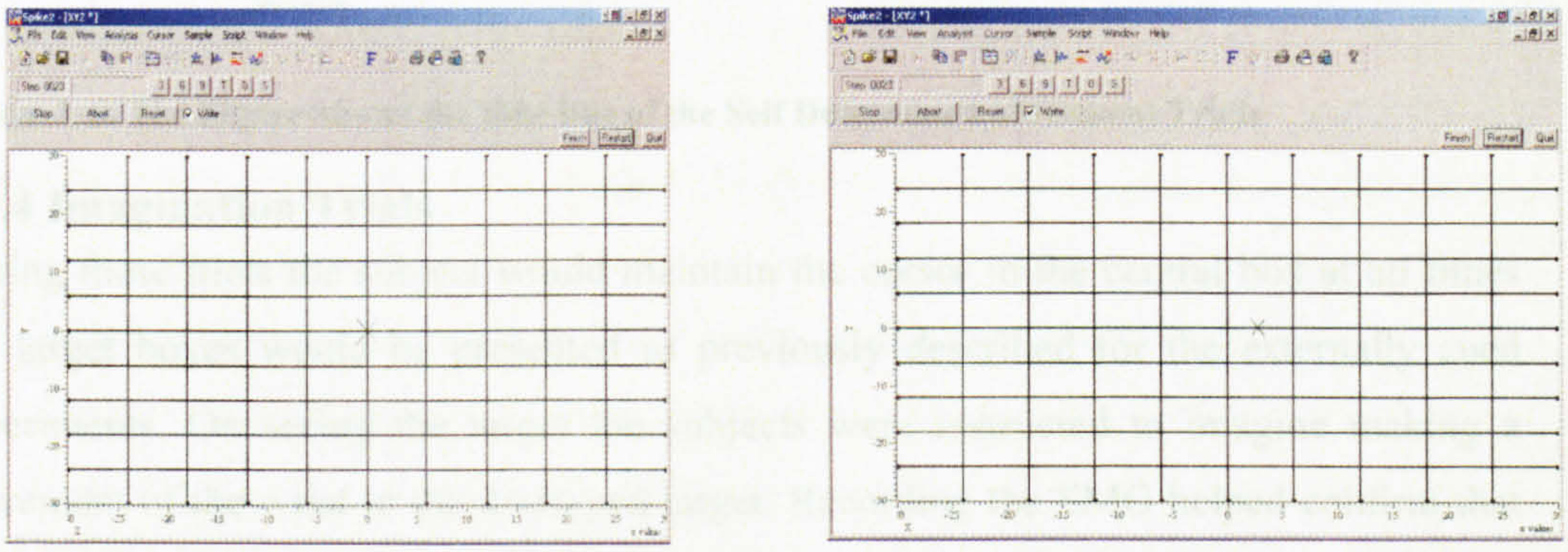


(a) (b)

Figure 3.4. The figure (a) shows the time line of the movement trials in which the subject had to choose from one of the two visual stimuli and move the cursor towards the chose target. The figure (b) shows the presentation of two visual targets to the subject.

3.1.3 Self Determined and Self Paced Movement Trials

These experiments were performed with a view to study and classify self-initiated and self chosen movements. In this experimental protocol the subject was presented with a grid on the PC monitor similar to that shown in the figure 3.5.



(a) (b)

Figure 3. 5. The Figure (a) shows the cursor position prior to movement initiation, (b) shows the cursor moving from one node to another after a self initiated movement.

In this experiment the participant could choose to move in any of the four directions. On moving, the cursor would track along the horizontal or vertical lines on the grid. Each trial started when the subject initiated a fast wrist movement greater than or equal to 15°

of displacement, the cursor then moved towards the next point in the grid along the direction of the wrist movement. The cursor motion occurred over a time period of six seconds. This time lag not only allowed the subject to return his wrist to the neutral position (this did not affect the cursor movement), but also allowed sufficient time interval between two successive trials. The participant was instructed to return his wrist to the neutral position when the cursor was half-way between the two points. It has to be noted that though the subject did not get visual feedback on the actual angular displacement of the wrist from the PC monitor they were able to see their wrist. As the experiment progressed the cursor moved around the grid thereby ensuring that multiple directions were selected. The timeline of the self-determined and self-paced movement trials is shown in figure 3.6.

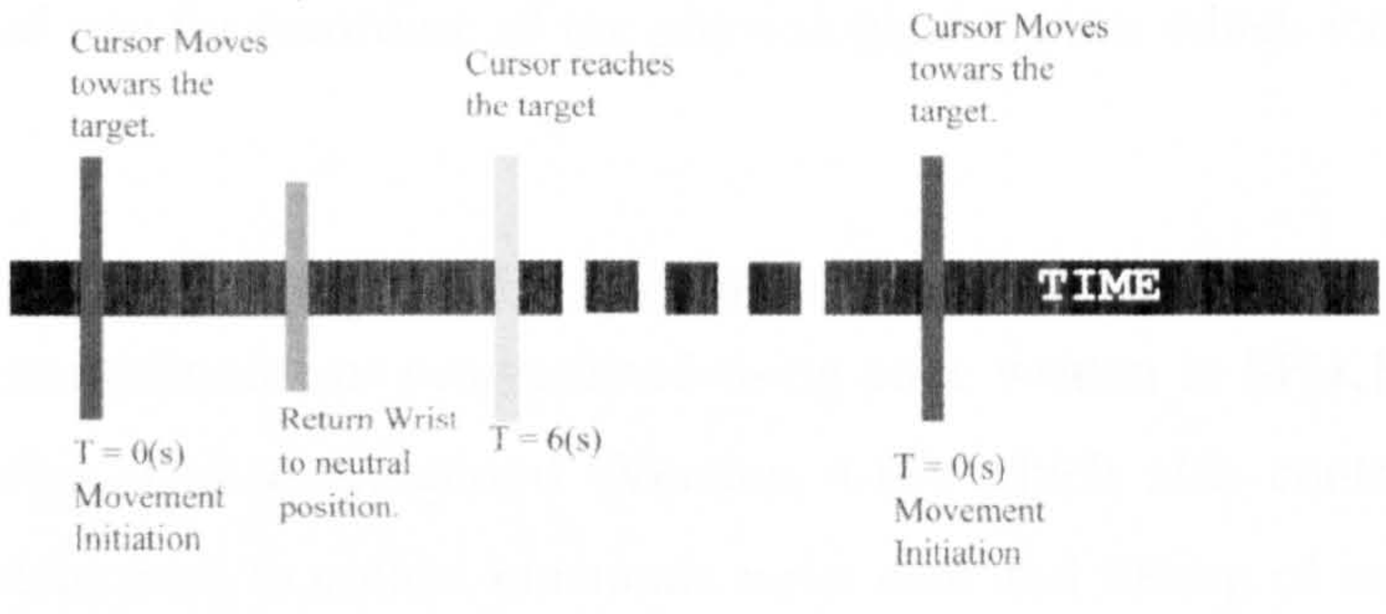


Figure 3. 6. The Figure Shows the time line of the Self Determined Movement Trials

3.1.4 Imagination Trials

During these trials the subject would maintain the cursor in the central box at all times but target boxes would be presented as previously described for the externally cued experiments. On seeing the target the subjects were instructed to imagine making a movement of the wrist to the displayed target. Recording the EMG helped confirm that subjects did not actually move their wrist. Figure 3.7 shows the time line of these experiments.

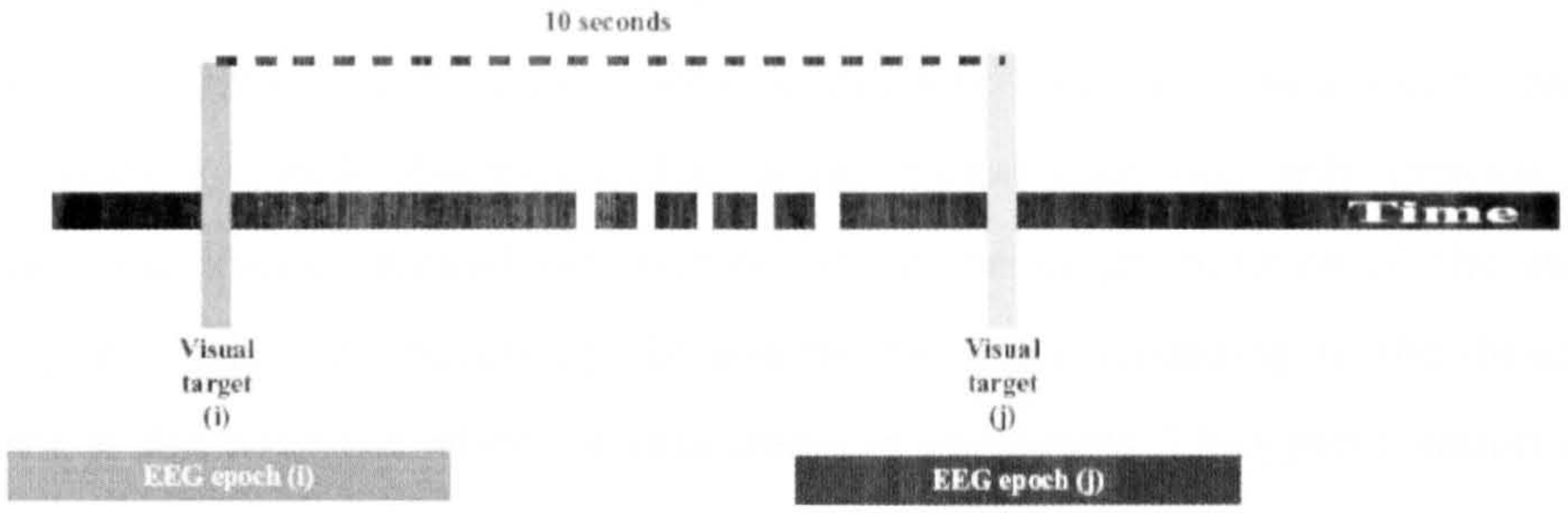


Figure 3.7. The figure shows the time line of the imagination trials.

3.2 Experimental Data Recording Arrangement

The experimental arrangement contained two systems: one for control and stimulus presentation and one for recording of the physiological signals which include EEG and EMG signals.

3.2.1 Stimulus Presentation and Experiment Control

The stimulus presentation was programmed using code written in SPIKE2 (Cambridge Electronic Design, United Kingdom) (Version 4.16) which also controlled the data acquisition system used to collect kinematic wrist data and timing of events outputted from the CED 1401 (Cambridge Electronic Design, United Kingdom). (See appendix for code). During the experiment the subject would initially see a box at the centre of the screen. This box represented the neutral wrist position and a cursor was adjusted to be in this box when the subject's wrist was held in the neutral position. For experiments where the subject is required to move from neutral to targets appearing at different positions on the screen the position of the computer cursor moved in response to the output of the manipulandum sensors. When the target was removed the subject was required to move the cursor back to the central or neutral position. Signals from two potentiometers tracked wrist movement in the X piane (flexion and extension) and Y plane (ulnar and radial deviation), and were recorded using a CED 1401.

These position signals were sampled at 100 Hz by the CED 1401 and were used to control the position of the cursor real time. The Spike2 code written to do this also

produced appropriate digital event markers, necessary for time synchronization between stimulus presentation and EEG data collection via the Neuroscan Synamps (Compumedics Limited, Australia). The 8 bit digital cues not only provide timing information but also contained information about the target position of the stimulus. These digital codes were necessary for sorting the trials according to the direction of movement of the wrist (or when the movement is imagined). Thus presentation of each target generated a unique digital output event that reflected the time of target appearance. Each of these signal events is used to trigger different digital ports on the Synamps which were then recorded with the EEG and EMG. Data files generated by Spike2 also logged these event times and the X, Y coordinates from the manipulandum. Tables 3.8 and 3.9 shows the digital cues generated during externally cued movement and imagination trials and forced choice trials.

Table 3.8 shows the interpretation of the digital codes in externally cued movement and imagination of movement trials.

Digital Code	Interpretation
03	Visual trigger presented at position 3 (wrist extension)
06	Visual trigger presented at position 6 (wrist abduction)
09	Visual trigger presented at position 9 (wrist flexion)
12	Visual trigger presented at position 12 (wrist adduction)
80	Disappearance of the visual stimulus

Table 3.9 shows the interpretation of the digital codes in forced choice trials.

Digital Code	Interpretation
01	Visual trigger presented at position 3 and 6
02	Visual trigger presented at position 3 and 9
03	Visual trigger presented at position 3 and 12
04	Visual trigger presented at position 6 and 9
05	Visual trigger presented at position 6 and 12
06	Visual trigger presented at position 9 and 12
80	Disappearance of the visual stimulus

During the self-paced trials the code written in Spike2 was used only to monitor and store the wrist movement and control the display of cursor position on the grid, EEG and EMG was recorded by the software controlling the EEG acquisition system (Synamp1 running under SCAN 4.3). A single digital cue produced by the code running on Spike2 at the start of the data collection by that system and recorded by both the systems was used for synchronization.

3.2.2 The Manipulandum

The manipulandum was an analog joystick that was used by the participants to control the cursor movement on the screen (see figure 3.10). It consisted of an ergonomic grip fitted to a two axis gimbal such that it allowed flexion/extension and ulnar/radial deviation of the wrist. To measure the angular movement of the wrist the manipulandum was fitted with two precision servo potentiometers (Vishay Spectrol) which had an electrical rotation range of ~ 340°. Each variable resistor was fitted along one of the axis of the gimbal such that the resistance of the variable resistor changes when the gimbal turns about that axis. In this configuration each potentiometer is sensitive to only one axis of rotation of the gimbal. Each variable resistor is connected through a current limiting resistor and a second potentiometer (for offset adjustment) to a 9v cell. By monitoring the voltage across the potentiometers fitted to the gimbal it was possible to track the rotation of the gimbal around each axis. A second set of potentiometers was used in the electrical circuit to provide an offset control for X and Y signals. This allowed fine adjustment of the cursor to correspond to the neutral position. At the start of each experiment the subject was instructed to hold the manipulandum in the neutral position and any cursor offset was adjusted so that the cursor was centrally located in the neutral box viewed by the subject on the PC monitor.

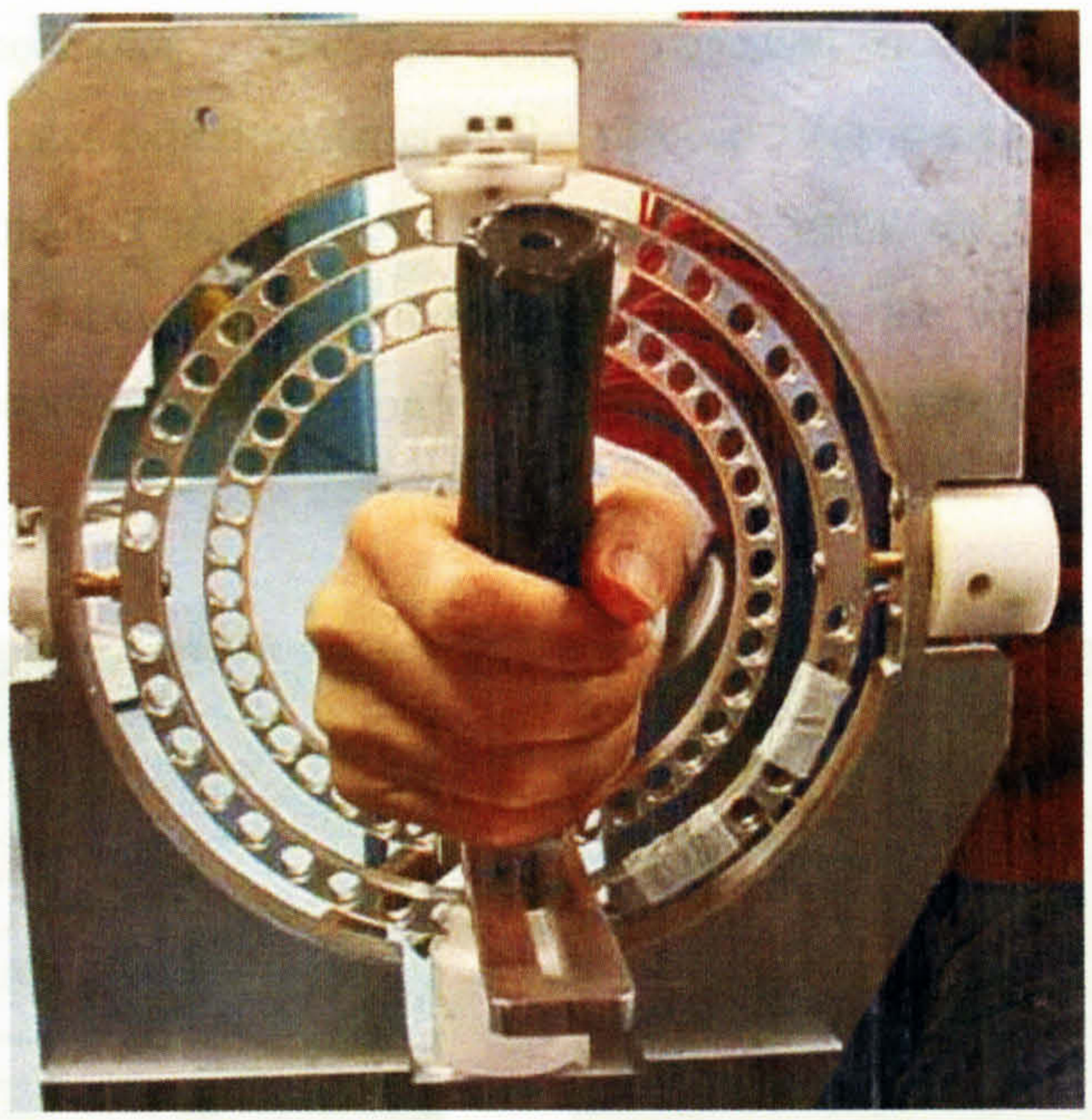


Figure 3.10. Shows the Manipulandum used to control the cursor.

3.2.3 The EEG Recording Setup

During all experiments 28 monopolar EEG channels and 4 bipolar EMG channels were recorded using a Synamps (Neuroscan) amplifier controlled by SCAN4.3 software. The EEG and EMG signals were amplified 1000 times by the Synamps. These signals were sampled at 2000 Hz. The EEG channels were band-pass filtered between 0.05Hz to 500 Hz this allowed both the slow and fast EEG waves to be recorded accurately. The EMG channels were band-pass filtered between 5Hz and 500Hz. The high-pass cut-off was set at 5Hz in order to reduce the effect of any motion artifact. During the experiment the EEG and EMG signals were displayed on a second monitor, which was placed out of the view of the subject, and permitted online visual inspection of the physiological signals.

During the initial trial experiments EEG was recorded with gold plated electrodes attached to the subjects scalp using a 32 electrode QuickCap. Signals during these experiments were recorded from electrodes placed at the standard 10-20 electrode sites . In the later experiments cintered Ag/AgCl electrodes were used and placed using a 128 electrode EasyCap which allowed denser recording arrays to be formed for areas of the

skull overlying the motor cortex. The results presented in this thesis are from data recorded from the later experiments using the 128 cap . Cap sizes were matched to head size for each subject. Figures 3.10, 3.11 and 3.12 show the Easy cap, the EMG electrodes and the EEG electrode montage used during the experiments. EEG was recorded in a monopolar configuration with linked-ear references and a ground placed at AFz.

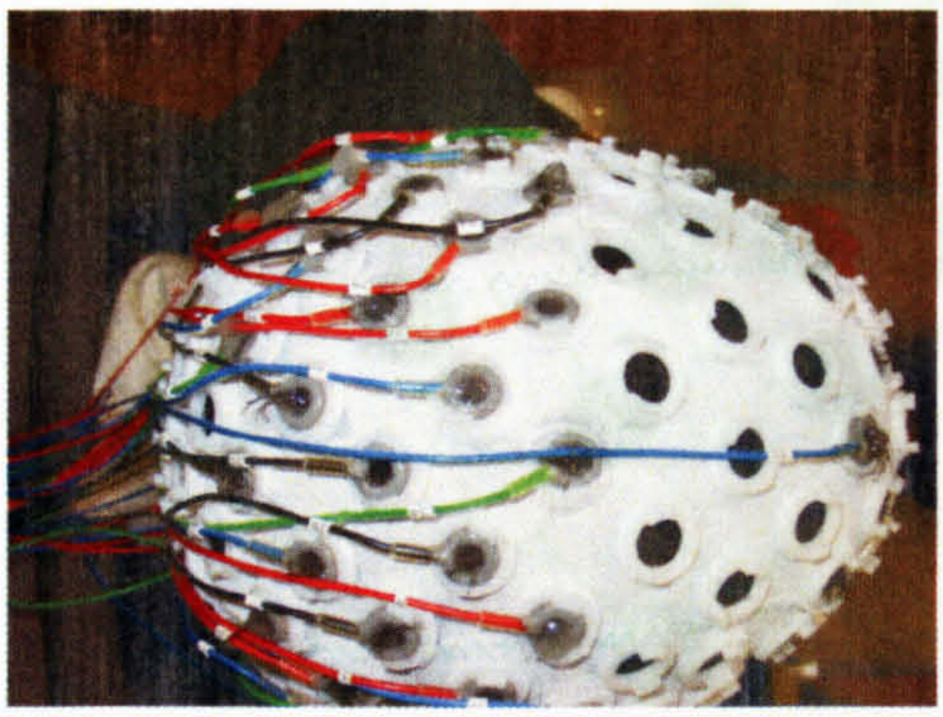


Figure 3.10. The figure shows the Quick cap and the electrode positions that were used.

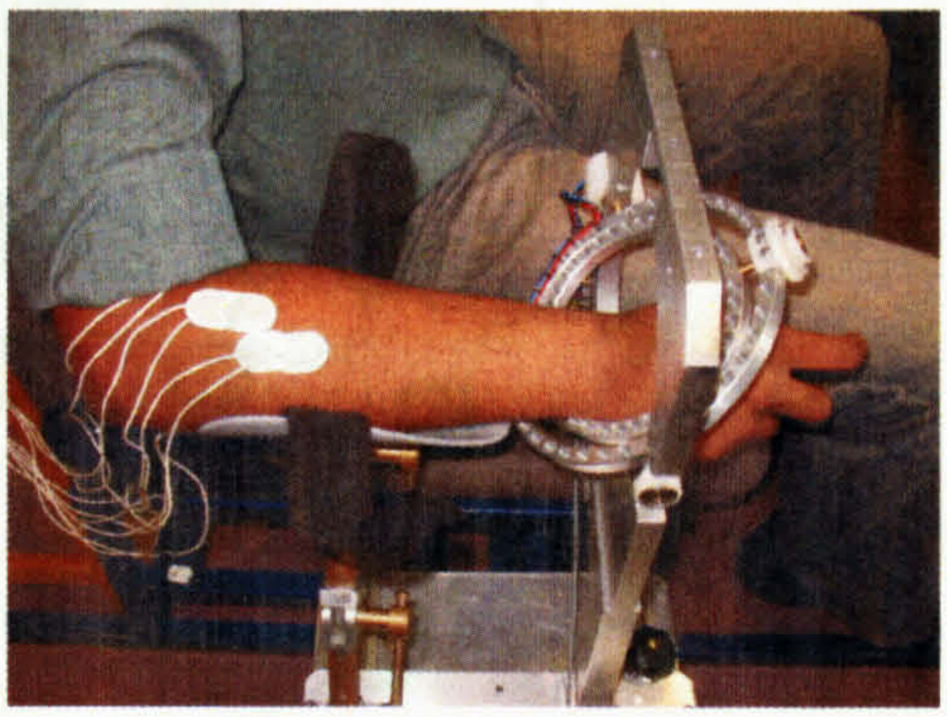


Figure 3.11. The figure shows the EMG electrodes on the subject's forearm

To ensure low contact impedances between the skin and EEG electrode the skin has to be prepared. The skin was abraded using a medically approved abrasive solution applied onto a cotton bud tip which was pushed through the apertures of each electrode. Once abraded a volume conducting gel was introduced between the skin and electrode. The contact impedance during the scalp preparation was monitored using impedance checking tool in the software SCAN4.3 which illustrated the impedance of each electrode as color map. Impedance was considered acceptable when it was below 5 kΩ. Figure 3.13 shows the contact impedances of the EEG and EMG electrodes after skin abrasion and gel application.

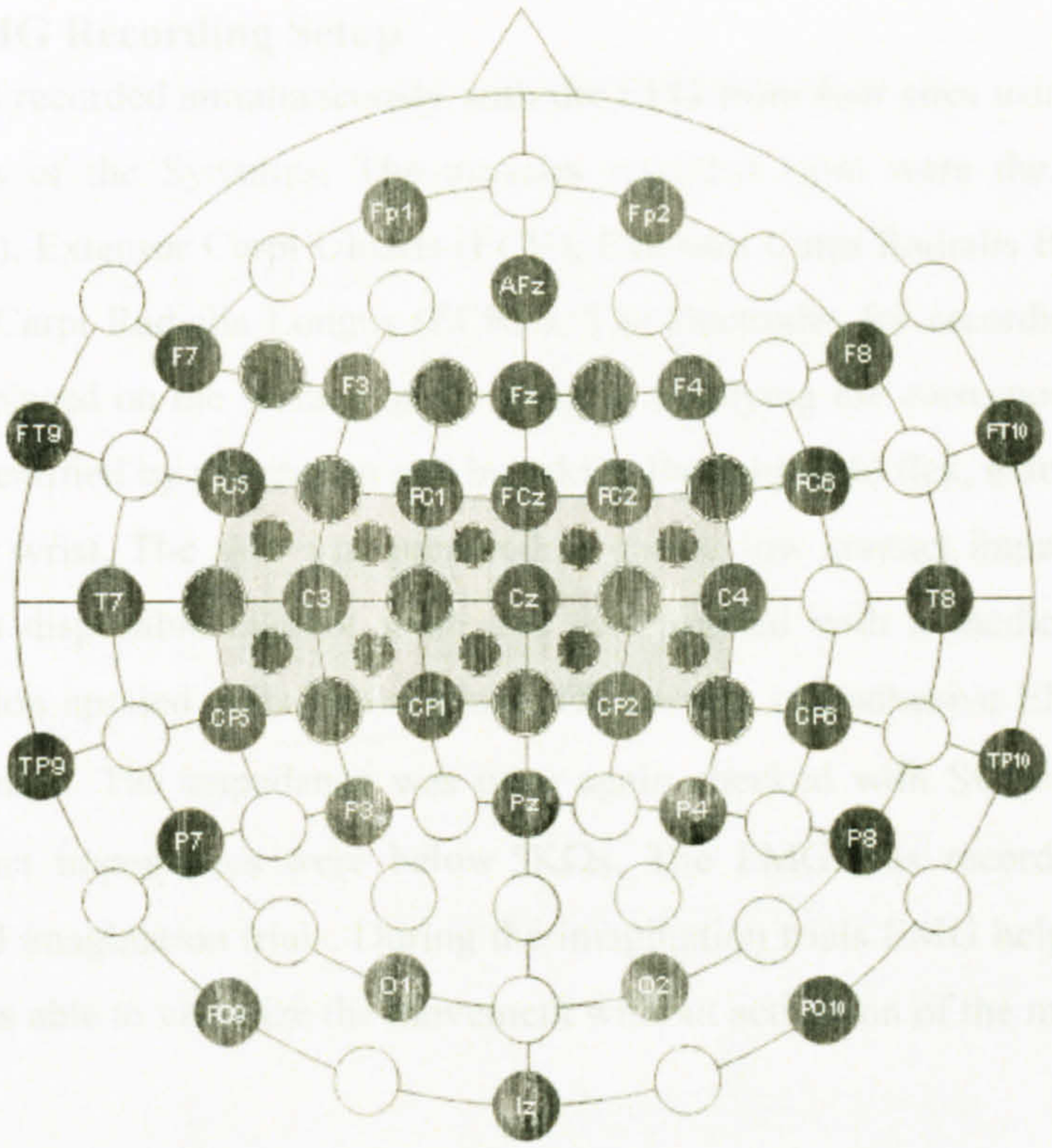


Figure 3.12. The figure shows the EEG electrode positions used during the experiment.

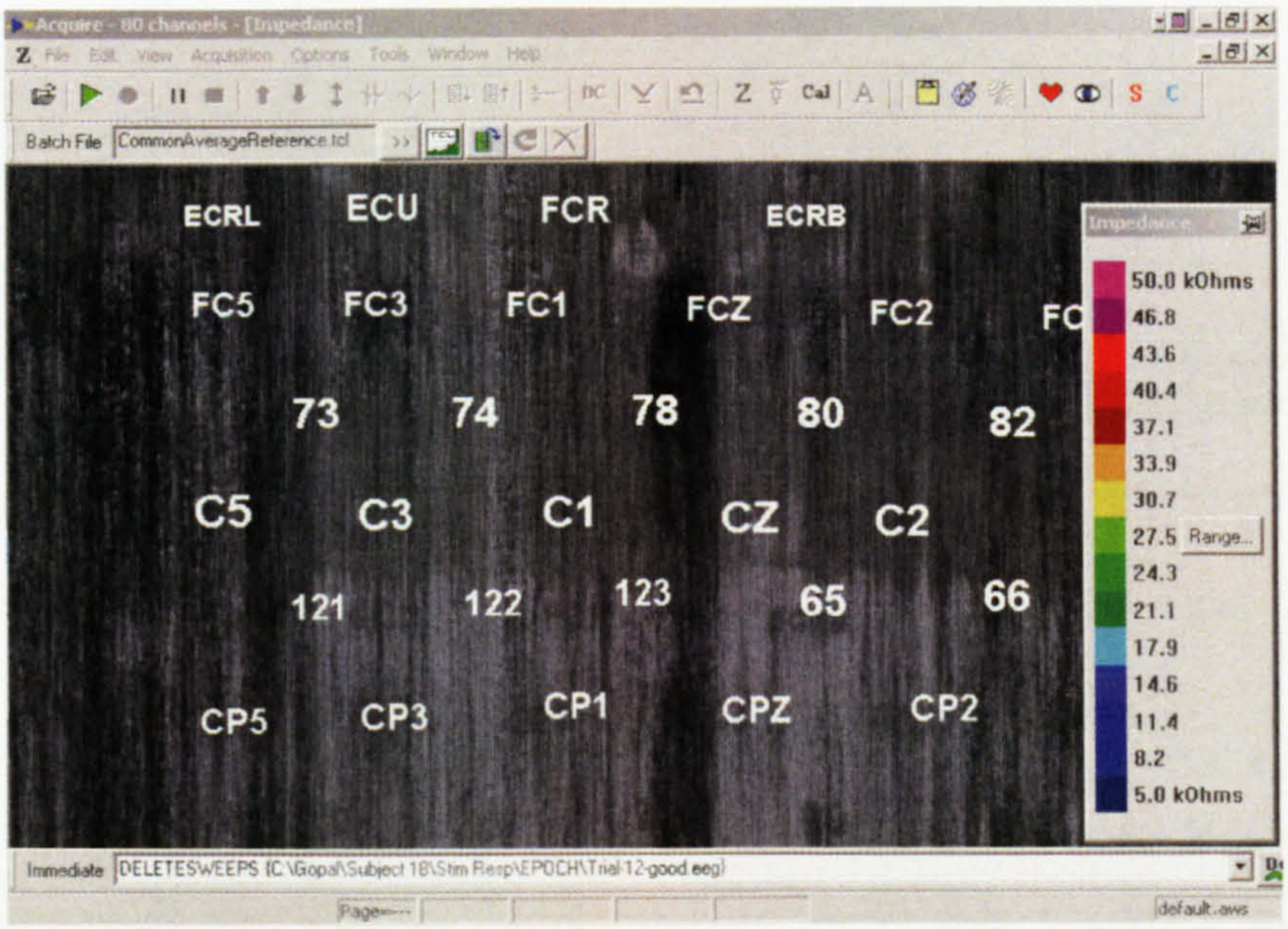


Figure 3.13. The Figure shows the contact impedance of the electrodes during experimental setup. In this example each electrode site has an impedance < 5kΩ.

3.2.4 The EMG Recording Setup

The EMG was recorded simultaneously with the EEG from four sites using the four bi-polar channels of the Synamps. The muscles recorded from were the Flexor Carpi Radialis (FCR), Extensor Carpi Ulnaris (ECU), Extensor Carpi Radialis Brevis (ECRB) and Extensor Carpi Radialis Longus (ECRL). The electrodes for recording the muscle activity were placed on the surface of the forearm overlying the corresponding muscles which were identified by palpitation and by asking the subject to flex, extend abduct and adduct his/her wrist. The skin was prepared to ensure low contact impedance by first wiping with a disposable alcohol swab and then rubbed with a medically approved abrasive solution applied onto cotton gauze. Disposable self-adhesive EMG electrodes were then applied. The impedance was once again checked with SCAN4.3, to ensure that the contact impedances were below 5KΩs. The EMG was recorded during the movement and imagination trials. During the imagination trials EMG helped to confirm if a subject was able to visualize the movement without activation of the muscle.

Chapter 4: Data Analysis and Signal Processing

Data collected online during experiments was processed offline in an attempt to extract information that could be used robustly to differentiate the EEG signals that preceeded and occured during movements (or motor imagery) to different directions. Figure 4.1 illustrates the sequence of steps used in processing the data.

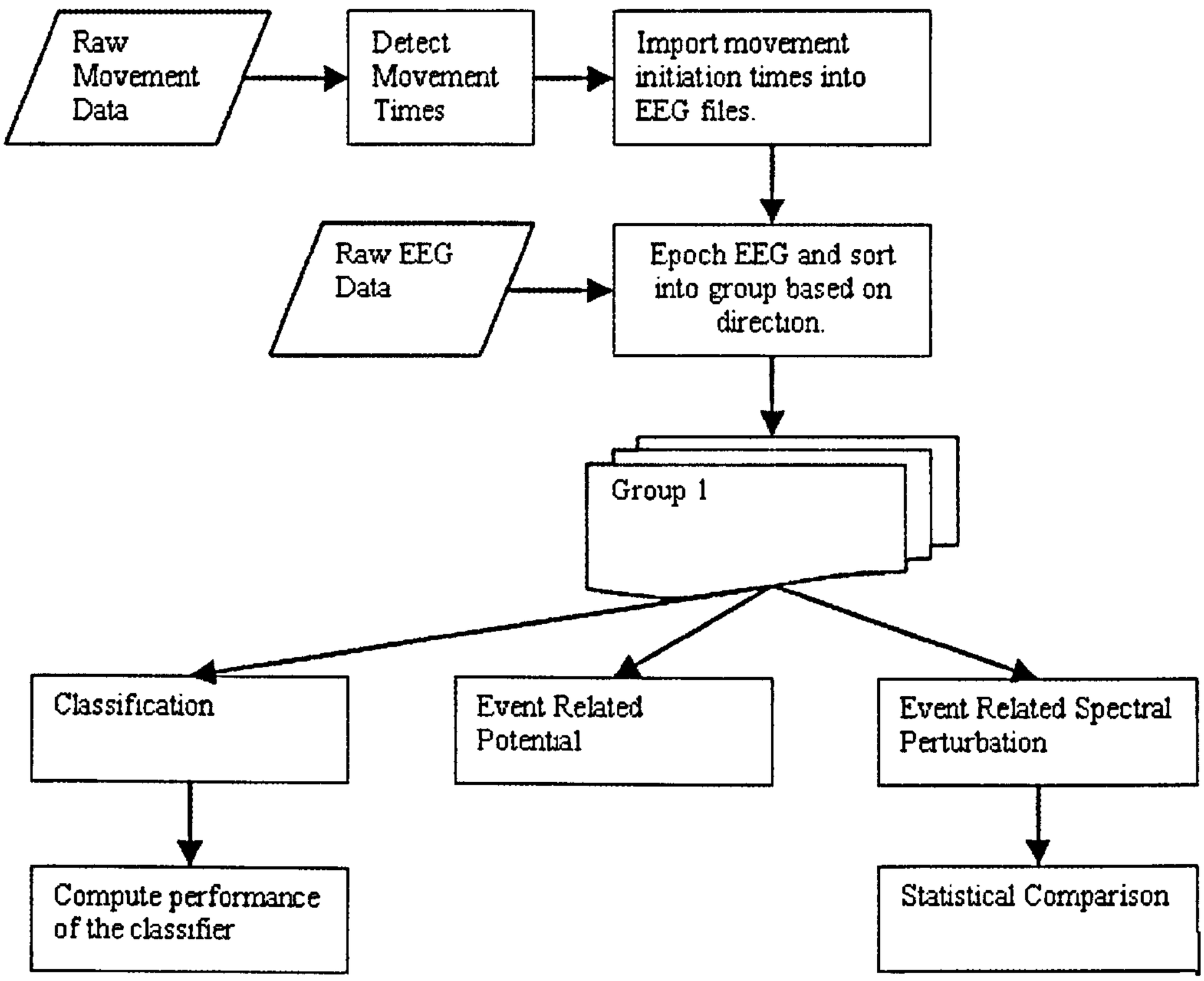


Figure 4.1. The flowchart shows the processing of the data collected during the experiments.

From the raw movement data recorded in SPIKE2 the movement initiation times were detected which were then offset corrected to be synchronized with the SCAN system. These movement times were then used for epoching the data. For imagination trials stimulus presentation times were used for epoching. Following the epoching the data

was grouped in 4 groups according to direction. These groups were then processed in time to and frequency domains by computing the motor related cortical potentials and the event related spectral perturbations. A further statistical comparison of the event related spectral perturbation for the different groups was also performed. A single trial based classification of the epoched data was then attempted and the performance of the classifiers was computed. The following sections in this chapter describe the various steps involved in extraction of information from the EEG that can be related to movement planning and direction of intended motion leading to classification based on a single trial basis.

4.1 Detecting Initiation of Movement.

The movement data from the manipulandum captured by SPIKE2 through the CED 1401 was first analyzed in order to identify the times of movement initiation. Since the wrist moves in the XY plane and not along the X or Y alone it was necessary to use the signal derived from both to calculate the actual point of movement initiation. To achieve this a new virtual channel was created in SPIKE2 derived from the data streams as follows:

$$XY = \mathrm{sqrt}(X^2 + Y^2) \quad \text{..... Eq 4.1}$$

The generation of this new derived signal was performed online during data acquisition and was stored. This position signal was differentiated in time to give a signal related to velocity. The points of minima (*) (See figure 4.2) from the differentiated signal correspond to the time at which each movement towards a target was initiated. The times of occurrence of each movement were then logged in an event marker channel. To ensure that the correct minima was identified two conditions had to be satisfied, the first being that the "minima" was "below" a certain threshold and the second being that the minima should not occur within 10 seconds of the previous occurrence movement initiation.

In view of the fact that two separate data acquisition systems (CED and Synamp) were used for each experiment it was also necessary to synchronize in time the data recorded by the two systems. This was done by aligning in time the first digital code that was recorded by both systems; to ensure that the subsequent time in both recordings can then aligned to a common reference time point.

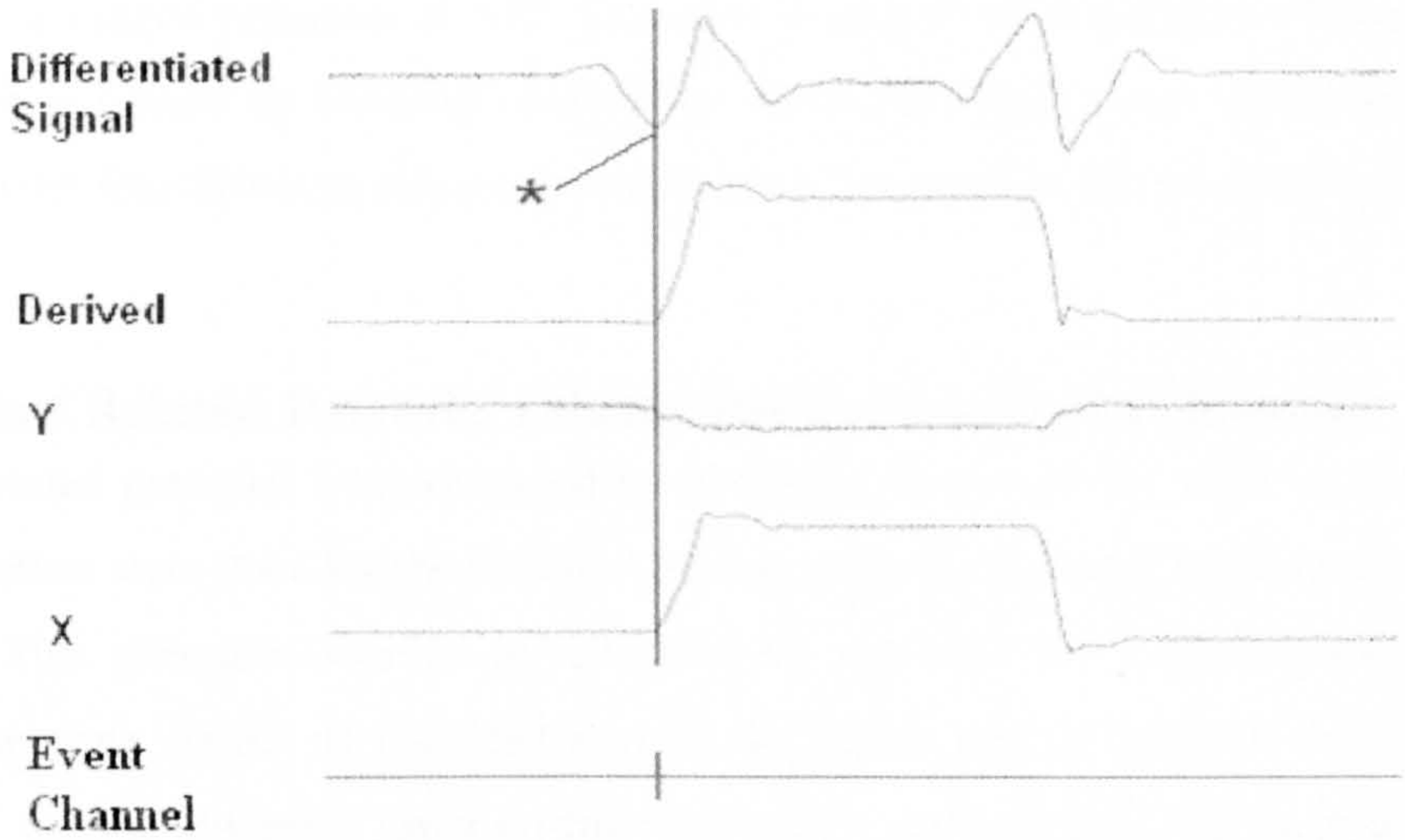


Figure 4.2. The figure shows the X and Y signals recorded from the manipulandum. It also shows the derived signal and the differentiated signal from which movement initiation is identified (*) and stored in the event channel.

4.2 Epoching

The EEG signals were epoched, using an inbuilt tool in SCAN 4.3, into time windows spanning the time of movement onset, as determined from the motion of the manipulandum. For imagination trials the epoch period was based on the time of appearance of the visual target.

In case of movement trials, before the epoching was performed each individual movement trial was checked visually to ensure that the movements were made to correct targets. Movement trials that were initiated after a delay of more than one second and movement trials that were too slow were discarded. In case of imagination trials the movement tracking data was checked to ensure that there was no actual movement. It

was only after these checks were completed that the EEG and EMG data were epoched. The EEG and EMG data were epoched to include data 3 seconds before and after the event (appearance of visual target or movement initiation). The epoched data was then visually inspected to remove trials that have obvious artefacts caused by blinking, swallowing/coughing, movement (during imagination trials), and inappropriate or wrong movement (during movement trials). The signals recorded were then re-referenced to the common averaged reference (CAR). Common averaged referencing also helped reduce the artefacts caused by blinking/swallowing. The CAR epochs were sorted into groups based on the four different directions which were then used in the subsequent processing stages.

4.3 Event Related Potential (Motor Related Cortical Potentials)

Event related potential was computed by averaging across all the trials in each group. Computation were done for the different groups using the average transformation tool in SCAN. This generates average for all channels recorded. It was thus possible to see study the time course of the MRCP over the entire area of interest. By overlaying MRCPs for the different groups (directions and conditions) it was also possible to compare MRCP (amplitude and time course) for the different experimental conditions.

4.4 Event Related Spectral Perturbation

While the averaging method provided a good representation of the phase locked signals in EEG it did not capture the non-phase locked evoked changes. Accordingly a frequency domain approach looking at event related changes in spectral power was used. The measure used was the event related spectral perturbation (ERSP) was which was computed using EEGLAB (version 4.5) (Delorme 2004, Makeig 2004, http://www.sccn.ucsd.edu/eeglab/) running within MATLAB 6. Neuroscan EEG files were first imported into EEGLAB and the ERSP was computed for the different groups. All ERSP were plotted to show spectral changes in the range of $\pm$ 5dB per frequency bin. Examination of the ERSP of the different groups allowed only a qualitative comparison. Further analysis was performed by conducting a statistical analysis, ANOVA, between the different groups allowing a quantitative comparison to be made.

The p values were computed at each time and frequency points in the time-frequency plot and the result was presented as a contour plot of p values there by allowing the identification of zones where the differences in the time-frequency plots existed. Time averaging and ERSP estimates therefore provided a description of each group of epochs associated with each condition and subject.

4.5 Classification

Most Brain Computer Interfaces (BCIs) make use of tasks that lead to distinguishable EEG signals of two or more classes. Any BCI has to be able to effectively distinguish the EEG signals of the two or more classes reliably, and without significant delay and ideally without averaging. Signal classification generally involves three steps:

- Pre-processing
- Feature Extraction
- Pattern Classification

4.5.1 Pre-processing

Before the data could be presented for feature extraction and classification it was necessary to pre-process the data. This includes epoching the data into different datasets as mentioned previously. The EEG data from each trial was cut into two 500ms windows – the first was when the subject was holding the manipulandum in the neutral position before stimulus presentation and the second just before the subject moves towards the target i.e., during the movement planning phase (it has been observed that the general reaction time i.e., the time between stimulus presentation and movement initiation is less than 500ms). These were the two datasets that were then presented for feature extraction and classification. Each dataset was then further split into two groups - the training dataset and the testing dataset. In case of Imagination trials the epoch lengths for the dataset was 1000ms and based on the ERSP and MRCP plots.

4.5.2 Feature Extraction

It was computationally expensive to try and treat each data point in a signal with the same importance. Feature extraction helps to identify the information which was more

useful for computation (classification). It was difficult to decide where feature extraction ended and pattern classification began because an ideal feature extractor would map the data into the respective class labels. Dimensional reduction which mapped of data to a lower dimension was one of the usual steps involved in feature extraction. The following were used for feature extraction in this study.

Power Spectrum

The power spectrum was computed using code adapted from the EEGLAB (version 4.5) (Delorme 2004, Makeig 2004, http://www.sccn.ucsd.edu/eeglab/). A 1024 point window length was used to compute the FFT. To reduce end effects (gibb's phenomenon) in the computed spectrum the 1024 point window was multiplied with a hanning window. The frequency resolution obtained was 0.9766 .A total of 200 windows were used to build the time-frequency plot. (Proakis and Manolakis 1996).

Principal Component Analysis

The trials were first split into a training dataset and a testing dataset. The code for PCA was implemented in Matlab. When input to the PCA was the periodogram, the two dimensional array was converted into a single dimensional array by rearranging the array elements. The eigen values for each eigen vector had a value that was proportional to the variance accounted by that vector. We found that the first twenty eigen vectors accounted for over 90 percent of the variance in the data. Thus by selecting these principle components we were able to reduce the dimension of each trial in our dataset to a 20 feature vector. The trials in the testing dataset were then transformed using the eigen vectors previously computed and retained (those eigen vectors used which accounted for 90 percent of the variance in the data).

4.5.3 Pattern Classification

Pattern classification or recognition was the operation of acquiring raw data and taking an action depending on the class to which the data belongs. The classification being made based on priori knowledge and/or statistical information derived from the data. The classification was usually based on data sets (training data sets) that have already been ordered. Several classifiers were designed and tested

Euclidean Distance

The code for calculating Euclidean distance was written in MATLAB. The code computed the weighted euclidean distance between the means and the unclassified trials. The weights used were the eigen values obtained from PCA this ensured that the difference between PC's were suitable weighted according the variance in the data that they accounted for.

K-Nearest Neighbours (KNN)

The code used to compute the KNN was adapted from the MATLAB code used to compute the euclidean distances. Once the distance to all the points in the training set were computed the KNN were calculated by ordering the points in the datasets in ascending order of their distances. The next step involved counting the number of points belonging to each group among the K nearest neighbours.

Binary Decision Tree Based Classification

Two decision tree based classifiers were implemented. Both the trees were designed with two decision levels. Figure 4.3 shows the first implementation. It shows that at the first stage an attempt was made to classify the intention to move as either horizontal movements (3 or 9) or vertical movements (6 or 12). At the second stage of this implementation the trial was then classified as the intention to move towards the two possible horizontal (3 or 9) or vertical (6 or 12) movements.

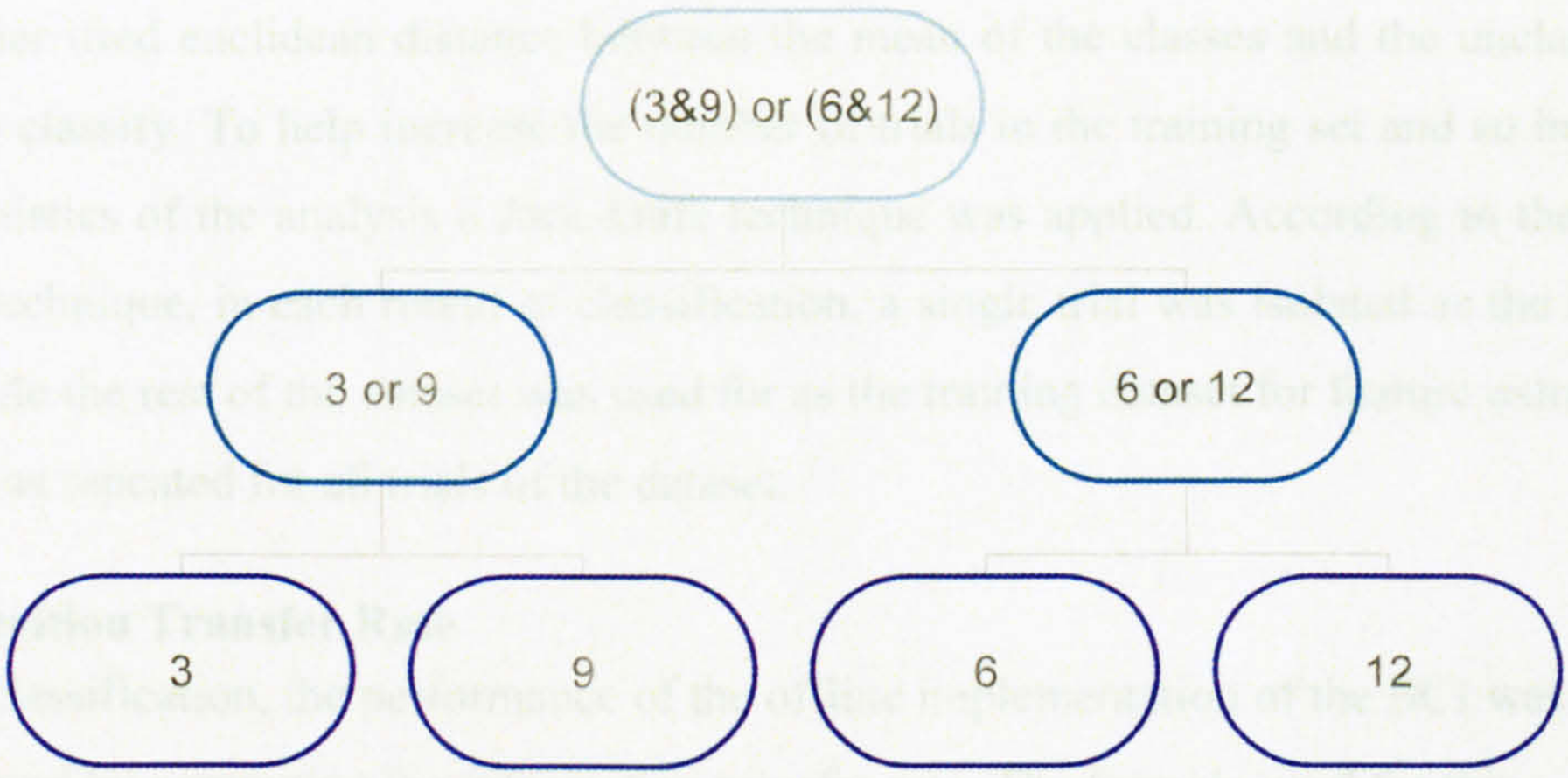


Figure 4.3. Shows the first implementation of the Binary tree based classifier.

Figure 4.4 shows the second implementation of the decision tree based classifier. In this implementation at the first stage the intention to move was classified between class 1 which included movements towards 3 or 12 and class2 which included movements towards 6 and 9. These classes were chosen based on the similar set of muscles involved in these movements. At the second stage of this decision tree the intention was then classified between the two remaining possible movements.

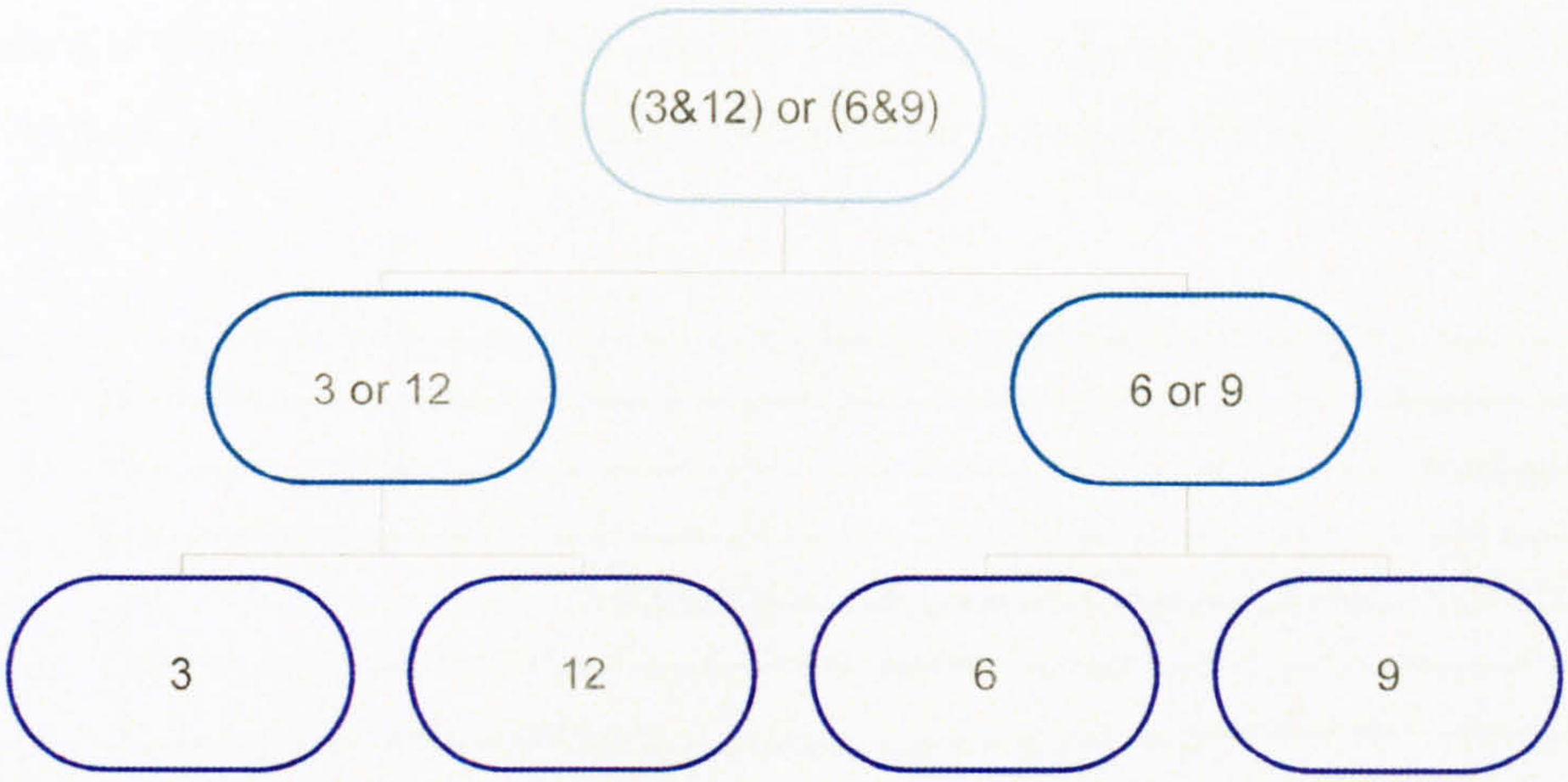


Figure 4.4. Shows the second implementation of the binary tree based classifier.

At each decision stage the ANOVA and PCA was used for feature extraction and the classifier used euclidean distance between the mean of the classes and the unclassified trial to classify. To help increase the number of trials in the training set and so improve the statistics of the analysis a Jack-knife technique was applied. According to the Jack-knife technique, in each round of classification, a single trial was isolated as the testing set while the rest of the dataset was used for as the training dataset for feature extraction. This was repeated for all trials of the dataset.

Information Transfer Rate

After classification, the performance of the offline implementation of the BCI was calculated by computing the information transfer rate. The formula used for this computation is as described by McFarland et al (1998).

$$\text{Rate} = \text{Log}_2(N) + P\text{x}\text{Log}_2(P) + (1\text{-}P)\text{x}\text{Log}_2((1\text{-}P)/(N\text{-}1)) \text{ – Eq 4.2}$$

Where N is the number of classes or groups

P is the accuracy of the classifier

The formula computes the information transfer rate by taking into account not only the accuracy of the classifier but also of the number of states or classes in the BCI.

Chapter 5: Results

5.1 The raw Data

Figure 5.1 shows a section of EEG, EMG raw data along with the digital markers recorded during a single movement trial. The first digital marker (09) shown in the top row was recorded when the visual stimulus was presented to the participant. The digital code recorded also contained information about the position of the visual target presented to the subject in this case target 9. The second digital code was recorded when the visual target disappeared indicating to the subject to return the cursor to the neutral position.

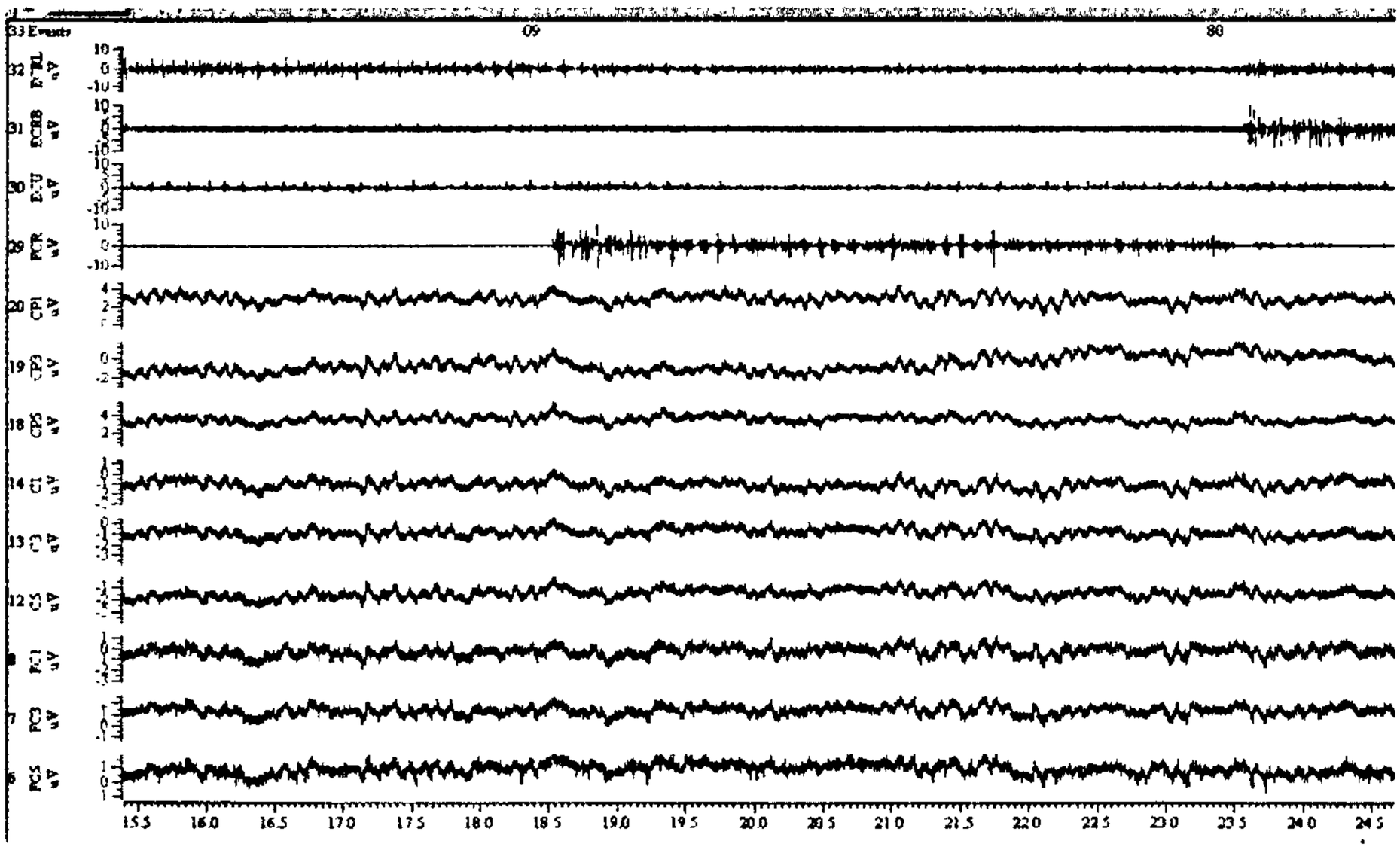
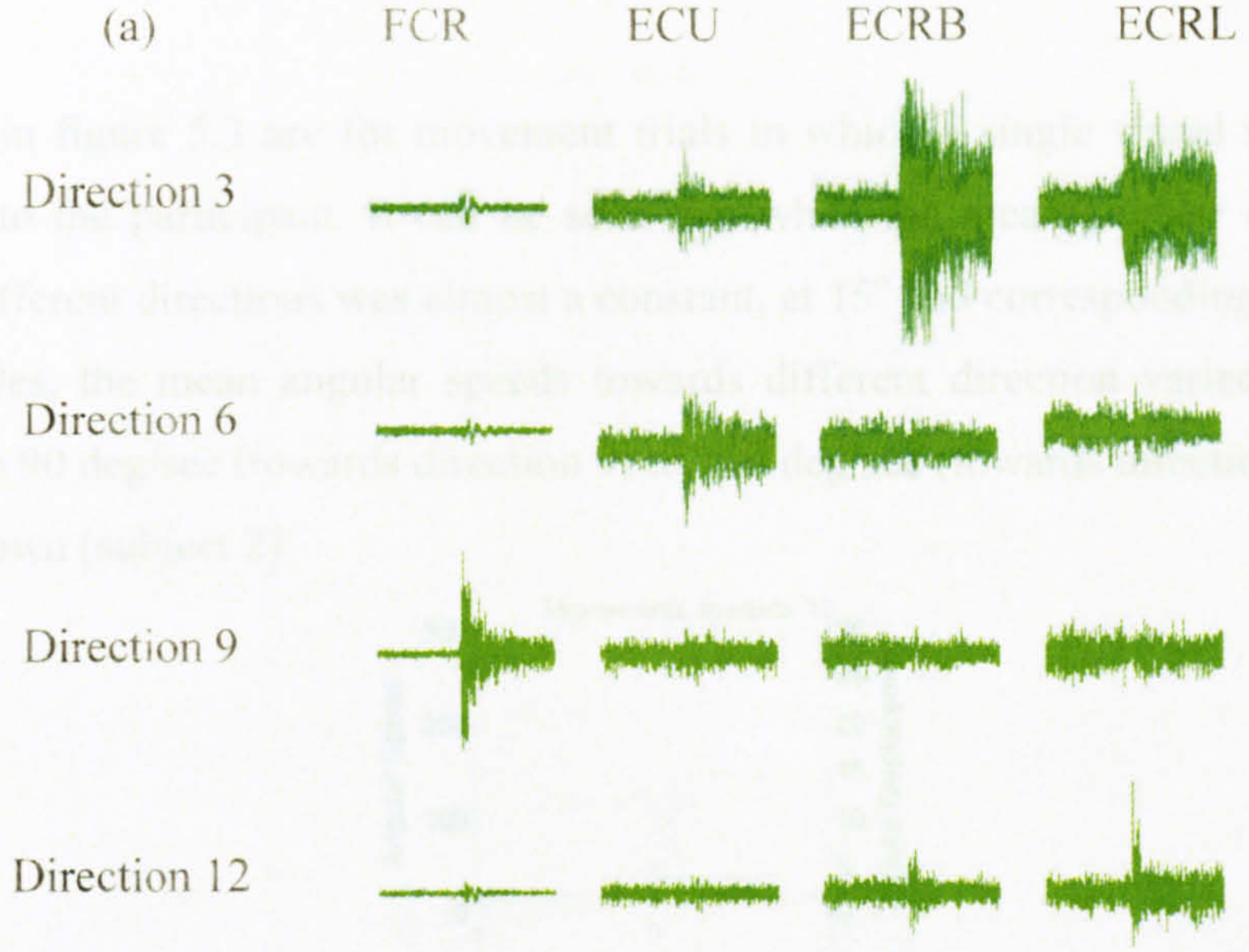


Figure 5.1 shows the EEG, EMG and the synchronization pulses recorded by the Neuroscan system.

Table 5.1 Shows the Muscles which are activated when the different movements are made.

Direction of Movement	Active Muscles
3	ECRL, ECRB and ECU
6	ECU
9	FCR
12	ECRL and ECRB

When the subject responded to the visual stimulus by moving the cursor to the target there was clear change in the EMG activity of the muscles controlling the wrist. Careful inspection of the EEG records also showed a change in the signal following target presentation and during the initial EMG bursts. Table 5.1 shows the synergist muscles that were active when wrist movements were made in different directions.



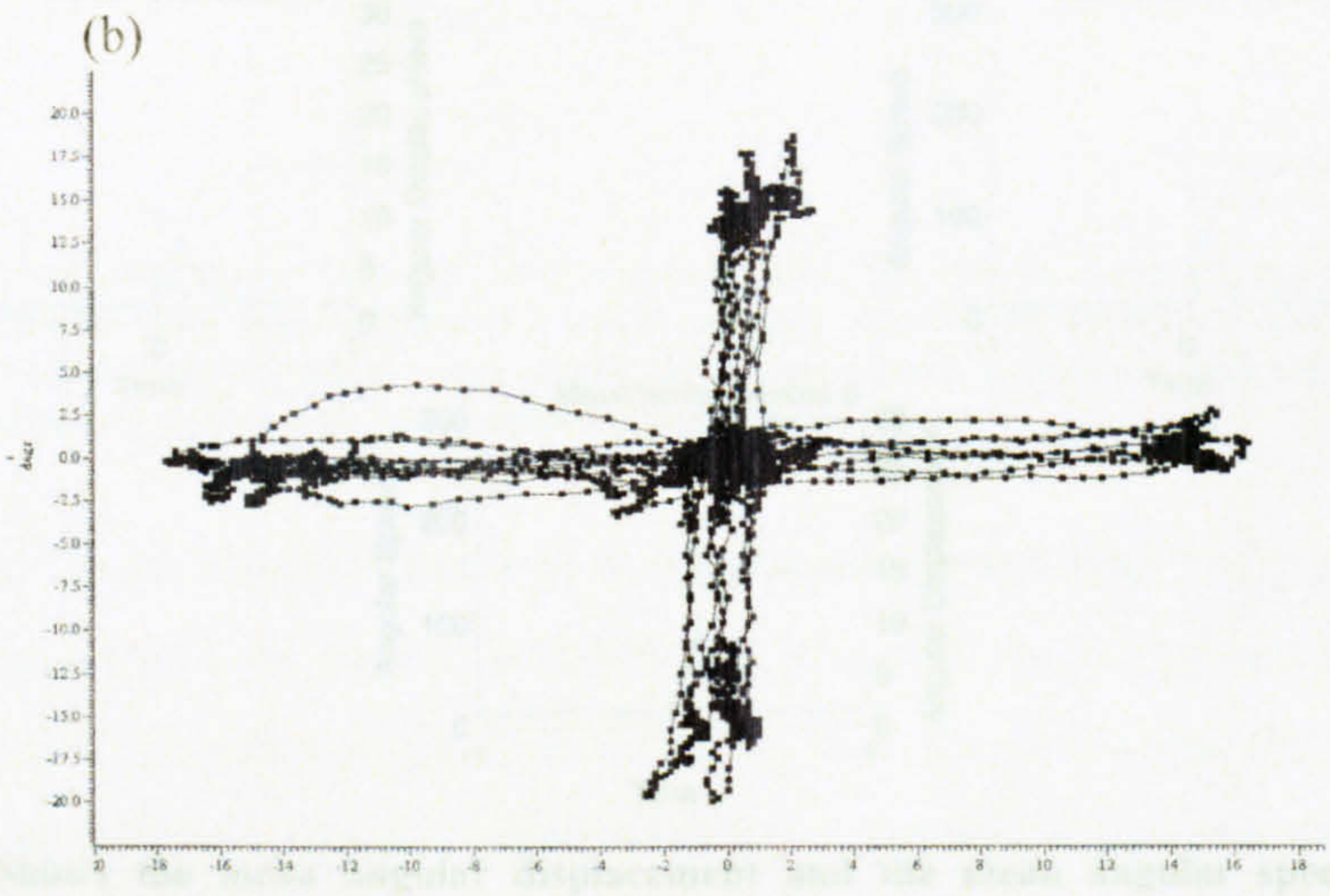


Figure 5.2 . (a). The figure shows activity of the muscles (FCR, ECU, ECRB and ECRL) as the subject performs movements toward different directions.(b). The Figure shows cursor trajectory for the 40 trials during a single session of the experiment (single visual target) for subject 2.

5.1 Kinematics

In an attempt to compare the movements made towards different direction the kinematics of the movements were studied. The results presented in this section show the mean angular displacement and speed of the wrist during movements made to different directions. Movement was initiated at time T = 0s for each of the 3 different types motor initiation tasks (externally cued, forced choice and self paced).

The plots in figure 5.3 are for movement trials in which a single visual stimulus was presented to the participant. It can be seen that while the mean angular displacement towards different directions was almost a constant, at 15° and corresponding to the target offset angles, the mean angular speeds towards different direction varied widely and range from 90 deg/sec (towards direction 9) to 110 deg/sec (towards direction 12) for the subject shown (subject 2).

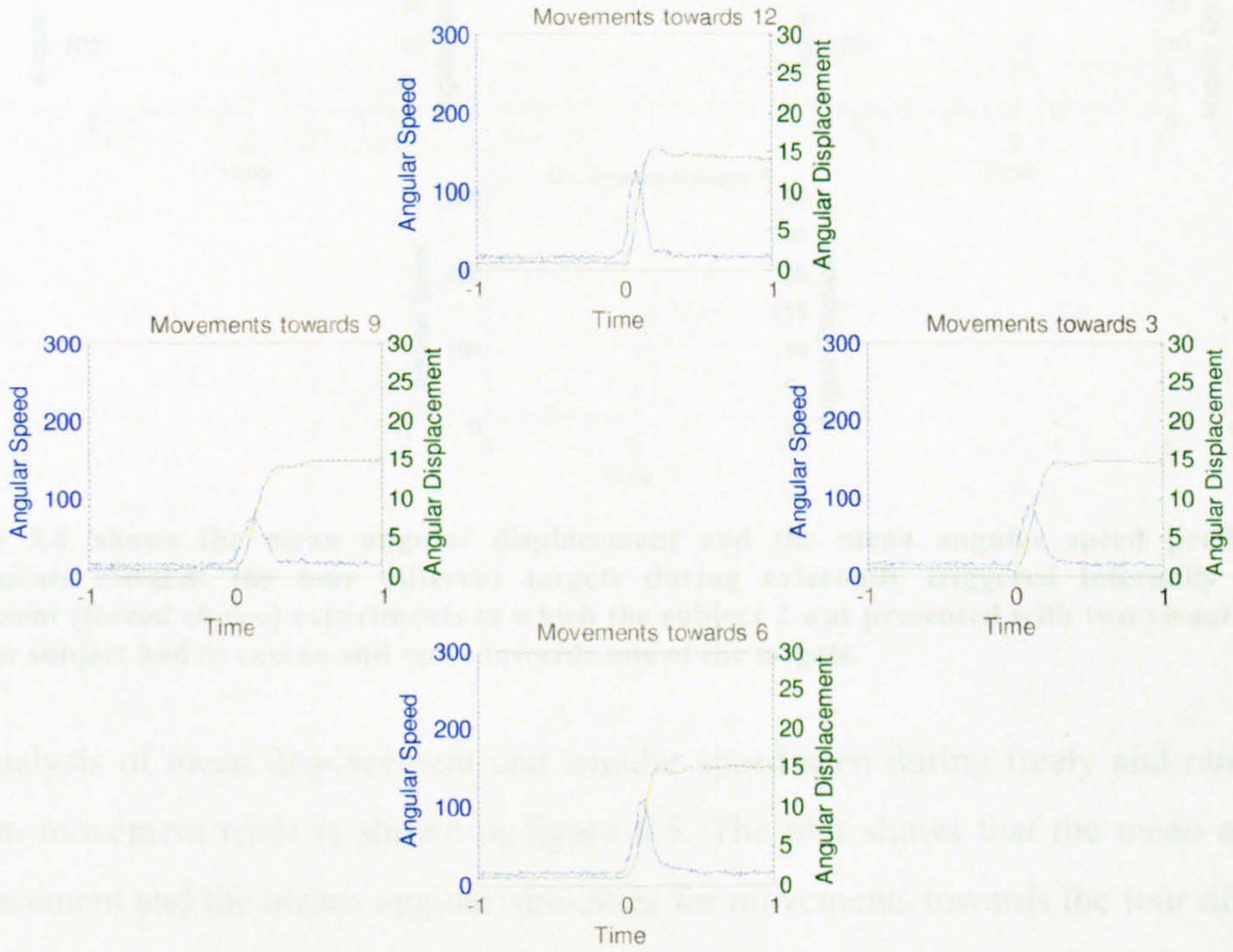


Figure 5.3 . Shows the mean angular displacement and the mean angular speed profiles for movements towards the four different targets during externally cued movement experiments in which a single visual target was presented to the subject 2.

The plots in figure 5.4 are for movement trials in which two visual stimuli were presented to the participant and the participant had to choose to move the cursor to one of the two targets (forced choice). It can be seen that again while the mean angular displacement towards the different directions was almost a constant at, approximately 15°, the mean angular speeds towards different directions varied and ranged from 75 deg/sec towards direction 9 to 125 deg/sec towards direction 12.

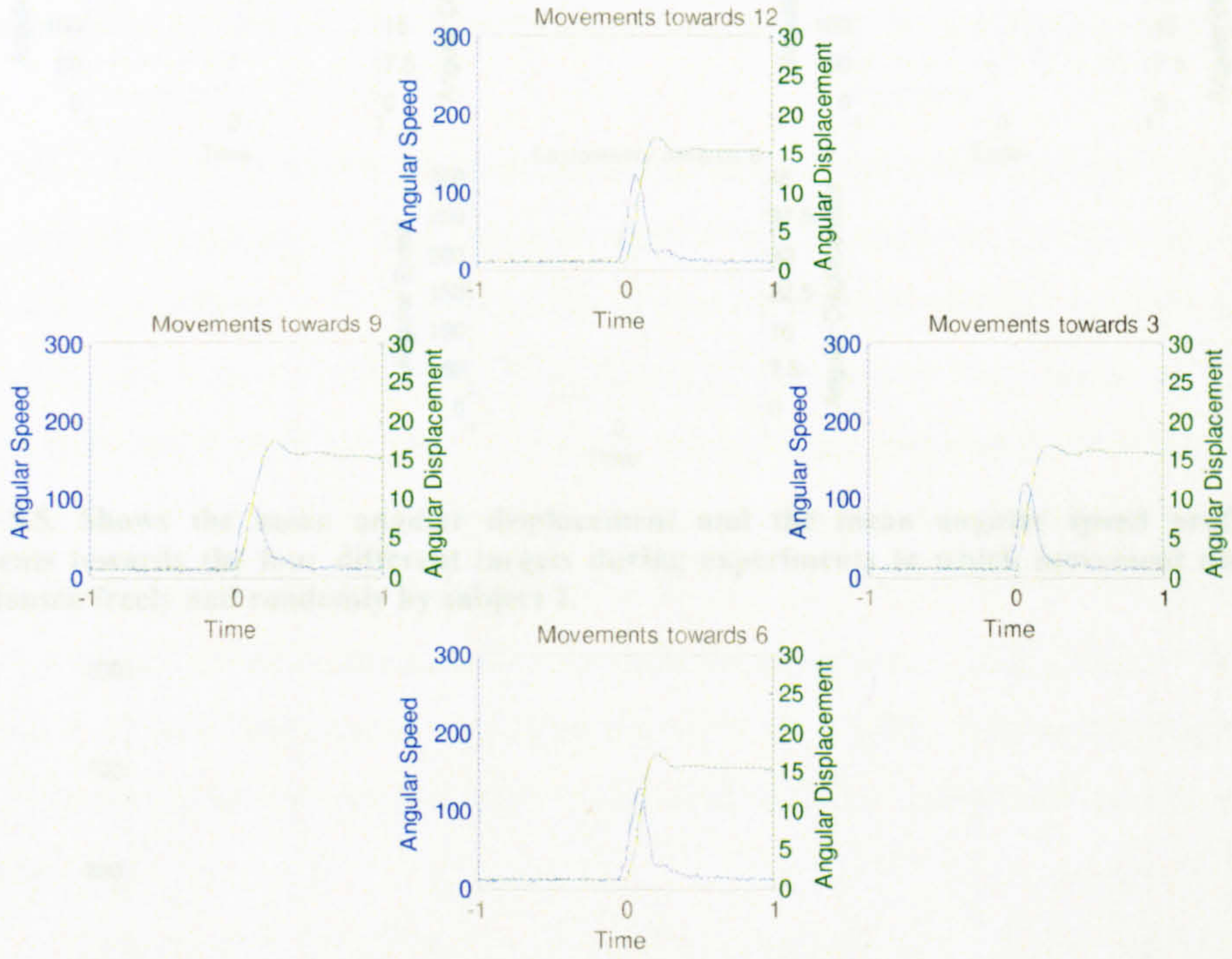


Figure 5.4 Shows the mean angular displacement and the mean angular speed profiles for movements towards the four different targets during externally triggered internally chosen movement (forced choice) experiments in which the subject 2 was presented with two visual targets and the subject had to choose and move towards one of the targets.

An analysis of mean displacement and angular speed seen during freely and randomly chosen movement trials is shown in figure 5.5. The plot shows that the mean angular displacement and the means angular velocities for movements towards the four different directions were different. In these experiments no target was shown and subjects tended to produce displacements that exceeded 15°. Accordingly these movements were associated with greater peak velocity estimates.

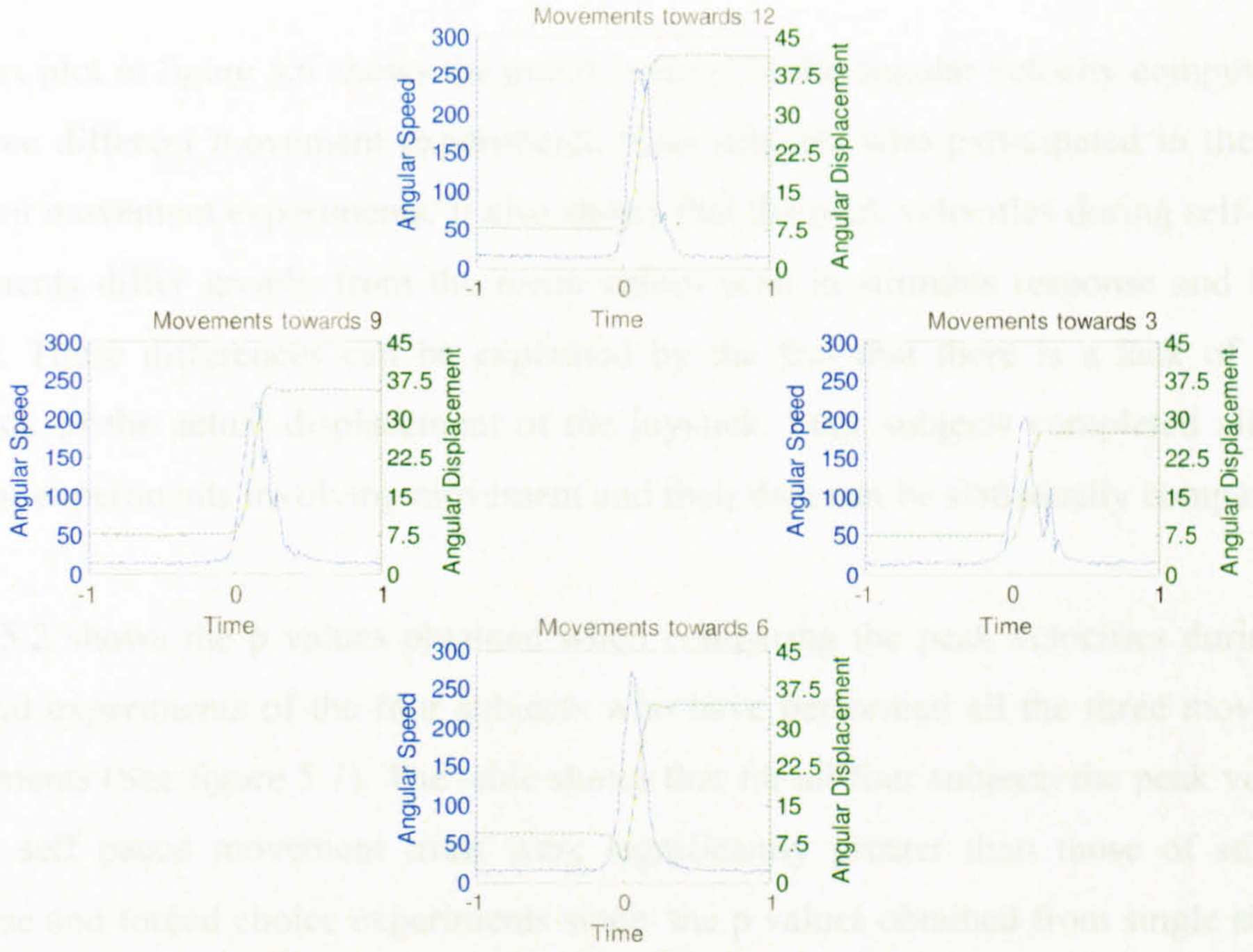


Figure 5.5. Shows the mean angular displacement and the mean angular speed profiles for movements towards the four different targets during experiments in which movement directions were choosen freely and randomly by subject 2.

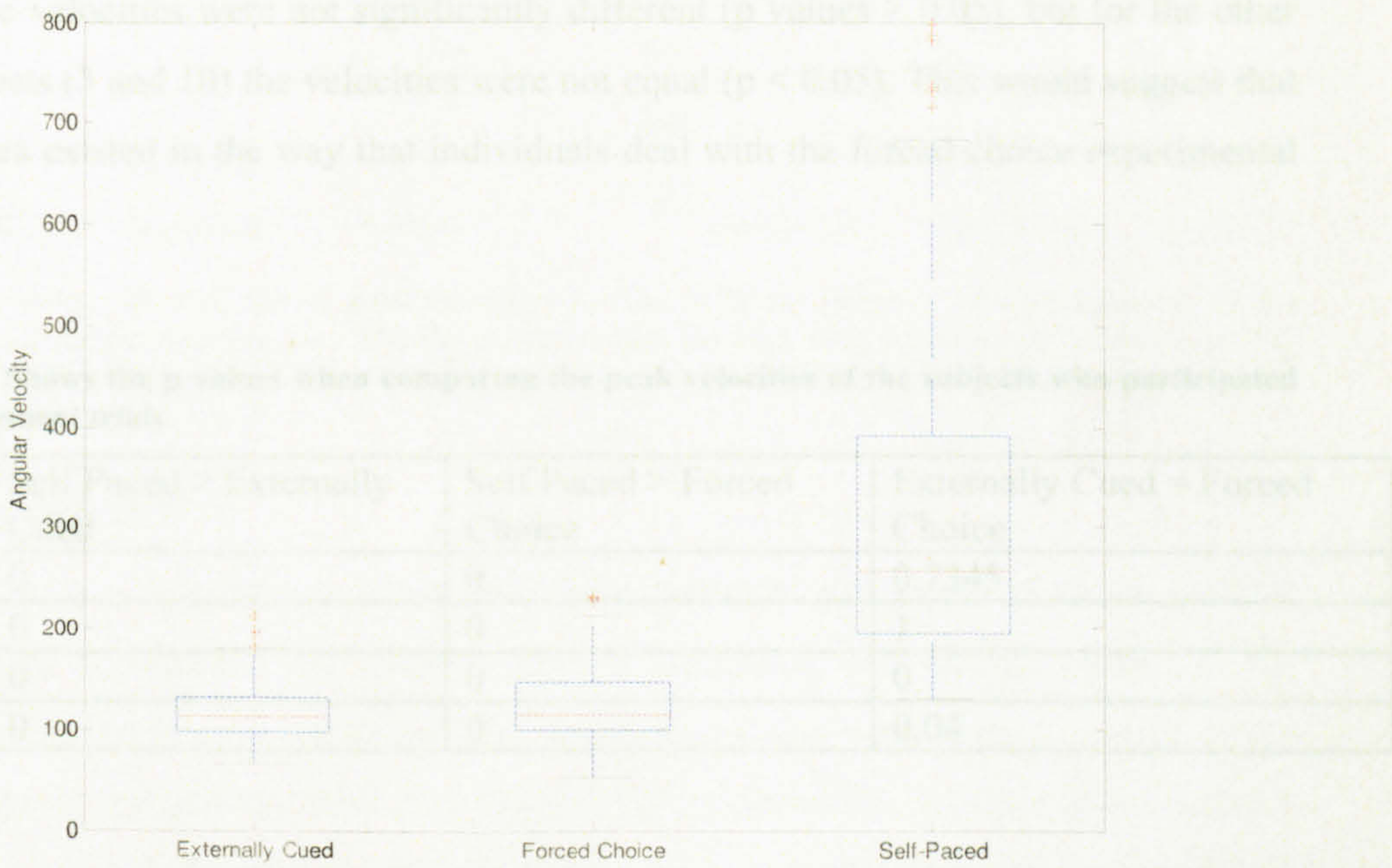


Figure 5.6. Shows the grand average angular velocity for the three different movement experiments for all subjects who participated in all movement experiments.

The box plot in figure 5.6 shows the grand average of the angular velocity computed for the three different movement experiments from subjects who participated in the three different movement experiments. It also shows that the peak velocities during self-paced movements differ greatly from the mean values seen in stimulus response and forced choice. These differences can be explained by the fact that there is a lack of visual feedback of the actual displacement of the joystick. Four subjects completed all three types of experiments involving movement and their data can be statistically compared.

Table 5.2 shows the p values obtained when comparing the peak velocities during the different experiments of the four subjects who have performed all the three movement experiments (See figure 5.7). The table shows that for all four subjects the peak velocity during self paced movement trials were significantly greater than those of stimulus response and forced choice experiments since the p values obtained from single sided t-tests were lesser than 0.05 . However while checking if the peak velocity during stimulus response and forced choice were equal it could be seen that for two subjects (1 and 2) the velocities were not significantly different (p values > 0.05), but for the other two subjects (3 and 10) the velocities were not equal ($p < 0.05$). This would suggest that differences existed in the way that individuals deal with the forced choice experimental paradigm.

Table 5.2. Shows the p values when comparing the peak velocities of the subjects who participated in all movement trials.

Subject	Self Paced > Externally Cued	Self Paced > Forced Choice	Externally Cued = Forced Choice
1	0	0	0.7345
2	0	0	1
3	0	0	0
10	0	0	0.04

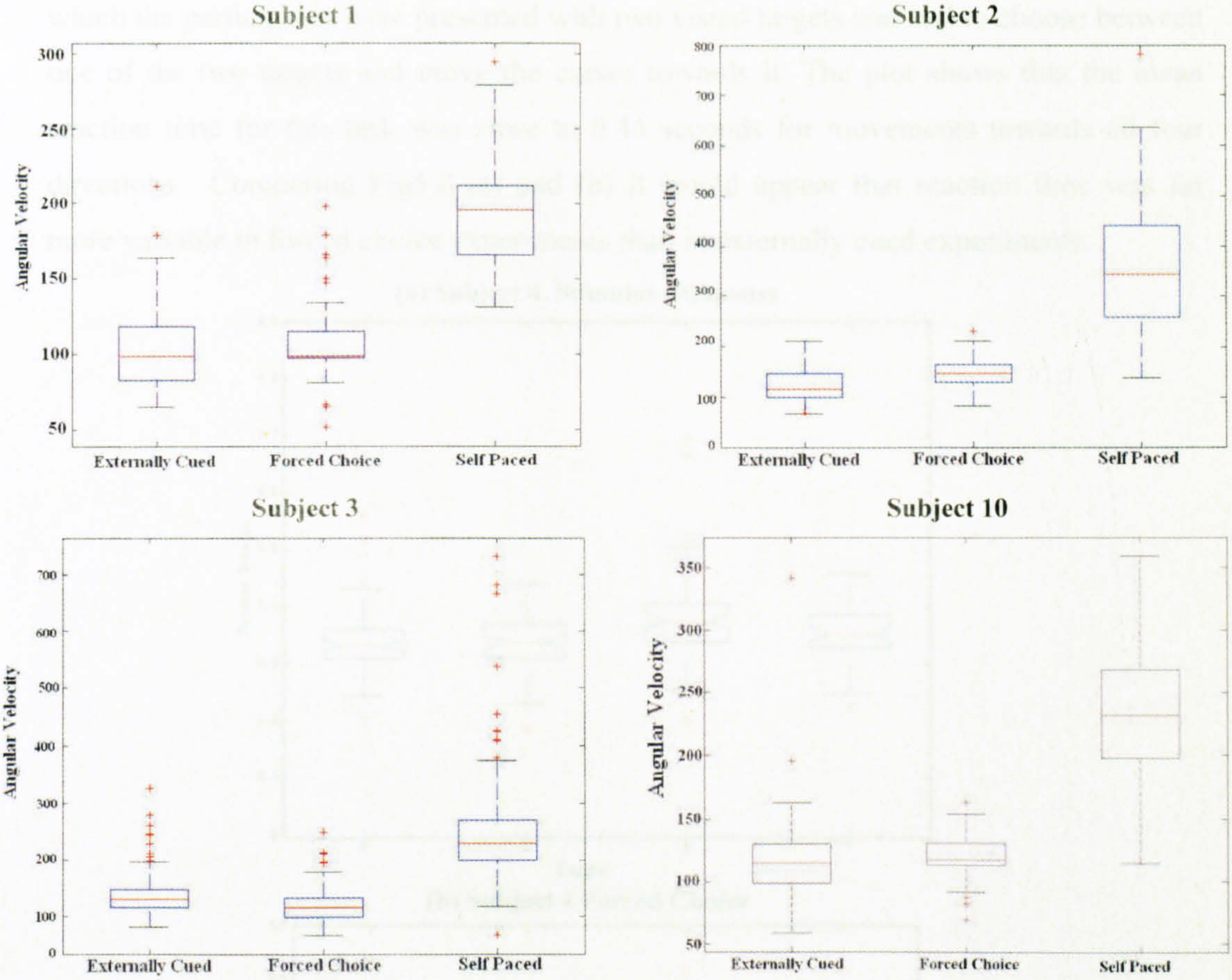


Figure 5.7 shows the box plot of peak velocities for the different subjects who participated in the different movement experiments. The figure shows that for each subject the peak velocities during self-paced trials were greater than the peak velocities reached during forced choice and externally cued movement trials.

5.2 Reaction Times

Reaction time is the time between the presentation of the visual stimulus and the initiation of movement. The reaction time is associated with the perception of the stimulus and movement planning and incorporates the time during which motor commands are being formulated by the brain. Fig 5.8 shows the box-plot of the reaction time for the two different experimental conditions (externally cued and forced choice) from subject 4. Fig 5.8a is the reaction time from experiments in which the movements

were based on a single external visual stimulus. The mean reaction times was close to 0.35 seconds for all movements. Fig 5.8b shows the reaction time from experiments in which the participants were presented with two visual targets and had to choose between one of the two targets and move the cursor towards it. The plot shows that the mean reaction time for this task was close to 0.45 seconds for movements towards all four directions. Comparing Fig5.8 (a) and (b) it would appear that reaction time was far more variable in forced choice experiments than in externally cued experiments.

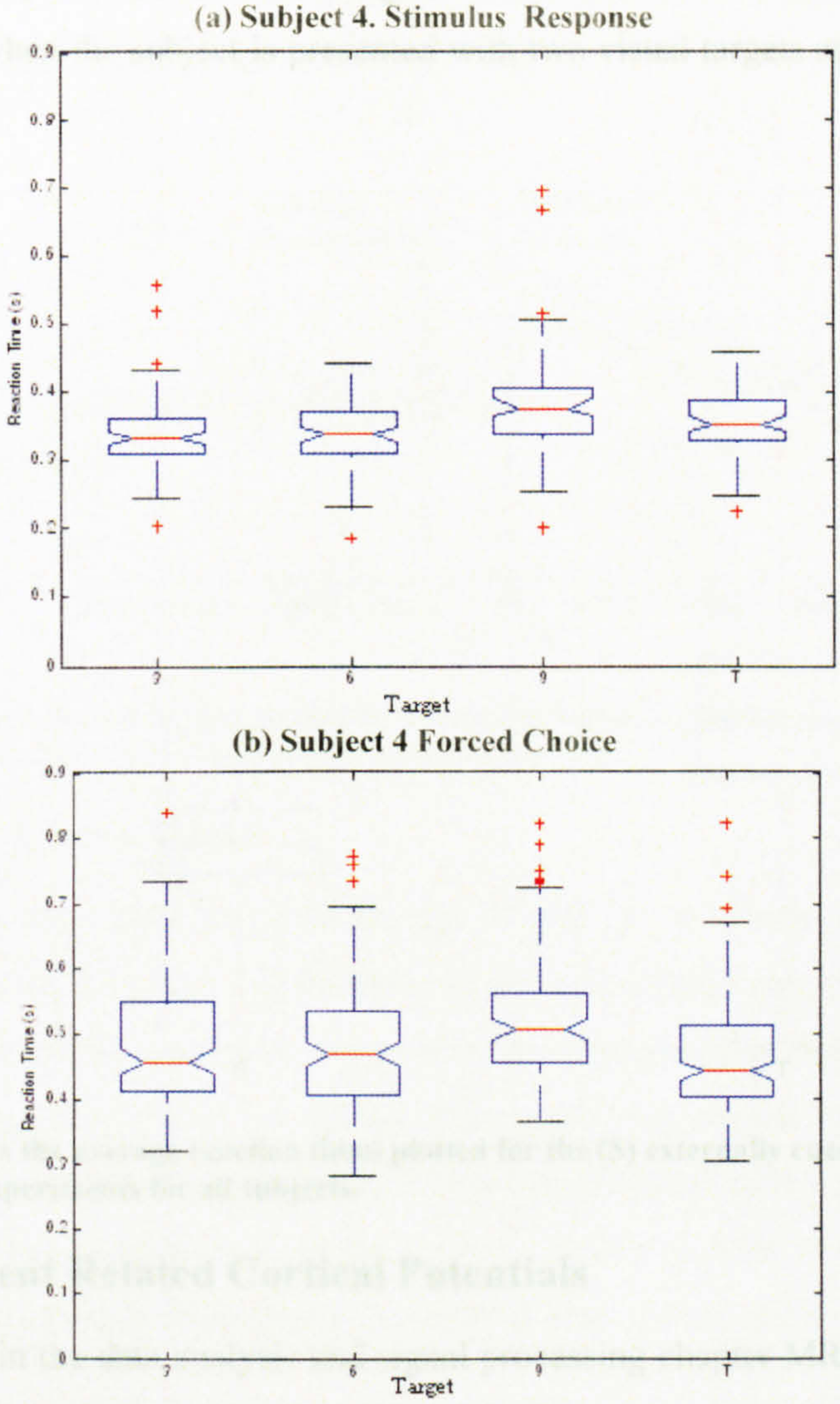


Figure 5.8 shows the reaction time for the externally cued experiments for Subject 4. (a) Shows is for the single stimulus experiments in which only a single visual target is presented to the subject. (b) The box plots show the reaction times for externally cued movements in which the subject is

presented with two visual targets and the subject has to choose and move towards one. The x-axis displays the direction moved to.

The length of the reaction time is indicative of the complexity of the task (Chapter 5 {Marteniuk, 1976). This is supported by the box-plot (see figure 5.9) which shows that reaction time in the externally cued experiments is shorter than the reaction time in the forced choice experiments. This difference in the RT was further confirmed by a two sample T-test, (p values < 0.05). Thus in the simple case where the participant has to respond to the presentation of the single visual stimulus the reaction time is generally shorter than when the subject is presented with two visual targets and has to choose and then respond.

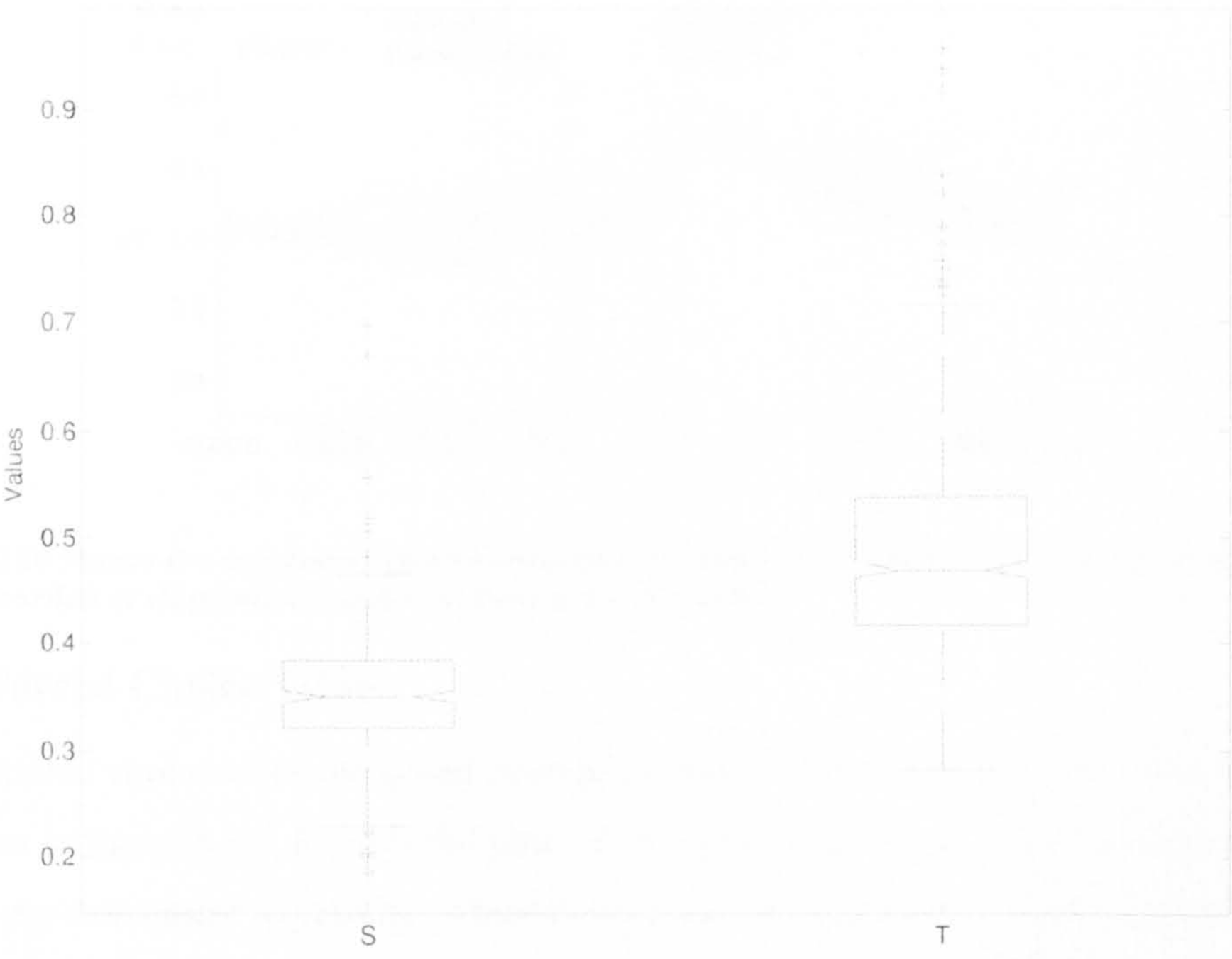


Figure 5.9 shows the average reaction times plotted for the (S) externally cued experiments and (T) forced choice experiments for all subjects.

5.3 Movement Related Cortical Potentials

As described in the data analysis and signal processing chapter MRCP's were estimated by simple triggered time averages using the onset of movement times or stimulus presentation time as triggers for movement and imagined movement trials respectively.

5.3.1 Externally Cued Movement Trials

Figure 5.10 shows the grand average of the MRCP waveforms, recorded at C3 and re-referenced to the common average reference (CAR), during movement towards the four different directions in externally cued trials. T = 0 is the point of movement initiation. The figure shows a slight negativity of the waveform before the initiation of movement. But in general each MRCP displayed a similar rise time to the peak before the potential slowly returned to baseline and no major differences were apparent in the waveform morphologies that would be easy to characterize.

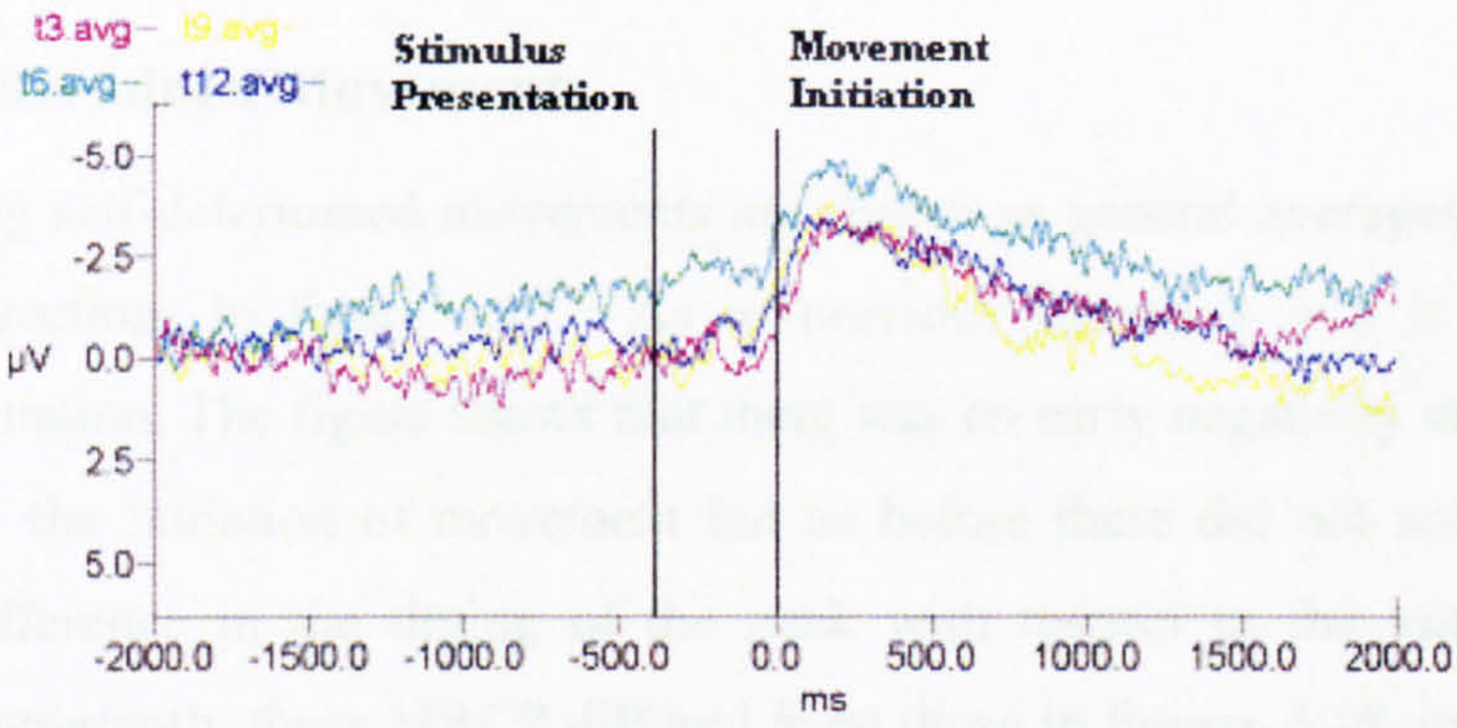


Figure 5.10 Shows the movement related potentials for Subject 1 during externally cued movement trials recorded at electrode C3 and re-referenced to the CAR.

5.3.2 Forced Choice Trials

In the forced choice trials the grand average of MRCP waveforms to different directions is shown in figure 5.11. T = 0 is the point of movement initiation. Here the figure shows a clear pre-movement negativity. Once more it can be seen that there did not seem to be any significant difference in the timing of the peak with respect to the initiation of the movement but there appeared to be differences in the amplitude of the waves observed after movement initiation and in their time associated with the return to baseline. However these changes were relatively small in terms of the difference in voltage levels measured.

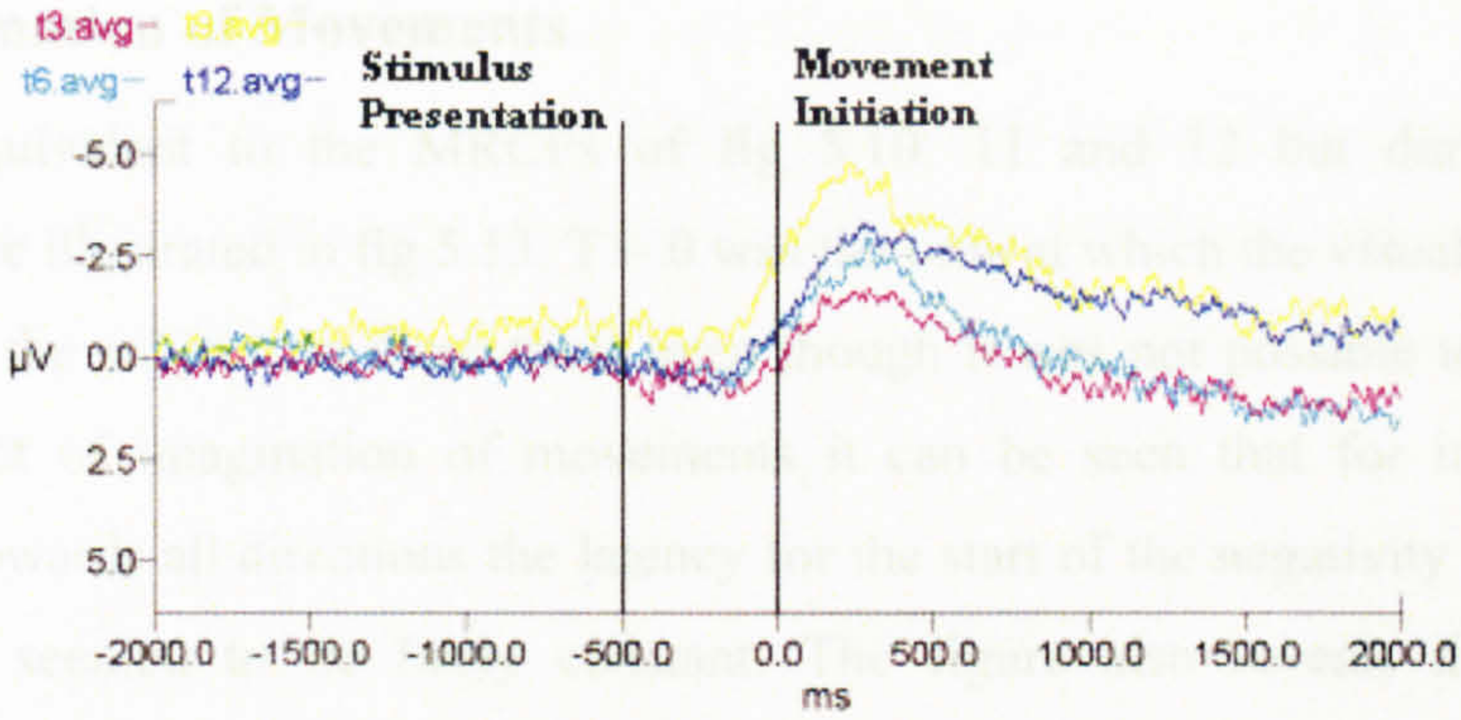


Figure 5.11 Shows the movement related potentials for the CAR derived signal from electrode C3 for Subject 1 during movement from forced choice trials.

5.3.3 Self Determined Movements

MRCPs during self-determined movements are shown as general averages for different movement directions in figure 5.12. As in previous figures T = 0 is the point of movement initiation. The figure shows that there was an early negativity starting almost 500ms before the initiation of movement but as before there did not seem to be any significant difference in the timing of the peak with respect to the initiation of the movement. Importantly these MRCP differed from those in figures 5.10 and 5.11 in that the pre-movement negativity started earlier in all movements. This is discussed further in the section 5.3.6 below. There was also evidence of amplitude differences in relation to the size of the peak associated with movement toward position 6.

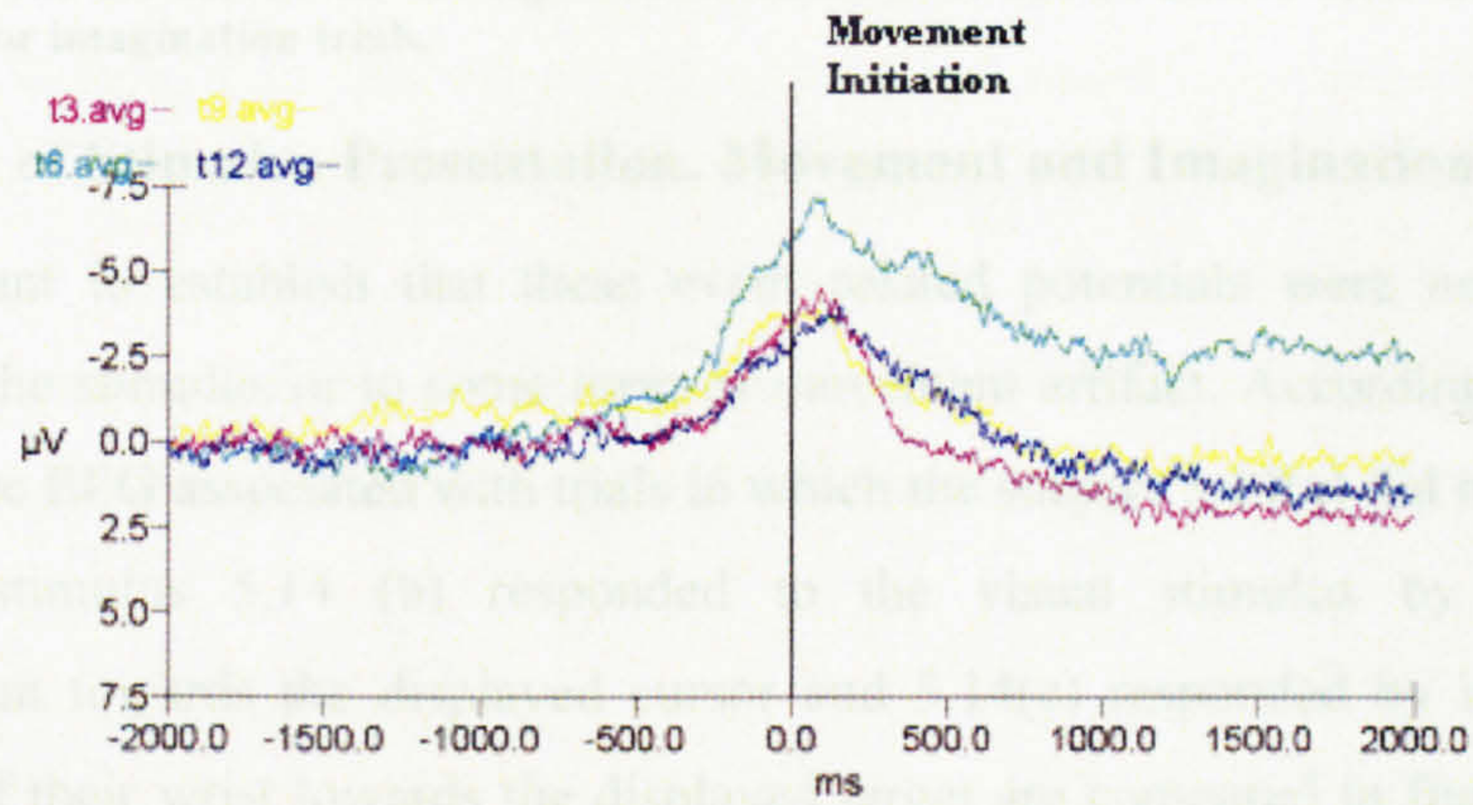


Figure 5.12 Shows the movement related potentials for the signal recorded at electrode C3 and re-referenced to the CAR for Subject 1 during self-determined movement trials.

5.3.4 Imagination of Movements

Averages equivalent to the MRCPs of fig 5.10, 11 and 12 but during imagined movement are illustrated in fig 5.13. T = 0 was the time at which the visual triggers were presented to the subject. In these trials even though it was not possible to measure the time of onset of imagination of movements it can be seen that for imagination of movement towards all directions the latency for the start of the negativity after stimulus presentation seemed to be fairly constant. The figure also reveals that while the morphologies were similar there were differences in the peak negativity with imagined motion to target 3 generating a larger peak amplitude than for other targets.

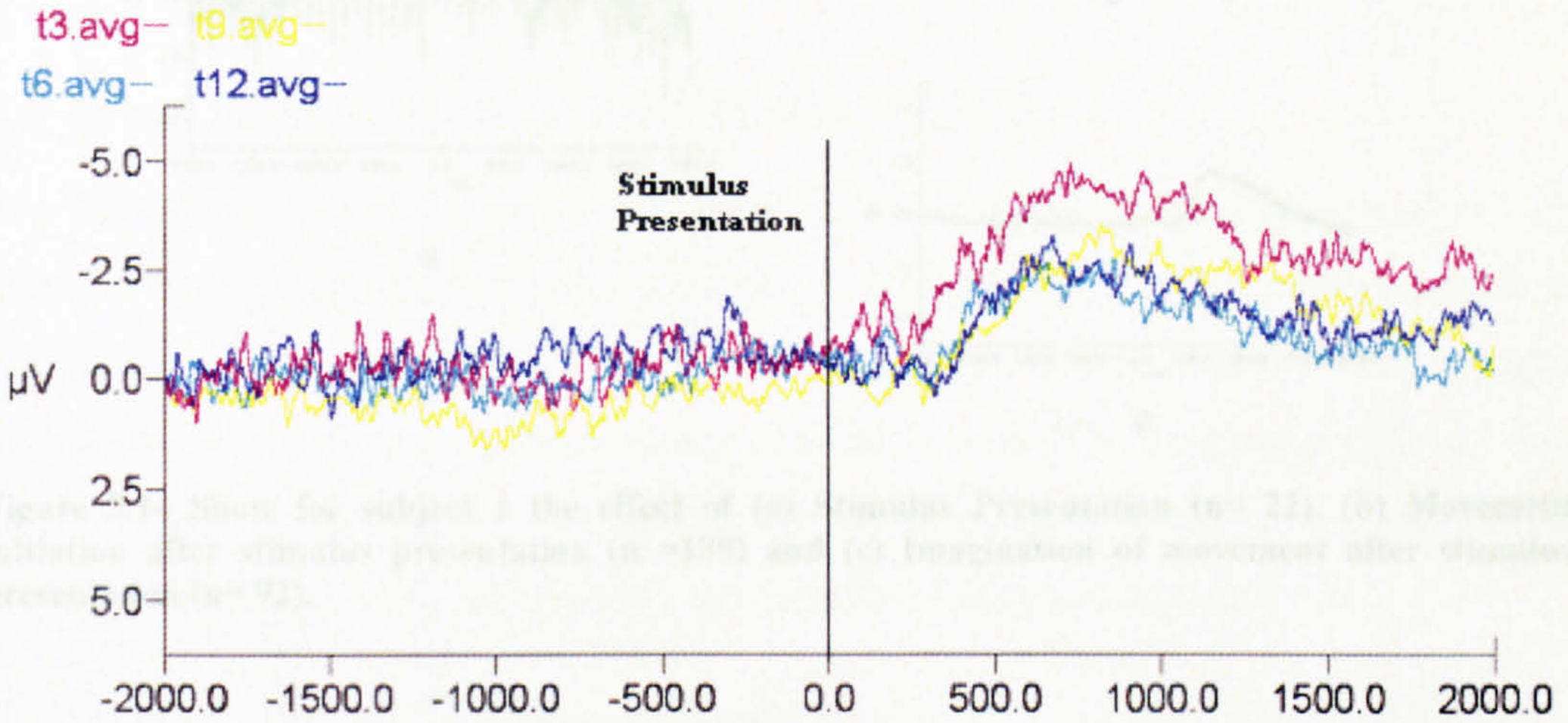


Figure 5.13 Shows the MRCP for the signal recorded at electrode C3 and re-referenced to the CAR for Subject 1 for imagination trials.

5.3.5 Effect of Stimulus Presentation, Movement and Imagination

It is important to establish that these event related potentials were not simply the response to the stimulus or to some form of movement artifact. Accordingly, the grand average of the EEG associated with trials in which the subject 5.14(a) did not respond to the visual stimulus 5.14 (b) responded to the visual stimulus by moving the manipulandum towards the displayed cursor and 5.14(c) responded by imagining the movement of their wrist towards the displayed target are compared in figure 5.14. The figure reveals that changes seen in the EEG recorded during movement and imagination

cannot be explained by visual evoked potentials, as no clear VEP is seen at the C3 electrode site in response to the appearance of the targets. In addition, figures 5.14 b and c are very similar in shape and strongly suggests that movement artifact can also be related as there is no movement in the trials used to construct figure 5.14c.

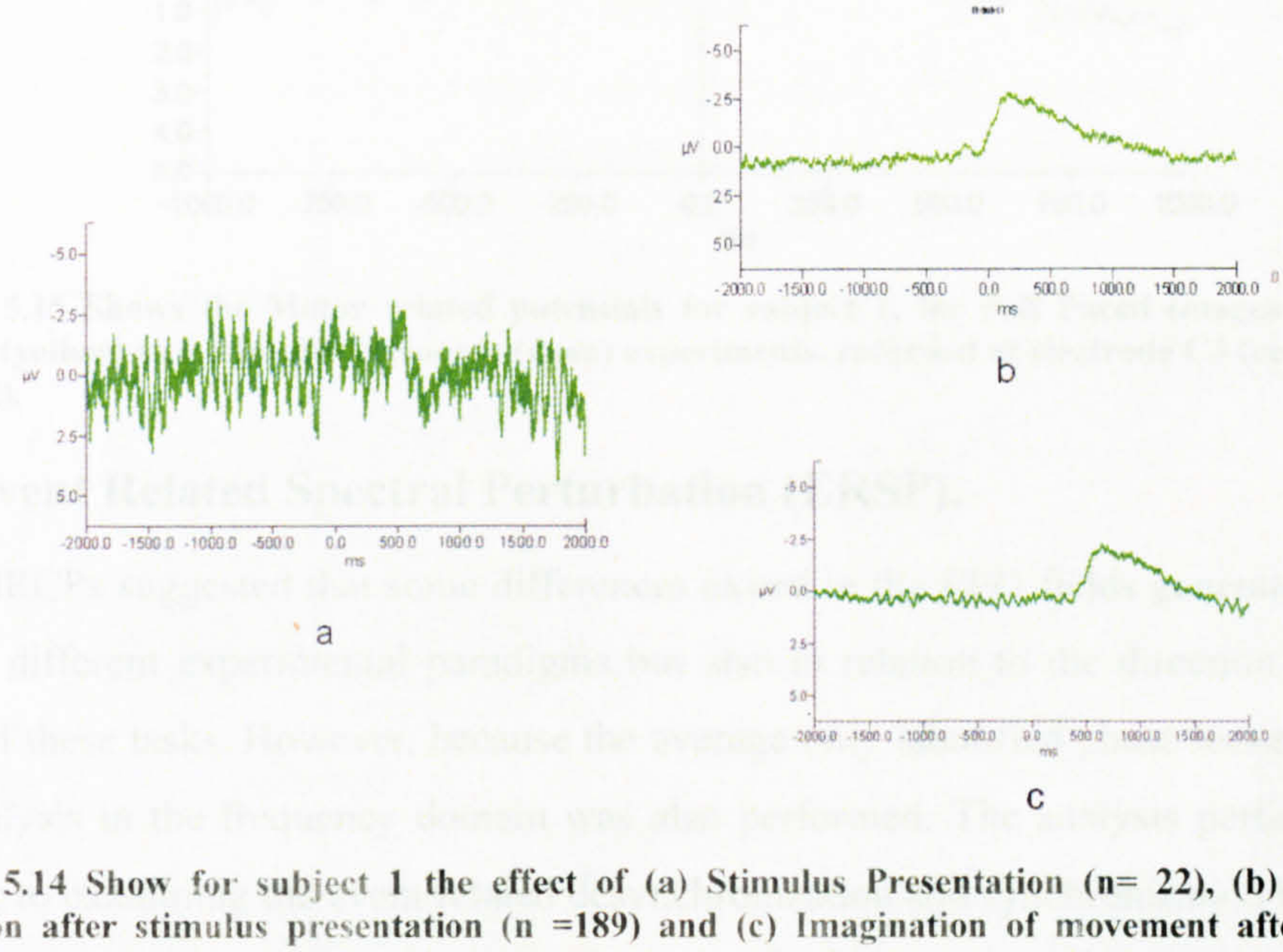


Figure 5.14 Show for subject 1 the effect of (a) Stimulus Presentation (n= 22), (b) Movement initiation after stimulus presentation (n =189) and (c) Imagination of movement after stimulus presentation (n= 92).

5.3.6 Comparing Externally Cued and Self Determined Movements

The figure 5.15 shows the MRCP recorded at electrode C3 for movements that were made based on an external cue (cyan and yellow) and volitional movements (magenta) for Subject 1. The figure shows that there was an earlier start to the slow negativity for self determined movements compared to movements initiated during externally cued conditions (stimulus response and forced choice). The waveform also peaked earlier and was of shorter duration than externally cued and forced choice trials.

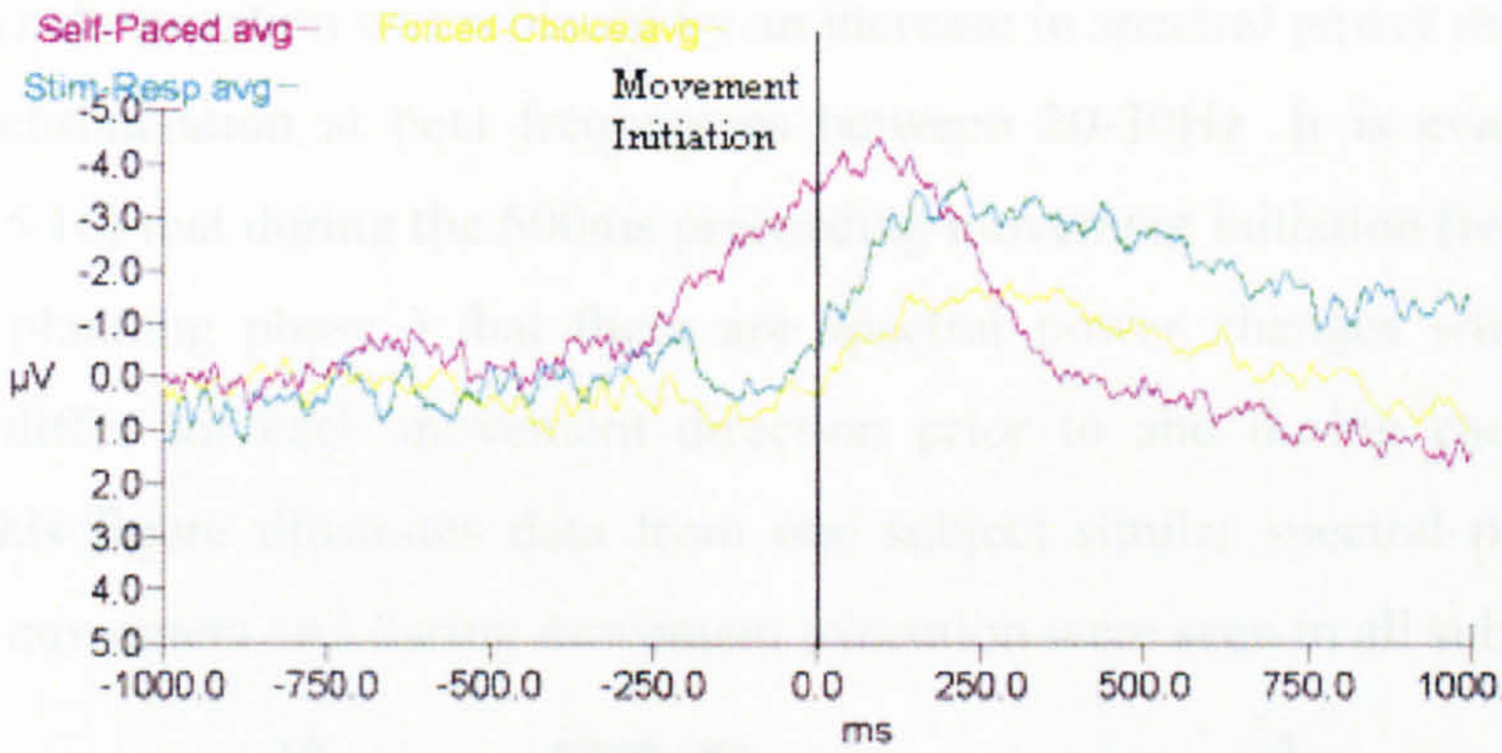


Figure 5.15 Shows the Motor related potentials for subject 1, for Self Paced (magenta), Forced Choice (yellow) and Stimulus Response (cyan) experiments, recorded at electrode C3 (re-referenced to CAR).

5.4 Event Related Spectral Perturbation (ERSP).

The MRCPs suggested that some differences exited in the EEG fields generated in each of the different experimental paradigms but also in relation to the direction moved in each of these tasks. However, because the average only identified phase locked changes an analysis in the frequency domain was also performed. The analysis performed was similar to examining the event related desynchronization and synchronization but looked at the entire spectrum of interest rather than specific frequency bands.

5.4.1 Externally Cued Movement Trials

In order to identify EEG signals generated locally to the motor cortex during each task condition it was decided to compute the common reference signal at the C3 electrode. This was a bipolar derivative of the C3 signal minus the average of all surrounding electrodes. This derived C3 signal was therefore highly localized and was then subjected to frequency domain analysis. All ERSP graphs shown in this section were computed from CAR derivative of the C3 recording. Figure 5.16 shows the ERSP associated with the CAR signal recorded at electrode (C3) when the subject made movements in different directions . T = 0 was the point of movement initiation as determined from the kinematic data. After the onset of the movement a prolonged desynchonization at frequencies in the alpha frequency range was seen (see individual plots). The figure also shows that at higher frequencies between 20-30 Hz, after movement initiation the event

related desynchronization was replaced by an increase in spectral power indicating event related synchronization at beta frequencies between 20-30Hz .It is evident from the figure (Fig 5.16) that during the 500ms preceeding movement initiation (reaction time or movement planning phase) that there are spectral power changes which on visual inspection differ for each movement direction prior to and during each movement. Although this figure illustrates data from one subject similar spectral power changes preceeding movement and during movement execution were seen in all subjects.

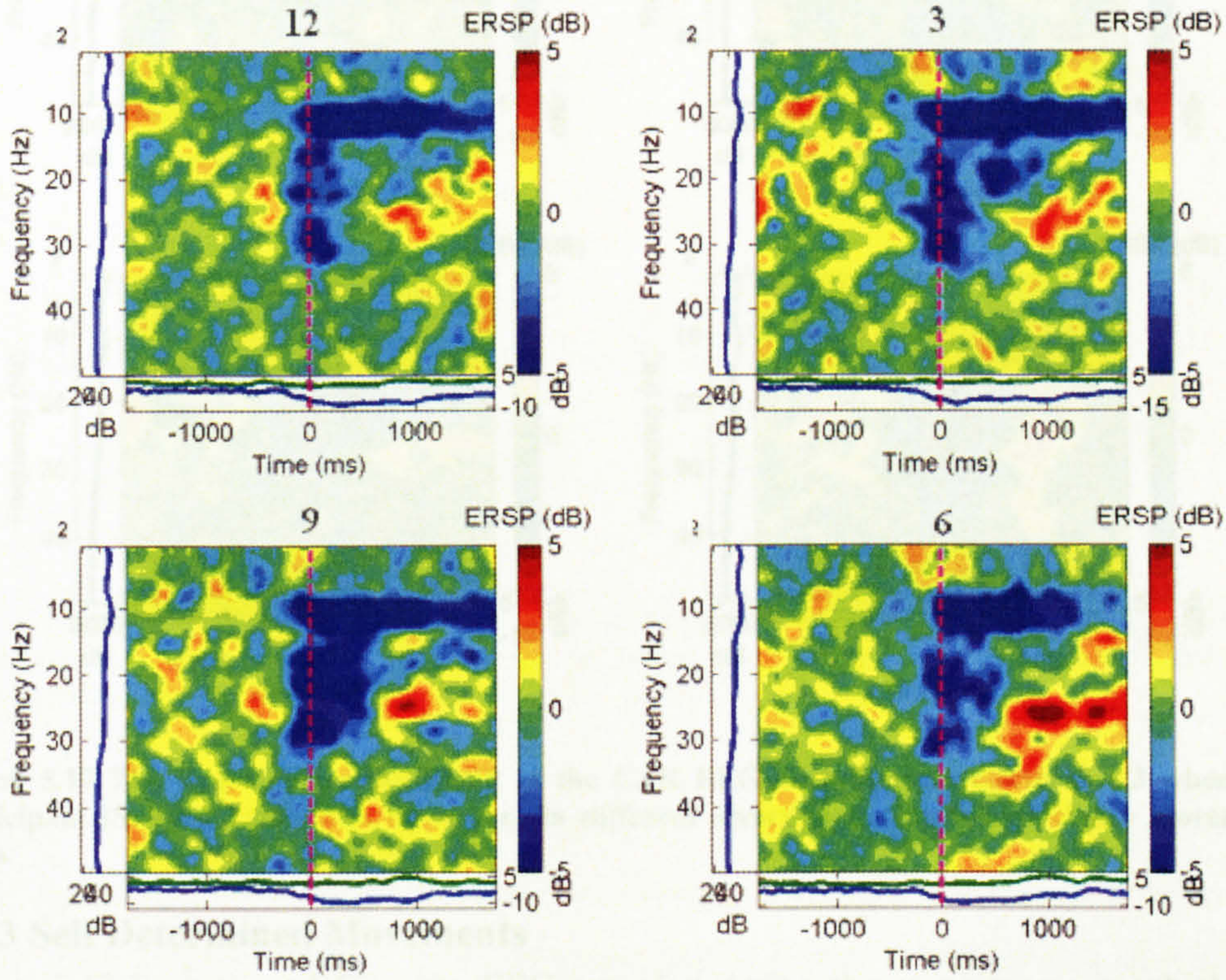


Figure 5.16 The figure shows the ERSP for the EEG recorded from electrode C3 and re-referenced to the CAR when Subject 1 initiates movement in different direction based on external cue.

5.4.3 Forced Choice Trials

Figure 5.17 is generated from the EEG recorded during experiments using the forced choice trial described in section 3.1.3. As in the previous results, T=0 is the time at which movement was initiated and the graphs related to recording from the C3 – CAR derived EEG. Just prior to and after the onset of movement each showed a prolonged period of desynchonization at frequencies in the alpha frequency range. The figure also

showed an event related synchronization after the initial event related desynchronization at frequencies between 20-30 Hz after movement initiation .Premovement spectral changes were also evident and appeared to vary with each direction of movement.

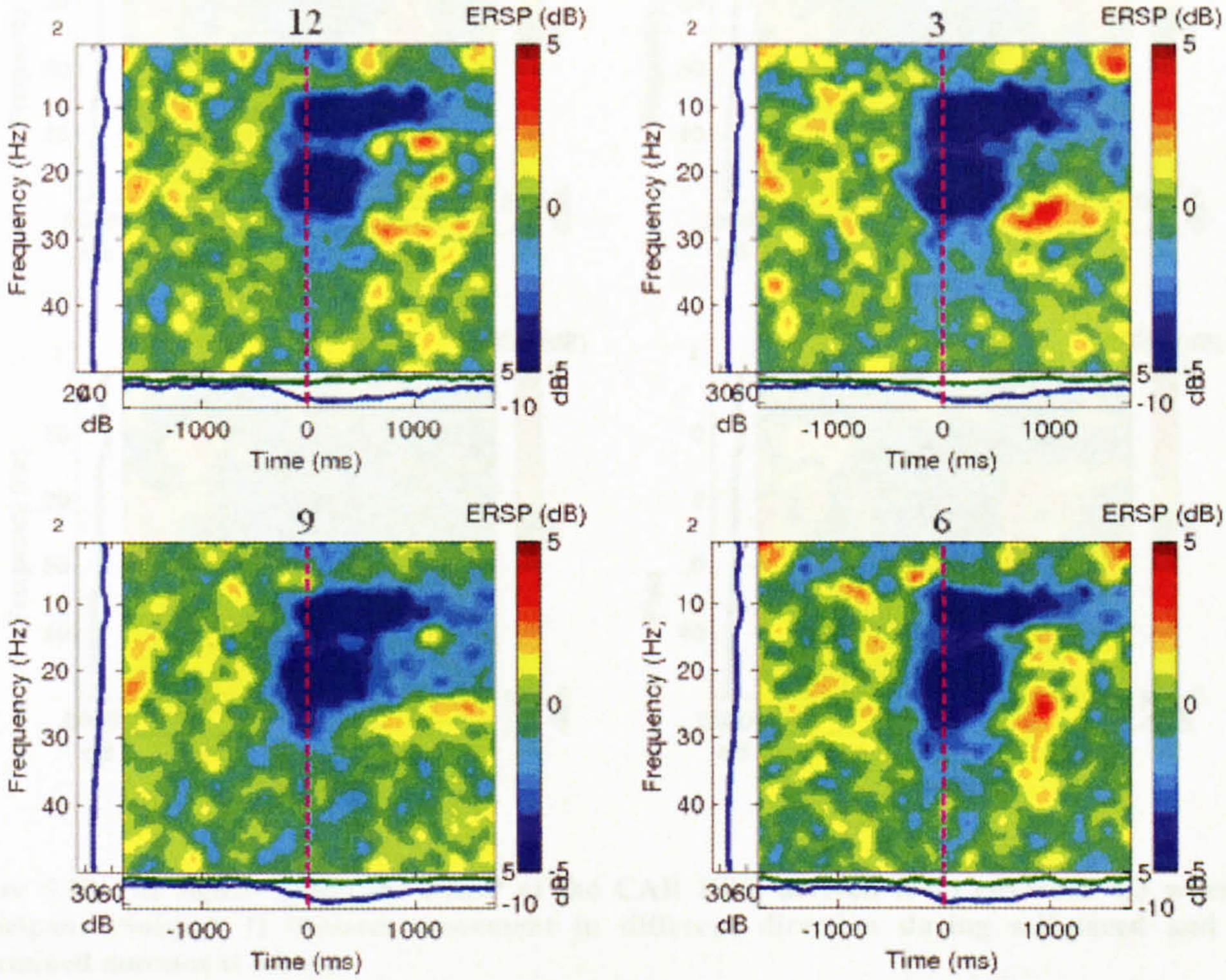


Figure 5.17 The figure shows the ERSP of the CAR EEG derived from electrode C3 when the participant (Subject 1) initiates movement in different direction during forced choice movement trials.

5.4.3 Self Determined Movements

Figure 5.18 is generated from the EEG recorded during the experiments in which the subjects make movements based on their own on choice of directions as described in section 3.1.4. As in the previous example T=0 is the time at which movement was initiated. The plots revealed a period of prolonged desynchronization of frequencies in the alpha range and event related synchronization prior to and during movement. However, it would also appear that the ERD at 10Hz was prolonged when compared with that seen in the other situations.

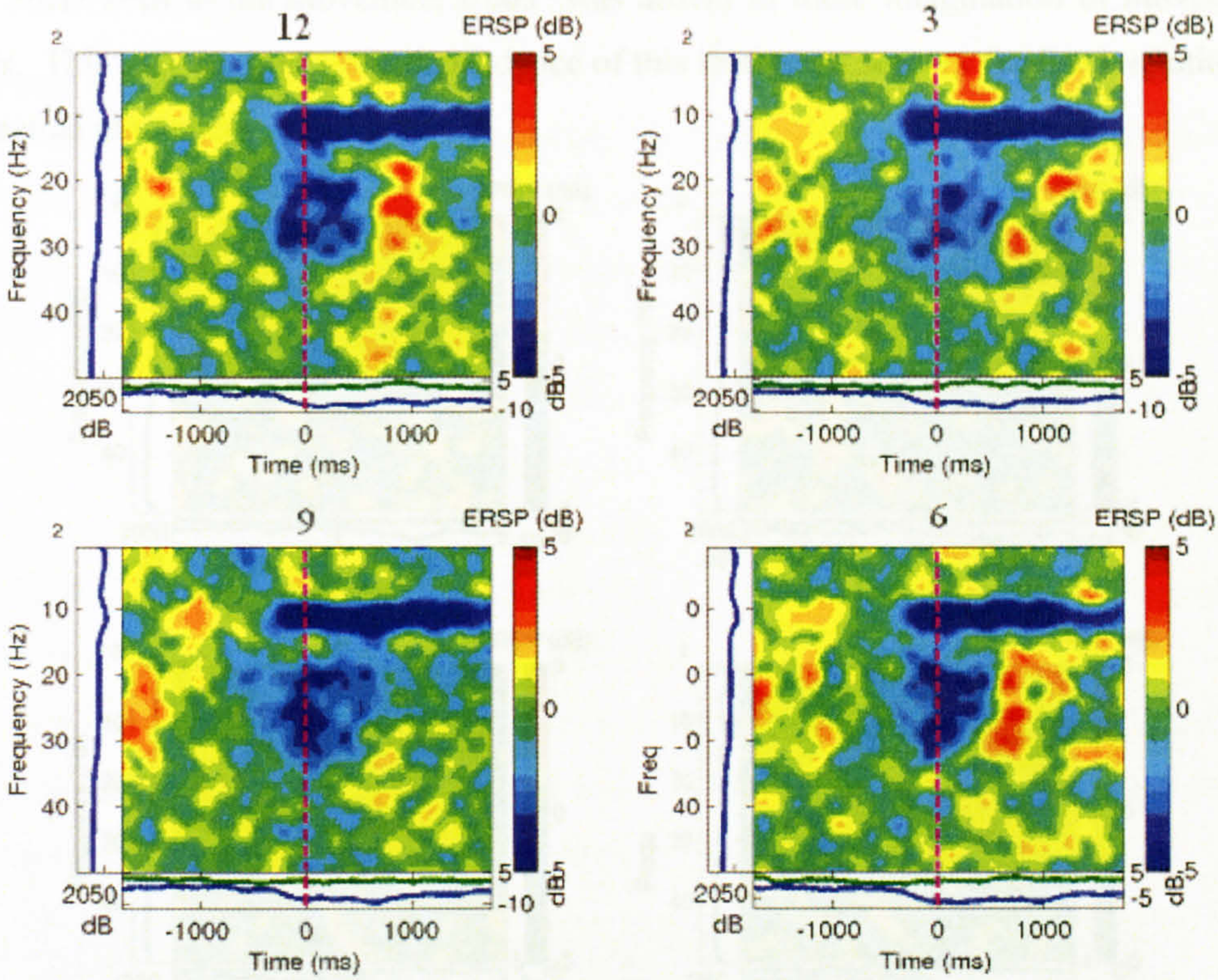


Figure 5.18 The figure shows the ERSP of the CAR EEG derived from electrode C3 when the participant (Subject 1) initiates movement in different direction during self-paced and self-determined movement trials.

5.4.4 Imagination of Movements

Figure 5.19 shows the ERSP associated with the CAR signal recorded at electrode (C3) when the subject (S1) imagines movement towards different directions (t=0 is time of target presentation). After a delay of approximately 500ms post visual stimulus, a prolonged desynchonization occurred at frequencies in the alpha frequency range and also at the higher beta frequency ranges between 20-30 Hz. From these figure it was evident that in addition to being similar to the ERSP obtained from movement trials there were differences in the ESRP obtained from imagination of movement to different directions and this observation strongly suggested that the EEG response to imagined movements could be used for classification purposes. It is to be noted here that the event related synchronization that followed the event related desynchronization between 20Hz

and 30Hz seen in the movement trials was absent in these imagination of movement trials. This may suggest some dependence of this feature on sensory feedback relating to the actual movement.

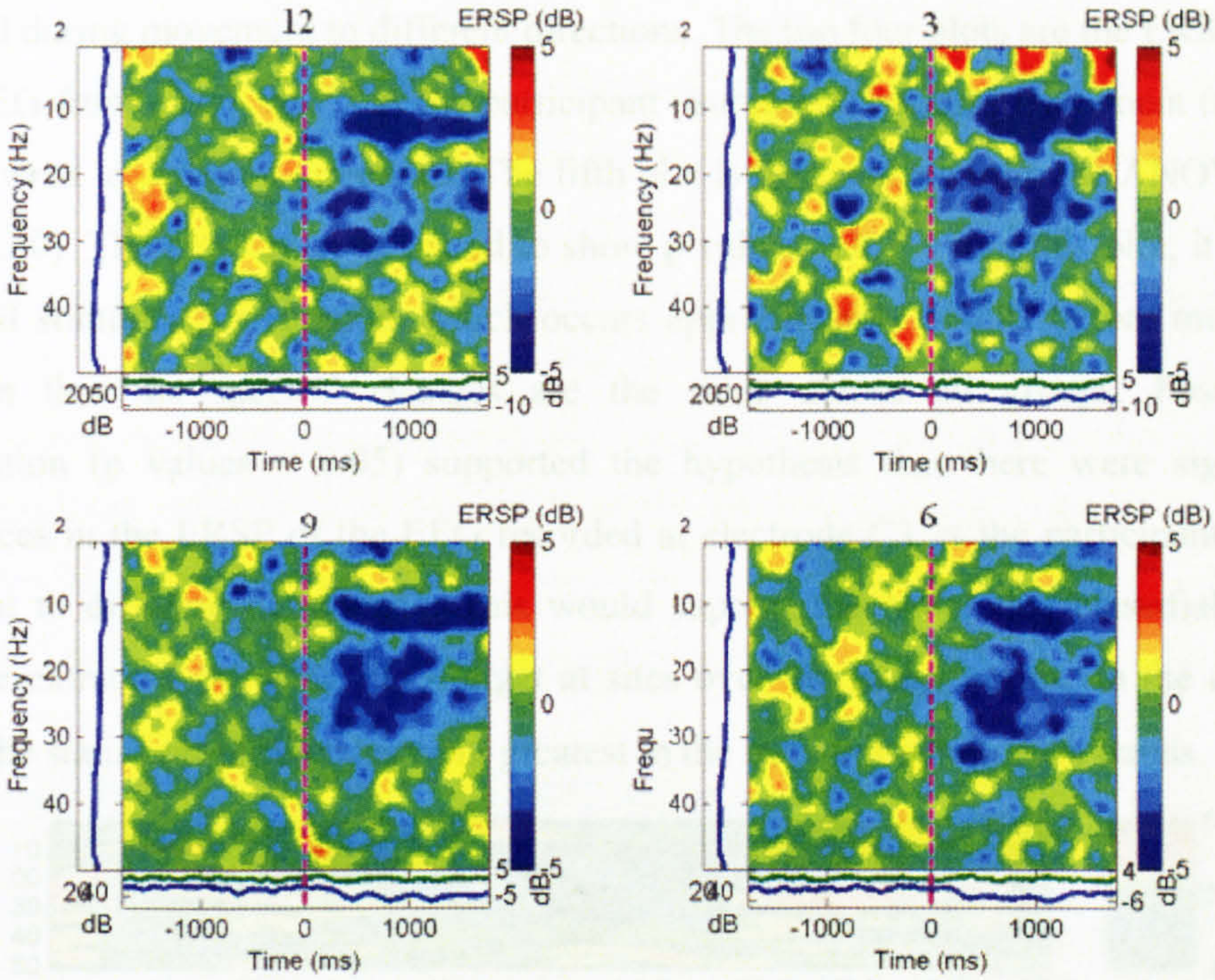


Figure 5.19 The figure shows the ERSP of the CAR EEG obtained from electrode C3 when the participant (Subject 1) imagines movement in different direction based on an external cue.

5.5 Statistical Differences in ERSP

The features selected for BCI classification on single trials must be robust and consistent across all trials. Accordingly there is a need to measure the statistical reliability of the features that can be used to distinguish the EEG in different experimental conditions (different experimental protocols) and classes (different movement directions). To achieve this an ANOVA approach was used to examine where time and frequency differences may have existed. The results presented here were obtained by performing ANOVA for ERSP values obtained from the EEG for different experimental conditions. The results shown were taken from a single subject but similar results were obtained for all subjects.

5.5.1 Effect of movement to different directions

Stimulus Response Trials

These results were obtained by comparing the ERSP values obtained from the EEG recorded during movement to different directions. The top four plots are the ERSP of the CAR EEG from electrode C3 as the participant (Subject 1) initiates movement (at t = 0) of their wrist in different directions. The fifth plot is the p values from the ANOVA (see figure 5.20). The plot has been scaled to show p values < 0.1. From this plot, it is clear that until stimulus presentation, which occurs approximately 500ms before movement initiation that the spectral changes are the same across all groups. Post target presentation (p values < 0.05) supported the hypothesis that there were significant differences in the ERSP of the EEG recorded at electrode C3 as the participant moved the wrist to different directions. This would support the belief that classifiable data could be extracted from the EEG target at sites over the motor cortex. In the example shown the statistical differences were greatest in the α, β and γ frequency bands.

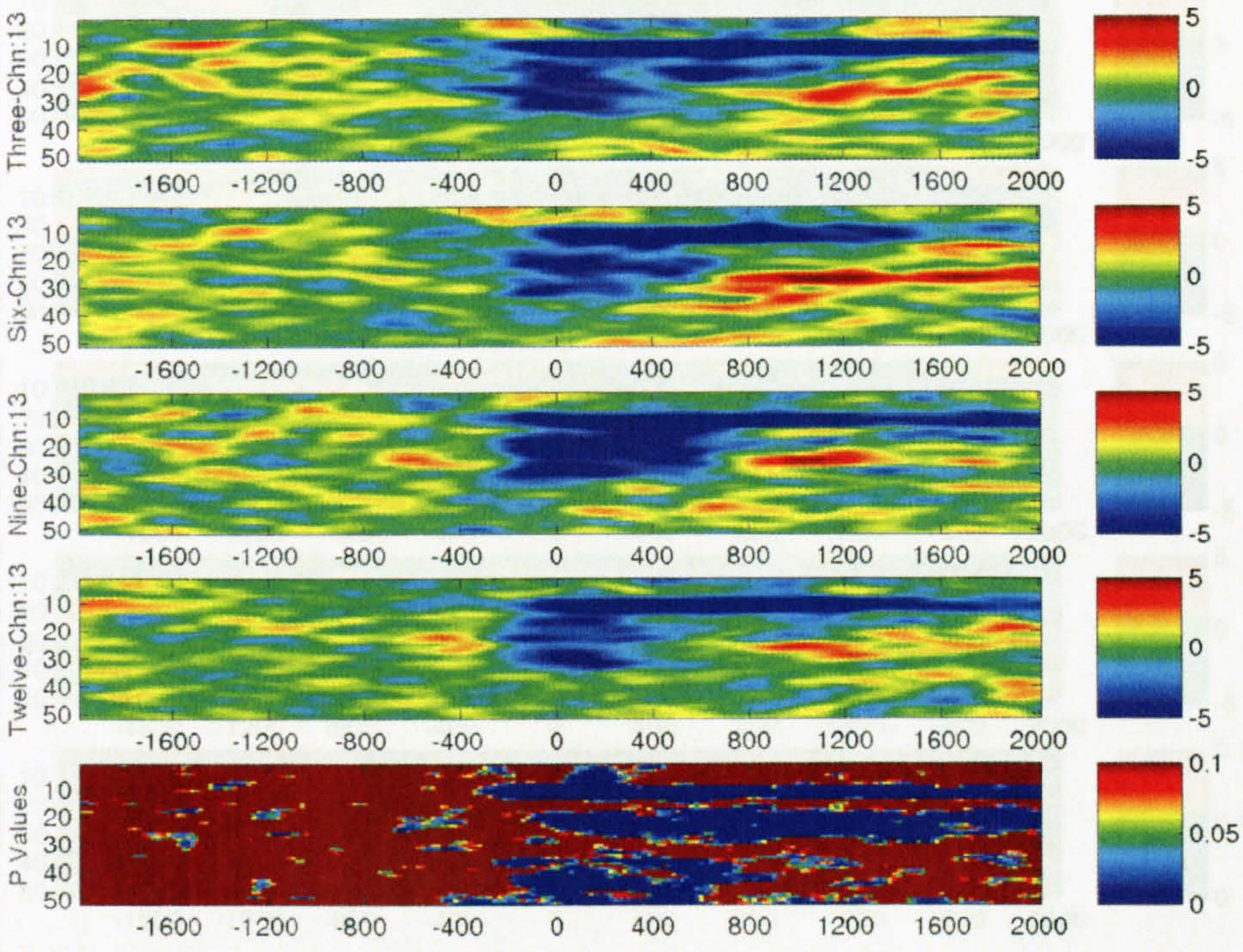


Figure 5.20 The figure shows the ERSP of the CAR EEG obtained from electrode C3 when the participant (Subject 1) moved the wrist in different direction during externally cued movement trials. It also shows the P values from a statistical test comparing the ERSPs.

Forced Choice Trials

ERSP statistical analysis for forced choice data are presented from subject 1 in Figure 5.21. The top four plots are the ERSP of the CAR EEG from electrode C3 as the participant (Subject 1) initiates movement (at t = 0) of their wrist in the four different directions. The fifth plot contains the p values from the ANOVA as described in the previous example (Fig 5.20). The plot has been scaled to show p values < 0.1. From this plot, it is clear that prior to stimulus presentation, which occurred at approximately 500ms below before movement initiation (t = 0) there were no significant differences in the spectral changes for each data set. The points in the time-frequency maps with p values < 0.05 after the presentation of the visual stimulus revealed the fact that there were significant differences in the ERSP of the EEG recorded at electrode C3 as the participant moves their wrist in different directions. In this example significant differences can be seen in α, β and specifically γ frequency bands.

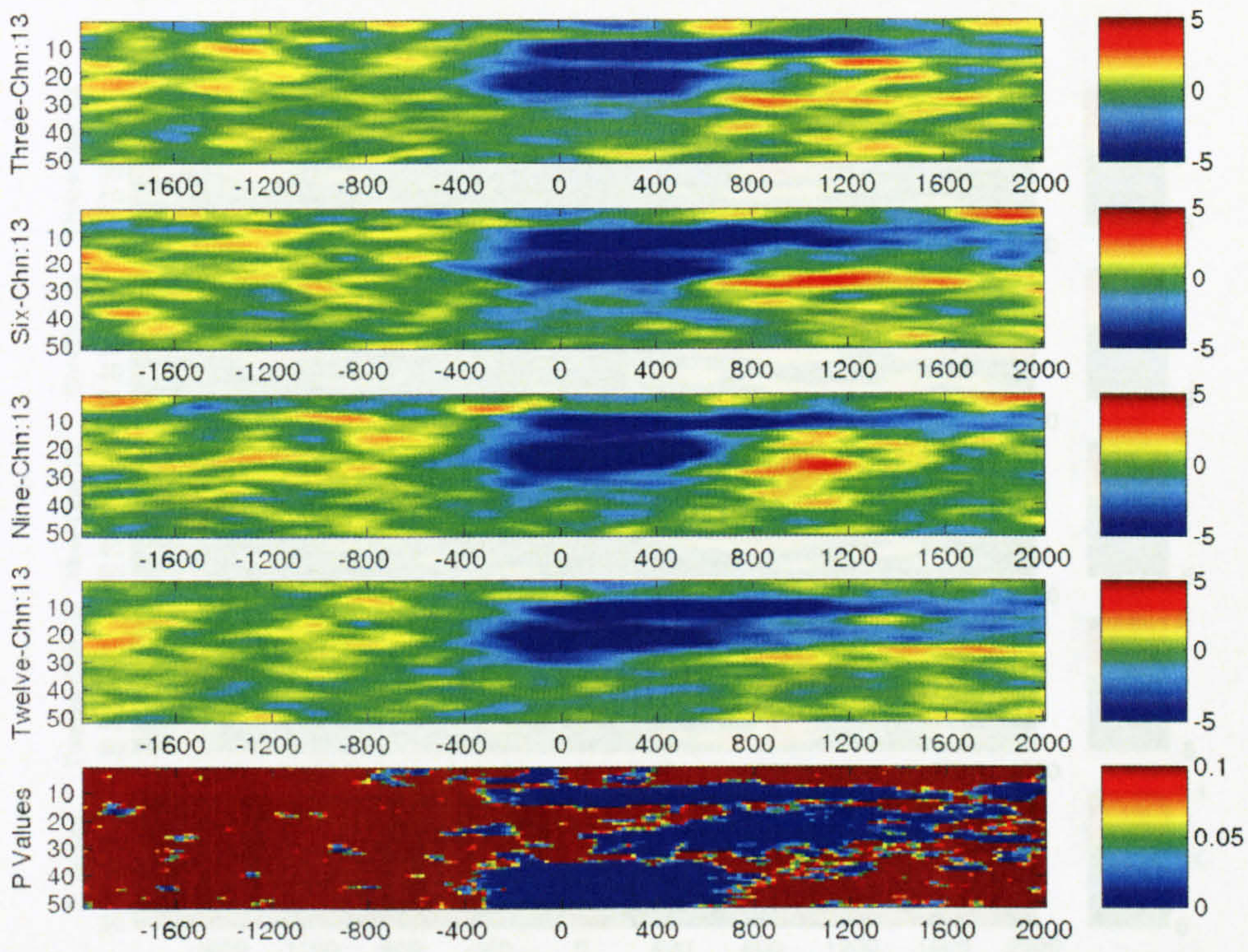


Figure 5.21 The figure shows the ERSP of the CAR EEG derived from electrode C3 when the participant (Subject 1) moves their wrist in different direction during forced choice movement trials. It also shows the P values from a statistical test comparing the ERSPs.

Self Determined and Self Paced Movement Trials

The results illustrated in figure 5.22 were obtained by comparing the ERSP values obtained from the EEG recorded during movement to different directions which were freely and randomly chosen by the subject as described in section 3.1.4. Once more the top four plots are the ERSP of the CAR EEG from electrode C3 as the participant (Subject 1) initiates movement (at t = 0) of their wrist in different directions. The fifth contains the p values from the ANOVA, the plot has been scaled to show p values < 0.1. Again it can be seen that until stimulus presentation (approximately 500ms before movement initiation) there were no clear statistical differences in the ERSP. However associated with the time just before and during movements there are significant differences in the ERSP. In this case the clearest changes were clustered in the α and γ bands before movement and in the α, β and γ bands post movement. Therefore just as in the previous cases there were significant differences in the spectral changes that occured when the subject made a wrist movement in different directions.

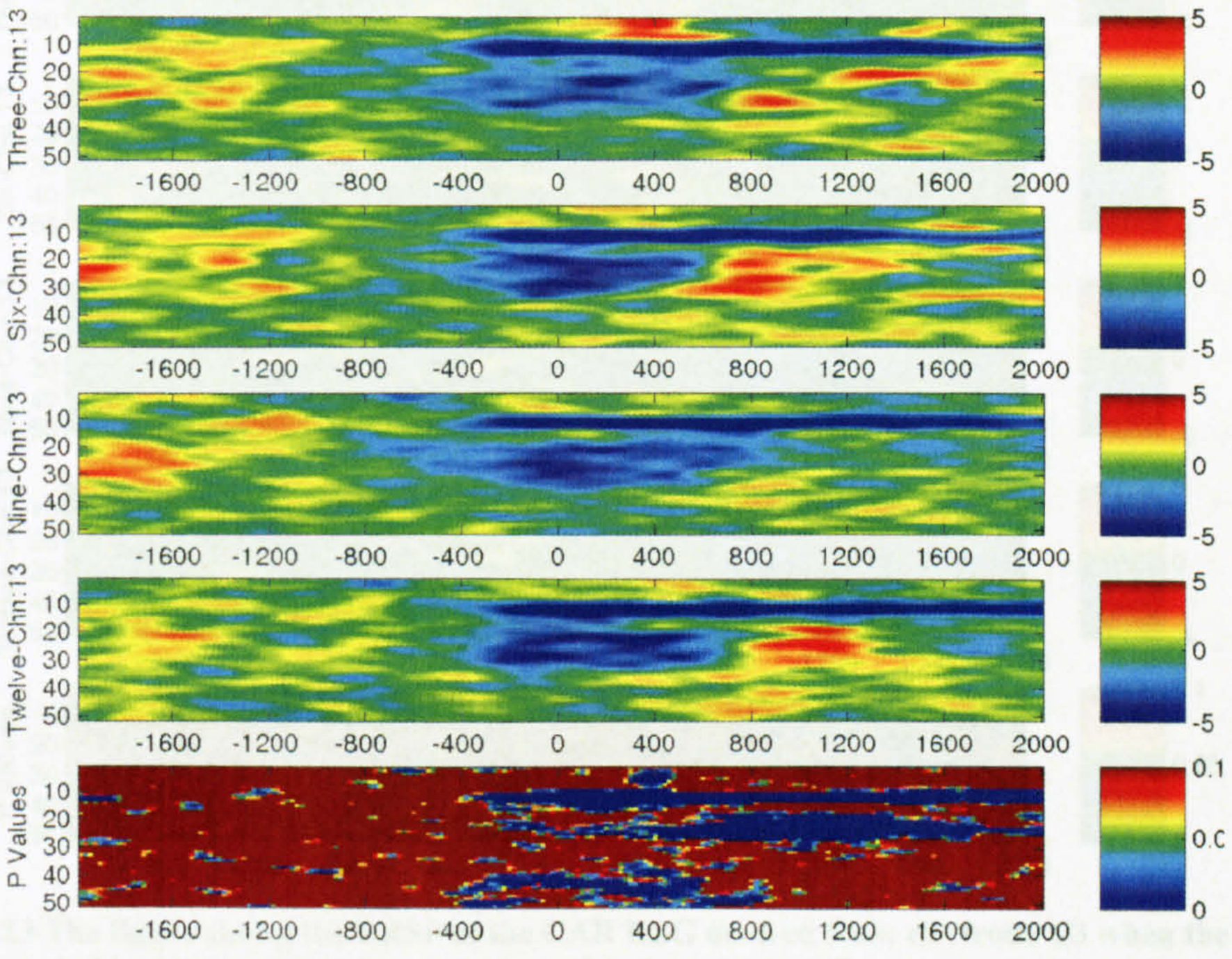


Figure 5.22 The figure shows the ERSP of the EEG recorded from electrode C3 and re-referenced to the CAR when the participant (Subject 1) moves their wrist in different direction during self determine movement trials. It also shows the P values from a statistical test comparing the ERSPs.

5.5.2 Imagination of Movement

Turning to trials of imagined motion Fig 5.23 shows results obtained by comparing the ERSP values from the EEG recorded during imagination of movement to different directions. The top four plots are the ERSP of the CAR derived EEG from electrode C3 for Subject 1. As in all cases of movement imagination t =0 was gives the time at which the visual stimulus was presented. The fifth plot is the p values from the ANOVA. The plot has been scaled to show p values < 0.1. Similar to the previous results for actual motion in the pre-stimulus period the spectral changes seen appeared the same across all groups. The p values (< 0.05) after the presentation of the visual stimulus revealed the fact that there were significant differences in the ERSP of the EEG recorded at electrode C3 as the participant imagined the movement of their wrist in different directions but that they occured at longer latencies than in cases where motion was actually executed.

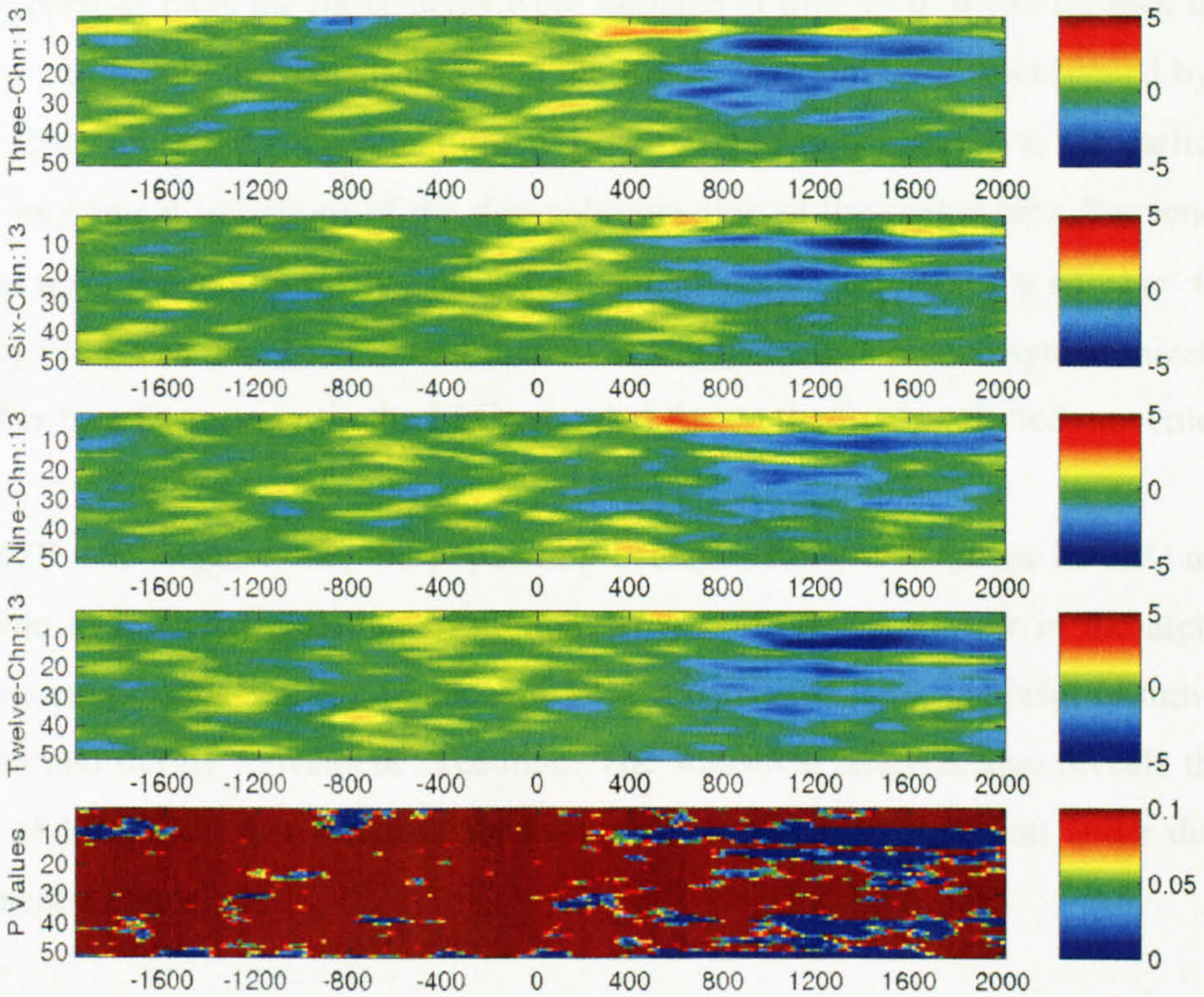


Figure 5.23 The figure shows the ERSP of the CAR EEG derived from electrode C3 when the participant (Subject 1) imagines the movement of their wrist in different direction based on an external cue. It also shows the P values from a statistical test comparing the ERSPs.

5.5.3 Comparing ERSP of Externally Cued and Internally Selected and Determined Movement

These results (see figure 5.24) were obtained by comparing the ERSP values obtained from the EEG recorded during movements to different directions that were selected based on an external cue and when the movements were freely and randomly selected. Four groups of plots are presented, one for each direction. In each group of plots the topmost plot is the ERSP for the CAR derived EEG from electrode C3 for externally cued movements in that particular direction, the middle plot is the ERSP for the CAR derived EEG from electrode C3 for movement trials which were self paced and self-determined. The lowest plot in the group of plots contains the p-values obtained by the statistical comparison of the ERSP for the two task conditions.

In these contour plots the movements were initiated at time t= 0. It can be seen that for the most part before movement initiation the ERSP were similar as highlighted by the p values which are > 0.05. The most important difference to be noted was the earlier start (before movement initiation) of the desynchronization of the higher beta frequencies in the EEG recorded during freely selected movements as underlined by p values < 0.05 in this subject. It can also be seen that there was a higher event related synchronization of the higher beta frequencies in the EEG recorded during the freely selected movements.

The ERSP data suggest that, the population averages show differences in EEG activity that relate to intended direction of motion. These differences appear in the alpha and beta frequency bands and can be recognised to exist in the time just prior to movement initiation and during movement execution. The statistical analysis also reveals that the pattern of ERS/ERD was different for movement to the same direction under different experimental conditions.

It would therefore appear that significant differences could be detected in the patterns of the event related spectral power changes in the EEG from the motor cortex when subjects performed movements in different directions and also in relation to different

levels of difficulty associated with single choice, forced choice and free choice experiments.

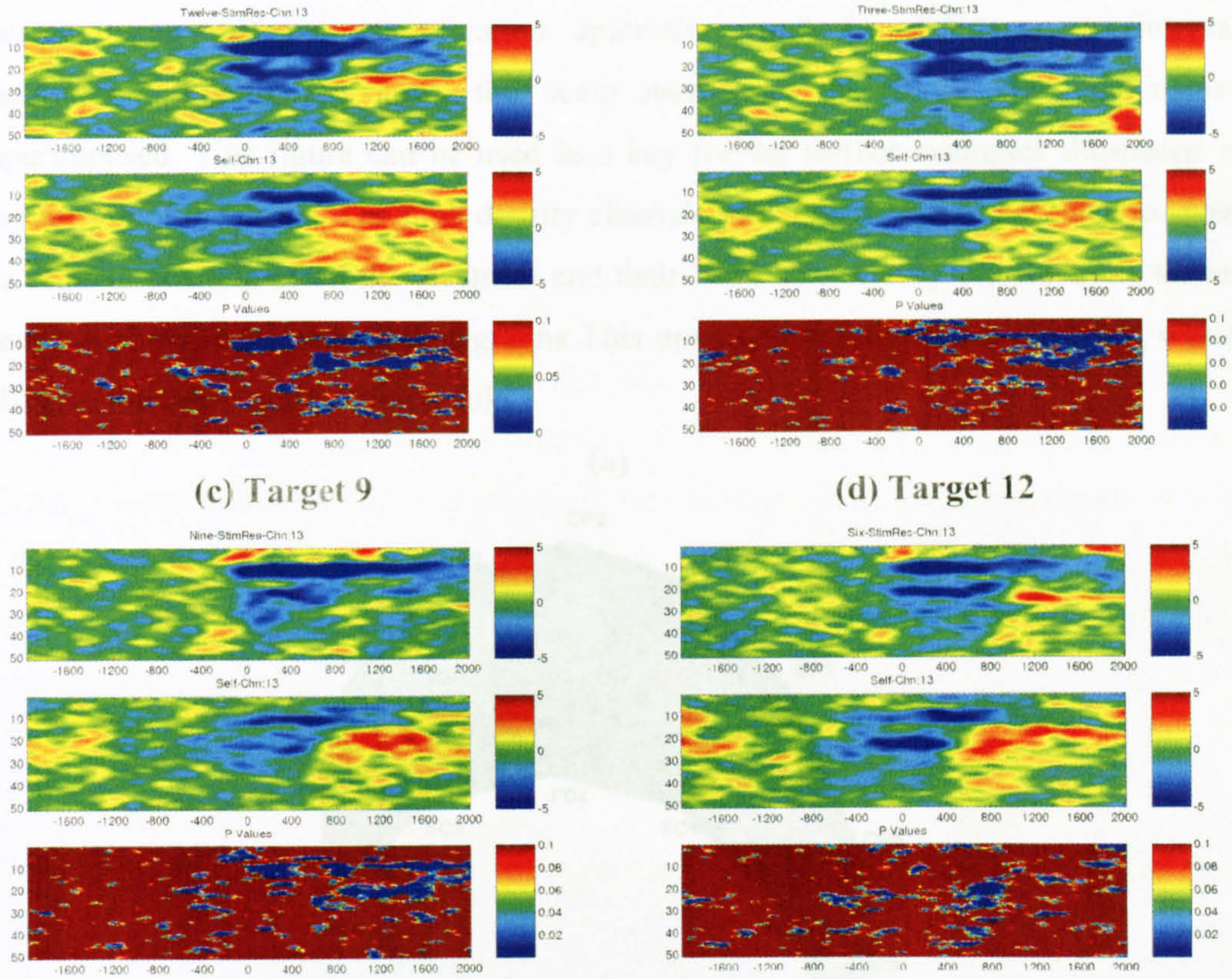


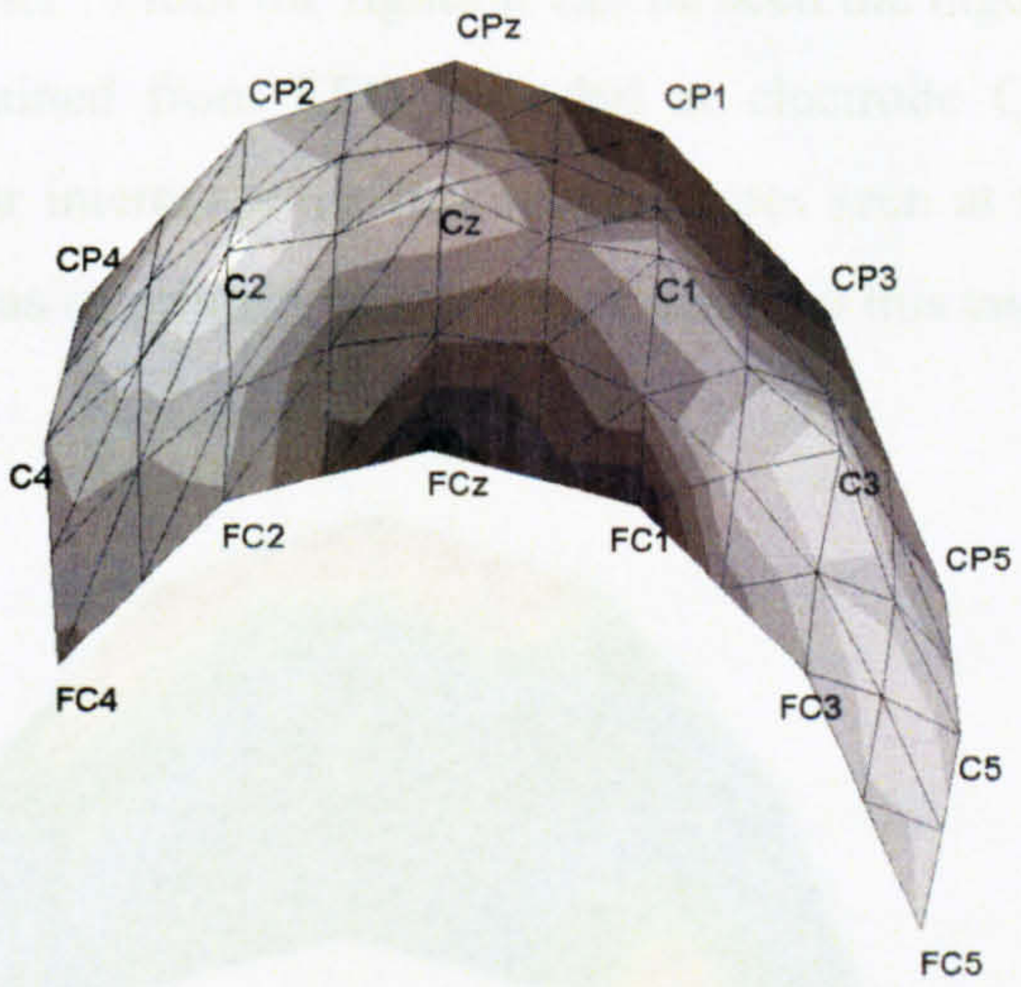
Figure 5.24 The figure shows four different sets of plots for the four directions of movement. In each set, the ERSP of the EEG recorded at electrode C3 when Subject 4 moves their wrist based on an external cue is shown on top, when the movement has been self-initiated in the middle and the p values from a statistical test comparing the ERSP on the bottom. (a) - 12,(b) - 3,(c) -9,(d) – 6.

5.6 Classification Results

A key need in the development of a BCI is that significant differences in EEG can be identifiable from single trials and that these single trials can be accurately classified. It is therefore important to examine what individual trial data analysis revealed based on classification results of each separate trial. The classification was attempted on EEG recorded from CAR derivatives of all the electrodes recorded from. The results from this classification process (based on euclidean distance and k-nearest neighbours) are then

presented as scalp maps in which the classification success rate (in percentage of trials that have been accurately classified) was coded using a colourbar for each EEG electrode. This helped to provide a useful view of the topography of classification success using different classification approaches and for different experimental conditions . Figure5.25 shows the scalp map with the 10-20 electrode names superimposed. This figure can be used as a key for the further examples illustrated in this section of the thesis. The high density elecrode montage was also presented to show the relative position of all the electrdes and their labels. For clarity the electrode names were not show in the subsequent graphs This approach highlights the electrode which will give the best classification result.

(a)



(b)

CP4		**CP2**		**CPZ**		**CP1**		**CP3**		**CP5**	
	66		**65**		**123**		**122**		**121**		
C4		**C2**		**CZ**		**C1**		**C3**		**C5**	
	82		**80**		**78**		**74**		**73**		
FC4		**FC2**		**FCZ**		**FC1**		**FC3**		**FC5**	

Figure 5.25 . (a) The figure shows the sparse electrode montage over a section of a scalp map. Only the sparse montage is shown for the sake of clarity (b) The figure shows the complete montage electrode montage used in the study.

5.6.1 Predicting Intention to Move

Stimulus Response Trials

Nine subjects (1,2,3,4,5,6,7,8 and10) completed this experiment. The classification results for predicting the intention to move are obtained by trying to classify the trials of the testing dataset into one of the two possible classes i.e., not intending or intending to move to particular direction. The data sections used correspond to the 500ms prior to movement initiation.

The result presented in figure 5.26 is from attempts to predict intention of movement independent of movement direction using PCA for feature extraction and a Eulidean Distance based classifier . From the figure it can be seen the higest classification of near to 90 percent is obtained from EEG recorded at electrode CPz from the available montage. Of particular interest is the low success rates seen at the C3 electrode which should overlay the areas of primary motor cortex active in this task.

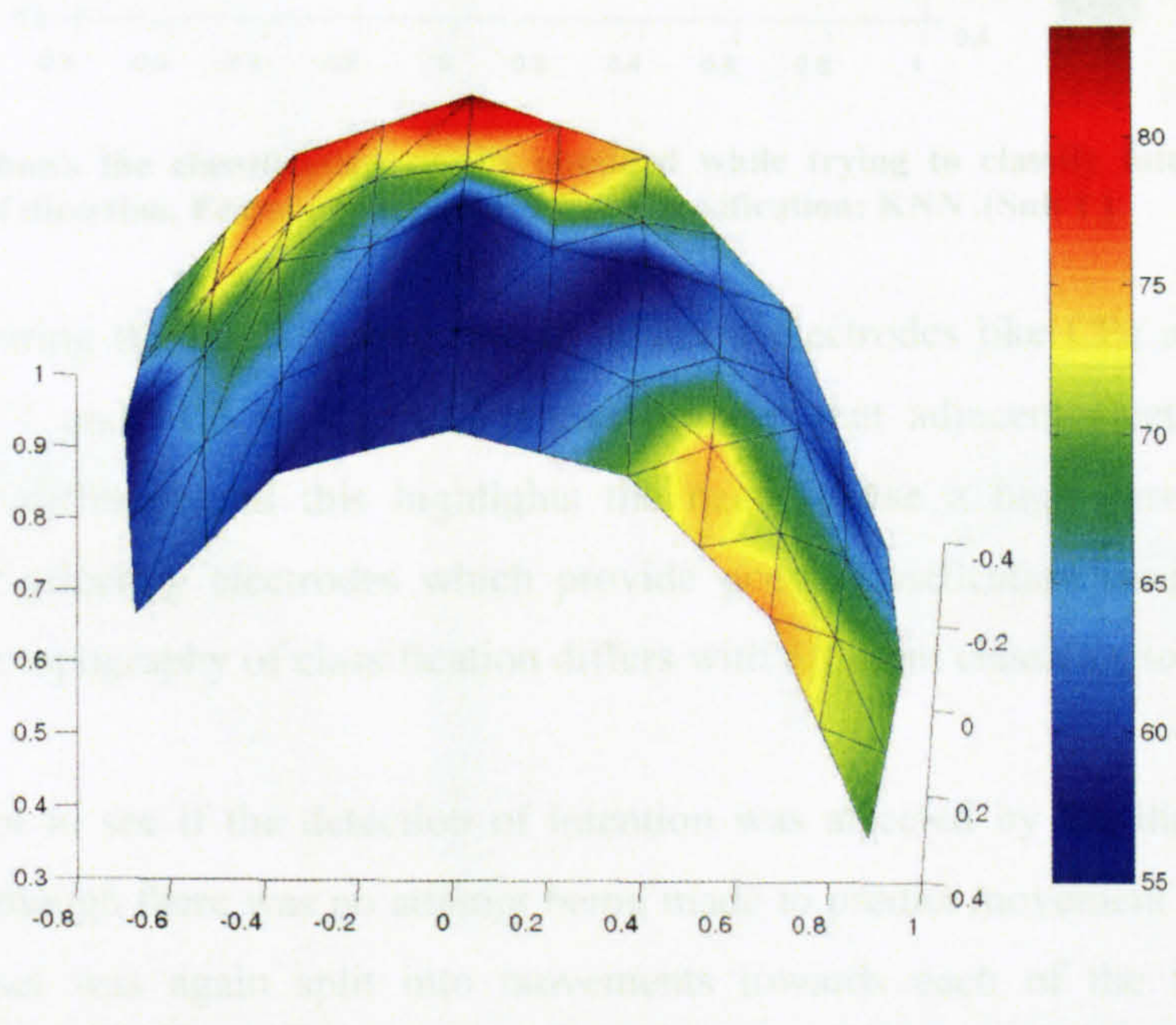


Figure 5.26 shows the classification results obtained while trying to classify intention to move independent of direction. Feature Extraction: PCA. Classification: Euclidean Distances .(Sub 1).

Classification topography associated with a K-NN approach is shown in figure 5.27 following PCA feature extraction. From the figure it can be seen that the highest classification of close to 90 percent is obtained from EEG recorded at electrode FC1.

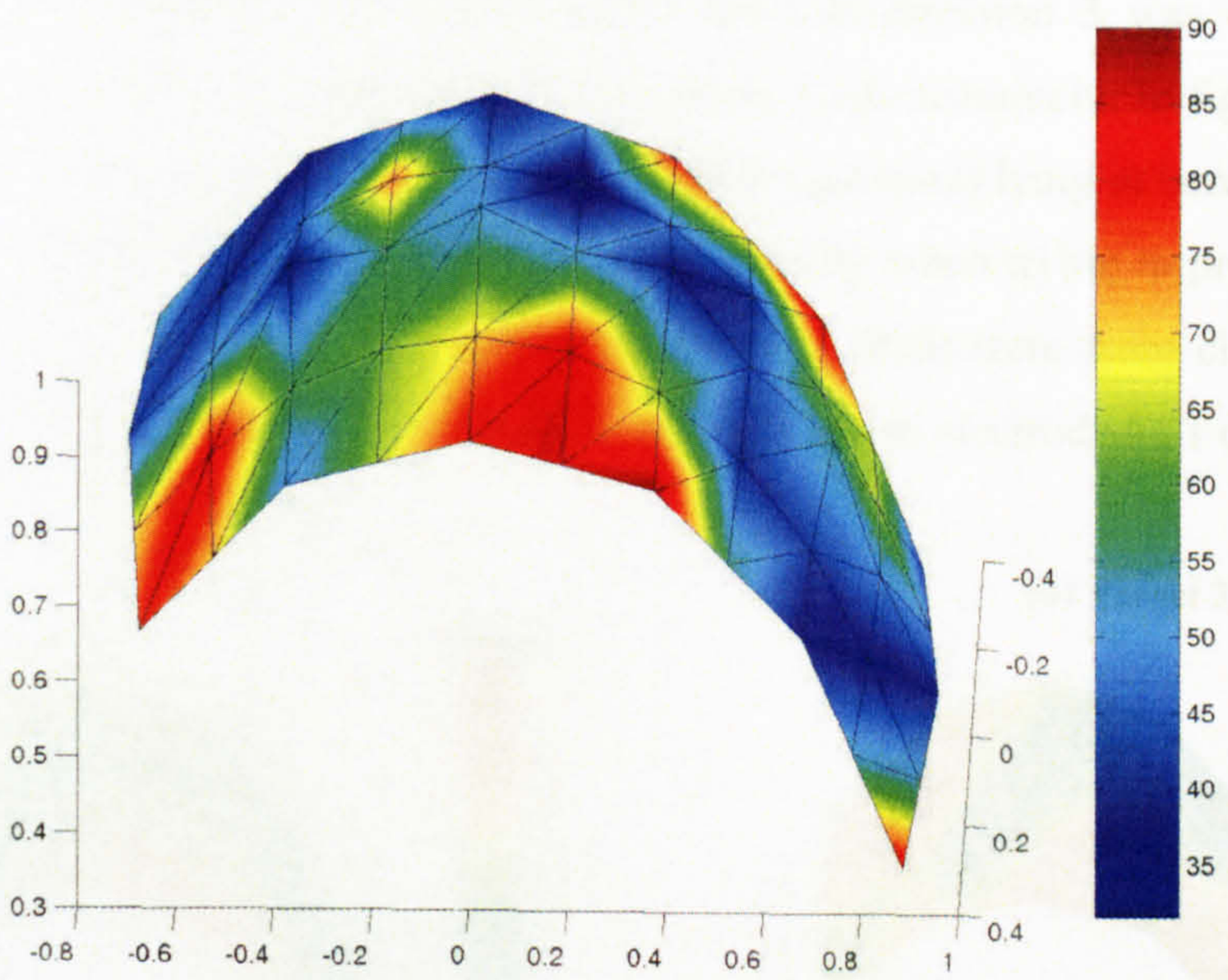


Figure 5.27 shows the classification results obtained while trying to classify intention to move independent of direction. Feature Extraction: PCA. Classification: KNN .(Sub 1).

While comparing the classification rate of adjacent electrodes like CPz and Cz in Fig 5.26 and FC1 and FC3 in Fig 5.27 it can be seen that adjacent electrodes can be significantly different and this highlights the need to use a high density electrode montage for selecting electrodes which provide good classification results. It is also clear that the topography of classification differs with different classification methods.

In an attempt to see if the detection of intention was affected by the direction of the movement (though there was no attempt being made to predict movement direction) the testing dataset was again split into movements towards each of the four different directions. These results are presented in figures 5.28 and 5.29 and discussed below.

The results presented in figure 5.28 are obtained from classification trials which used PCA for feature extraction and euclidean distances for classification. Figure 5.28(a) shows that while predicting intention to move towards direction 12, the electrodes FCz and FC1 classified 90 percent of the trials accurately. Figure 5.28 (b) shows that the best result for predicting intention to move towards direction 3 was obtained from electrode FC1 which classified close to 95% of the trials accurately. In figure 5.28 (c) it can be seen that the electrode (Label 78 in the montage used) lying in between FC1, C1, FCz and Cz classifies over 85% of the trials accurately when trying to predict intention to move towards direction 9. The results in figure 5.28(d) were from classification of intention to move towards direction 6 show that EEG from electrode FC1 classifies close to 95% of the trial accurately.

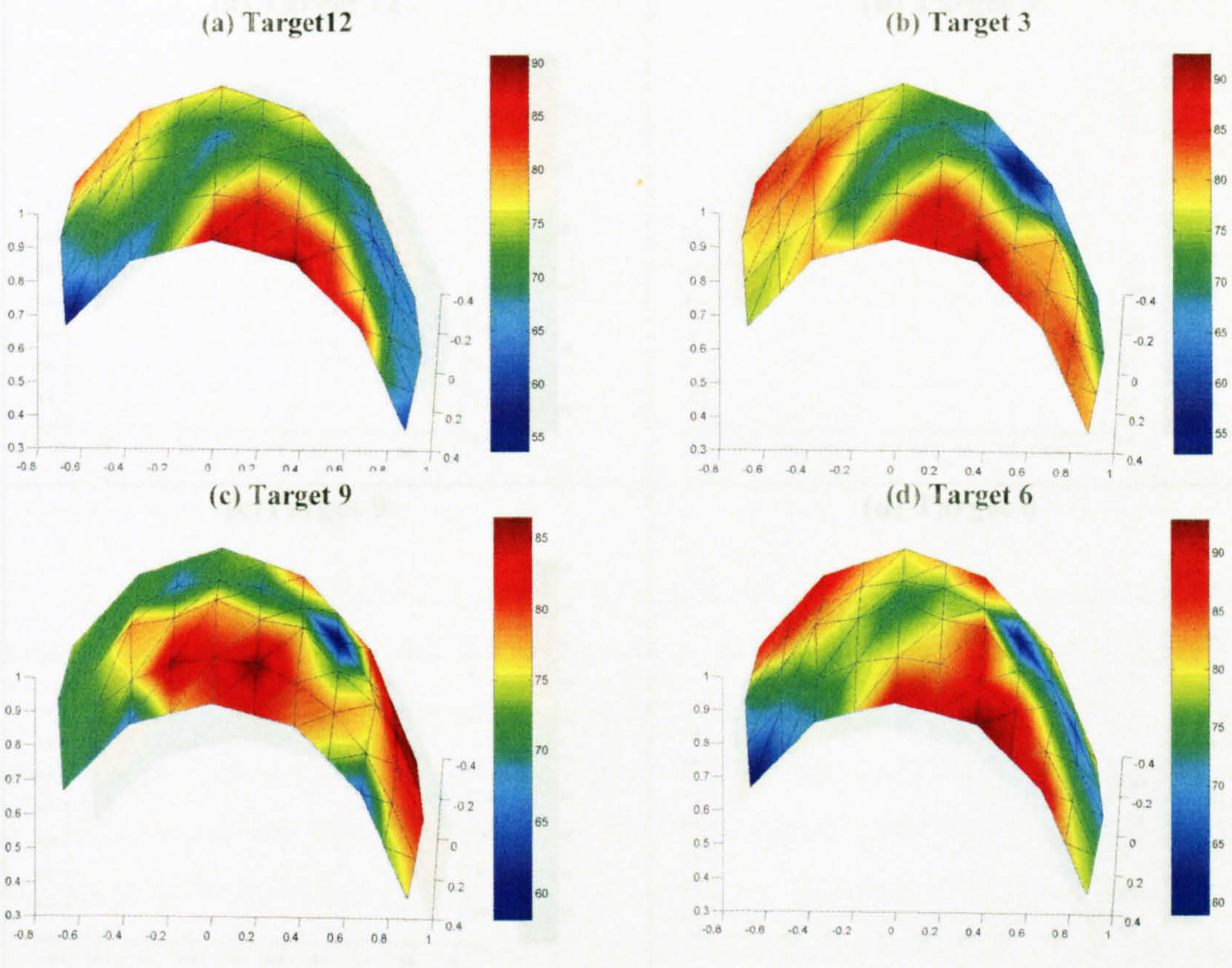


Figure 5.28 shows the classification results for subject 3 obtained while classifying intention to move in different directions during externally cued trials. Features Extraction: PCA. Classifier: Euclidean Distances.

Using the same dataset but a KNN classification with PCA for feature extraction generated figure 5.29. Figure 5.29 (a) showed that while predicting intention to move towards direction 12, the electrodes C3 and 74 (between FC1,C1,FC3 and C3) classified close to 90 percent of the trials accurately. Figure 5.29 (b) shows that the best result for predicting intention to move towards direction 3 was obtained from electrode C3 which classified close to 95% of the trials accurately. From figure 5.29(c) it can seen that the electrode FC3 and its surronding electrodes correctly classified over 95% of the trials accurately when trying to predict intention to move towards direction 9. Finally in figure 5.29 (d) classification of intention to move towards direction 6 is shown and revealed that the EEG from electrodes C1 andC3 also classify close to 95% of the trial accurately.

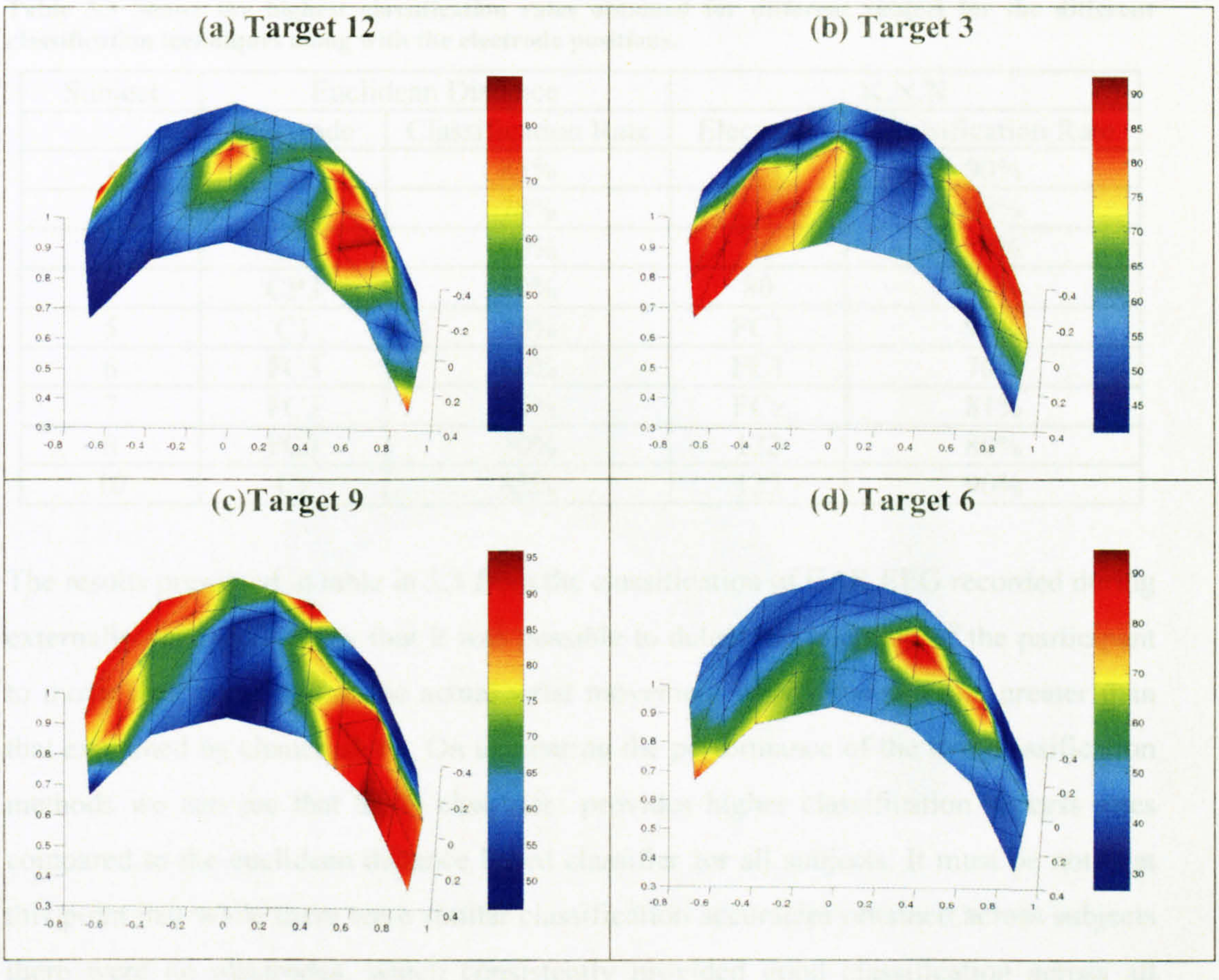


Figure 5.29 shows the classification results obtained while trying to classify intention to move in different directions during externally cued movement trials. Features Extraction: PCA. Classifier: KNN. (Subject 3).

The results presented in figure 5.28 and 5.29 show that the set electrodes providing better classification result differ for different directions and also with the method of classification. This then raises the possibility of using features from multiple electrodes in a BCI for classification of intention to move.

The summary of results obtained from the subjects who completed this section of the study is provided in table 5. The table summarises the highest classification rates and the corresponding electrodes obtained for different subject when different classification techniques were used to classify intention to move.

Table 5.3 Shows the highest classification rates obtained for different subject for the different classification techniques along with the electrode positions.

Subject	Euclidean Distance		K.N.N	
	Electrode	Classification Rate	Electrode	Classification Rate
1	CPz	85%	FC1	90%
2	FC1	78%	FC1,74	90%
3	C3	60%	74	70%
4	CP3	80%	80	82%
5	C1	70%	FC1	95%
6	FC3	60%	FC1	70%
7	FC3	75%	FCz	81%
8	FC3	70%	122	80%
10	Cz	85%	122	90%

The results presented in table in 5.3 from the classification of CAR EEG recorded during externally cued trials show that it was possible to detect the intention of the participant to move their wrist before the actual wrist movement with a success rate greater than that explained by chance alone. On comparing the performance of the two classification methods we can see that KNN classifier provides higher classification success rates compared to the euclidean distance based classifier for all subjects. It must be noted at this point that while there were similar classification accuracies obtained across subjects there were no electrodes, which consistently provided good classification across all subjects. Significantly and surprisingly the C3 electrode rarely provided the best

classification result and more frontal sites appear the most successful. This again emphasized the need to use high density montages for selecting electrodes which provide the best classification results.

Forced Choice Trials

The results presented in this section review attempts to predict the intention to move during forced choice trials in which the subject was presented with two possible targets and the subject had to choose and move the cursor towards one of the two. Four subjects (1,2,3 and 10) particiapted in these experiments.

The figure 5.30 shows the result of trying to predict movement initiation independent of movement direction.The classifier used PCA for feature extraction and euclidean distances for classification. It can be seen that at electrodes FC3, FC1 and 74 the EEG had consistent features that helped classify over 72% of the trials accurately.

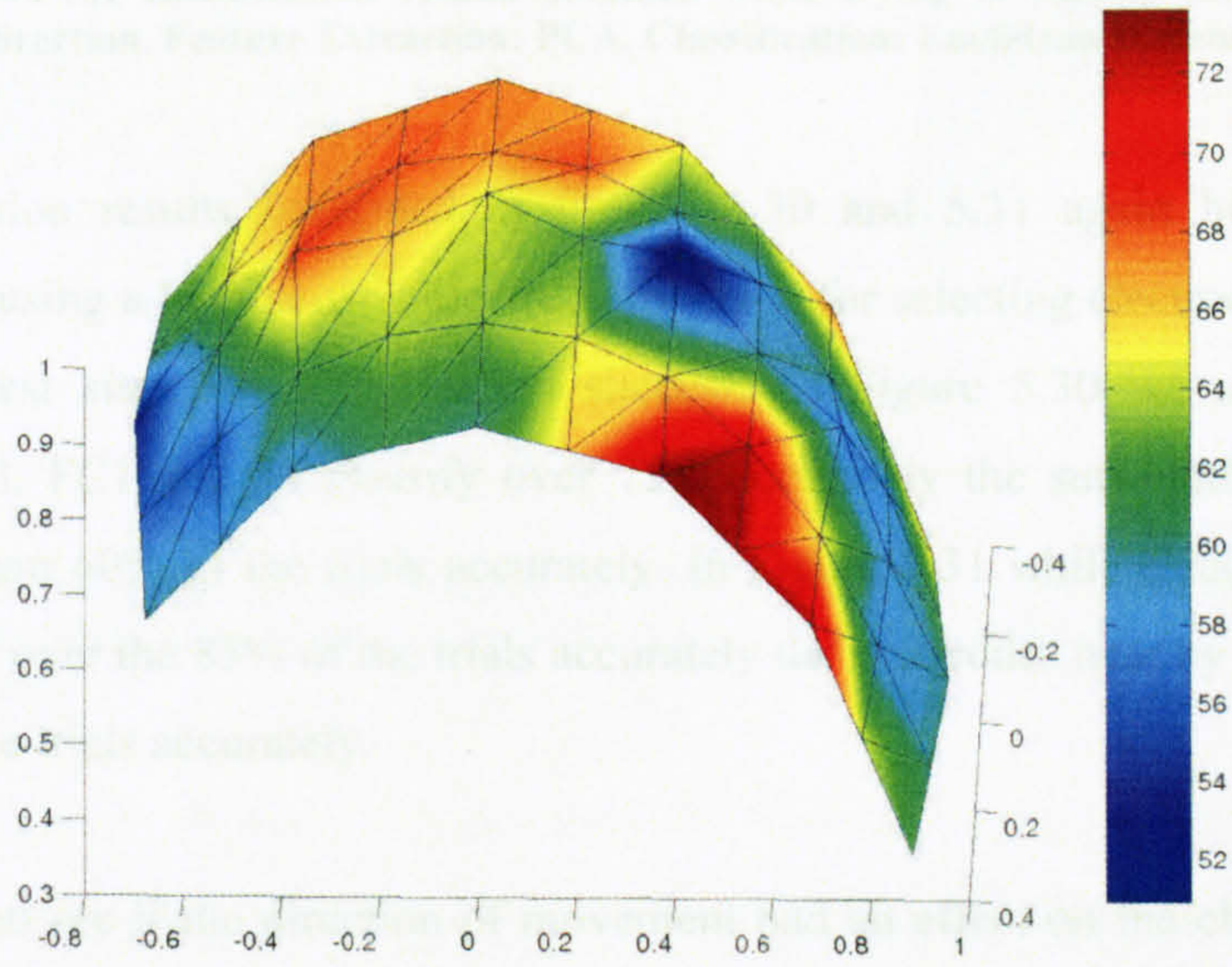


Figure 5.30 shows the classification results obtained while trying to classify intention to move independent of direction. Feature Extraction: PCA. Classification: Euclidean Distances .(Sub 1).

When KNN was used as the classifier instead of euclidean distance it can be seen that features extracted from electrodes FC3 and CPz classified over 85% of the trials accurately (see figure 5.31).

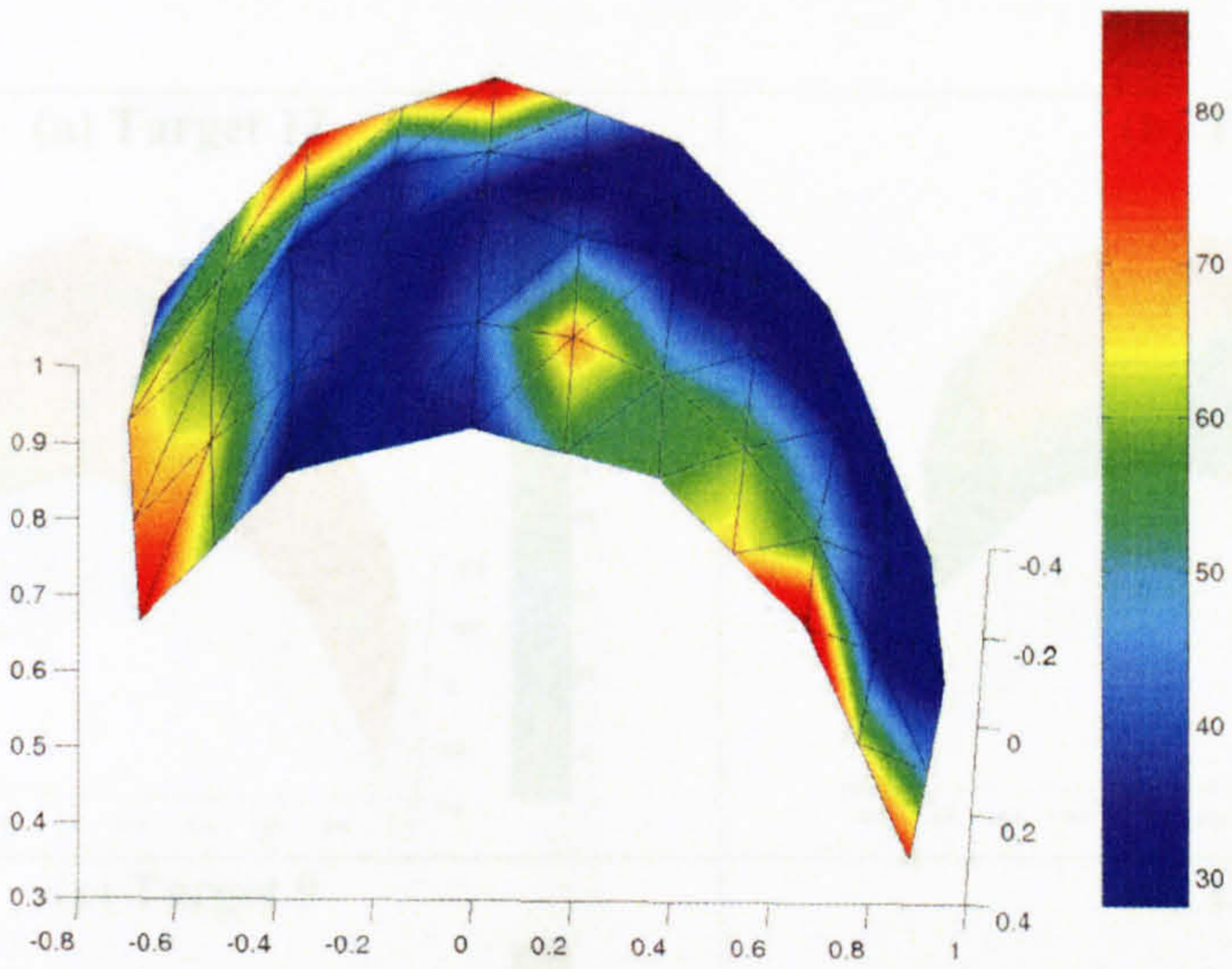


Figure 5.31 shows the classification results obtained while trying to classify intention to move independent of direction. Feature Extraction: PCA. Classification: Euclidean Distances .(Sub 1).

The classification results presented in figures 5.30 and 5.31 again highlighted the importance of using a high density electrode montage for selecting electrodes in order to identify the best sites for classification success. In Figure 5.30 we see that while electrodes FC3, FC1 and 74 classify over 72% accurately the surrounding electrodes classify less than 60% of the trials accurately. In Figure 5.31 while electrode FC3 and CPZ classified over the 85% of the trials accurately the electrodes near by classified less than 50% of the trials accurately.

In an attempt to see if the direction of movement had an effect on the classification of intention to move the trials in the testing set were split into 4 groups depending on the movement direction and their individual classification rates were computed. These results are presented in the figure 5.32 and 5.33.

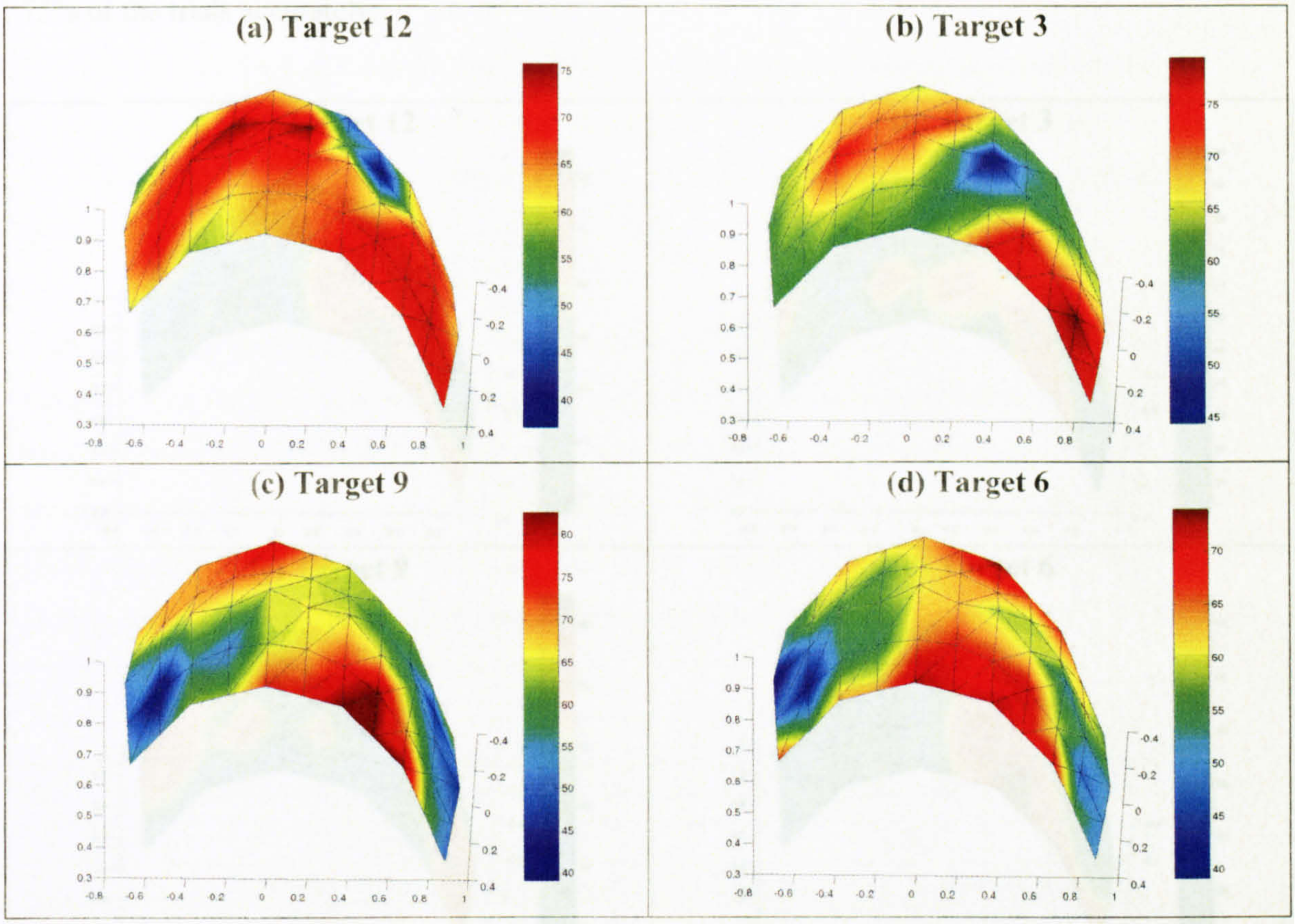


Figure 5.32 shows the results for detecting the intention of Subject 1 to move in different directions during externally cued two choice movement trials. Featreus Extraction: PCA. Classifier: Eucliedean Distance.

The results presented (figure 5.32) are from the classifier based on PCA for feature extraction and euclidean distances for classification. Figure 5.32(a) shows that while predicting intention to move towards direction 12 the majority of electrodes classify close to 70 % of the trial accurately, the electrodes 123 and 65 classify 75 % of the trials accurately. Figure 5.32(b) shows that the best result for predicting intention to move towards direction 3 is obtained from electrode 73 which classifies close to 95% of the

trials accurately. From figure 5.32(c) it can be seen that for movement to target 9 the electrodes FC3 and FC1 classify over 85% of the trials accurately. The results shown in figure 5.32(d) are from classification exploring the subjects intention to move towards direction 6 and it shows that EEG from electrodes FC1,FCz and CP1 classifies close to 75% of the trials accurately.

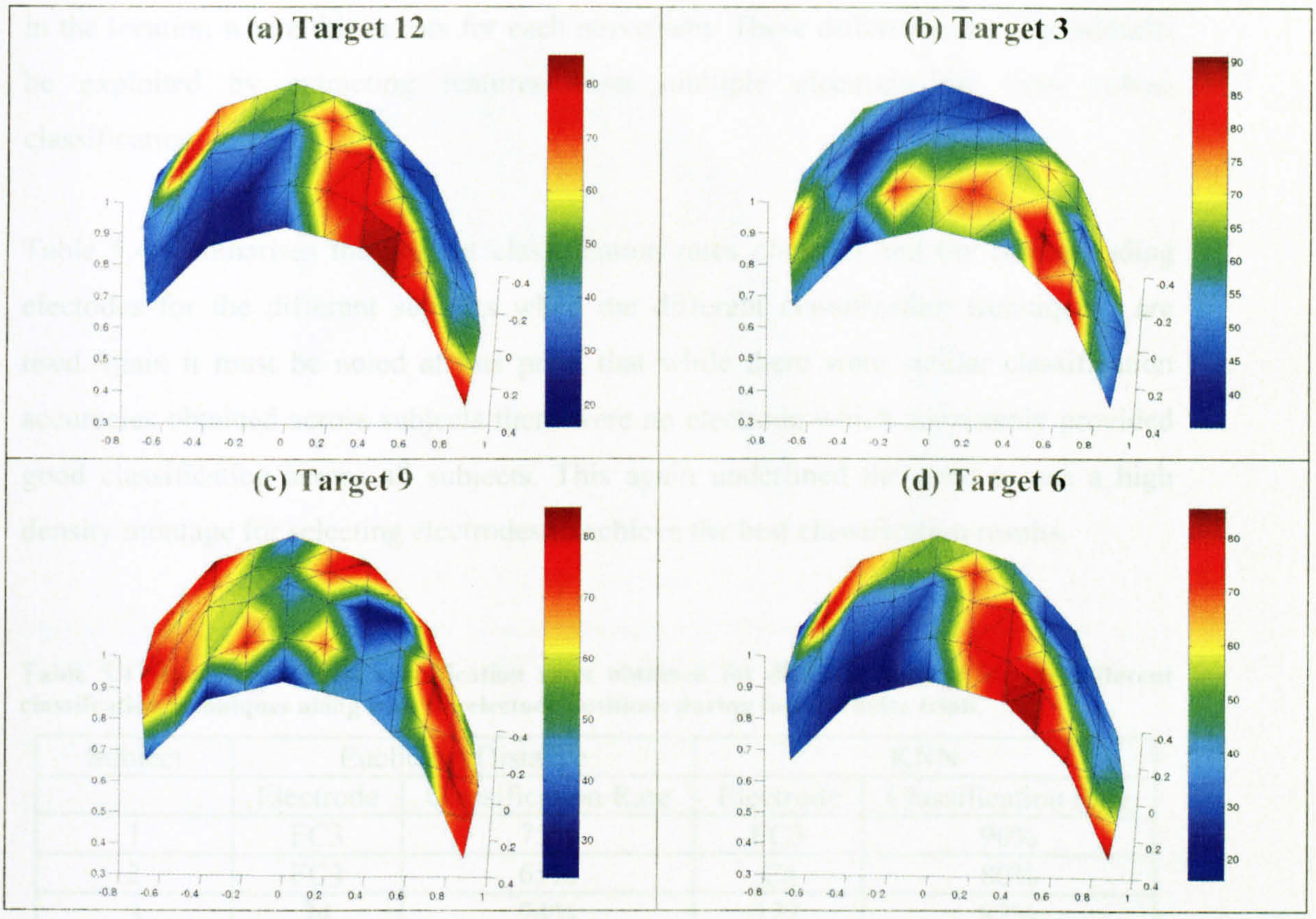


Figure 5.33 shows the results from classifcation of intention to move in different directions during externally cued two choice movement trials. Featreus Extraction: PCA. Classifier: Eucliedean Distance. (Subject 1).

Figure 5.33 is generated by using KNN for classification of the same trials recorded from subject1 . Figure 5.33(a) shows that the electrodes FC1, 78 and C1 classify 85 % of the trials accurately while trying to predict the intention to mvoe towards direction 12. Figure 5.33(b) shows that the best result for predicting intention to move towards direction 3 is obtained from electrode 74 which classifies 90% of the trials accurately.

And for direction 9 (Fig. 5.33c) it can be seen that the electrodes C3 and 73 classify close to 85% of the trials accurately. The results shown in figure 5.33(d) are from classification of intention to move towards direction 6 and it shows that EEG from electrodes FC1, 78 and C1 classify 85% of the trial accurately.

Figure 5.32 and 5.33 again show the variability in the percentage success achieved and in the location where this occurs for each movement. These difference could potentially be exploited by extracting features from multiple electrode for more robust classification.

Table 5.4 summarises the highest classification rates obtained and the corresponding electodes for the different subjects when the different classification techniques are used.Again it must be noted at this point that while there were similar classification accuracies obtained across subjects there were no electrode which consistenly provided good classification across all subjects. This again underlined the need to use a high density montage for selecting electrodes to achieve the best classification results.

Table 5.4 Shows the highest classification rates obtained for different subject for the different classifcation techniques along with the electode positions during forced choice trials.

Subject	Euclidean Distance		KNN	
	Electrode	Classification Rate	Electrode	Classification Rate
1	FC3	75%	FC3	90%
2	FC3	65%	Cz	80%
3	74	74%	122	82%
10	73	80%	FC3	90%

Self Paced and Self Determined Movement Trials

Five subjects (1,2,3,8,10) completed the self paced and self determined movement trials. The results presented in this section are from attempts to predict the intention to move in self determined and self paced movement trials. In these experiments the subject had free choice over the selection of direction of movement.

The figure 5.34 showed the result of trying to predict movement initiation independent of movement direction (i.e., move or not to move). The classifier used PCA for feature extraction and euclidean distances for classification. Electrode 74 had consistent EEG features that helped to classify over 67% of the trials accurately.

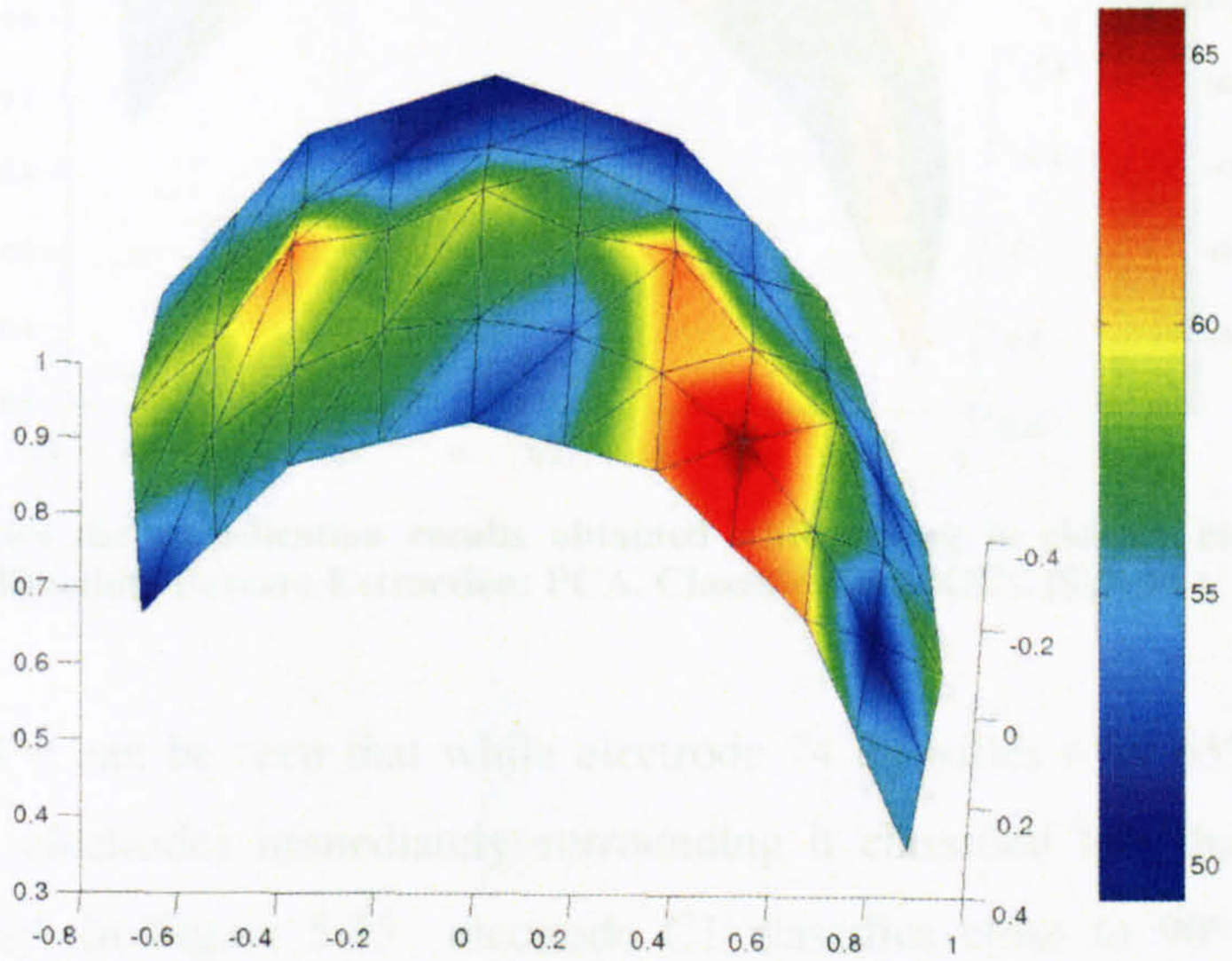


Figure 5.34 shows the classification results obtained while trying to classify intention to move independent of direction. Feature Extraction: PCA. Classification: Euclidean Distances .(Sub 5).

When KNN was used as the classifier the highest classification was obtained at electrode C1 which classified 90% of the trials accurately. (see figure 5.35)

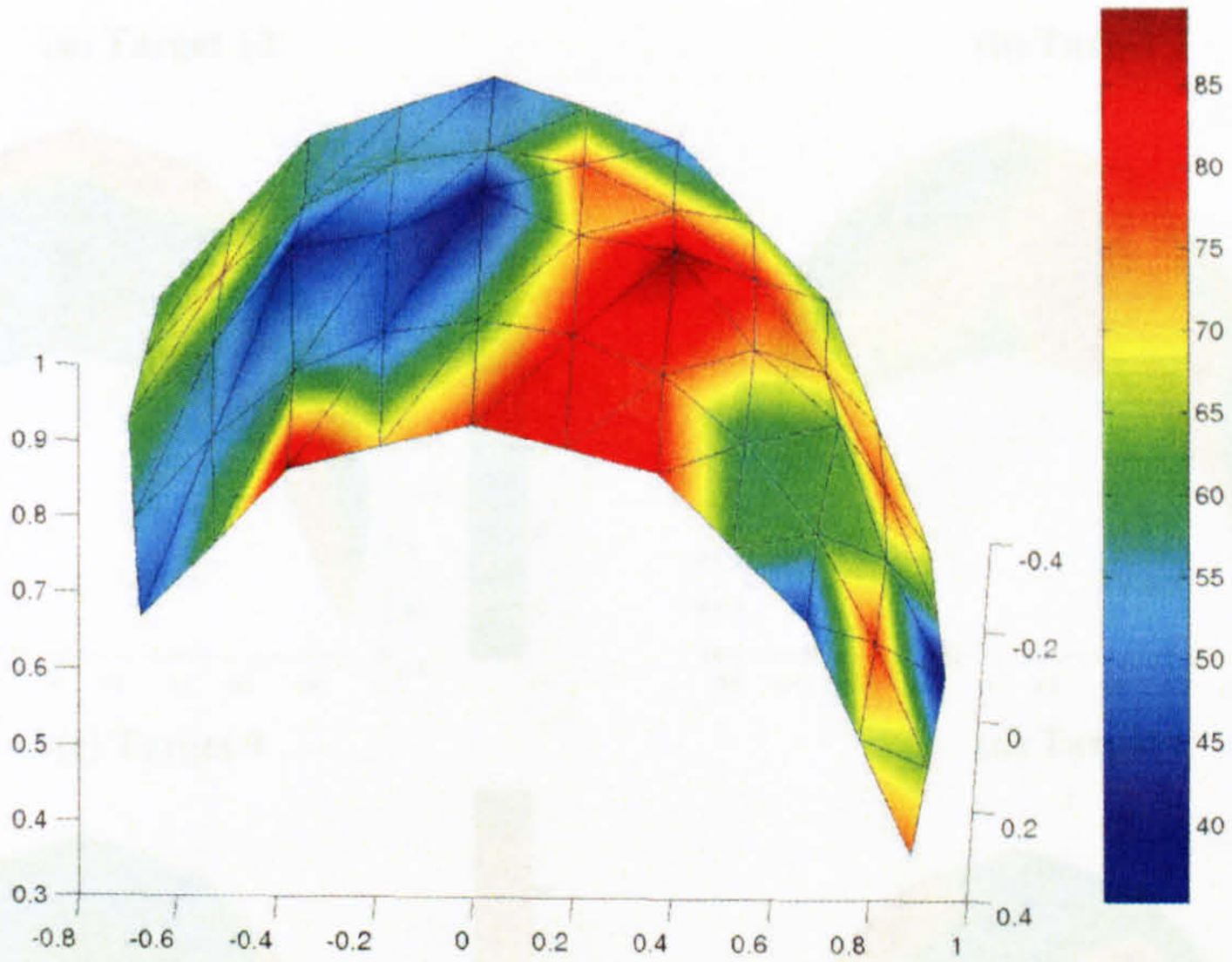
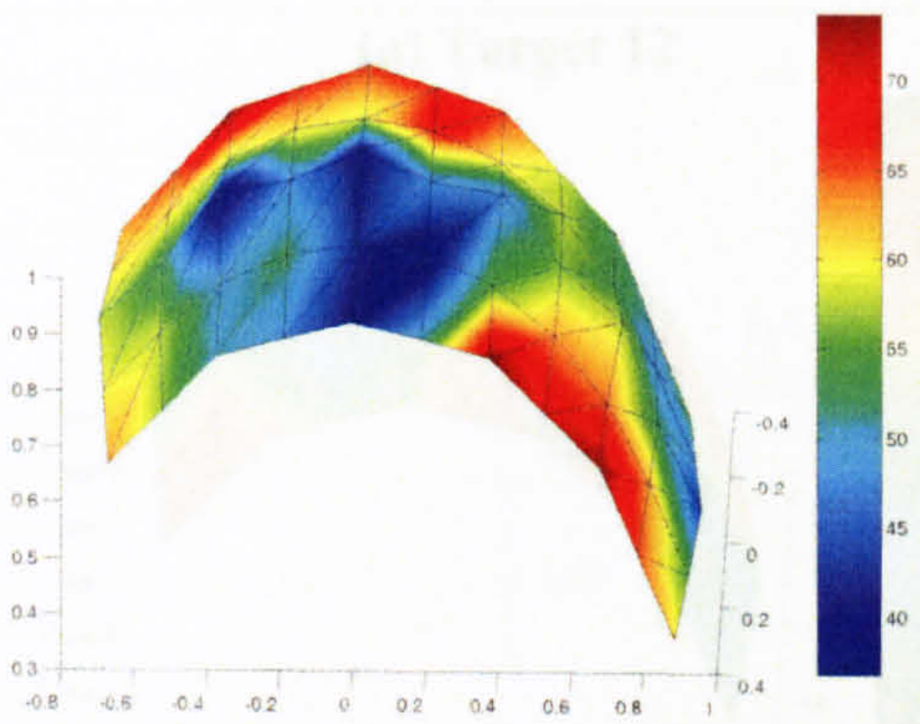


Figure 5.35 shows the classification results obtained while trying to classify intention to move independent of direction. Feature Extraction: PCA. Classification: KNN. (Sub 10).

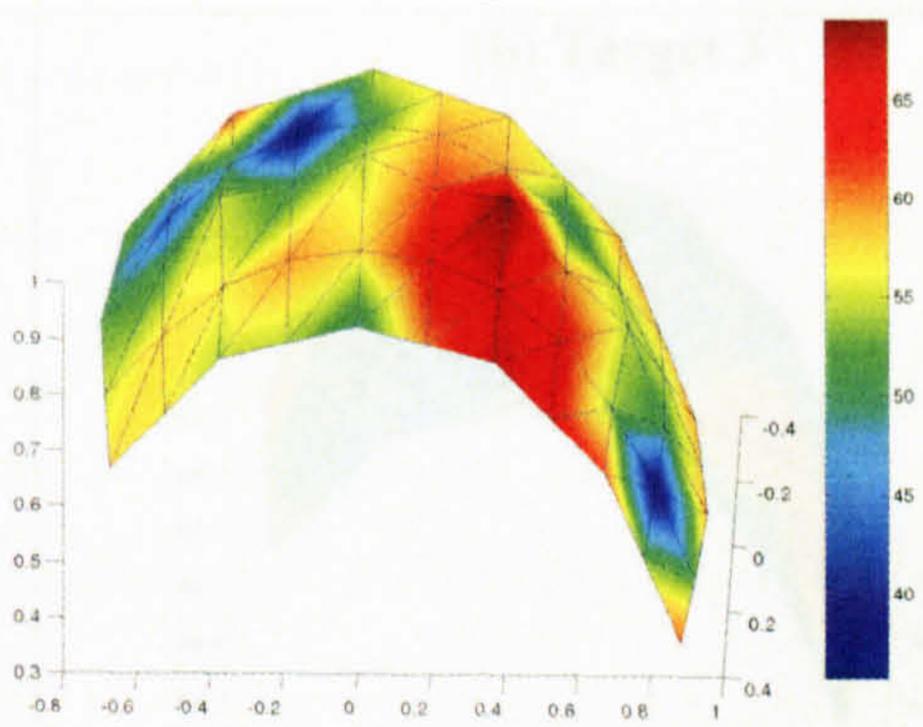
In Figure 5.34 it can be seen that while electrode 74 classifies over 65% of the trials accurately the electrodes immediately surrounding it classified less than 55% of the trials accurately. In Figure 5.35 electrode C1 classifies close to 90% of the trials accurately and the electrode Cz classified less than 50% of the trials accurately. These classification results again highlight the advantage of using high density electrode montages for selecting sites which provide good classification.

The results presented below are from attempts to see if the detection of intention to move was affect by the movement direction. This was done by dividing the trials which were classified successfully into four groups depending on the movement directions. The results presented in figure 5.36 are from the results obtained from the classifier using PCA for feature extraction and euclidean distances for classification.

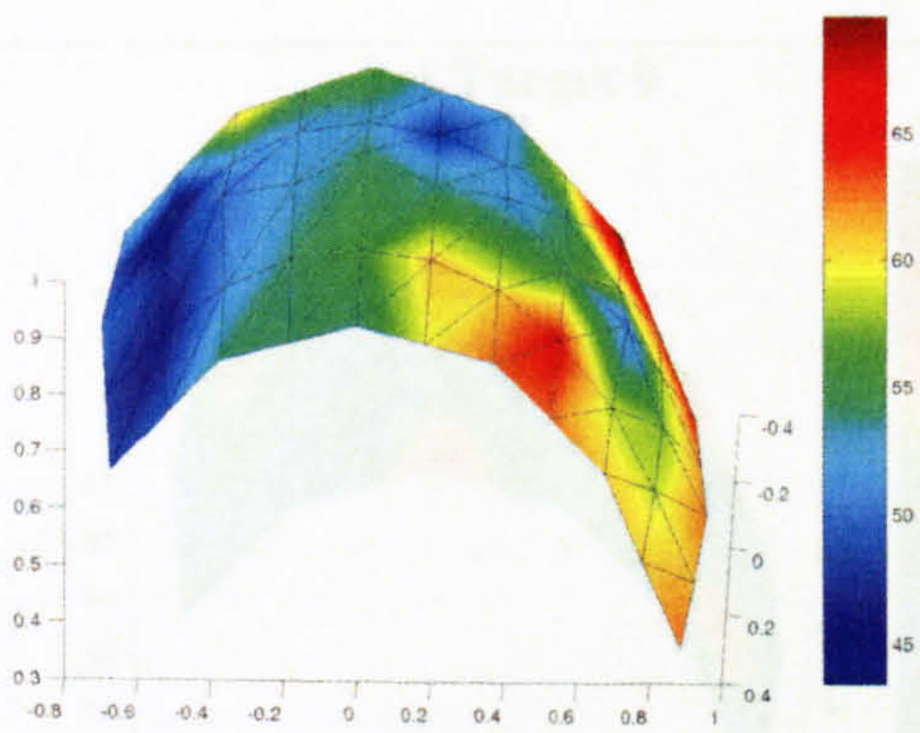
(a) Target 12



(b) Target 3



(c) Target 9



(d) Target 6

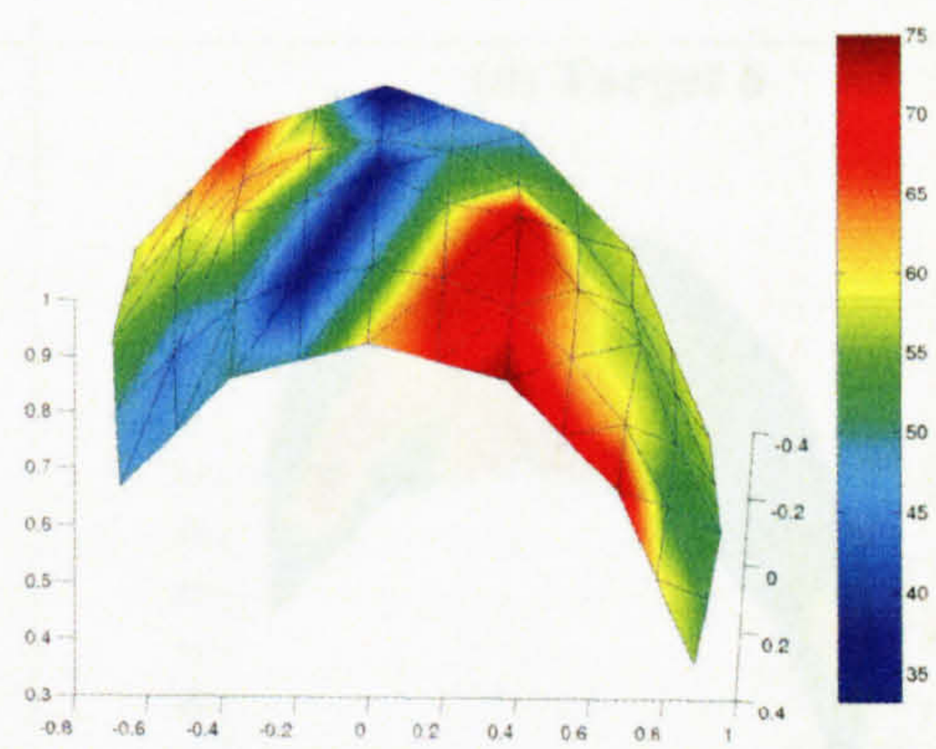


Figure 5.36 shows the classification results obtained while trying to classify intention to move in different directions during self determined movement trials. Featreus Extraction: PCA. Classifier: Euclidean Distances. (Subject 10).

Figure 5.36 (a) shows that electrodes FC1 and FC3 classified more than 75% of the trials when trying to predict intention to move towards target 12. From figure 5.35(b) it can be seen that while trying to predict intention of the participant to move towards direction 3 the electrode C3 classified about 70% of the trials correctly. Figure 5.35(c) shows that when trying to classify movement intention to direction 9 electrode 74 classified more than 65% of the trials accurately . From figure 5.35(d) it can be seen that electrode FC1 classified about 75% of the trials accurately when the subject intended to move towards direction 6.

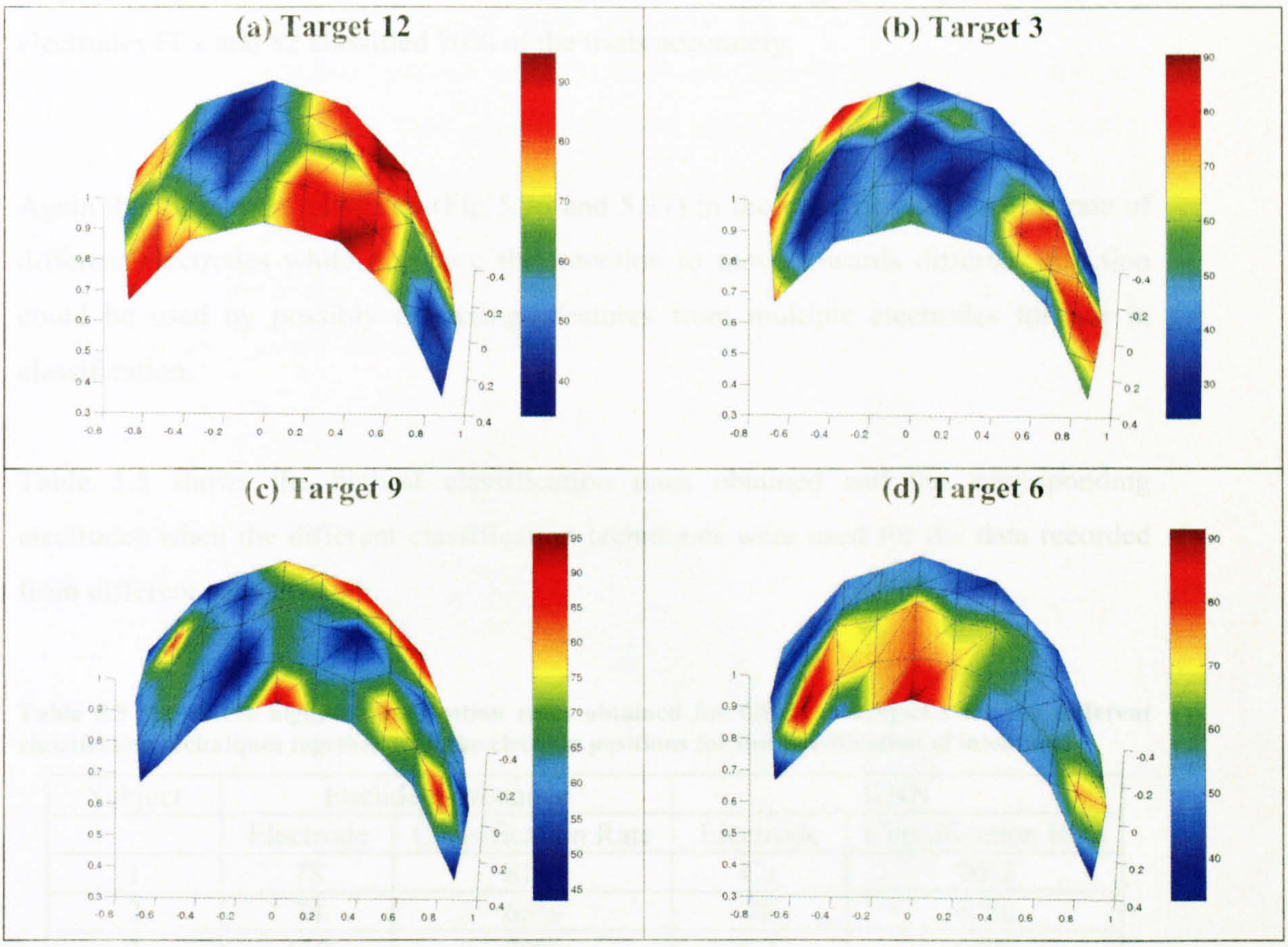


Figure 5.37 shows the classification results obtained while trying to classify intention to move in different directions during self determined movement trials. Featreus Extraction: PCA. Classifier: KNN. (Subject 10).

Using a KNN classifier resulted in differences between the classification rates described previously (Fig 5.36) . KNN results are presented in figure 5.37. Here the results for classifying the subjects intention to move their wrist to direction 12 (Fig 5.37a) shows that electrodes FC1, 74 and 122 classified over 90% percent of the trials accurately. The results presented in figure 5.37(b) correspond to attempts to predict intention to move towards direction 3, with the EEG from electrodes 74 and FC1 classifying about 90% of the trials accurately. While trying to predict intention to move towards direction 9 the electrodes FCz and 73 classify 95% of the trials accurately, see Fig 5.37(c) . In the case

of predicting intention to move towards direction 6 the figure 5.37(d) showed that electrodes FCz and 82 classified 90% of the trials accurately.

Again the differences observed (Fig 5.36 and 5.37) in the classification success rate of different electrodes while detecting the intention to move towards different direction could be used by possibly extracting features from multiple electrodes for use in classification.

Table 5.5 shows the highest classification rates obtained and the corresponding electrodes when the different classification techniques were used for the data recorded from different subjects.

Table 5.5 Shows the highest classification rates obtained for different subject s for the different classifcation techniques together with the electode positions for the classification of intention.

Subject	Euclidean Distance		KNN	
	Electrode	Classification Rate	Electrode	Classification Rate
1	78	81%	Cz	90%
2	74	66%	78	87%
3	122	70%	C3	75%
8	FC3	60%	FC3	80%
9	C1	68%	78	77%
10	74	67%	C1	90%

Again the table shows that no electrode performs consistently across all subjects. Once again this stresses the need to use high density electrode montages.

5.6.2 Classification of movement in different directions.

While in the previous section results from classification of intention are presented in the current section results are presented from attempts to distinguish the participant's intention to move their wrist in each of the different directions.

Stimulus Response Trials

Figure 5.38 shows the classification head map from attempts to predict direction of movement during stimulus response trials. It can be seen that the electrodes 123 and FC3 classify close to 65% of the trials accurately when using PCA and euclidean distances. Table 5.6 shows the highest classifications obtained and the corresponding electrode sites giving the highest classification success for the different subjects. In this classification process any result above 25% was greater than that expected by chance. For each subject classification rates better than chance were obtained.

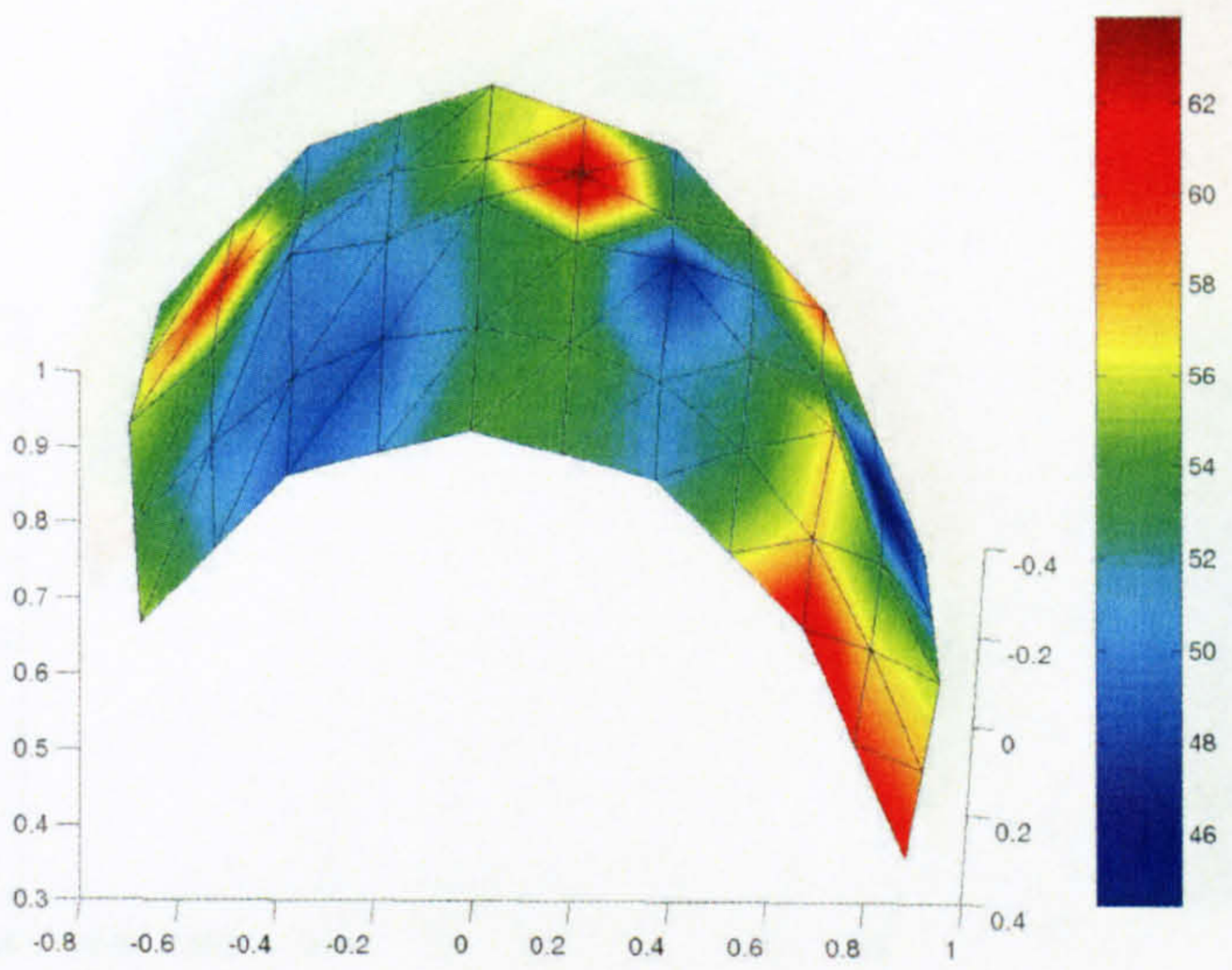


Figure 5.38 shows the classification results obtained while trying to classify intention to move in different directions during externally cued movement trials. Features Extraction: PCA. Classifier: Euclidean Distances. (Subject 10).

Table 5.6 Shows the highest classification rates obtained for different subjects.

Subject	Electrode	Classifcation
1	82	85%
2	78	48%
3	CP5	56%
4	CPz	54%
5	78	50%
6	74	48%
7	CP1	47%
8	122	70%
10	123	64%

Forced Choice Trials

The results in figure 5.39 shows the classification head map from attempts to predict direction of movement during self initiated and self determined movement trials. In the figure it can be seen that the electrodes 80 and 122 classify more than 65% of the trials accurately. However very low classification success was achieved in near by electrode sites highlighting the importance of finding optimal electrode sites.

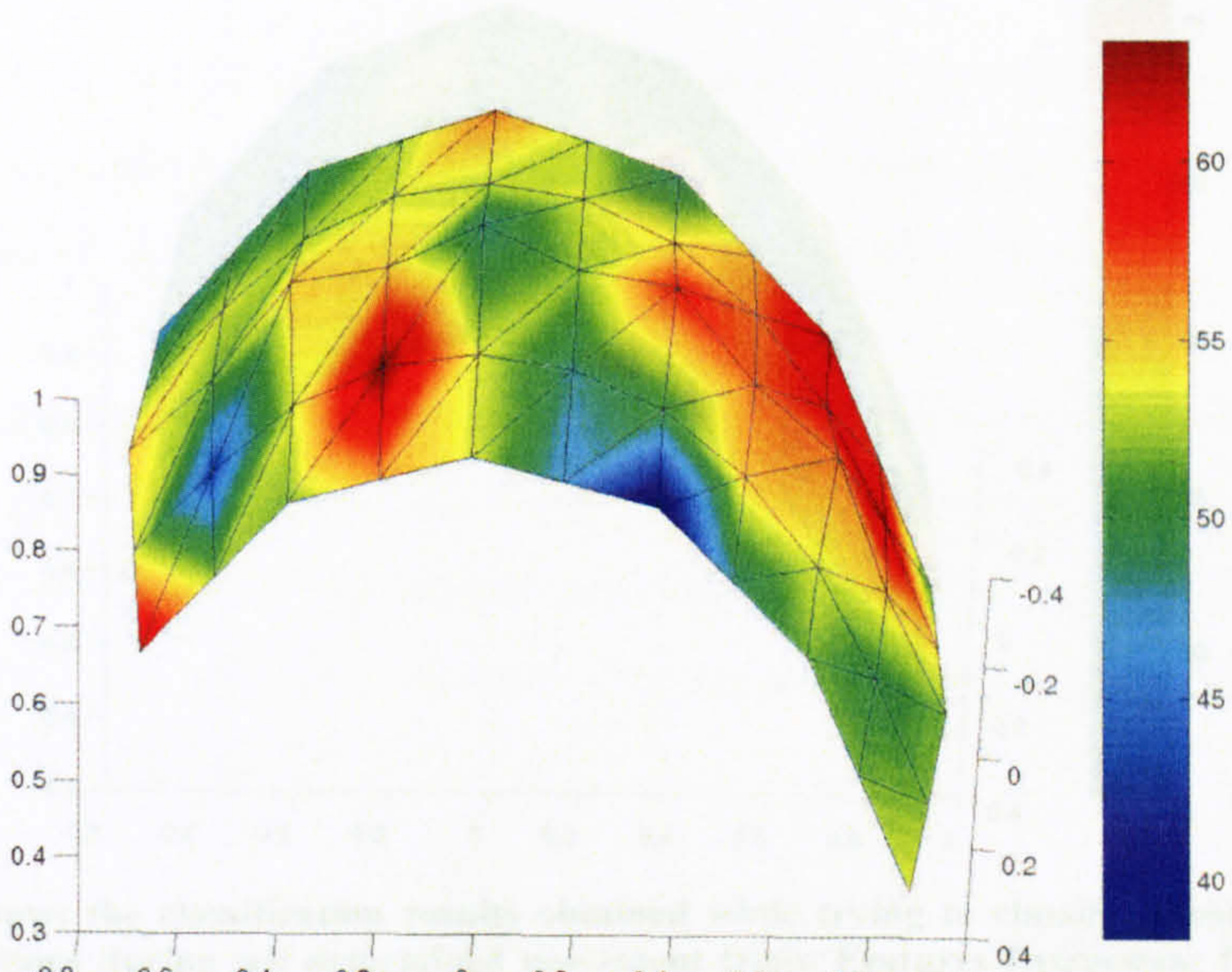


Figure 5.39 shows the classification results obtained while trying to classify intention to move in different directions during externally cued two choice movement trials. Features Extraction: PCA. Classifier: Euclidean Distances. (Subject 10).

Table 5.7 shows the highest classification rates obtained and the corresponding electrodes for different subjects. Again considerable variability existed in the location and the success rates obtained.

Table 5.7 Shows the highest classification rates obtained for different subject s

Subject	Electrode	Classification
1	FC3	80%
2	Cz	65%
3	FCz	74%
10	80	65%

Self Determined Movement Trials

Figure 5.40 shows the classification head map from attempts to predict direction of movement during self initiated and self determined movement trials. The illustrated results show that the electrodes C1 and FC1 classify close to 75% of the trials accurately.

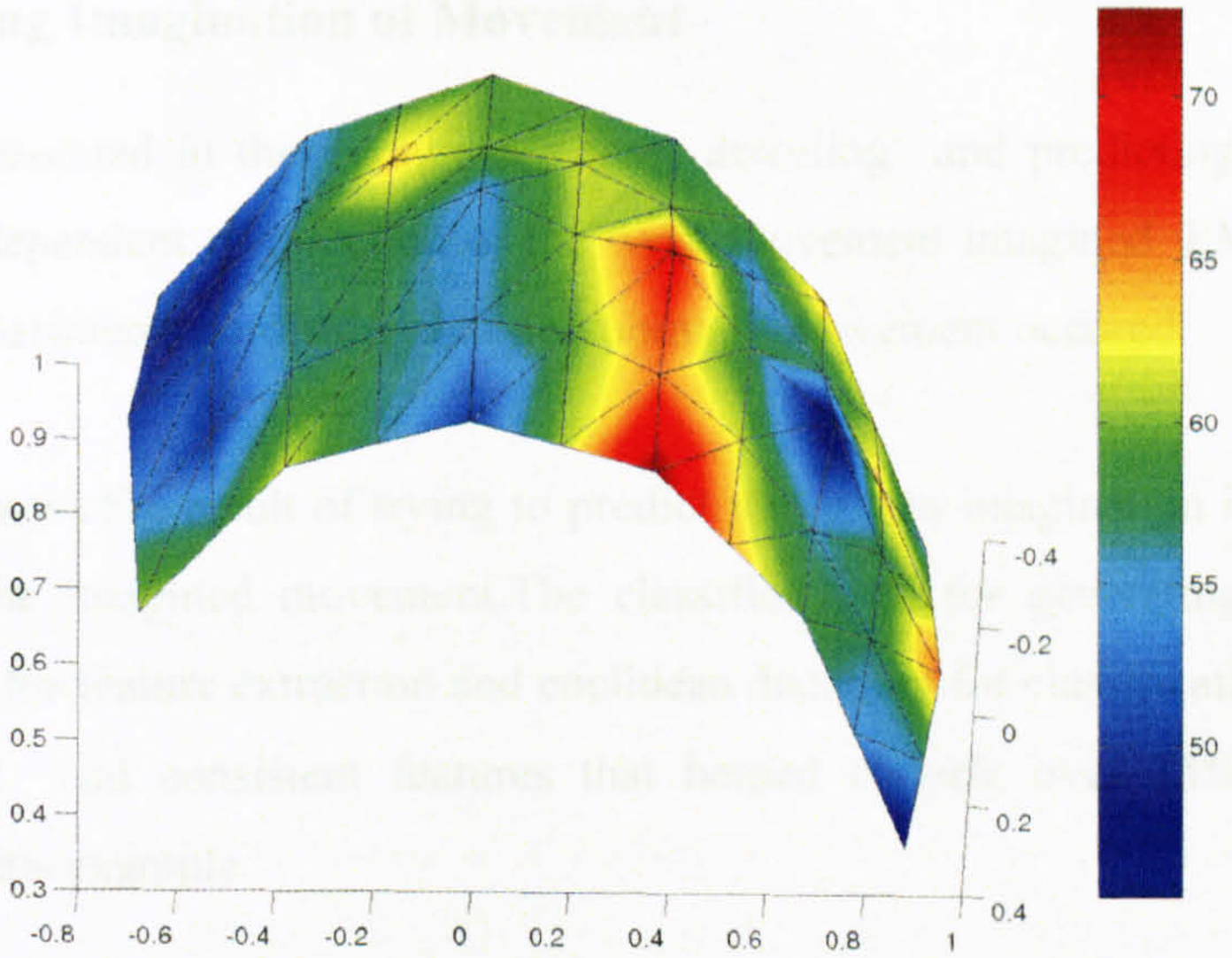


Figure 5.40 shows the classification results obtained while trying to classify intention to move in different directions during self determined movement trials. Features Extraction: PCA. Classifier: Euclidean Distances. (Subject 8).

Table 5.8 shows the highest classification rates obtained and the corresponding electodes for different subjects.

Table 5.8 Shows the highest classification rates obtained for different subjects

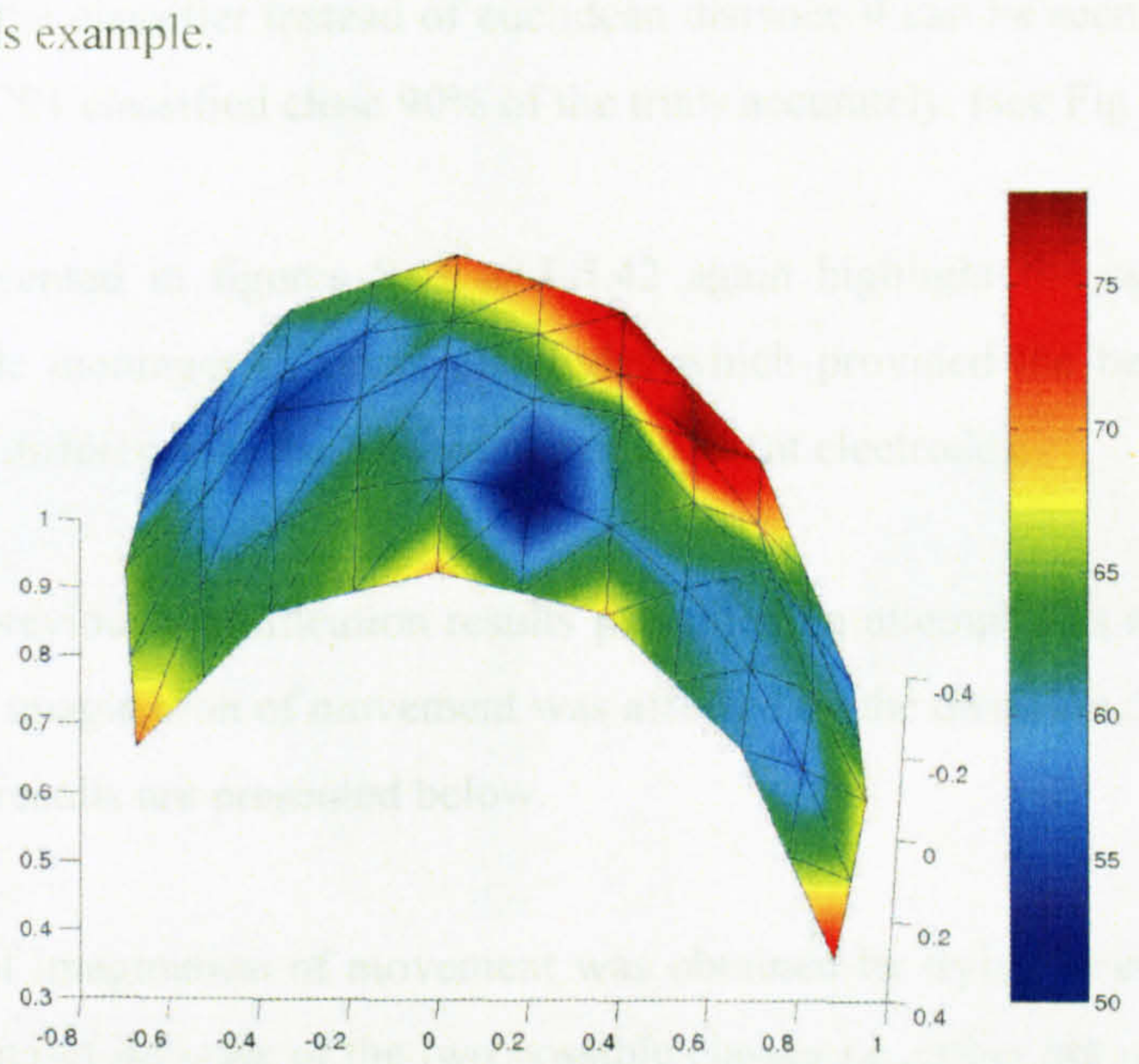
Subject	Electrode	Classifcation
1	73	62%
2	FC5	60%
3	CPz	52%
8	FC3	75%
9	CPz	62%
10	78	60%

The results presented in this section show that there are no electrodes which consistently perform well across subjects and that there are a considerable differences the performances of adjacent electrodes, thus highlighting the need to use high-density electrode montages during initial experiments with each participant for the selection of electrodes which provides the best classification.

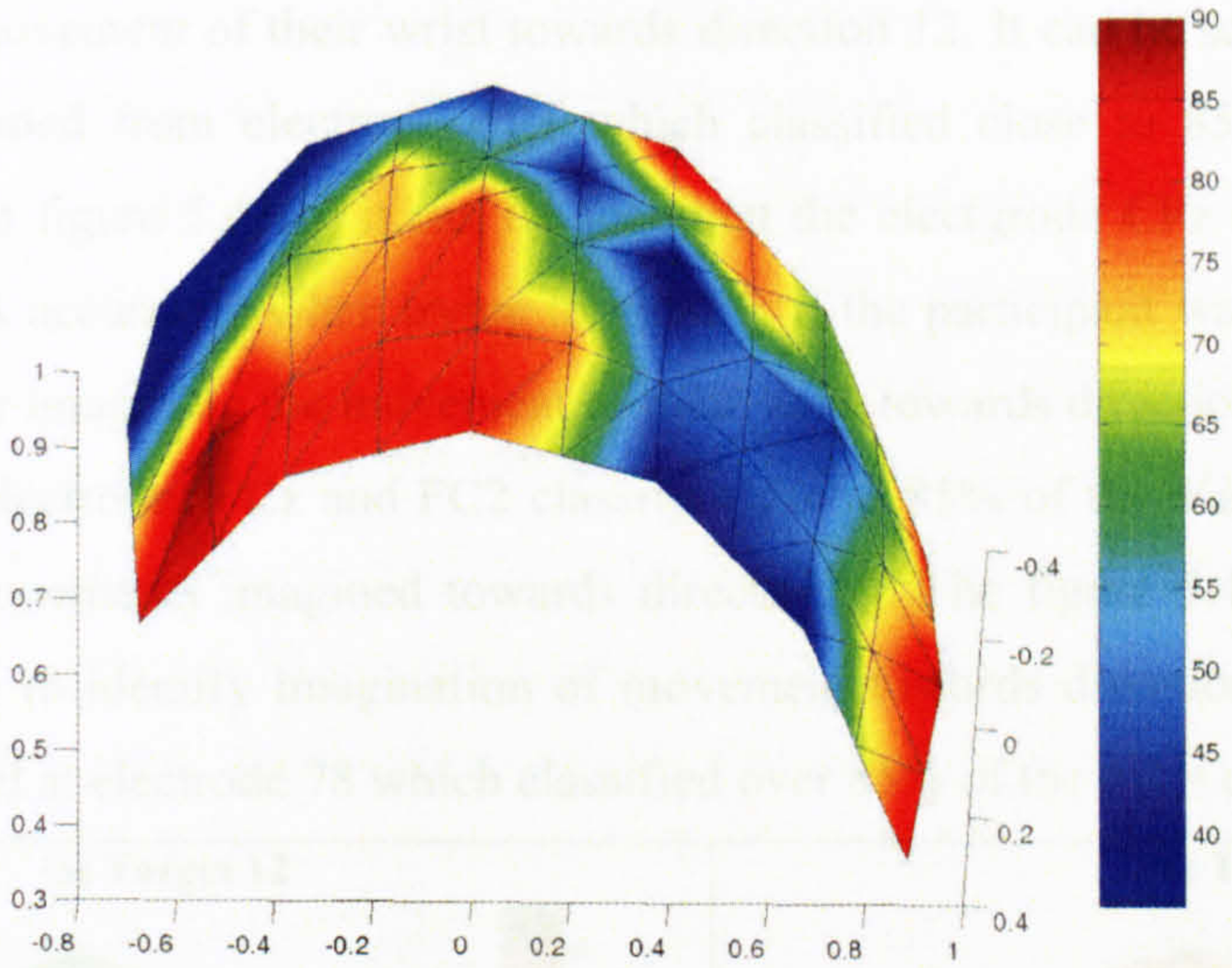
5.6.3 Detecting Imagination of Movement

The results presented in this section are from detecting and predicting the imagined movement independent of direction of the wrist movement imagined. EMG recordings from these experiments confirmed that no voluntary movement occured.

Figure 5.41 shows the result of trying to predict movement imagination independent of direction of the imagined movement.The classifier used for generating these results employs PCA for feature extraction and euclidean distances for classification. EEG from Electrode 122 had consistent features that helped classify over 75% of the trials accurately in this example.



5.41 The figure shows the classification results obtained while trying to movement imagination. Features Extraction: PCA. Classifier: Euclidean Distances. (Subject 1)



5.42 The figure shows the classification results obtained while trying to movement imagination. Features Extraction: PCA. Classifier: KNN. (Subject 1)

Using KNN as the classifier instead of euclidean distance it can be seen that electrodes 83 and C5 and CP1 classified close 90% of the trials accurately. (see Fig 5.42).

The results presented in figures 5.41 and 5.42 again highlight the need to use high density electrode montages to select electrodes which provided the best classification due to the large difference in the performace of adjacent electrodes.

Similar to the previous classification results presented an attempt was made to study if the detection of imagination of movement was affected by the direction of the movement imagined. The results are presented below.

The detection of imagination of movement was obtained by trying to classify the trials of the testing dataset into one of the two possible classes i.e.,either not moving or motor imagery of the movement to a particular direction (3,6,9 or 12).

Figure 5.43 (a) shows the results obtained when trying to identify if the subject was imagining the movement of their wrist towards direction 12. It can be seen that the best result was obtained from electrode CP1 which classified close to 85% of the trials accurately. From figure 5.43(b) it can be seen that the electgrode CPz classified obout 90% of the trials accurately when trying to identify if the participant was not imagining the movement or imagining the movement of their wrist towards direction 3. Figure 5.43 (c) shows that electrodes FCz and FC2 classify close to 85% of the trials accurately in relation with movements imagined towards direction 9. The figure 5.43(d) shows the results of trying to identify imagination of movement towards direction 6.The highest rate was obtained at electrode 78 which classified over 85% of the trials correctly.

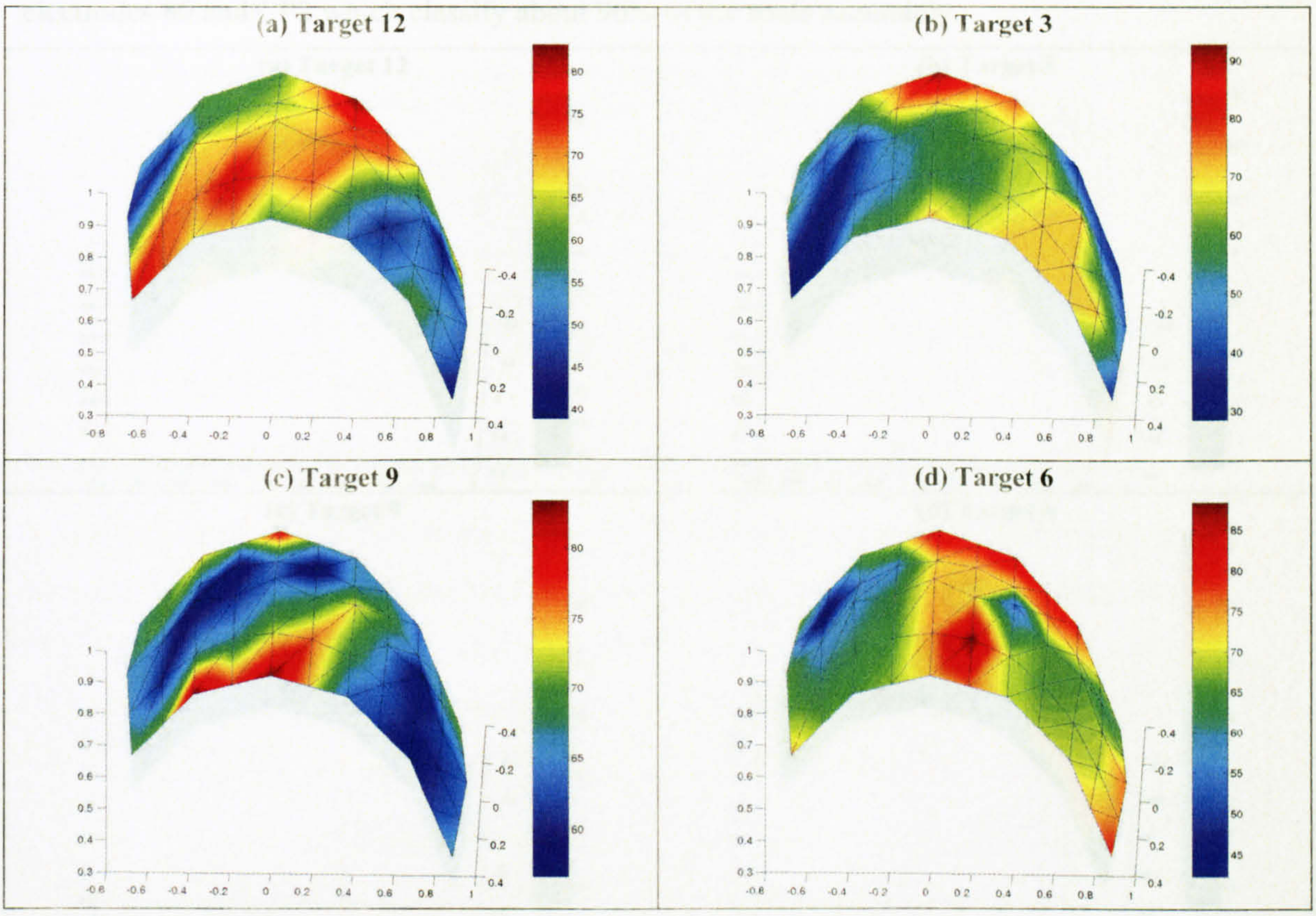


Figure 5.43 shows the results obtained while classifying an EEG epoch into two cases one: subject is imagining the movement of their wrist in different directions, two: is not imagining. Features Extraction: PCA. Classifier: Euclidean Distance. (Subject 1). (a) - 12,(b) - 3,(c) -9,(d) – 6.

Figure 5.44(a) shows the results obtained when trying to identify if the subject is imagining the movement of their wrist towards direction 12. It can be seen that the highest classification result is obtained from electrode 80 which classifies over 85% of the trials accurately. From figure 5.44 (b) it can be seen that the electrode CP5 classifies 100% of the trials correctly when trying to identify if the participant is imagining the movement of their wrist towards direction 3 or is not. Figure 5.44(c) shows that electrodes 80 classifies close to 85% of the trials accurately for this subject when trying to identify if or not a subject is trying to imagining the movement of their wrist towards direction 9. The figure (d) shows the results of trying to identify if or not if they are imagining the movement of their wrist towards direction 6.The best result is obtained at electrodes 80 and CP2 which classify about 90% of the trials accurately.

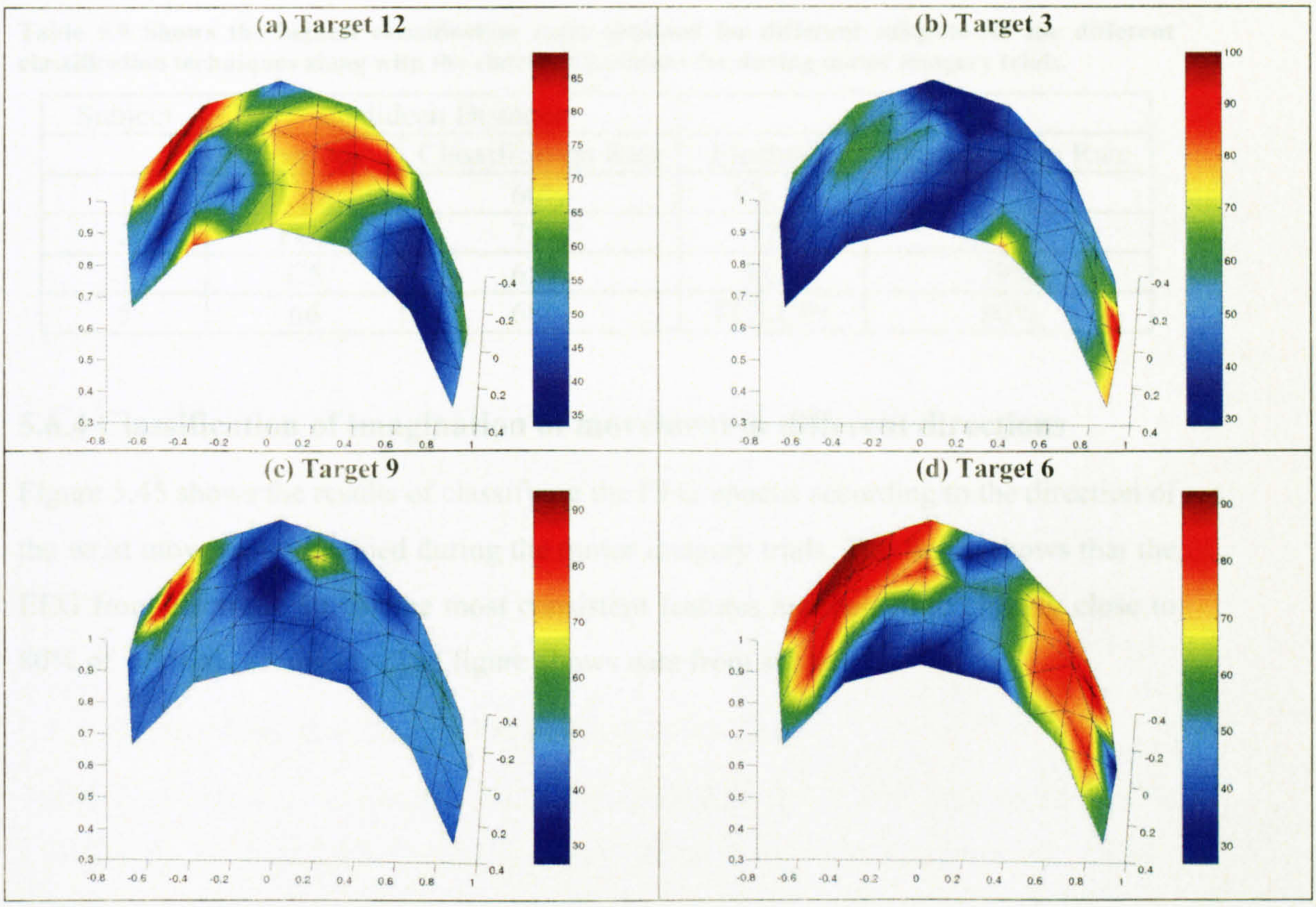


Figure 5.44 shows the results obtained while classifying an EEG epoch into two cases one: subject is imagining the movement of their wrist in different directions, two: is not imagining. Features Extraction: PCA. Classifier: KNN. (Subject 1). (a) - 12,(b) - 3,(c) -9,(d) – 6.

The results presented in figure 5.43 and 5.44 show that the electrodes that provided high classification rates while detecting the imagination of movement were different for different directions. Thus as in the case for actual movement trials there was possibility for using features extracted from multiple electrodes for classification.

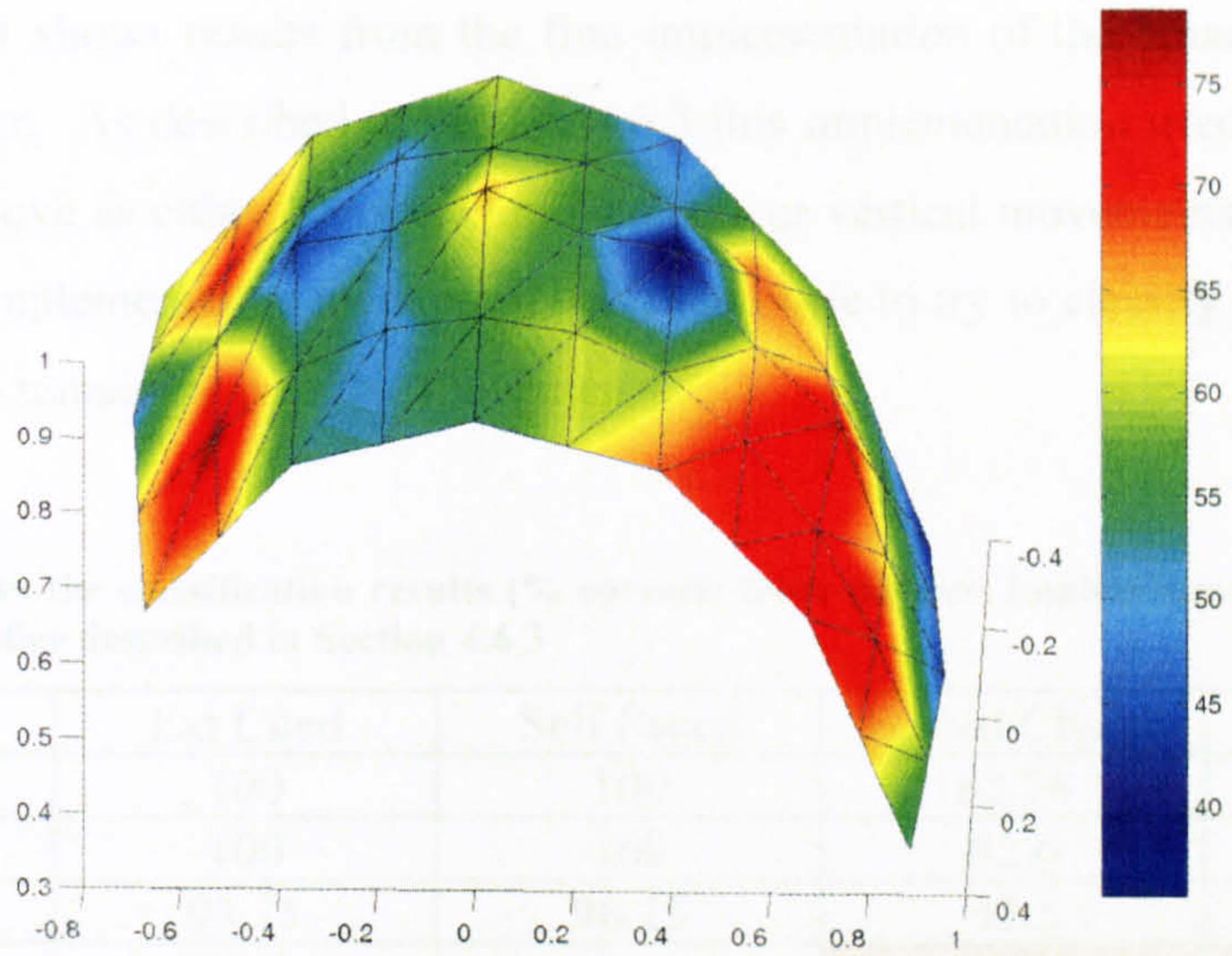
Table 5.9 shows the highest classification rates obtained and the corresponding electrodes when the different classification techniques are used for the data recorded from different subjects. As with previous data sets there is no single electrode site which performs best across all subjects and KNN appears to achieve higher success rates than euclidean distance.

Table 5.9 Shows the highest classification rates obtained for different subjects for the different classification techniques along with the electrode positions for during motor imagery trials.

Subject	Euclidean Distance		KNN	
	Electrode	Classification Rate	Electrode	Classification Rate
1	Cpz	60%	Cz,78	81%
2	FCz	75%	122	82%
3	C5	65%	FCz	79%
5	66	68%	FC3,CPz	80%

5.6.4 Classification of imagination of movement in different directions

Figure 5.45 shows the results of classifying the EEG epochs according to the direction of the wrist movement imagined during the motor imagery trials. The figure shows that the EEG from electrode 80 has the most consistent features and helped to classify close to 80% of all trials accurately. The figure shows data from subject 1.



Figures 5.45 shows the results from trying to differentiate motor imagery of the wrist movement in different directions for Subject 1.

Table 5.10 shows the highest classification rates obtained and the corresponding electrodes for different subjects. As in the previous classification results these results highlighted the need to use high density electrode montages for selecting electrode which provided good classification.

Table 5.10 Shows the highest classification rates obtained for different subject s

Subject	Electrode	Classifcation
1	66	95%
2	122	58%
3	65	62%
5	FCz	74%

5.6.5 Results from the Binary Tree Based Classifier

Tables 5.11 and 5.12 shows the results obtained from the Binary decision tree based classifier for different subjects who have participated in the various experiments. Subject 8 and Subject 5 were not able to participate in all the experiments.

The table 5.11 shows results from the first implementation of the binary decision tree based classifier. As described in section 4.6.3 this implementation tried to classify the intention to move as either horizontal movements or vertical movements. At the second stage of this implementation an attempt was then made to try to classify the intention as one of the two remaining possible movements.

Table 5.11 Shows the classification results (% correct) from the first implementation of the binary tree based classifier described in Section 4.6.3

	Ext Cued	Self Paced	Forced Choice	Imagination
Subject 1	100	100	62.76	62.5
Subject 2	100	100	82.6	90
Subject 3	93.75	96.25	92.5	75
Subject 8	82.5	72.5		
Subject 10	94.44	95.14	88.75	

The table 5.12 shows the results from the second implementation in which the movements were initially grouped based on similar muscles involved in these movements (3 and 12 Vs 6 and 9). At the second stage of this decision tree the intention was then classified between the two remaining possible movements.

Table 5.12 Shows the classification results from the second implementation of the binary tree based classifier described in Section 4.6.3

	Ext Cued	Self Paced	Forced Choice	Imagination
Subject 1	90.74	100	43.62	70
Subject 2	100	100	81.52	90
Subject 3	76.25	96.25	80	72.5
Subject 8	65	55		
Subject 10	100	87.5	87.5	

While studying the results presented in tables 5.11 and 5.12 which were obtained with the two different binary tree based classifiers we see that results obtained are higher than the results obtained with euclidean distance based classifier. While comparing the results of the two implementations we see the overall results presented in table 5.11 are higher than the results presented in table 5.12. Specifically the first implementation provides

higher classification accuracies for the data recorded from subject 1 during externally cued and forced choice experiments, for subject 3 during externally cued trials and for subject 8 for both externally cued and forced choice trials. Higher classification results are obtained from the 2nd implementation of the binary tree classifier only from the data recorded from subject 10 during externally cued trials.

5.6.6 Information Transfer Rates

The tables 5.13 and 5.14 show the information transfer rate for the different classification attempts for the different experiments. The information transfer rate (ITR) has been computed using formula described by McFarland et al 2003. This has been computed using the highest classification that has been obtained. While the number of classes was 2 for detection of intention to move (real or imagined) the number of classes was 4 when trying to distinguish movements (real or imagined) in different directions.

Table 5.13 shows the ITR computed from the best results obtained from the classification methods, which used features extracted from EEG recorded at a single electrode after FFT and using ANOVA to pick variables which show significant differences between the groups and PCA for dimension reduction and a Euclidean classifier. The table shows the ITR computed for classification results obtained from both attempts to predict only intention and from attempts to predict the direction of wrist movement (imagined and movement). The table shows that ITR computed while trying to predict the direction of movements (N = 4) are almost twice the ITR obtained for attempts to prediction intention (N=2). The only exception to this being stimulus response trials in which for N= 2 and N=4 the ITR is 4.23 and 4.83, however this can be explained by low classification accuracy obtained for the case when N = 4. If the same classification success was achieved one would expect the ITR to double when going from N =2 to N = 4. In fact it is seen that the ITR that is consistently less than a double highlighting the fact that ITR also depends not only on the number of classes but also on the classification success rate.

Table 5.13 Shows the information transfer rates best classification results obtained for the simple classifier which utilizes PCA for feature extraction and a either a Euclidean Distance classifier or KNN classifier.

Experiment	Detecting Intention (N =2)	Predicting Direction of Movement Using Single Electrodes (N =4)
Stimulus Resp	4.23	4.87
Two Choice	3.12	5.36
Self Determined	5.71	7.9
Imagination	4.23	7.69

Table 5.14 shows ITR computed for the best classification results obtained based on the binary decision tree based classifier. While computing the ITR for 100% accuracy with the formula 4.7, P = 0.999999 was used since the denominator of the equation would be equal to 0 if P = 1. Comparing the ITR in Table 5.14 against the corresponding ITR in table 5.13 (N =4) we see that ITR are considerably higher due to higher classification results obtained.

Table 5.14 Shows the information transfer rates best classification results obtained for the binary decision tree based classifier.

Experiment	Detecting Intention (N =4)
Externally Cued	12
Forced Choice	8.98
Self Determined	20
Imagination	13.73

The results presented in this chapter have shown that it is possible to differentiate on a single trial basis wrist movements and the imagination towards different direction with success greater than that explained by chance. Thus showing that it is possible to extract features related to movement (and imagination of movement) consistently and translate them into control signals for use in BCI technology .It demonstrated the increase in the ITR obtained due to increase in the dimensionality of the control signal. It was also discussed the importance of using a high density electrode montage for the selection of electrodes which provide good classification.

Chapter 6: Discussion

The present study has demonstrated through statistical comparison of the ERSPs of EEG that there are significant differences in the changes to spectral components of EEG signals recorded during actual and imagined movement of the wrist towards different directions. This is further confirmed by the ability to predict from the EEG signals prior to movement initiation the direction of intended movement on a single trial basis. This thus strengthens the argument that EEG recorded over the scalp contains features which are relevant to movement (real and imagined) intention and movement directions and that these features could successfully be used to provide multi-dimensional control signal for a BCI. The aim of the project, which was achieved, was to study the EEG associated with fast point-to-point wrist movements made in different directions (or their imagination) and extract information relevant to movement intention and direction for potential use as a reliable control signal in a BCI.

The movement tasks for experiments were chosen because they caused large activation of the motor cortex (Hoffman and Strick 1999; Kakei, Hoffman et al. 1999; Kakei, Hoffman et al. 2001; Reid 2005) and also because there was evidence from primate studies which showed that the neurons in the motor cortex were directionally tuned(Georgopoulos, Kalaska et al. 1982). In the study of cortical activation during step wise activation of tracking movement of the wrist, Reid (2005) observes that fast wrist movements can be considered as stereotyped movements which are based on intrinsic movement parameters and are correlated (i.e., are coherent) with activation of the motor cortex The motor imagery tasks were also chosen because research into internal simulation and imagination of movement has revealed the presence of partially overlapping neural networks for the processing of the real and imagined movements. (Beisteiner 1995; G. Pfurtscheller 1997; Gerardin, Sirigu et al. 2000; Pineda, Allison et al. 2000; Ramoser, Muller-Gerking et al. 2000; Cincotti, Mattia et al. 2003). Researchers (Rizzolatti, Fogassi et al. 1997; Kakei, Hoffman et al. 1999; Kakei, Hoffman et al. 2001) have demonstrated that various pre-motor areas of the cortex also

contain neurons whose discharges alter with voluntary movement, which therefore dictates the need to use a wide recording montage in order to find the best sites for recording classifiable activity. At present no work has been done to study the effect of electrode location and most of the non-invasive BCI developed so far utilize features from signal recorded directly over the motor cortex. As discussed by Fetz (2007) it is evident that cortical signal recorded from both pre-central and post-central areas can be used to predict movement which is one of the key requirements of a BCI system. While several studies have employed features relating to movement (actual and imagined) of different body segments from signals recorded both non-invasively and invasively for developing one dimensional control signals for BCIs (Haselsteiner and Pfurtscheller 2000: Ramoser, Muller-Gerking et al. 2000; Romero, Lacourse et al. 2000; Simon P. Levine, Jane E. Huggins et al. 2000; Guger, Schlogl et al. 2001: Cincotti, Mattia et al. 2003; Pfurtscheller, Brunner et al. 2006) very few studies have used features relating to movement parameters for developing multi-dimensional control signals for BCI. The advantage of using features relating to movement and its imagination for controlling a BCI are pointed out by Fetz (Fetz 2007)who discusses the ease with which the initial original movements that were used for modulating the cortical activity can be stopped. The study by Leuthardt, Shalk et al. 2004 also discusses that with practice clinical subjects often feel that they can eventually control a BCI cursor directly without the intermediate "motor imagery" used to evoke changes in the cortical signal. In this study, the aim was to extract features, from the scalp EEG electrode montages recorded during actual and imagined movements to different direction which are easy to perform and are highly stereotyped with a clear dependency on motor cortical activity. For these reasons the fast centre-out movements of the wrist are studied by Hoffman and Strick (1999) was used.

The quality of the data was assessed by examining both the kinematics of the movements and also the EMG and EEG that were recorded during the different experiments. The analysis of the position data recorded during the movement trials confirmed that the movements were made to the displayed targets during the externally

cued and forced choice trials. In self-paced trials it would be valid to assume that all the movement trials were accurate since participant moved to a self-determined direction. In the motor imagery tasks the participant confirmed after each session that in each trial they imagined the direction of the movement towards the displayed target. The analysis of peak angular velocities obtained during the three movement trials: externally cued, forced choice and self-paced, show that the externally cued and forced choice trials are more consistent having a small variance and can thus be considered to conform to stereotyped movements. The analysis also demonstrated that the peak velocities obtained during self-paced trials while more variable are faster. This is related to the larger displacement seen in this task and it can be assumed that like other movement protocols this is associated with a synchronisation in the motor drive via the cortical spinal system. The analysis of the kinematic data and EMG recorded during the motor imagery tasks confirmed that there was no active involvement of the muscles during these experiments. The EEG recorded during these trials should therefore contain features relating to the motor imagery without signals associated with the execution and subsequent sensory feedback normally seen in movement trials.

The analysis of data recorded during the experiments started with the computation of the MRCP. Due to the lack of information of non-phase locked changes in the time-averaged MRCP, the ERSP were computed. Both MRCP and ERSP show changes in relation to the tasks performed. To objectively compare the changes seen during the different experimental tasks the ERSP computed was further investigated using statistical methods. This helped to identify robust features which could be used for generating the control signals for a multi-dimension BCI. The successful classification of data on a single trial basis helped confirm that it is possible to extract features, from the scalp recorded EEG, which relate to the intention and direction of the movement. Based on adopting a centre-out movement task the results presented suggests that 2 to 4 dimensions can be classified using simple methods that would be easily adapted for BCI use.

The subsequent section in this chapter discusses both the significance and critically analyses the methodology and the different results obtained from this study.

6.1 Methodology

One of the major problems faced during the study was related to the concentration of the subjects. Some of the subjects who participated in the study found it difficult to maintain the level of attention and concentration required for the duration of an experiment which would last for several hours. In an attempt to combat this problem, the recording sessions were split to give the subject time to relax. Where a subject's attention to a task diminishes it would be expected to have lead to poor results during classification due to errors in direction and a loss of how well the tasks were completed. The low error rate and variance during externally cued trials and forced choice trials suggests this did not happen.

During the study it was found that several types of artefacts corrupted the quality of the signals. The major causes of the artefacts include blinking, swallowing, yawning and coughing. However, these artefacts being much larger than the EEG signal, were easy to recognize and the EEG epochs that were corrupted by these artefacts were rejected during the initial processing of the data. To assist in minimising the number of blink and swallowing the subjects were shown the effects of blinking, coughing, yawning and swallowing prior to the commencement of the experiment and were instructed to try to avoid un-necessary eye blinks and swallows. This ensured that the subjects agreed to the next experimental session when they felt that they were alert and not drowsy.

In the movement experiments it was possible to verify the accuracy of the movement, in the imagination trials it was not possible to confirm if the subject did imagine the appropriate wrist movement for the target displayed. For the movement trials all subjects accurately moved towards the displayed target. In an attempt to ensure that all the trials were performed accurately the subjects were asked at the end of each imagination session if they inaccurately performed any single trial. By keeping a constant vigil on the

subject it was possible to see if the subject was alert throughout the experimental session. It is therefore the opinion of the author that the subjects complied with the task conditions and attained a satisfactory task performance in all experiments completed.

6.2 Kinematics

Comparing the angular displacement and angular velocity in figures 5.3, 5.4 and 5.5 it can be seen that the angular displacements are the same across all directions indicating that all the subjects acquired the target displacement angle for each direction. Schwartz [1999] has shown that the activity of the cells in the motor cortex is modulated by both the direction and the speed of the movements. They also showed that the speed related modulation of cell activity generally preceded the actual movement. Thus in the present study for the movement trials with a displayed target the differences observed in EEG could only be due to differences related to the planning of movement in different directions. However this was not the case for free-choice experiments.

It can be seen that during movements made to the different targets the mean angular displacement in externally cued experiments were similar but for the internally chosen movements the angular displacements are greater for the internally chosen movements. Associated with this greater displacement was a higher angular velocity. This can be explained by the lack of a target and lack of direct visual feedback of the actual displacement in the self determined movements the subjects do not get any visual feedback of the actual wrist displacement. Thus the movements in the self-chosen trials tend be of larger displacement and the velocities are exaggerated On this basis it would be a safe assumption to suggest that cortical activation in this task may be higher and comprise a factor related to the increased velocity. This may explain why in some subjects we obtained higher classification rates with self-determined movement trials than when they perform movements with visual feedback.

Since in the imagination of movement trials there were no external movements, it can be claimed here that the differences seen in the EEG was only because of the imagination

of movement of the wrist in different directions. The EEG changes observed are therefore more likely to relate to movement preparation than to movement execution.

6.3 Reaction Times

It can also be seen that the reaction times of the participants during externally cued single visual target trials are shorter than the reaction time of the participants during externally cued double visual target trials. This is consistent with the literature [Marteniuk, Information Processing in Motor Skills] which argues that as the complexity of the task increases the reaction time also increases. Again this high cognitive demand was going to be reflected in longer pre-movement preparation times.

6.4 Movement Related Cortical Potentials

A study of the MRCP potential show that prior to movement initiation there is an increase in negativity of the signals recorded at the different electrodes. This change observed is consistent with Bereitschafts or Readiness potentials reported in literature. (VaezMousavi SM 1993; A. Starr 1995).

When the MRCP for the stimulus response trials and forced trials is plotted along with MRCP for self-determined movements it can be seen that the Bereitschafts potentials are observed for longer duration prior to self-initiated movement than movements initiated due to a stimulus. (Pineda, Allison et al. 2000) Thus we can argue that during self-initiated movements there a longer planning phase or movement preparatory phase. This is important for picking out features for the classifier since a longer section of data is available for feature selection. While it can be argued that the longer data length used for self-paced trials might result in the reduction of the information transfer rate (ITR) in a BCI. It has to be noted the recovery of the MRCP in self-paced trials is faster than both externally cued and forced choice trials and so even though a longer data section can be used for classification this need not result in a reduced ITR.

When event related potentials for imagination trials were computed they demonstrated similar negative variations to those observed in movement trials. The results indicate that although there are similarities in the time course of the ERP for imagination of movements in different directions, there are differences in the peaks. However, these time domain measures are difficult to classify when only a few parameters can be used (slope and amplitude).

Similarities can also be noticed between the event related potentials computed at the same electrode during movement and imagination. This is consistent with the literature which lends support to the idea that similar neural structures are involved in the preparation and the imagination of the same movement. (Pfurtscheller and Neuper 1997).

To study the effect of stimulus presentation on EEG the average of the EEG epochs recorded when the subject was asked not to respond to the stimulus we also calculated. The results of these have been presented in figure 5.13. These results show that there is no significant change in the EEG when the subject is instructed not to respond to the visual stimulus. It is therefore unlikely that any significant visual evoked potentials contaminate the MRCPs. It is also unlikely that the CAR procedure which essentially subtracts out any far fields would minimize any attributes due to stimulus perception.

It can be argued that the EEG recorded can be contaminated by eye saccades and this can affect the results since the eye saccades to different directions can lead to different EMG signals being recorded along with the EEG for the different visual stimuli presented. However, given that the angular displacement from the centre target to each of the other targets will be less than 1^{o} it is unlikely that significant EOG will be generated. Moreover, the changes seen in the EEG prior to movement initiation last close to 300 ms which would be significantly greater than the trial for eye saccades or 1^{o}. In addition given that similar EEG changes were observed during self determined movement experiments which did not have an external visual target the likelihood of

EOG contamination is considered low. The study of event related potentials show that there is no significant change in the EEG when the subject was instructed not to respond to the stimulus presented. As these stimuli will also lead to the same eye saccades as those in the other tasks it can be argued that the changes seen in the averages of the EEG were not due to EOG. It would also be expected that frontal electrodes would consistently show the highest classification results if EOG was a major artefact. The fact that this also did not happen supports the view that EOG contamination was not a problem.

Additionally the recorded EEG signals were referenced to the common average reference (CAR), which helps to accentuate components with highly focal distribution and this would also counter to the effects of signal components related to EOG.

6.5 Event Related Spectral Perturbation

While comparing the ERSP of EEG epochs prior to and during movements towards different directions it is seen that there are significant differences in the α, β and γ bands (figures 5.15, 5.16 and 5.17). It also seen that these differences are present irrespective of whether the movements were made in response to a single external cue or if the movements were made after a forced choice or are made based on an internal self-paced choice. More important for this study is the statistically significant differences observed prior to movement initiation in the α and β bands, since it is these differences that can be used to recognize intention of the participant to move their wrist in different directions.

Looking at the ERSP of the EEG during imagination trials (see figure 5.18) we can see that there are statistically significant differences between ERSP of the EEG during imagination of movement in different directions. Again these statistically significant differences can be exploited to recognize the direction of the imagined movement. To the authors knowledge although ERS/ERD changes related to movements have been reported and used for BCI classification no report has demonstrated differences in the ERS/ERD pattern associated with movement in different directions. (Pfurtscheller and

Lopes da Silva 1999; Pfurtscheller, Woertz et al. 2003; Pfurtscheller, Neuper et al. 2005; Pfurtscheller, Brunner et al. 2006; Pfurtscheller, Leeb et al. 2006)

While comparing the ERSP of the EEG prior to and during movements to the same direction under different experimental conditions (figure 5.23 externally cued Vs self chosen) we find that there are again statistically significant differences. It can be seen that prior to movement initiation in self paced and directed movements there is a longer event related desynchronization in the beta frequencies and there is stronger and prolonged event related synchronization when the subject is in hold phase of the trial the spectral changes prior to movement initialized correlate in time with the differences seen in the duration of the early phase of the MRCPs.

6.6 Classification and Information Transfer Rate

From the results it is clear that the 500ms to 1000ms of EEG prior to movement initiation can be used to predict and classify movement intention and direction in both externally cued and self initiated movements. It has also been shown that the imagination of movement can be reliably detected, and that it is also possible to deduce the direction of the imagined movement from single EEG epochs. When attempting to predict whether a participant is intending to move or not, we obtain the best classification rates between 75% and 95% across all subjects. While trying to detect if the participant is imagining movement or not; the best classification rates is between 65% and 100%. In both cases we obtain classification rates much higher than the 50% that we would get by pure chance. It is worth noting that it is not the same electrodes that give the best result across all subjects and electrodes generally lying over the pre-motor cortex or the primary motor cortex areas on the contra-lateral side give the best classification results. We see that in some cases that higher classification rates were obtained for the imagination trials this but could be attributed to the longer EEG epoch of 1000ms that were taken from the imagination trials as compared to the 500ms of EEG prior to movement initiation that was taken from the movement trials.

The classification results show the success achieved from EEG recorded at all the 28 electrodes available. For the movement trials it is seen that electrodes which lie close to the frontal areas provide the highest classification. This higher classification can be attributed to the fact that the frontal areas of the cortex overly the premotor cortex (please refer figure 2.3) which is involved in movement planning. Thus it is possible that the EEG recorded from these electrodes contain classifiable information corresponding to movement planning or goal selection. The classification scalp maps also show the importance of initially using a high density electrode montage to pick out electrodes which perform better than the neighbouring electrodes. Importantly small deviation from the ideal site can lead to collapse of the classification success. Electrode placement is therefore very critical for good classification.

Results from two different classifiers have been presented in section 5.5 for classifying movement intention and imagination of movement. The first classifier uses the euclidean distances between the means of the training set and the new unclassified trial; the second identifies the class of k nearest neighbours to the unclassified trial and classifies the new trial to the group which has the maximum presence around the new trial. The results show that in all cases the KNN classifier consistently classifies more trials accurately and out performed the euclidean distance based classifier.

While it is clear that it is possible to reliably predict the intention of the participant to move, the next step was to try and predict the movement direction from the EEG which just preceded the movement. This result is not given in thesis. Thus features from the frequency domain were used as the ERSP data showed clear statistical differences could be seen in the population datasets. The dimensionality of the problem was reduced using PCA and the euclidean distance based classifier was used after feature extraction. The classification results for the group studied were noted to be significantly better than would be expected by chance (25%). Use of the Binary Decision Tree based classifier which works on the "divide and conquer" approach produced significantly higher classification success rates that those obtained with euclidean classifier which used PCA

and FFT for feature extraction. The implication from these observations is that at minimum four different classes or dimensions can be extracted and used for BCI control.

The information transfer rates were computed for the different classifiers for the different experiments. It can be immediately seen that when the number of classes is increased the information transfer rate also increases. This increase occurs despite the fact that the classification accuracy when N=4 is not as high as when N=2. However this increase is still expected since the amount of information transferred per trial is more (twice) when there are more classes. It can also be seen that among both the cases (N=2 and N=4) the information transfer rate for self-determined movement experiments is higher. This is because the average number of trials per minute for self determined movements is 10 which is greater than the number of trials per minutes for the other experiments which is 6 trials per minute. The reduction in the inter-trial interval to improve the information transfer rate depends on the duration of the event related changes seen in the EEG. From the ERSP plots it can be seen that on an average for the stimulus-response and the two choice experiments these changes last for 2 seconds. Thus the inter-trial duration can be reduced from 10 seconds to 4 seconds allowing for some leeway. This would result in a 2.5 times increase in the number of trials per minute and hence a 2.5 times increase in the information transfer rate. For the Self determined trials, the changes last on an average for 2 seconds, thus the inter-trial duration can be reduced from 6 seconds to 4 seconds which in-turn will help increase the information transfer rate by a factor of 1.5. Thus the maximum ITR obtained for externally cued, forced choice and self paced trials are 30 bpm, 22.5 bpm and 30 bmp respectively.

While comparing the BCI developed against the BCI work done in other labs (refer Table 7.1) it can be seen that the classification success rates obtained are at par or higher than those reported in literature. While most of the work reported in literature involves extracting a one or two dimensional control signal. the current work demonstrates that it possible to extract at least 4 separate control signals using EEG prior to movement initiation and from EEG recorded during imagination of movement. The information

transfer rates obtained with the current system are higher than the BCIs that have been developed for humans and reported in literature (refer table 2.1).

The classification success rates obtained in the current system also match the performance of the invasive BCI reported in literature. Researchers (Leuthardt, Schalk et al. 2004; Donoghue, Nurmikko et al. 2007) reports that significantly robust feature and hence higher performance can be obtained with invasive BCI techniques; the current work highlights the ability of obtaining robust features from EEG recorded from non-invasive techniques for developing BCI. Wolpow (Wolpaw 2007), based on a review of current BCI, concluded that the performance of BCI using non-invasive techniques matches the performance of BCI using invasive techniques. Thus there is scope for further development of both approaches towards more functional BCIs.

There is a lack of information in the literature which deals with the electrode positioning and its importance for BCI performance. The present study used a high-density electrode montage and studied the classification success rates obtained for the different electrodes. The results presented highlight the need for using high density electrode montage for selecting electrode location initially and which can help identify electrodes where the most robust features for obtaining high classification rates are located. The maps of classification would also suggest that using multiple electrode sets for classification of different direction (commands) would out perform any single electrode site classification scheme.

While the current study shows that it is possible to extract a multi-dimensional control signal from the EEG "recorded" during movement and imagination of wrist movement in normal subjects future work will necessitate collecting and analysing data from subjects who are paralysed. Future work will also involve developing an online BCI. The online BCI will help answer the questions pertaining to the effect of feedback on BCI use and will help in studying the long term stability of the features extracted.

Chapter 7: Conclusion

7.1 Summary of study

The study of the kinematics of the movements showed that there are no significant differences in the angular velocities of movements towards different directions during each of the three different movement experiments. The study also showed that due to lack of visual feedback during self-paced and determined movement trials these movements are of greater displacement and faster than stimulus response and forced choice trials.

Bereitschafts potentials observed during the analysis of the ERPs of both movement and imagination trials are consistent with what the literature reports. The comparison of the ERPs of externally cued and internally initiated movements showed the Bereitschafts potentials are of a longer duration prior to movement in internally initiated movements than in externally cued movements.

A more detailed frequency domain analysis of the epochs performed by computing the ERSP showed that for movement trials there is a significant change in the EEG spectrum which starts within 500ms prior to movement initiation. Similar changes are also observed in the EEG epochs of imagination trials. The study also showed that there are statistically significant differences between ERSP of the EEG prior to and during movements towards different directions. Statistically significant differences are also observed between ERSP of EEG recorded during imagined wrist movements towards different directions. While comparing the ERSP of externally cued and internally selected movements it was found that there are significant differences not only during movement but also prior to movement initiation. In particular it was found that the changes to the EEG spectrum start earlier prior to movement during self-initiated compared to externally triggered movements.

The detailed analysis performed shows that it is possible to reliably detect the intention of the participant to move or the participant's imagination of wrist movement. The study shows that the EEG recorded from the scalp contains robust feature which can be extracted to consistently identify movement and imagination of movement of the wrist in different directions. The study thus showed that it is possible to extract multi-dimensional control signals, from the EEG prior to movement initiation towards different directions and also during imagination of wrist movement towards different direction, for use as control signals in BCIs despite the lack of any actual movement.

The study critically highlights the need to use a high density electrode montage during initial BCI studies to identify optimal electrode sites for recording EEG from which reliable feature can be extracted for classification and used within a BCI.

7.2 Functional Significance

The study reports that there are statistically significant differences in the ERSP of EEG recorded prior to and during movement and imagination of the wrist towards different directions. The study also showed that the significant differences found in the EEG prior to movement and during imagination of movement can be used to predict the direction of the movement. This study provides the first report on ability of extracting 4 separable control signals from EEG recorded at a single electrode on the scalp during actual and imagined movement of the wrist for use in BCI. The study also shows that the multi-dimension control signals extracted can be used to boost the communication rate (bit rate) of EEG based BCI.

The study highlights the fact that there can be significant differences in the classification performance of adjacent electrodes and thus stresses the importance of initially using a high-density electrode montage for selecting electrodes which perform the best for use in BCIs. Based on this it is feasible that improved classification rates could be achieved by using groups of electrodes of electrodes rather than relying on one recording site.The work is now at the stage were further studies involving patient groups are needed.

7.3 Future Work

While good classification has been obtained with the normal subjects performing movement and imagination trials, certain epochs were not used during processing since they were corrupted with artefacts or the trials. Thus further work has to be done before this system can be implemented in real time applications to include automatic artefact removal. In addition, further work specifically addressing how the attention levels of the subject and contamination from Electrooculograms and Electromyogram affect classification success.

The trials that were used for classification were obtained over experiments with a duration of approximately one hour. For optimal performance of the BCI over a long term it is important that the features selected for classification have good time stability. It is thus important that further work be done to study the time-stability of extracted features. It would also be important in this respect to consider different classification processes such as genetic algorithms which adapt over time.

The communication rate or the bit rate of the BCI can be increased by (a) improving the classification of the BCI and (b) by increasing the dimensionality of the control signal that the BCI can extract. It is suggested that future work involve non-linear classification techniques and possible features extracted from multiple-electrodes. It would also be useful to attempt to include more directions of wrist movement to increase the dimensionality of signal.

For a BCI system to be of any practical use it has to work online and be able to accurately identify the users intention and translate this intention into appropriate device commands. Thus, the next step in the developmert of a BCI is to develop a system which would identify and classify EEG online and provide real-time feedback to the subject of the success or failure of the classification. Online testing of the BCI in the potential BCI user groups is also important to study and validate the performance of the system and also its ease of use. Real time testing of the system is also necessary to study

the effects of (a) feedback on the user's ability to use the system (b) time stability of the features used classification on system performance. It is proposed that the online testing be done with different participants over prolonged periods to study the variation of system performance both over time and for different participants. The online BCIs being developed from the current work will operate in an asynchronous mode that is the system will classify on-going EEG and not be stimulus driven. There is therefore a need to do further testing of methods which scan the incoming EEG to recognise classifiable events associated with the user thinking about moving in different directions. The BCI would be an interface that identifies different intentions or goals and these would activate device commands that produce specific acts. For example, it would be theoretically possible to map the intention to move in 4 different directions into commands that initiate motion in an electric wheelchair. Commands might be go, stop, turn right, and turn left. To test this, a computer game approach may be used with the BCI user commands navigating within a virtual environment.

The main purpose in developing motor neuroprosthetics is to be able to help restore independent control of the body and to enable control of assistive devices for individuals who are paralysed. While the present study showed the possibility that it is possible to extract robust features from the EEG of normal participants for classification of intention of real and imagined movement further studies need to be carried out on participants with different levels of paralysis to investigate the changes in their EEG. These studies, which will include only "imagination of movement" trials, will help study and extract robust features for classification.

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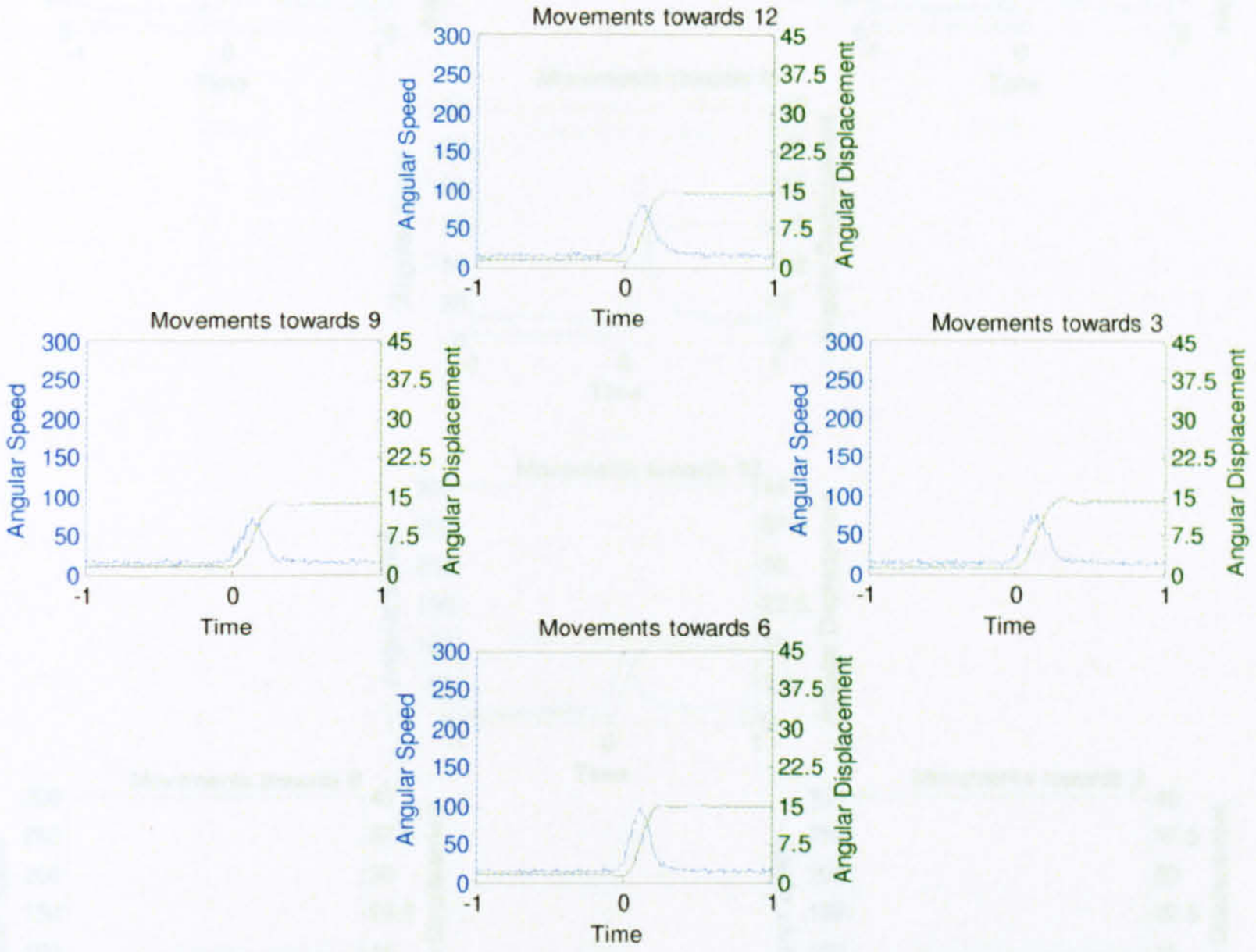
Appendix I: Figures

Kinematics

In this section the figures show the mean angular displacement and speed as the different participants make movements towards different direction in the different movement experiments.

Externally Cued

Subject 1



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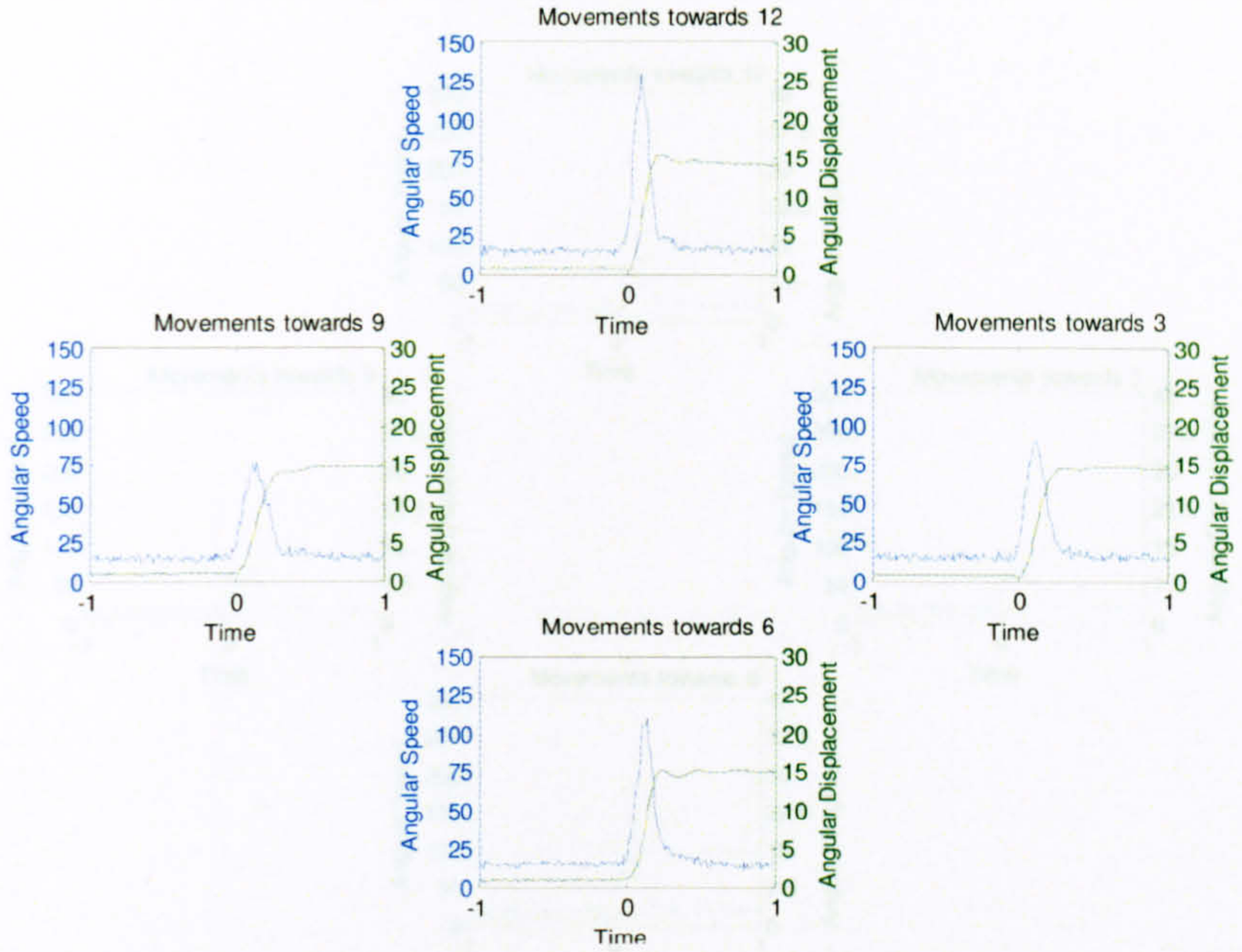

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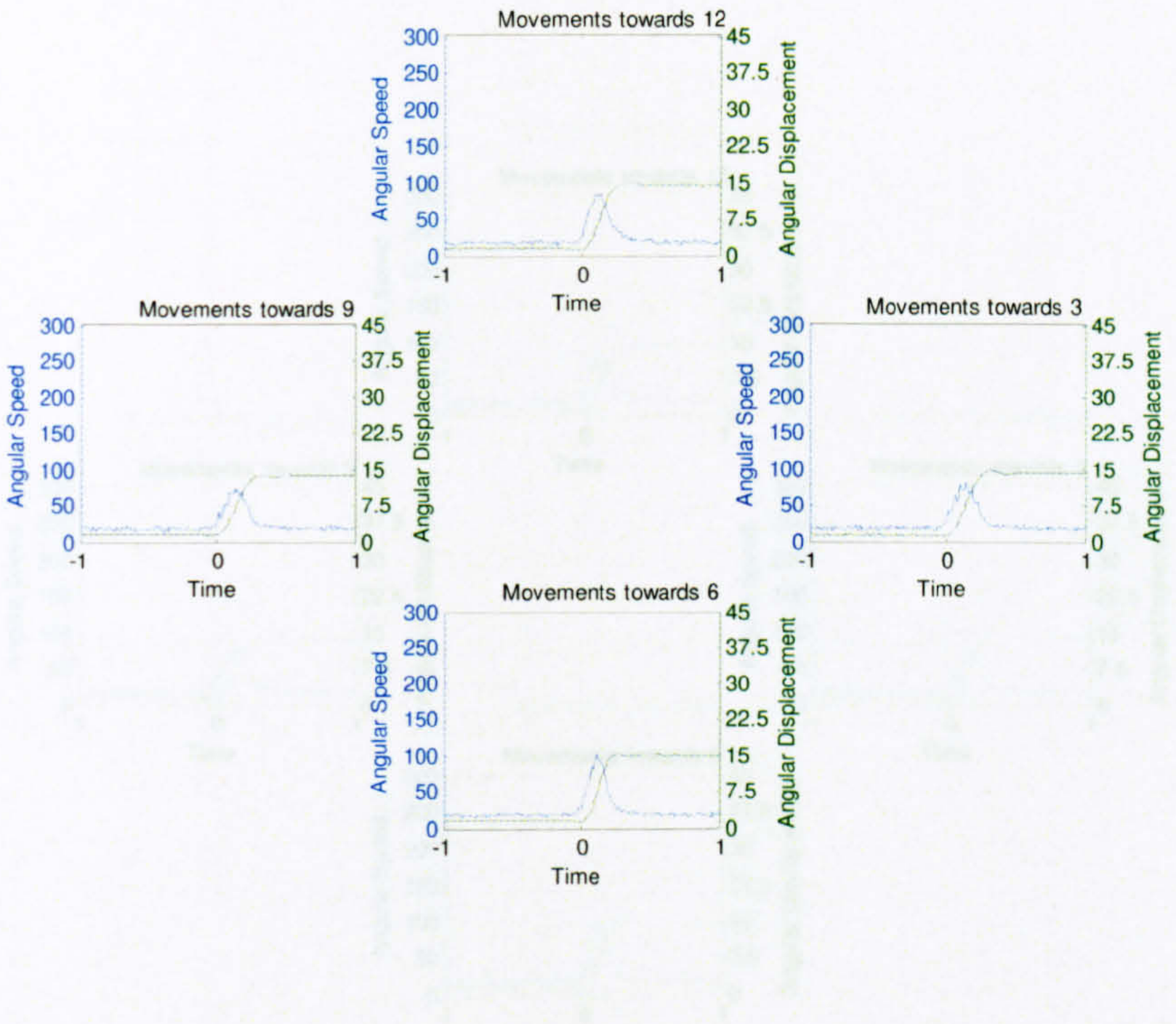

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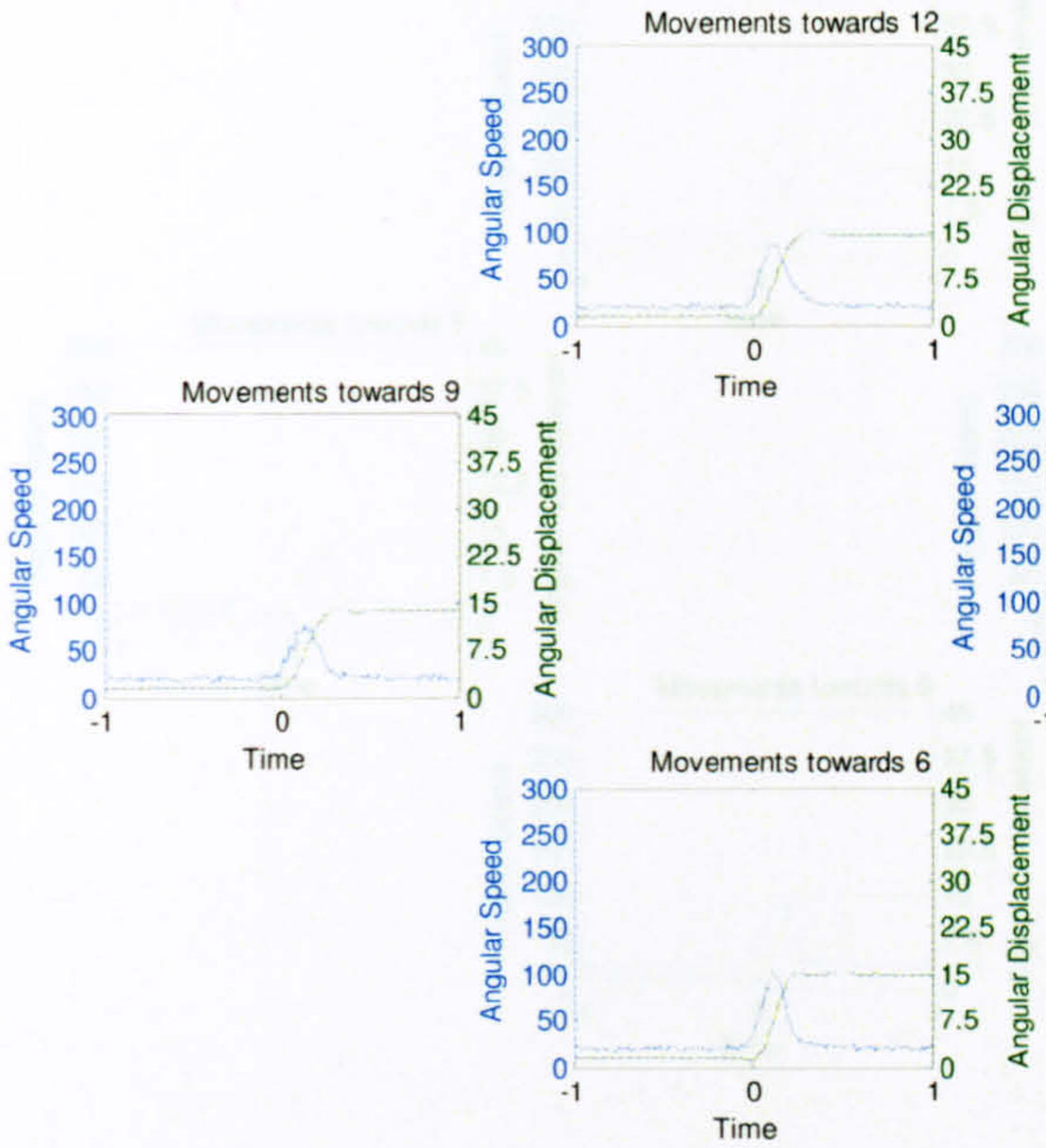

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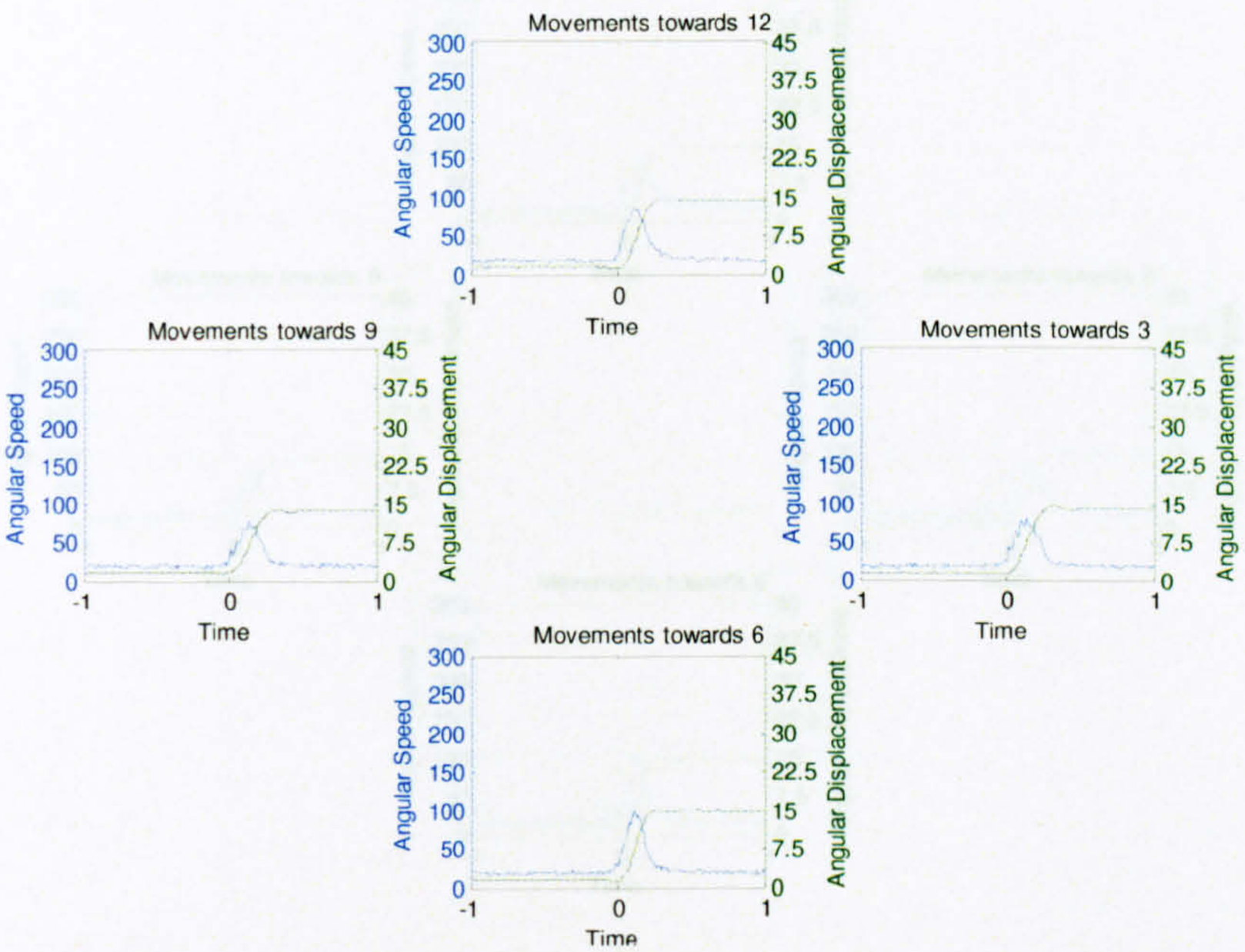

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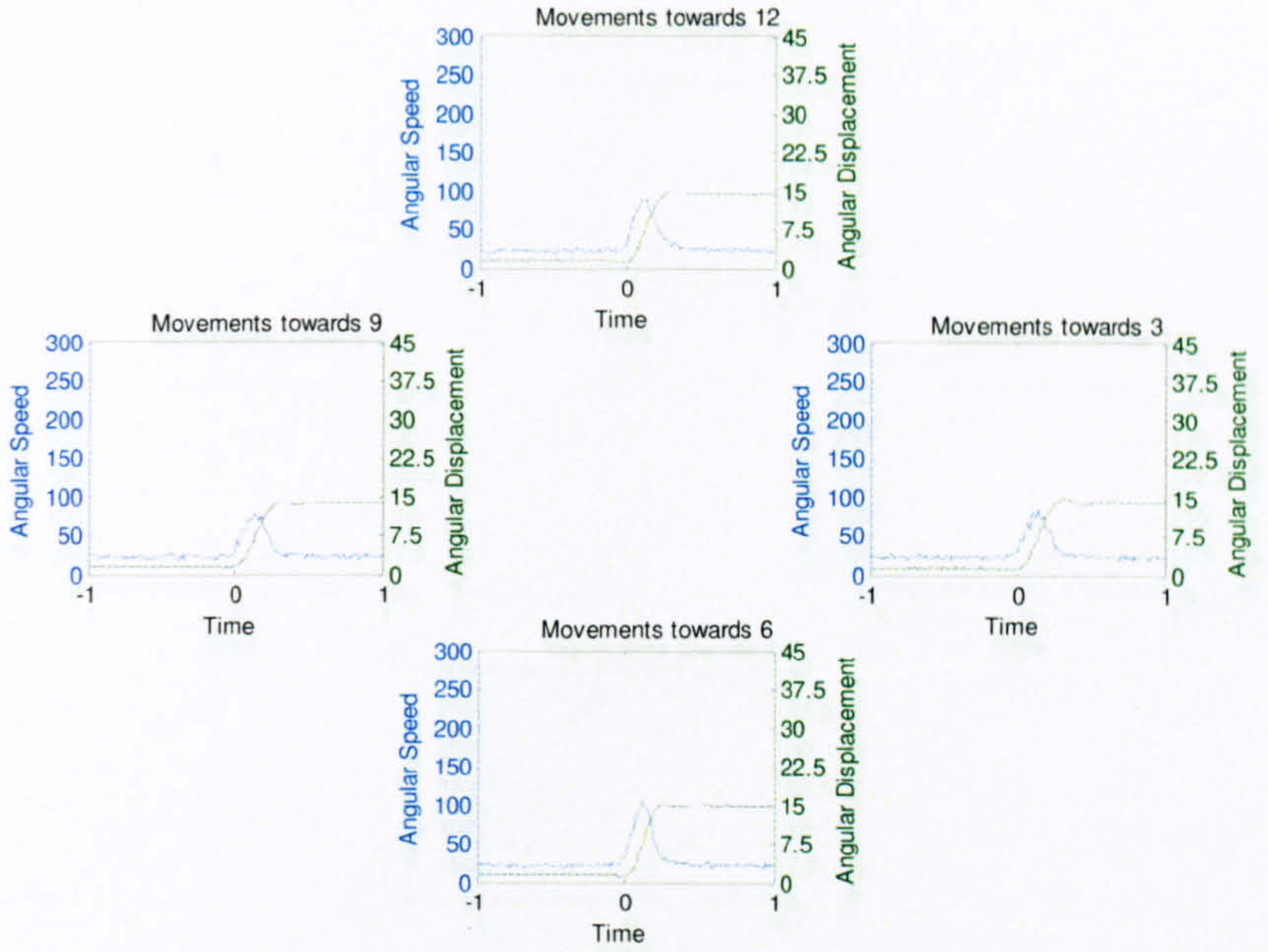

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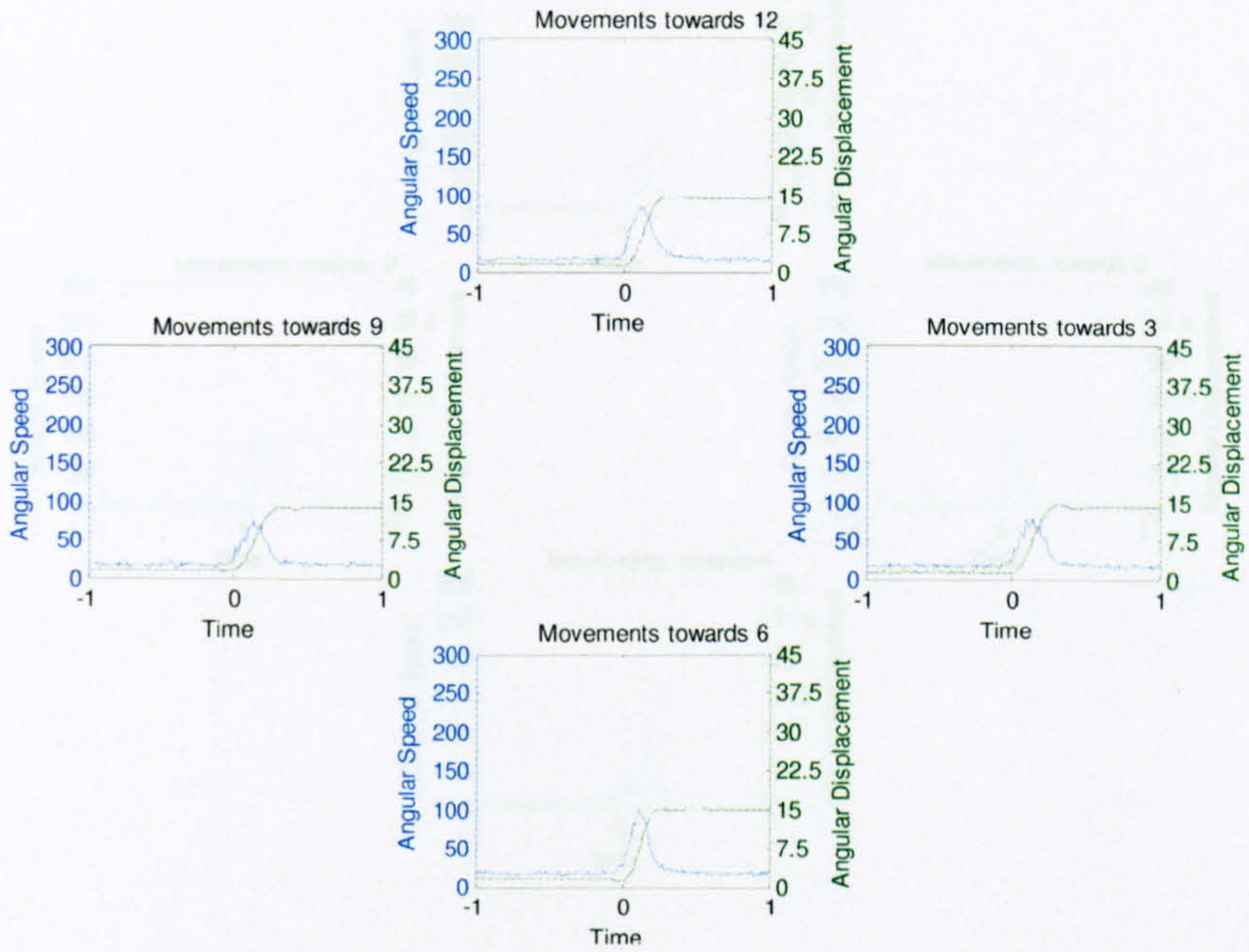

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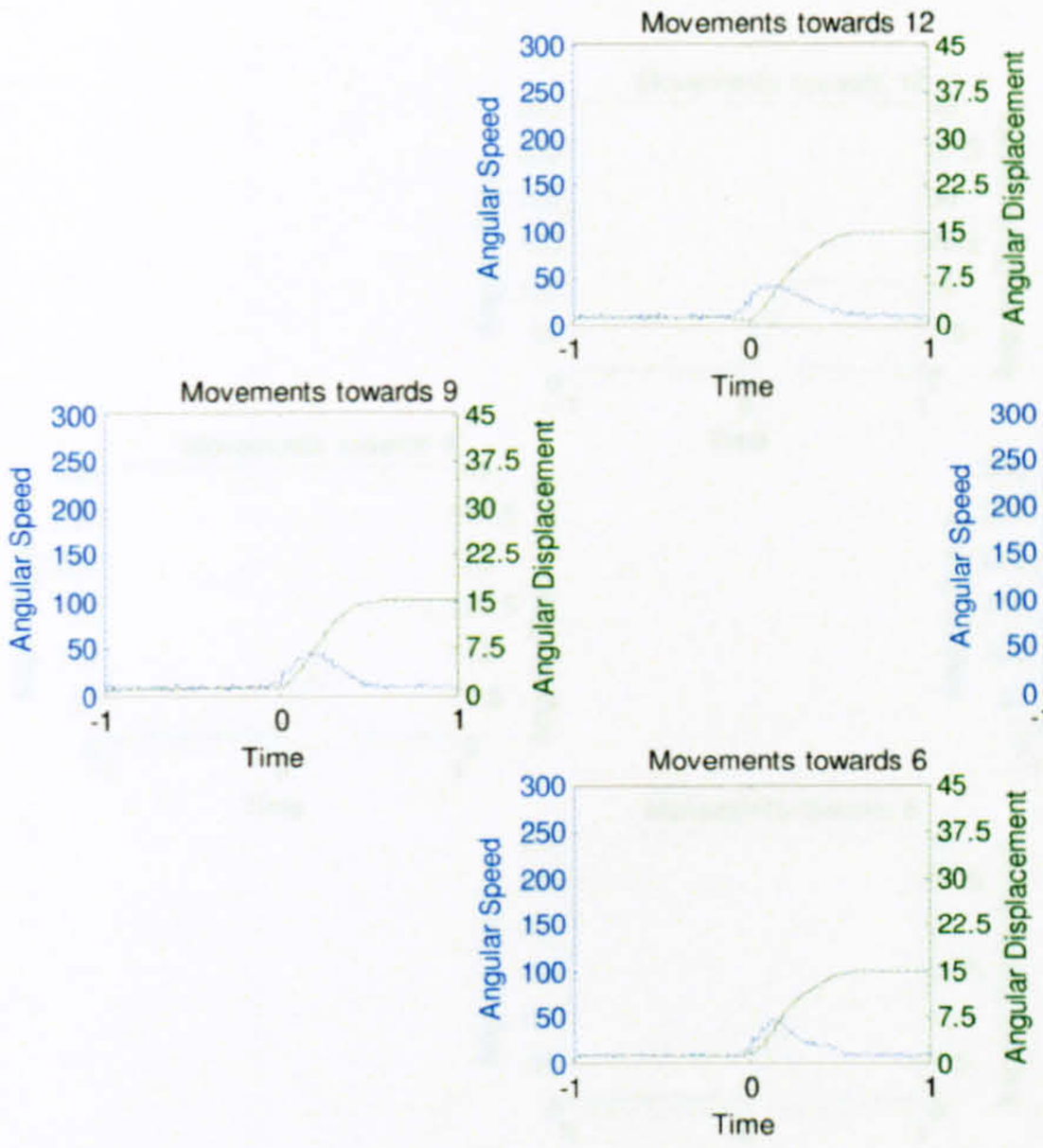

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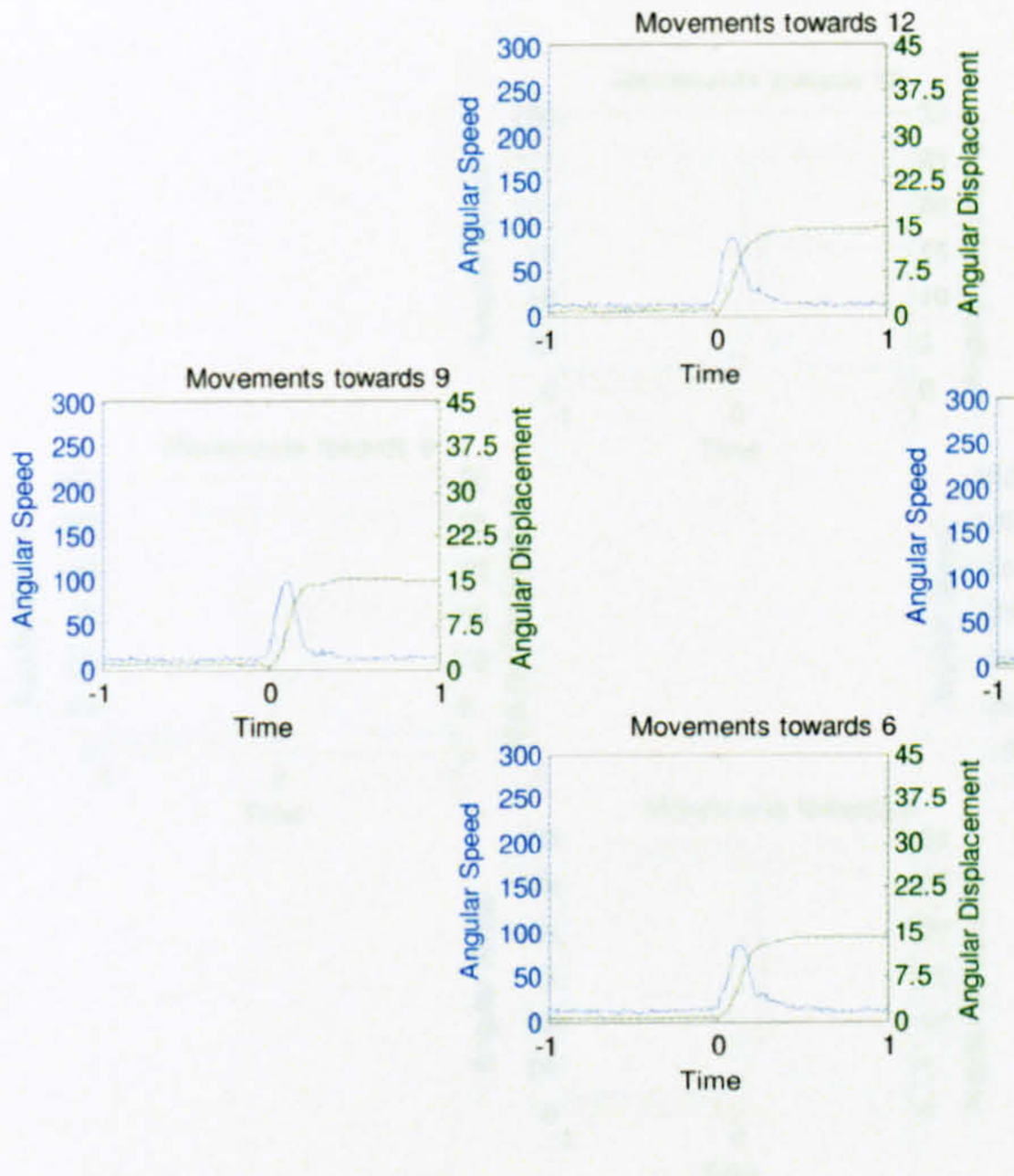
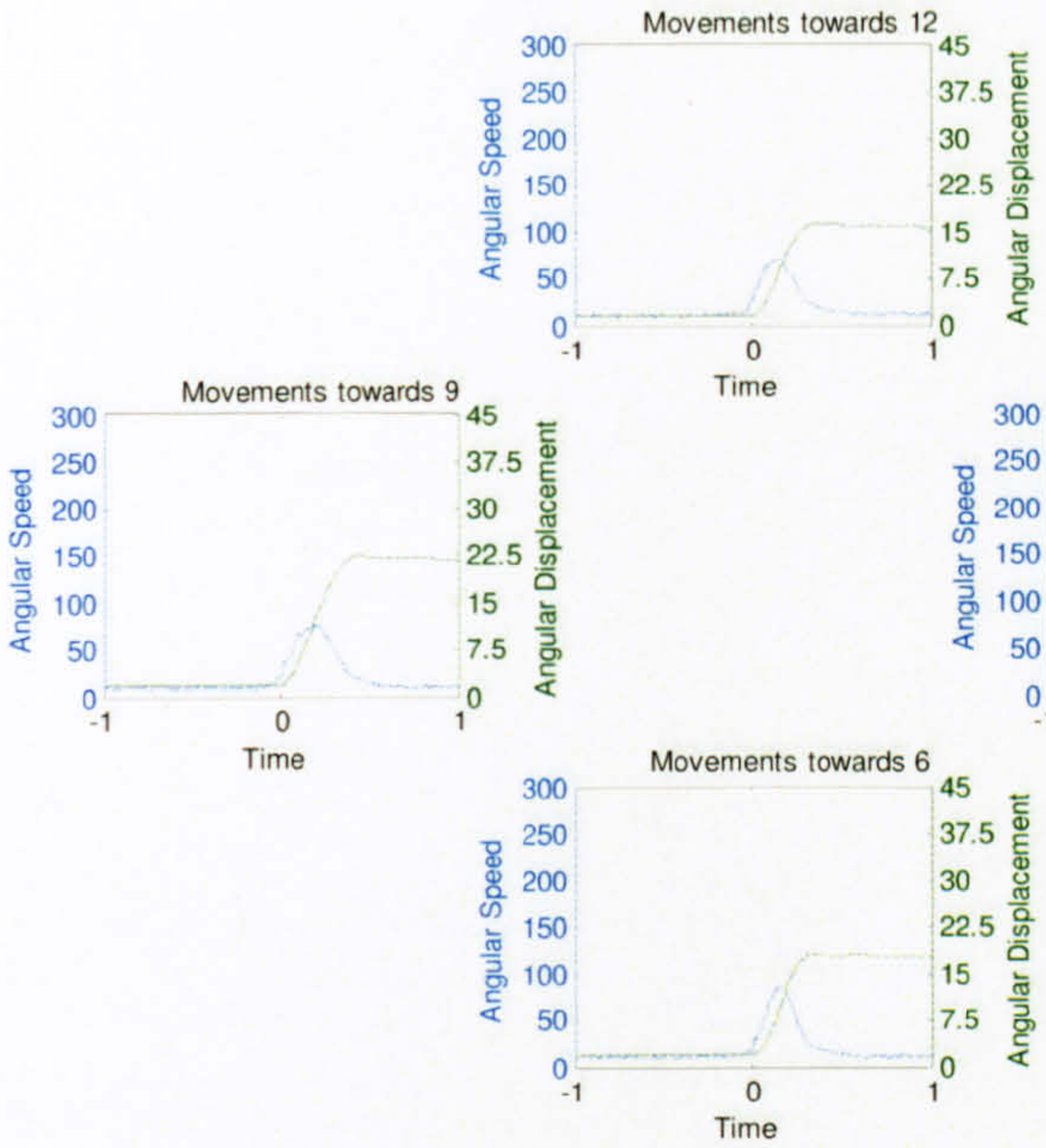


Forced Choice Trials

Subject 1



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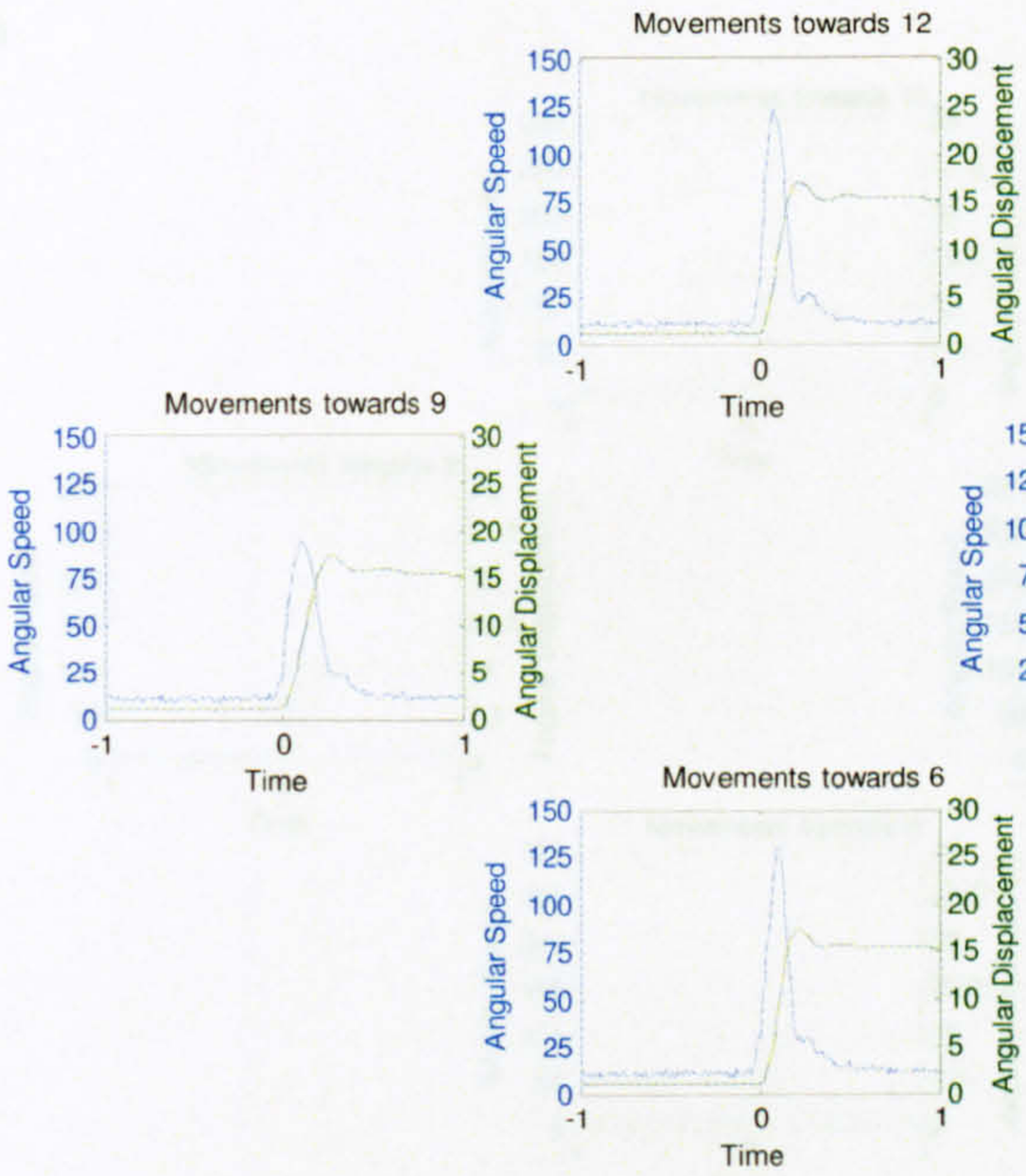

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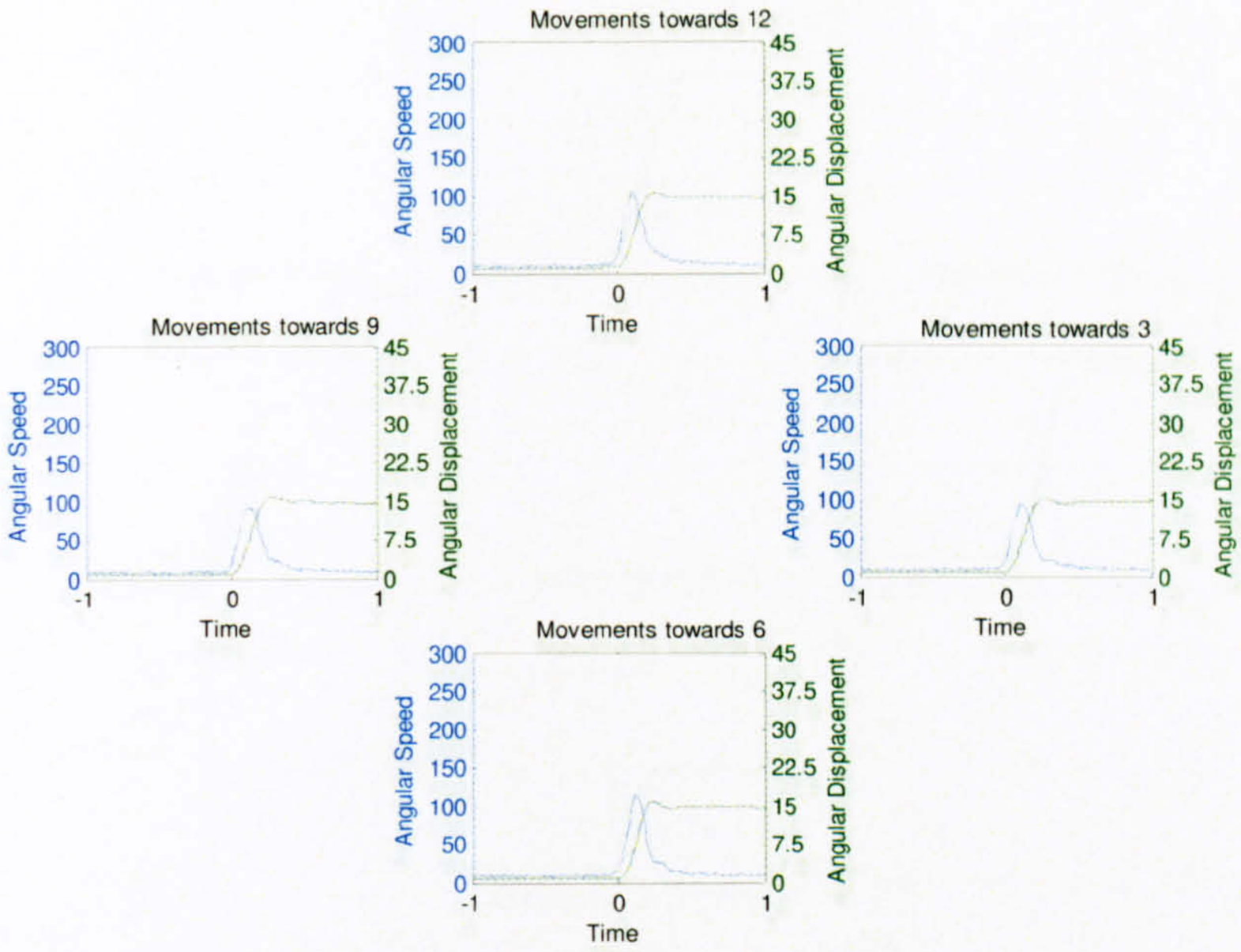

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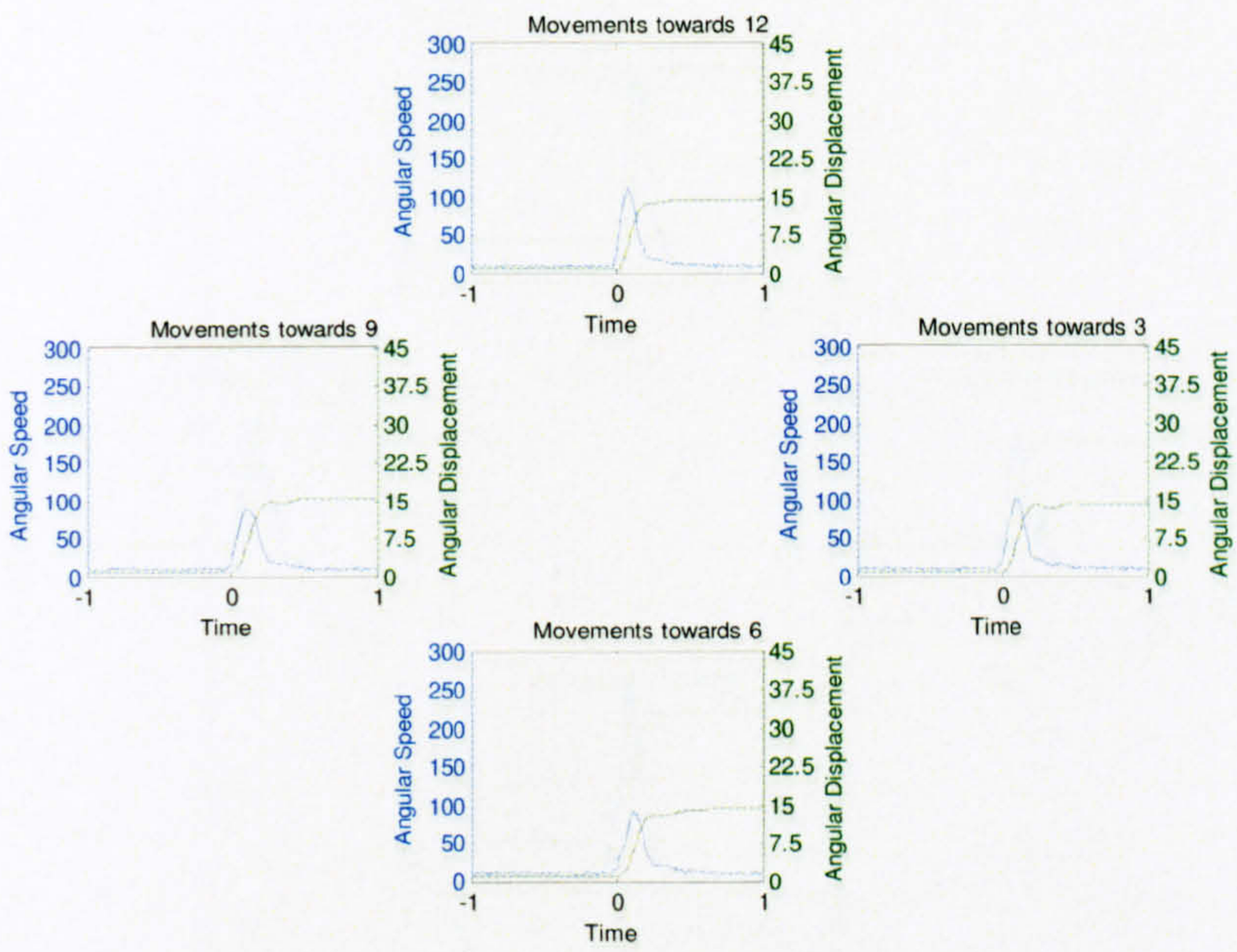
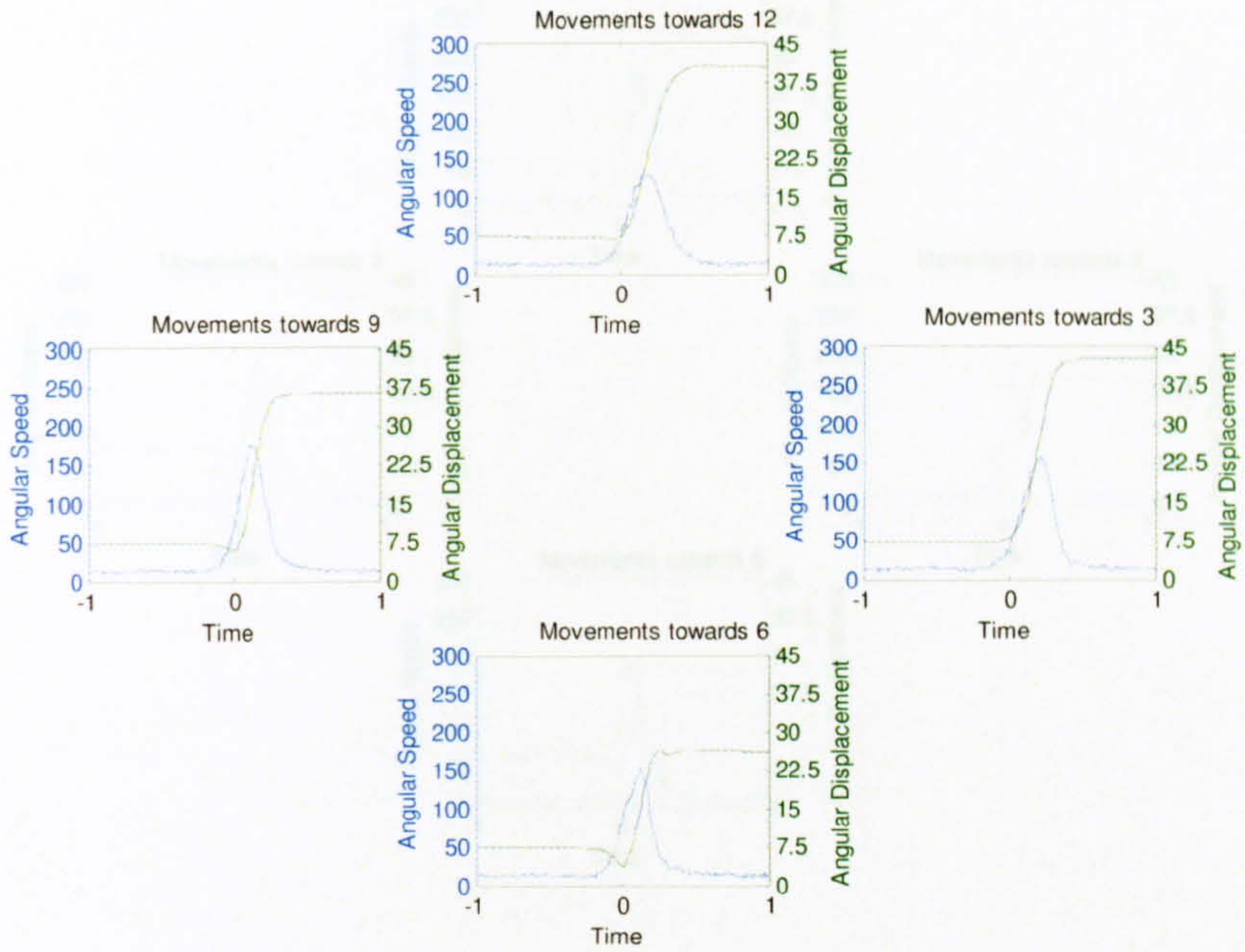


Self Determined

Subject 1



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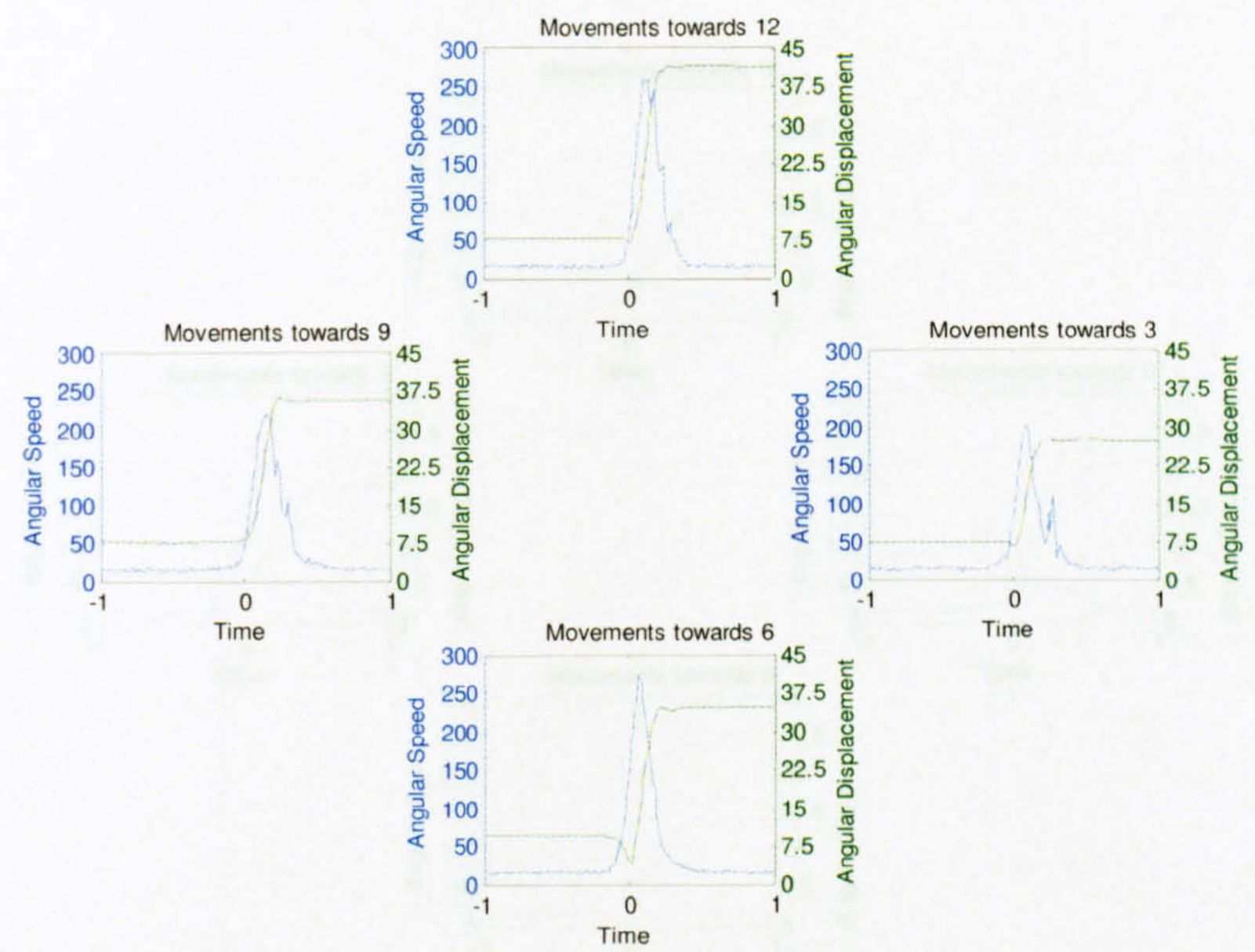

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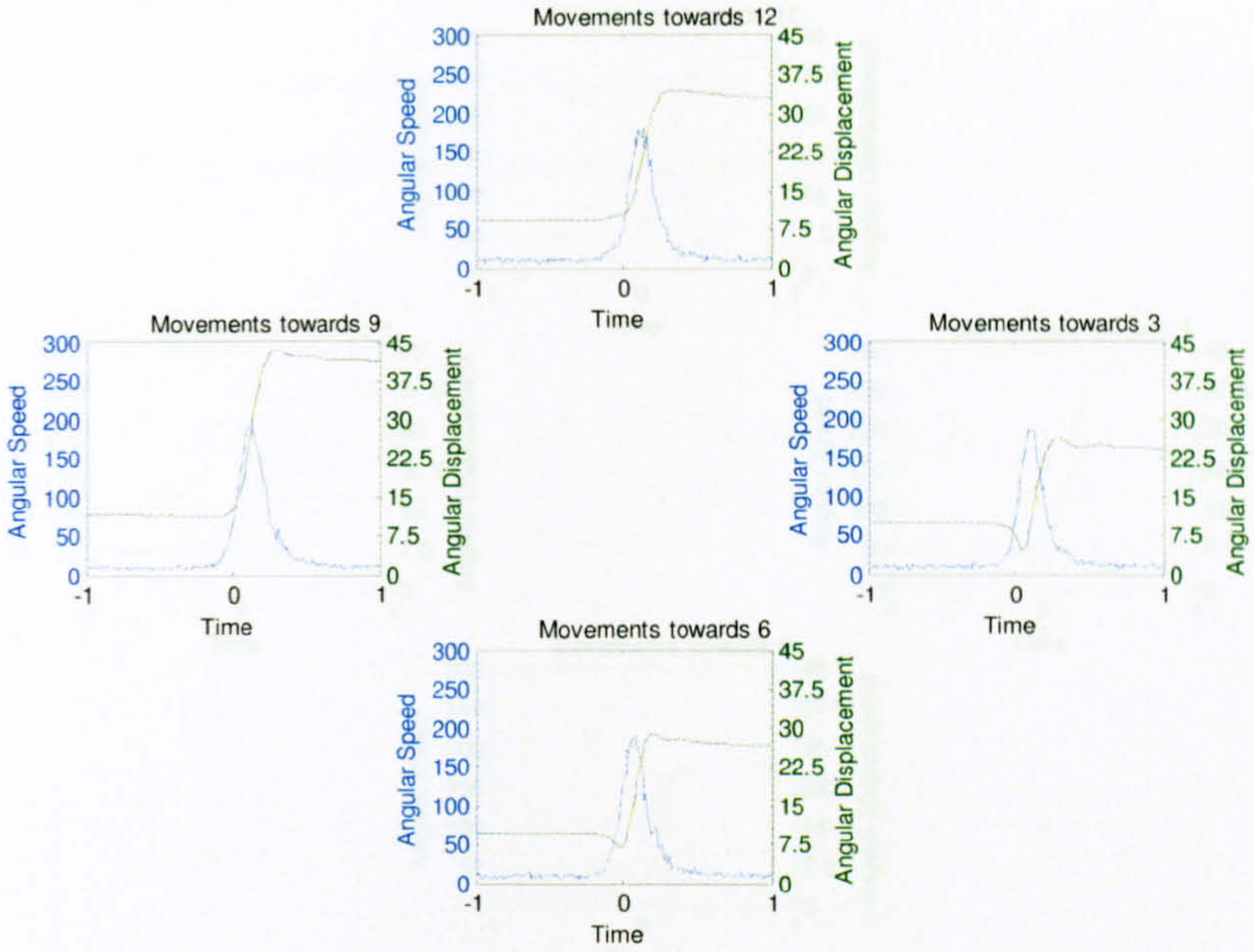

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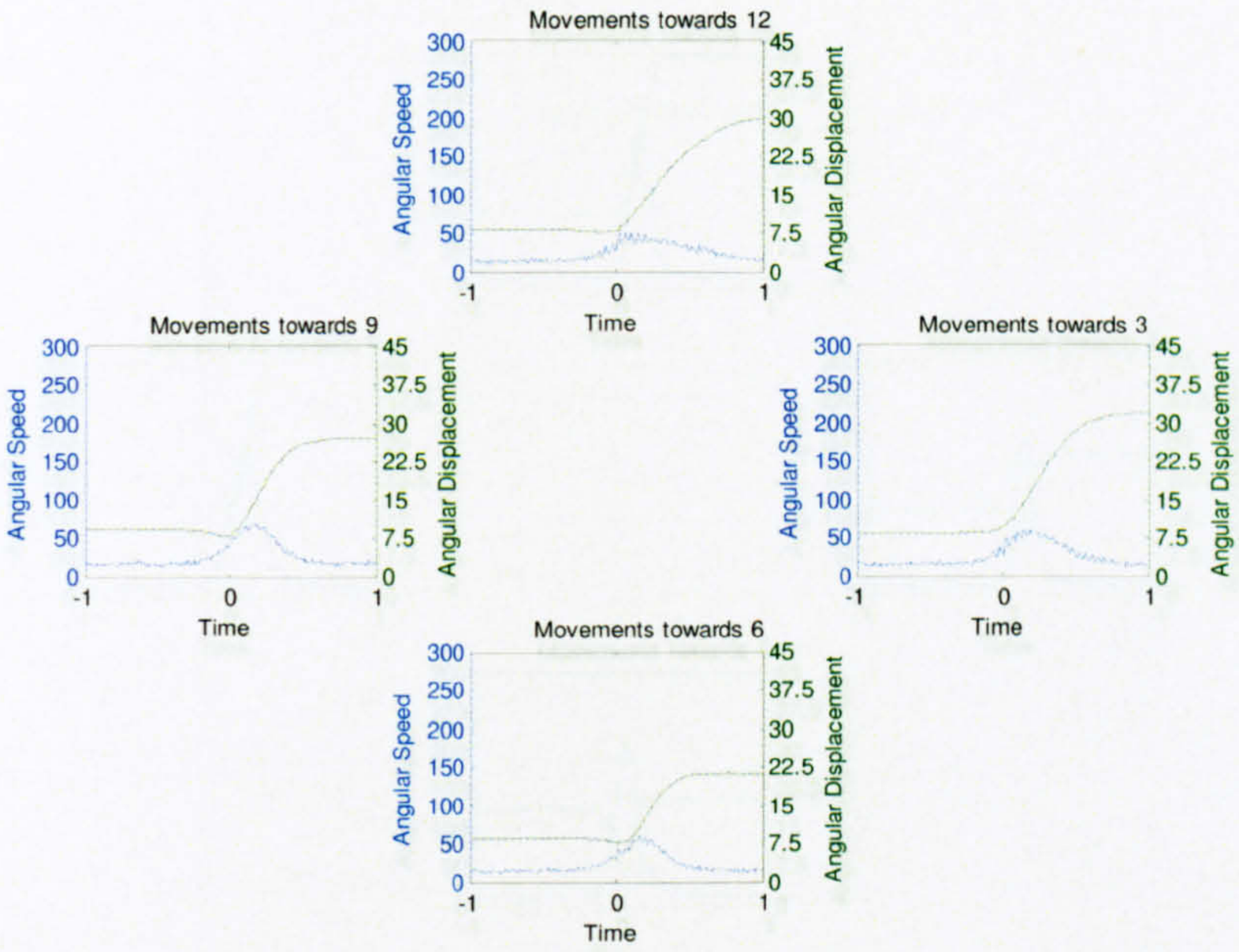

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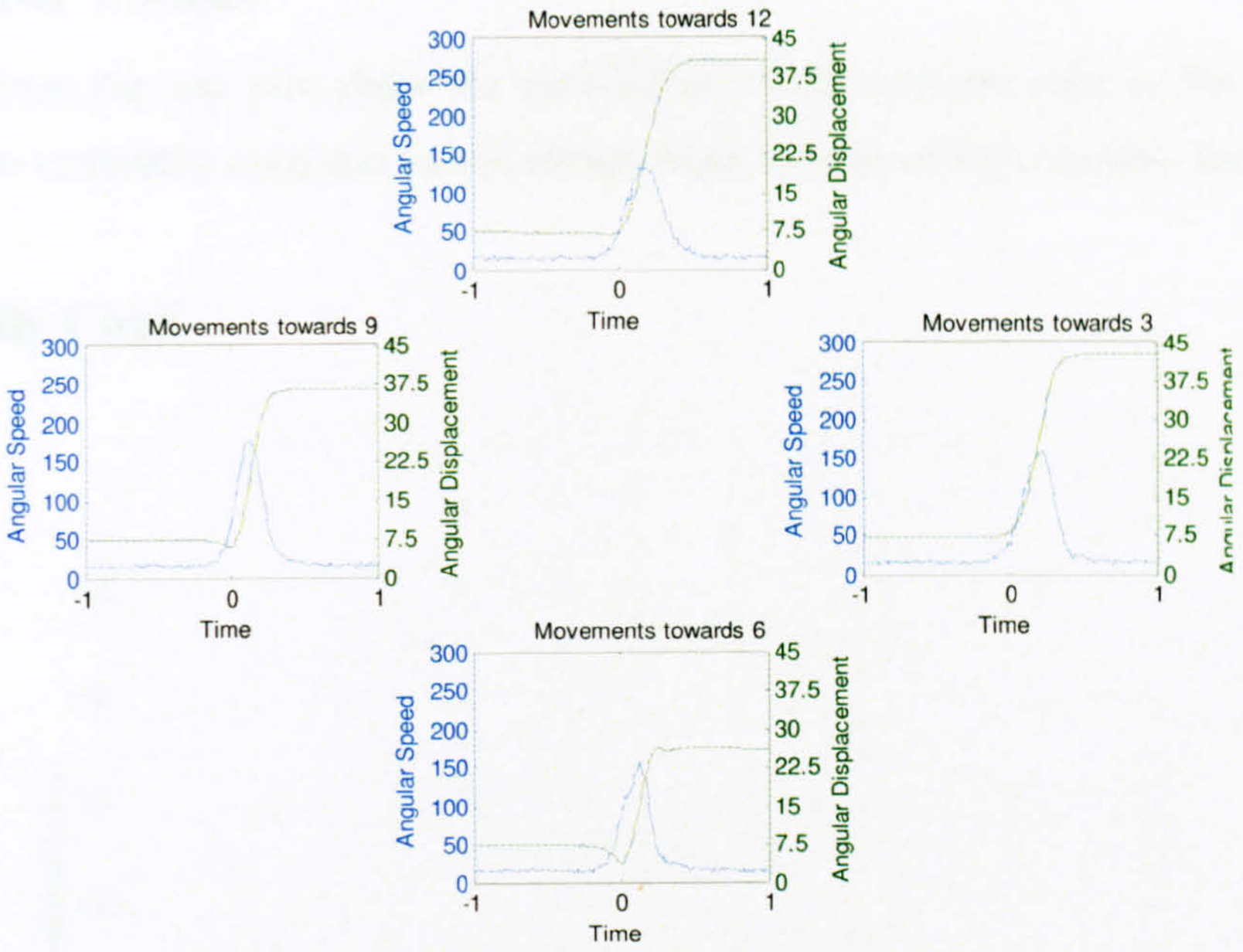

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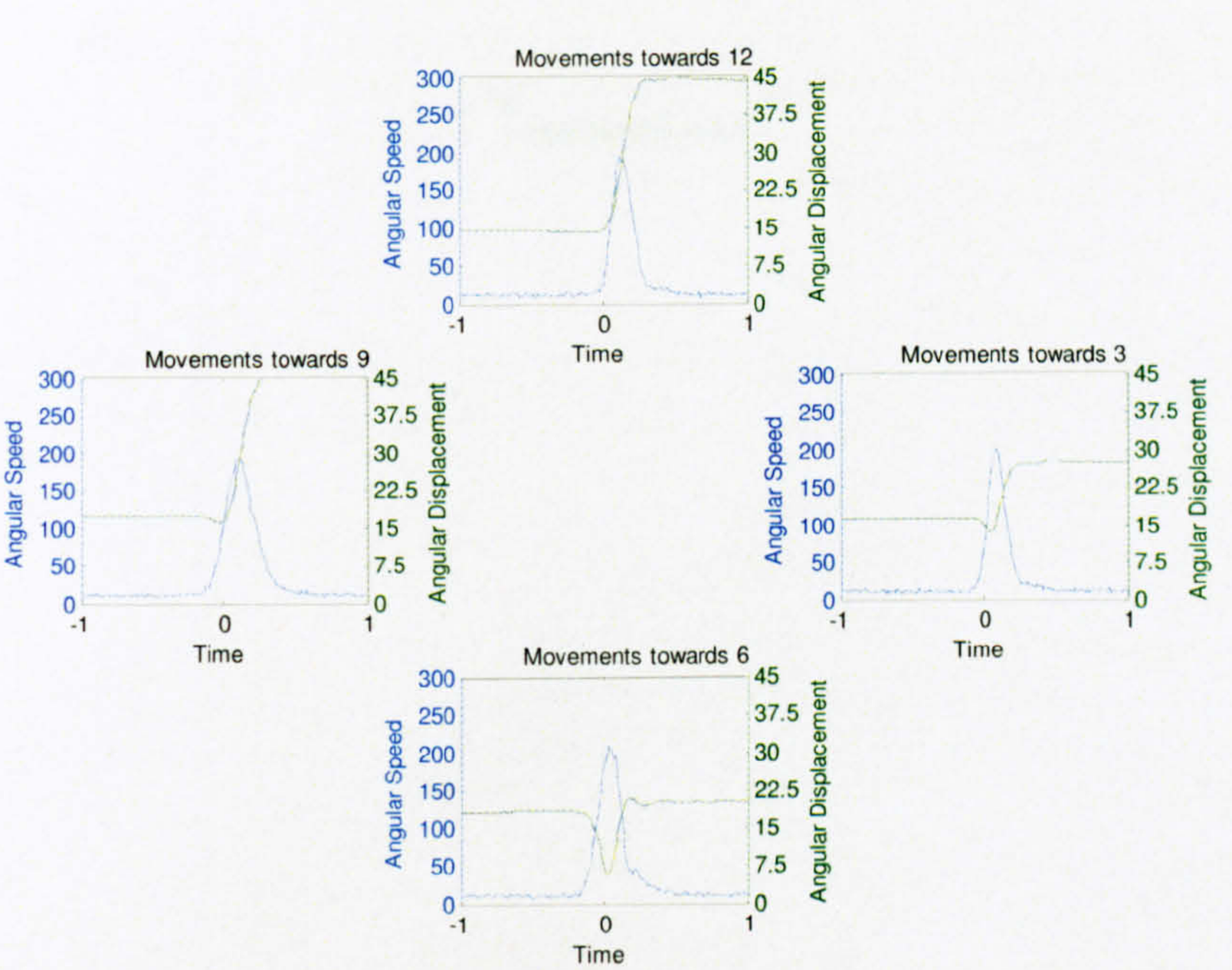
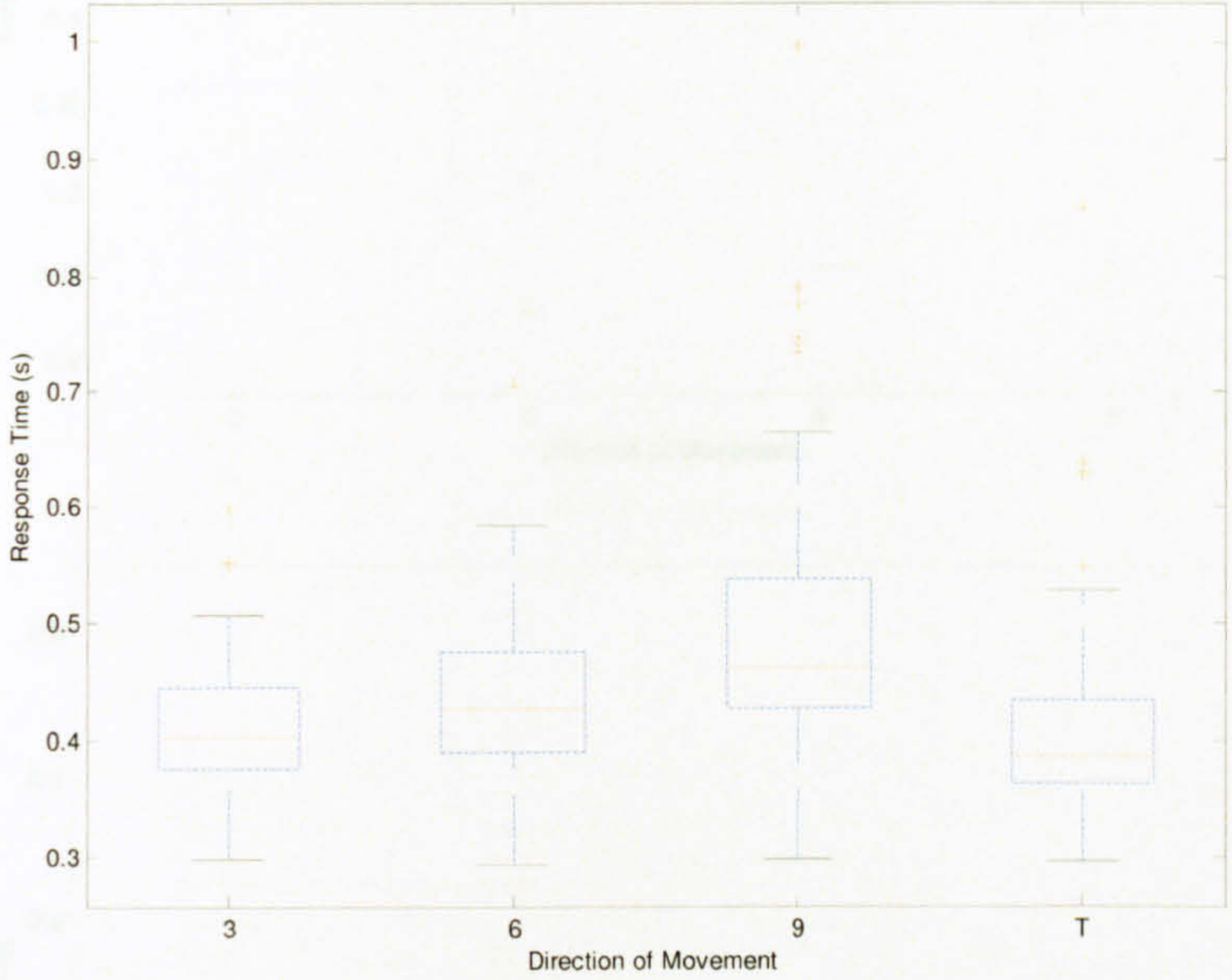


Reaction Times

In this section the box plot show the distribution of the reaction time or the response time for the externally cued and forced choice trials for movements towards the different targets.

Externally Cued

Subject 1



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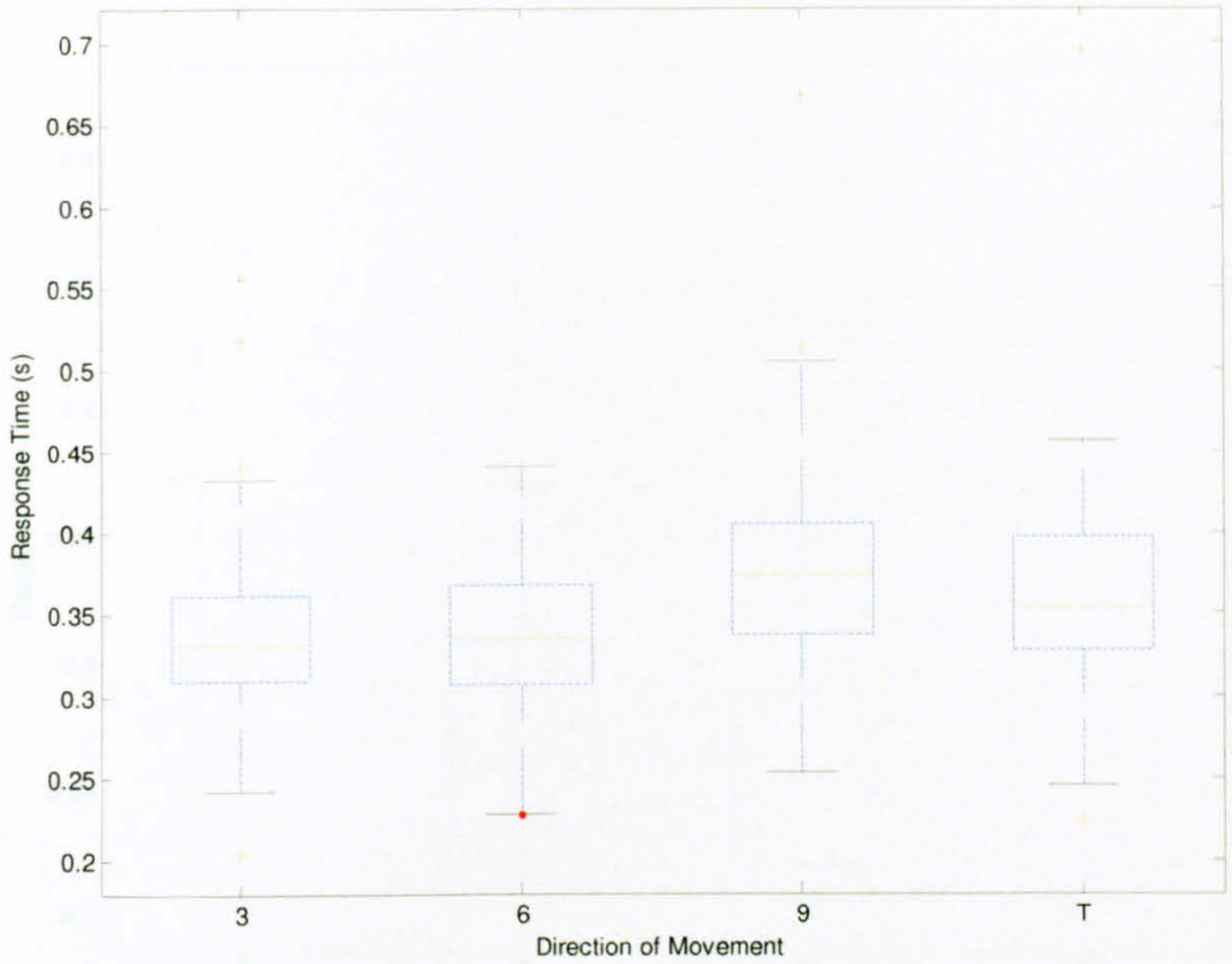
0.7
0.65
0.6
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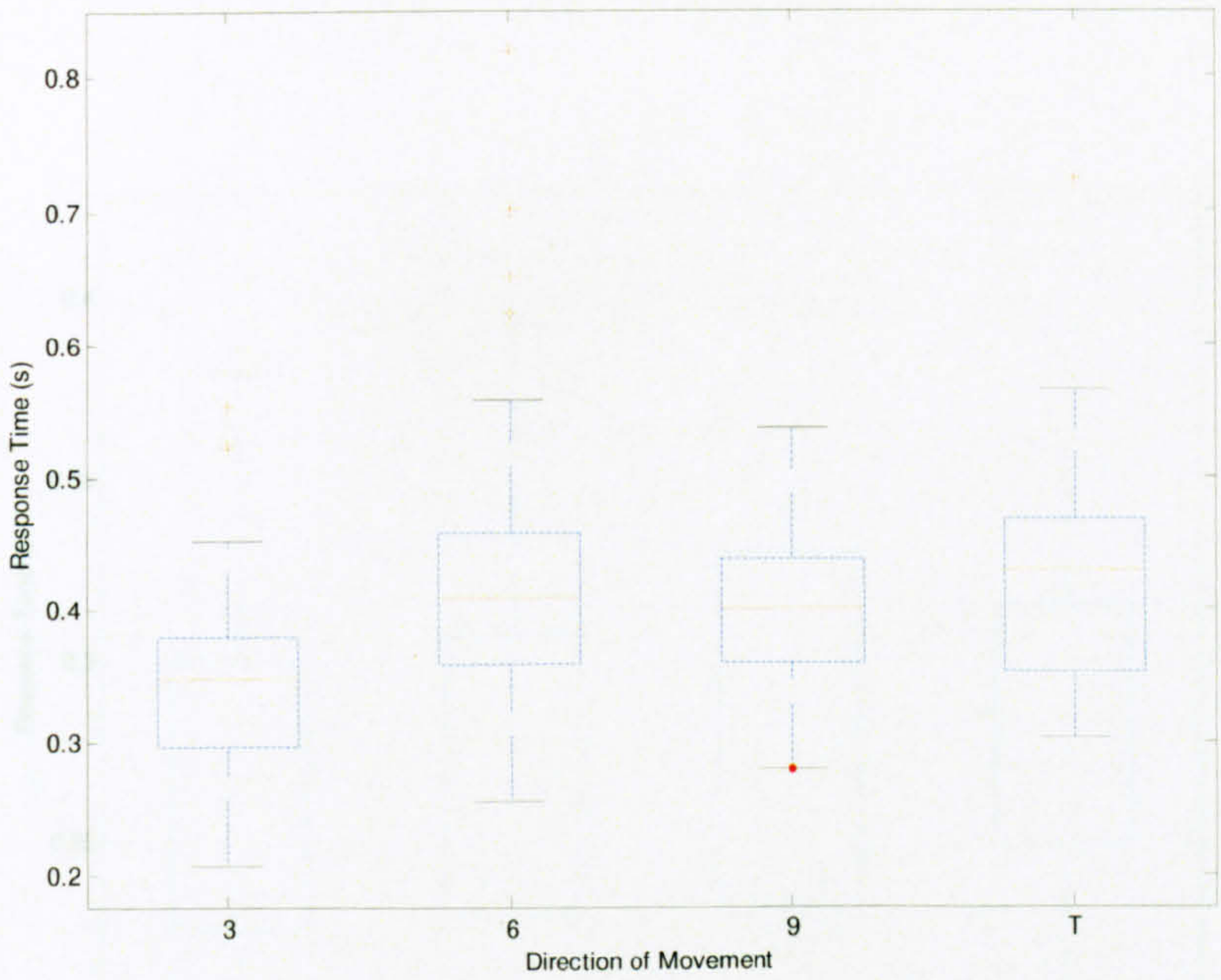
0.3
0.25
0.2
Response Time (s)
3
6
9
T
Direction of Movement

Subject 3


0.8
0.7
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0.4
0.3
0.2
Response Time (s)
3
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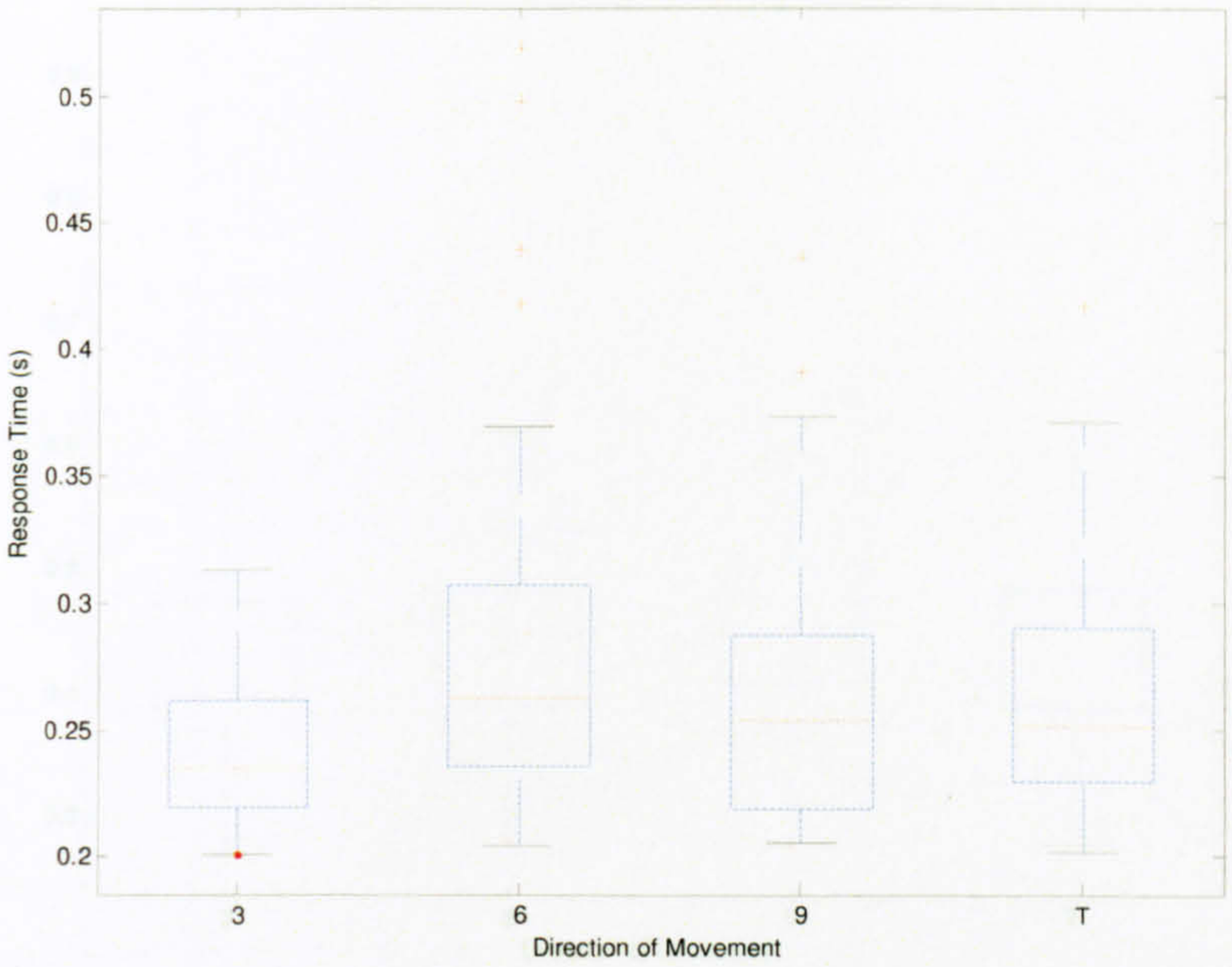
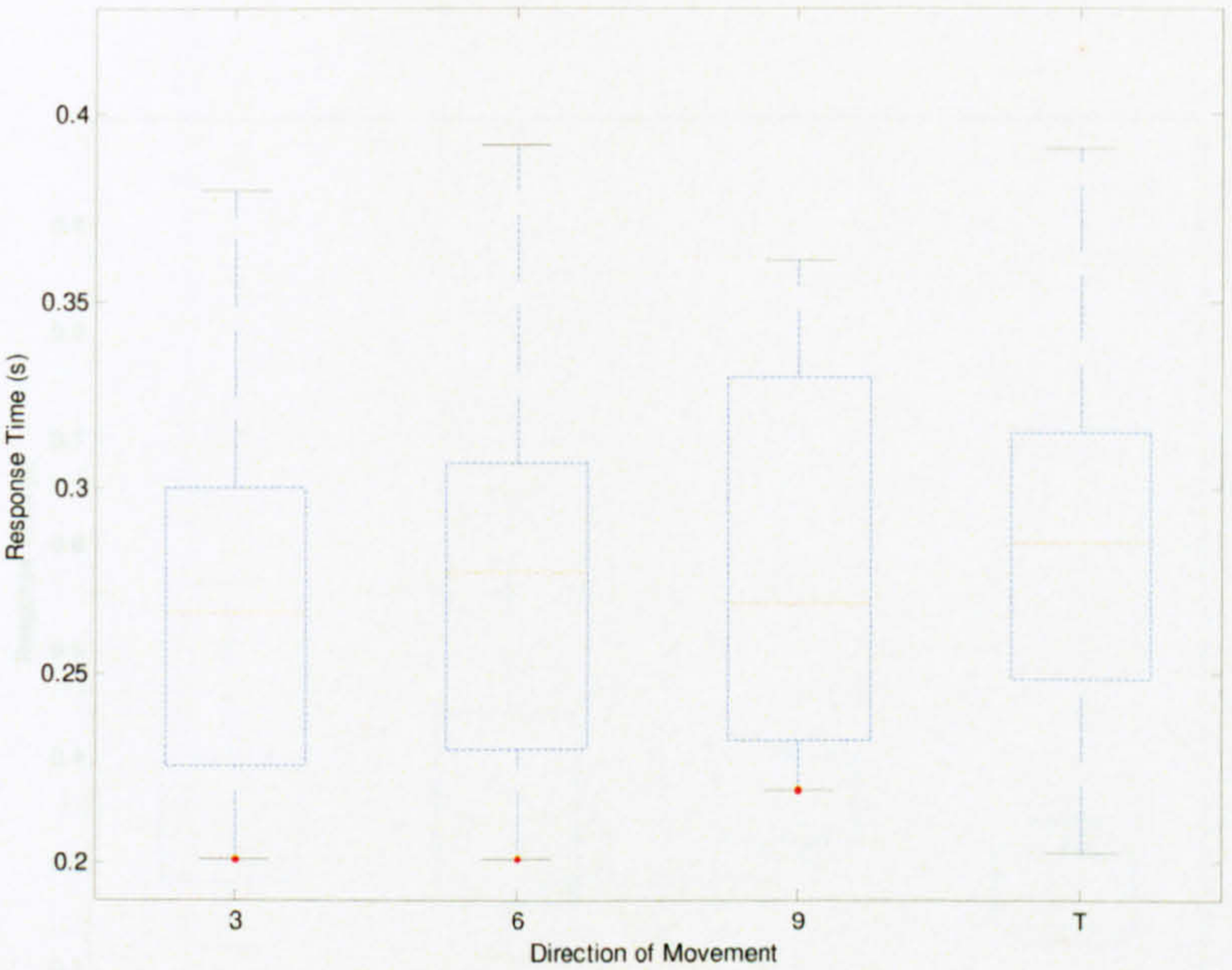
9
T
Direction of Movement

Subject 4



Subject 5



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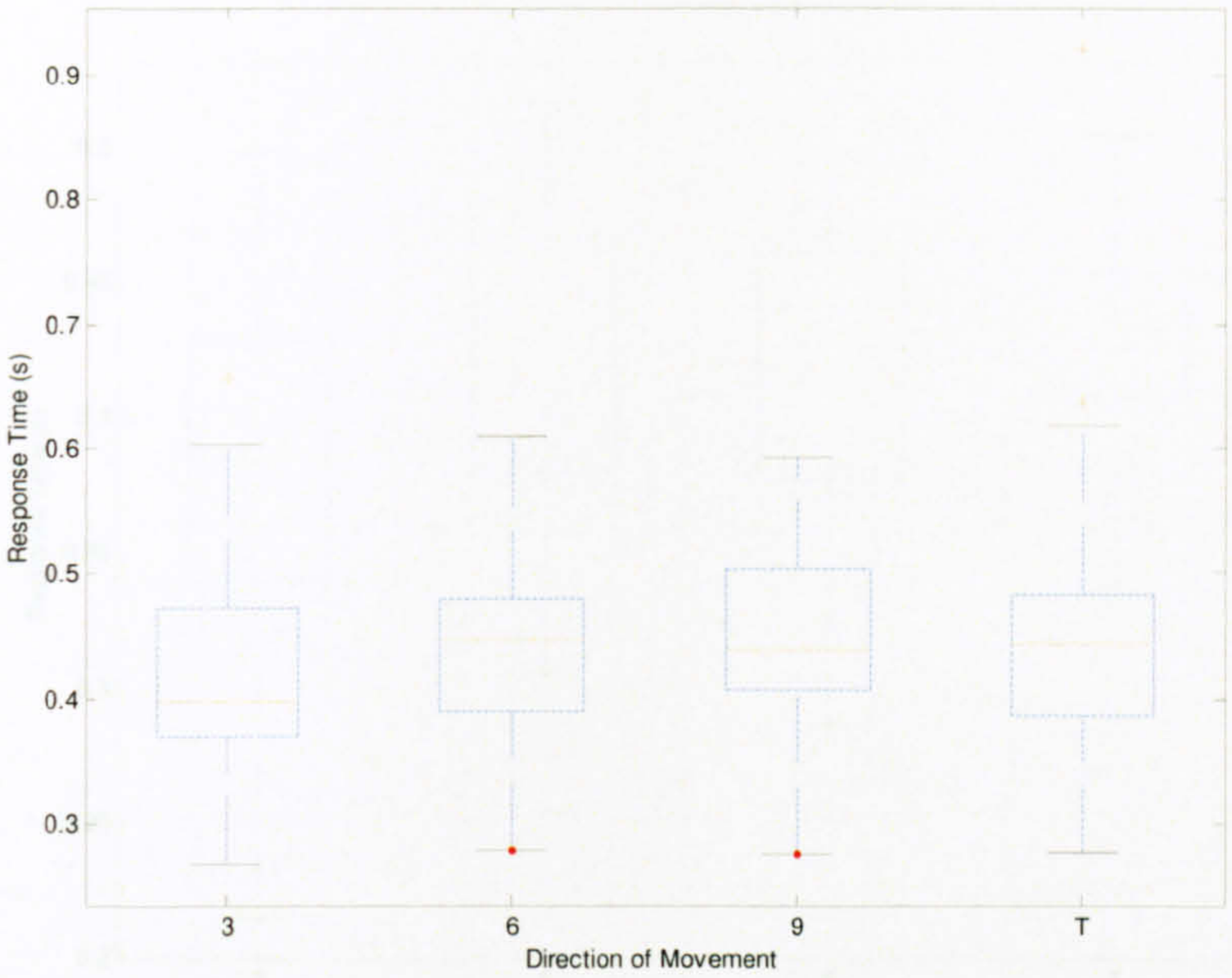
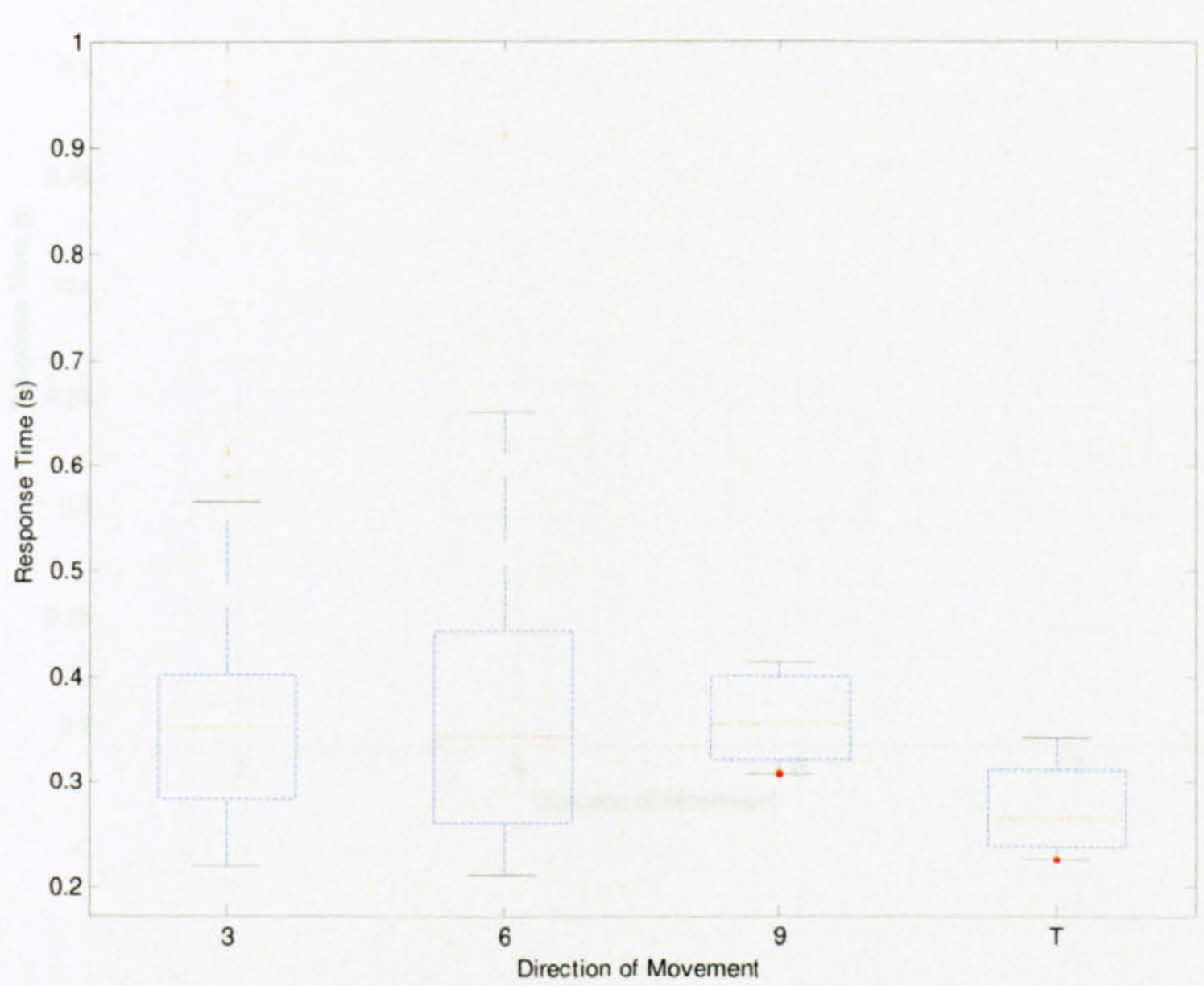
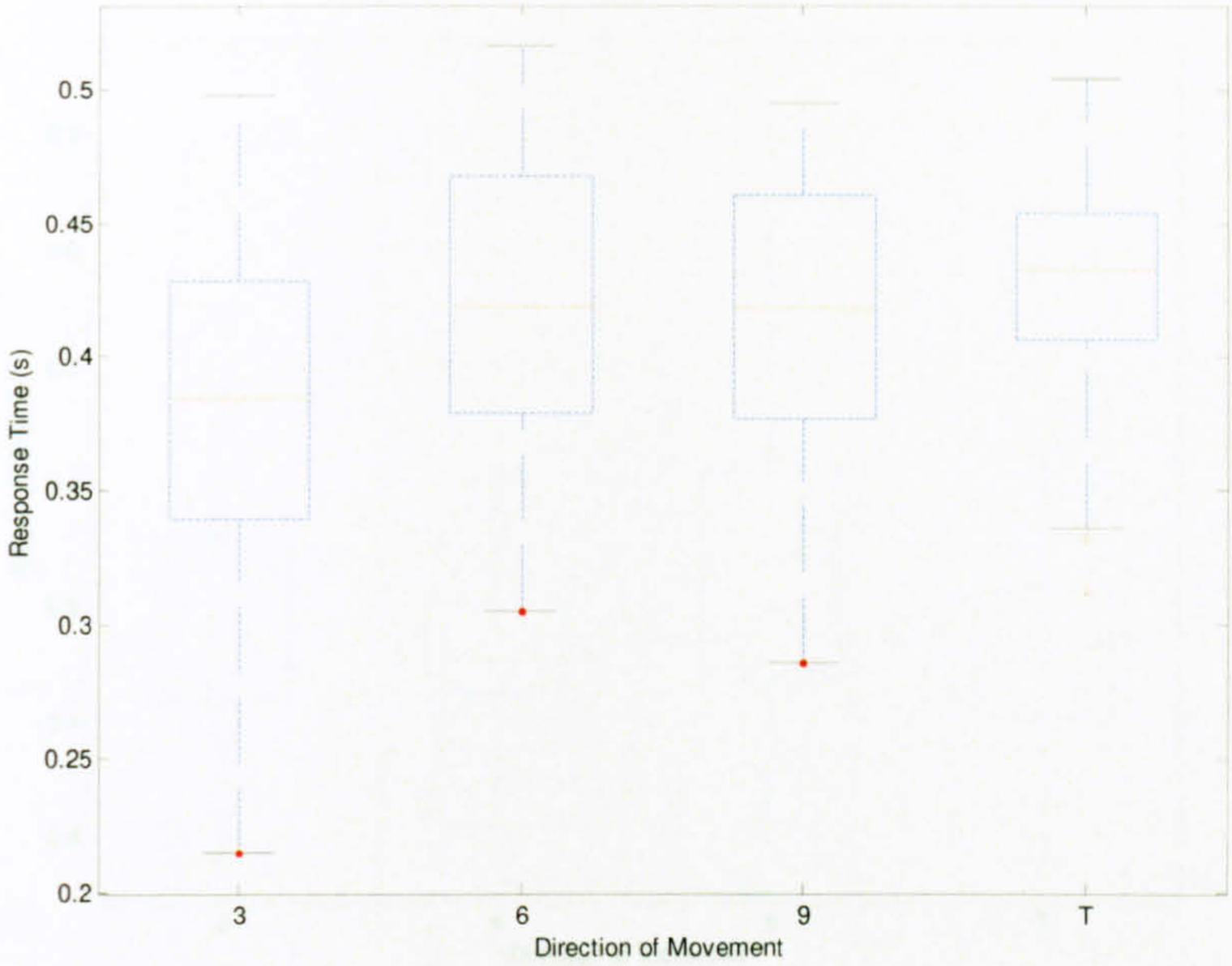


Subject 7

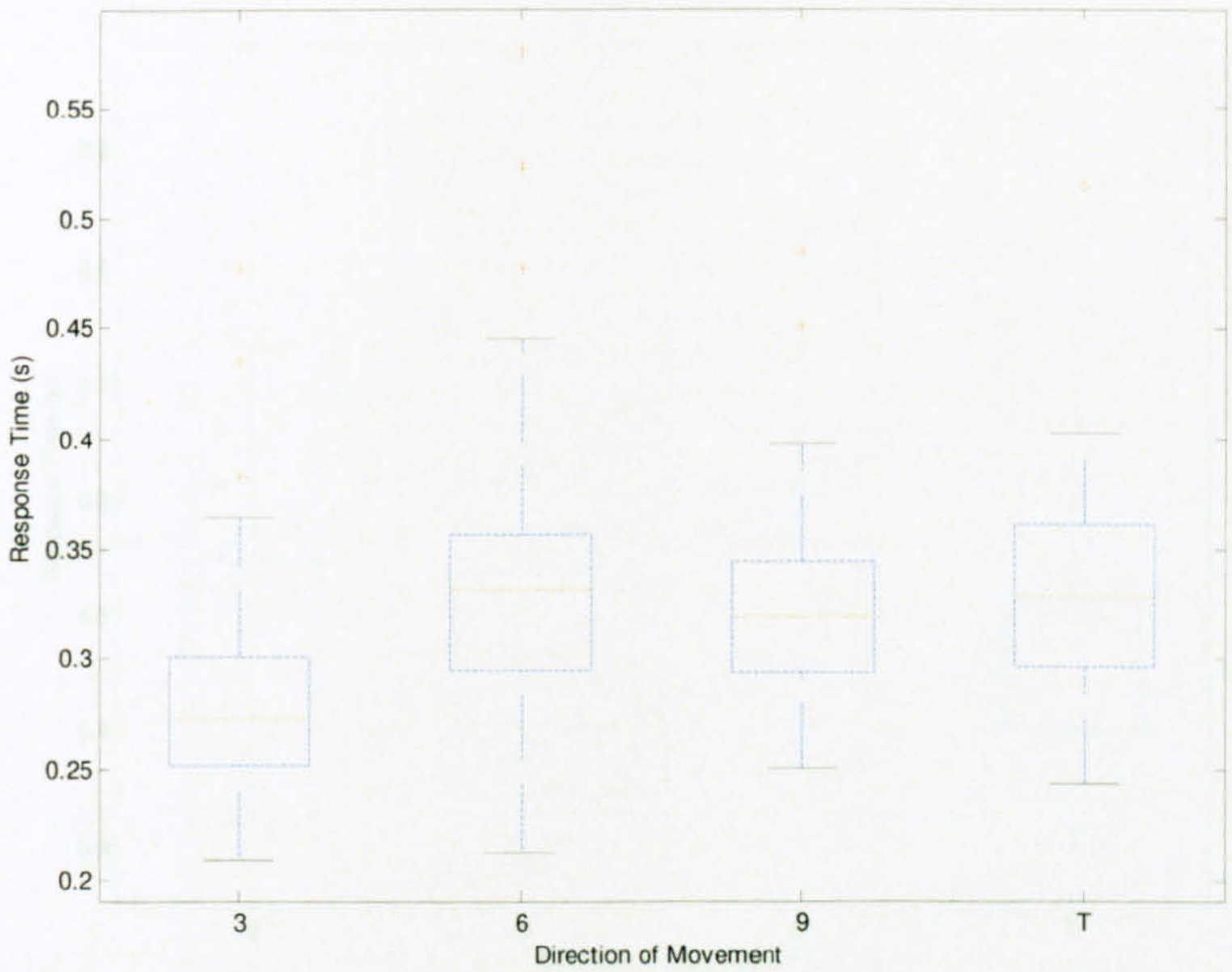


Forced Choice Trials

Subject 8

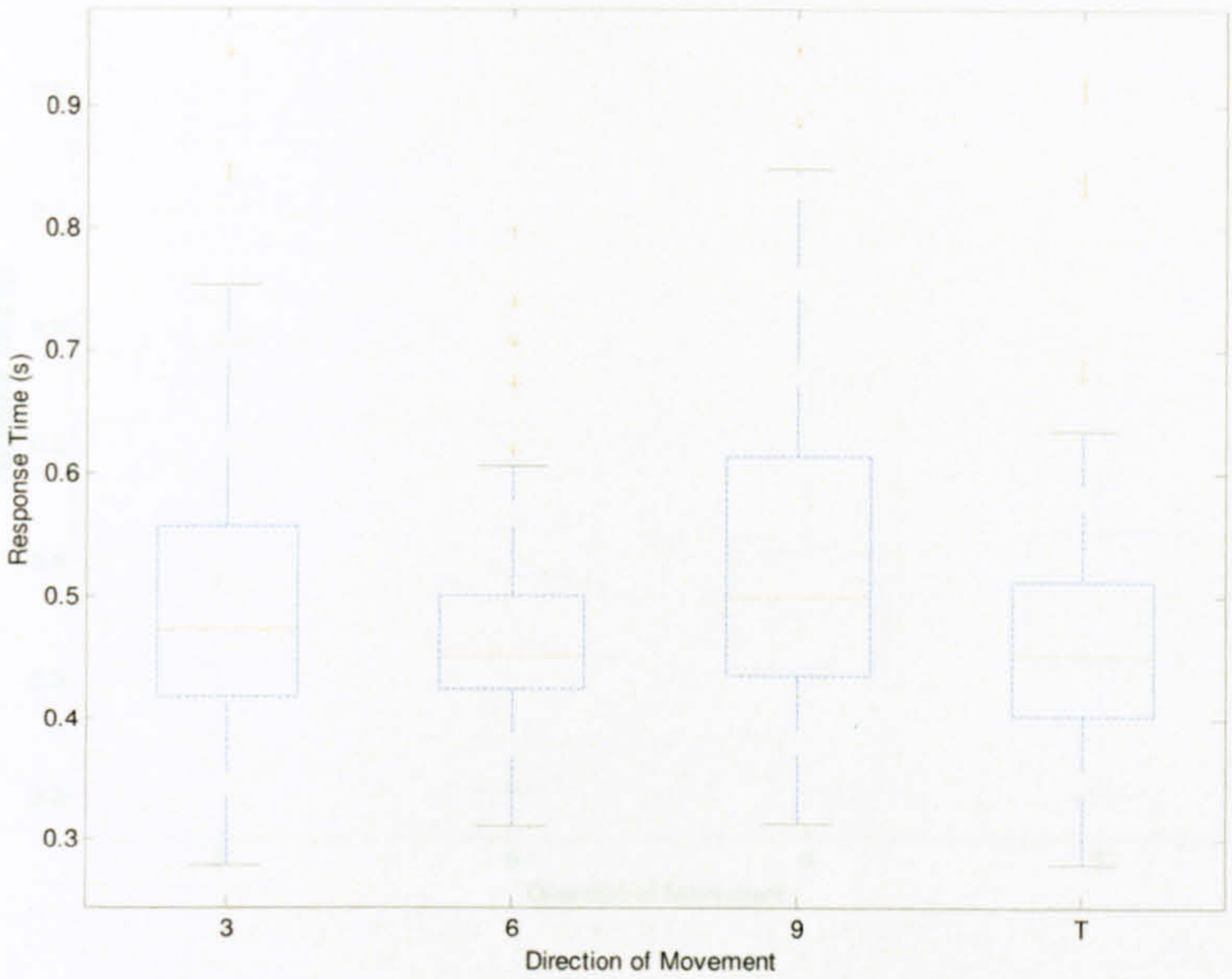


Subject 10



Forced Choice Trials

Subject 1



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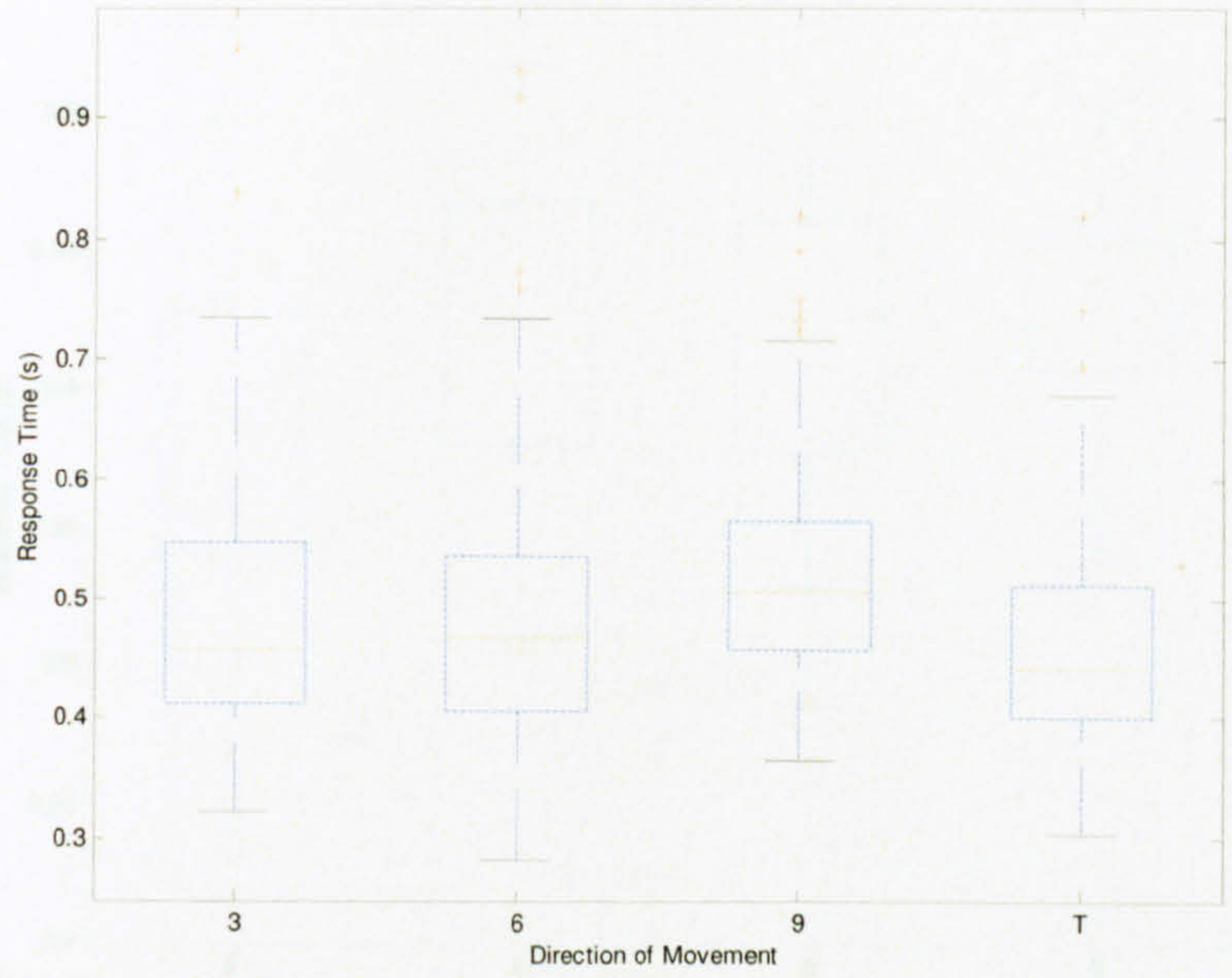

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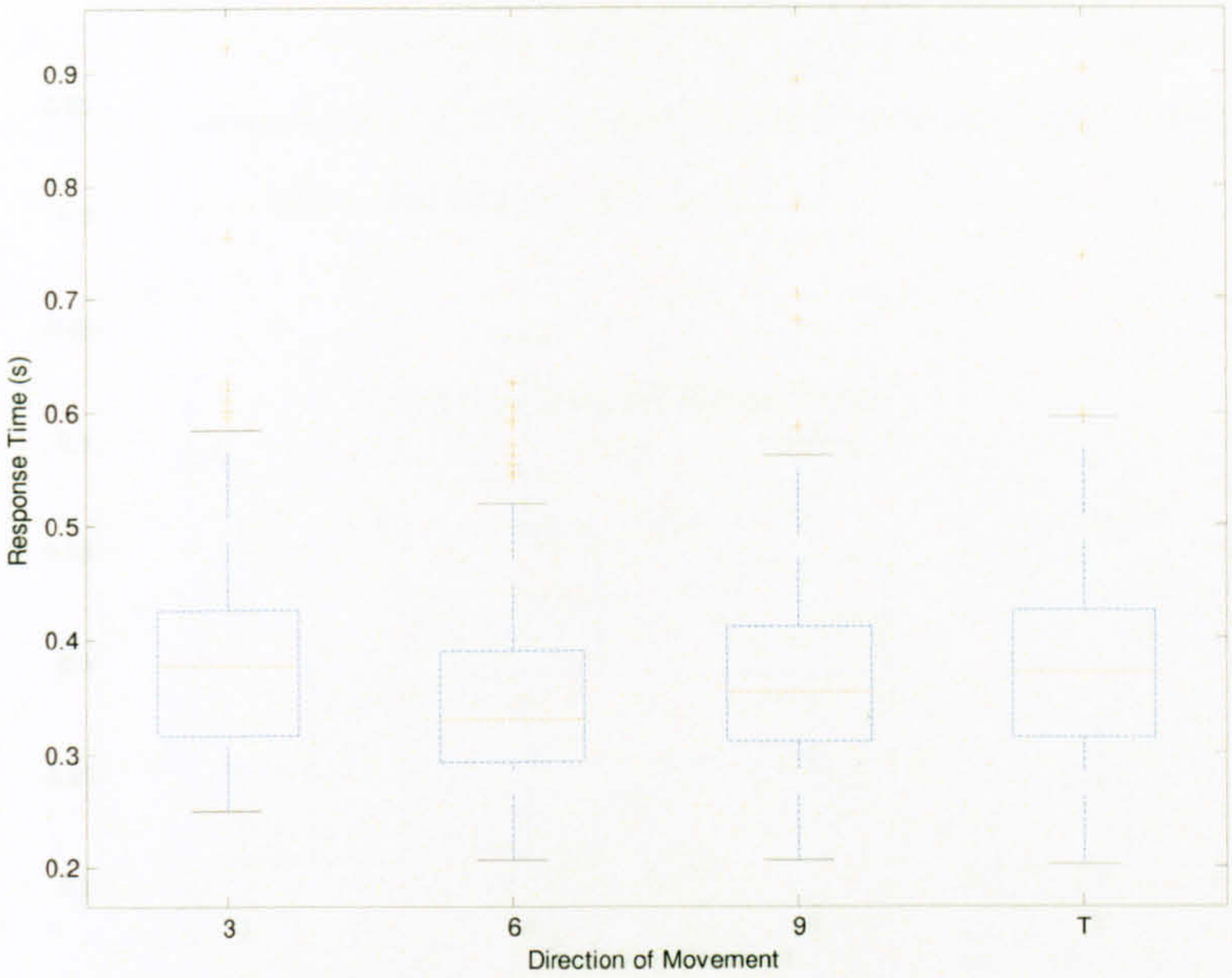
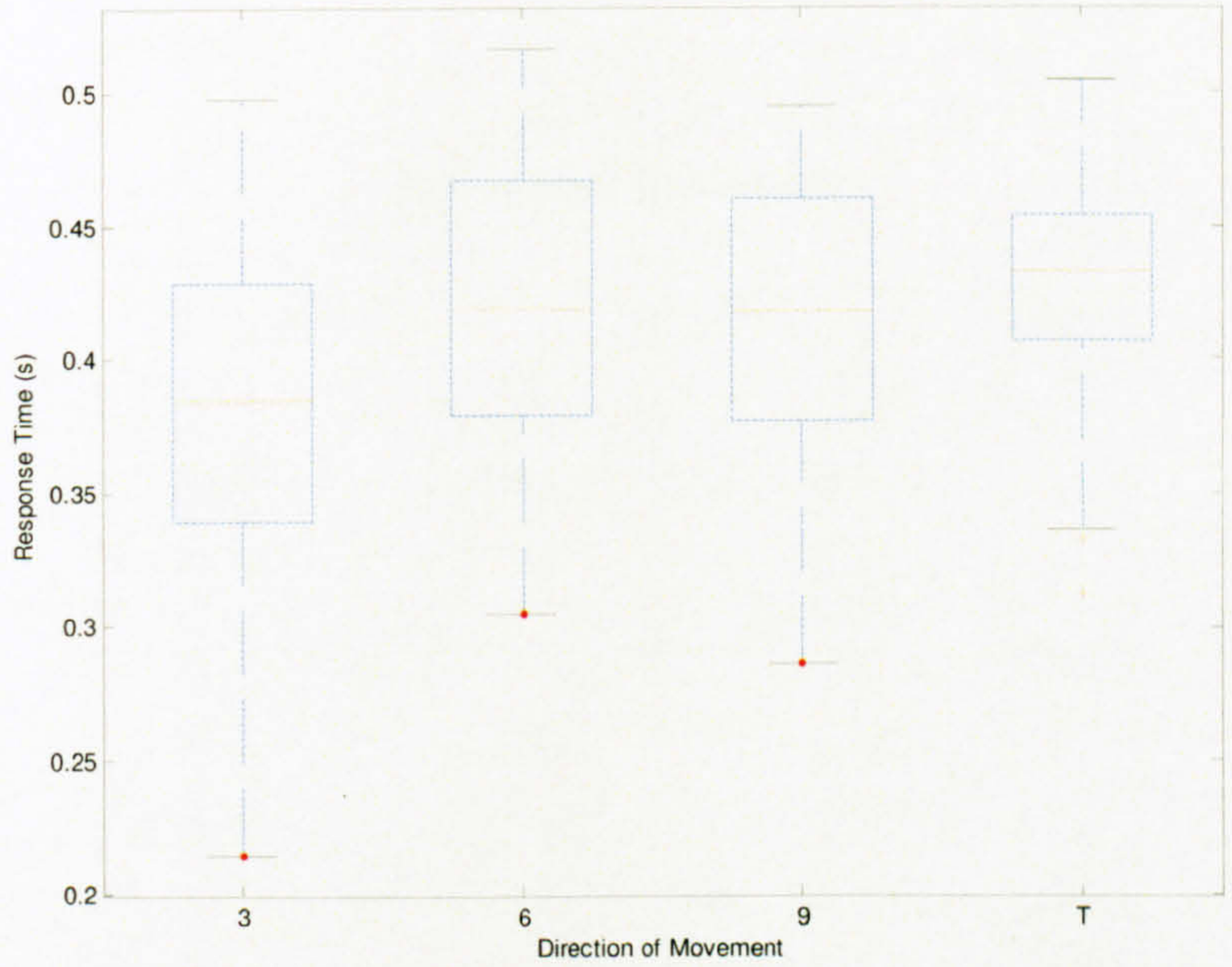
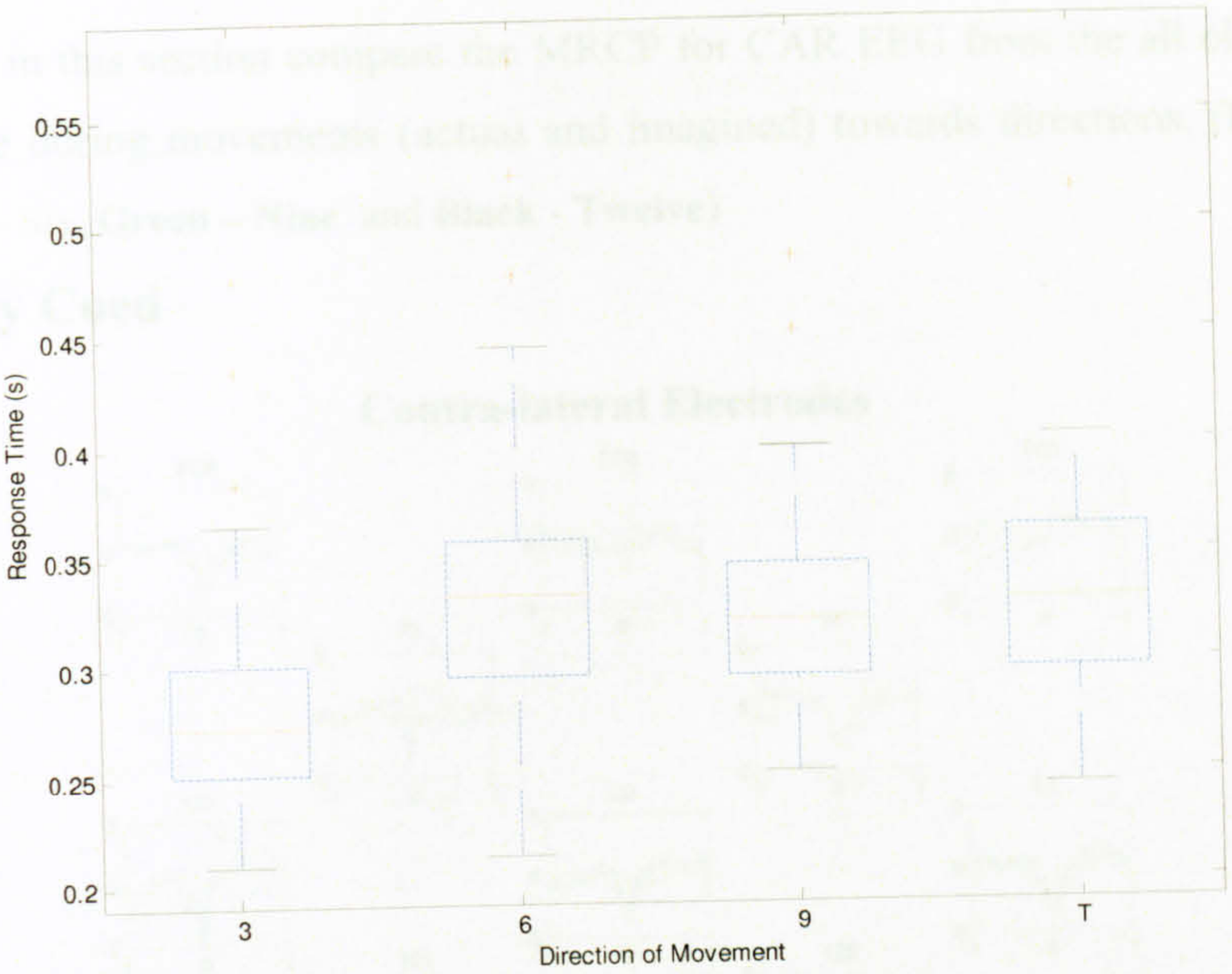


Subject 8



Subject 10


0.55
0.5
0.45
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0.35
0.3
0.25
0.2
Response Time (s)
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T
Direction of Movement

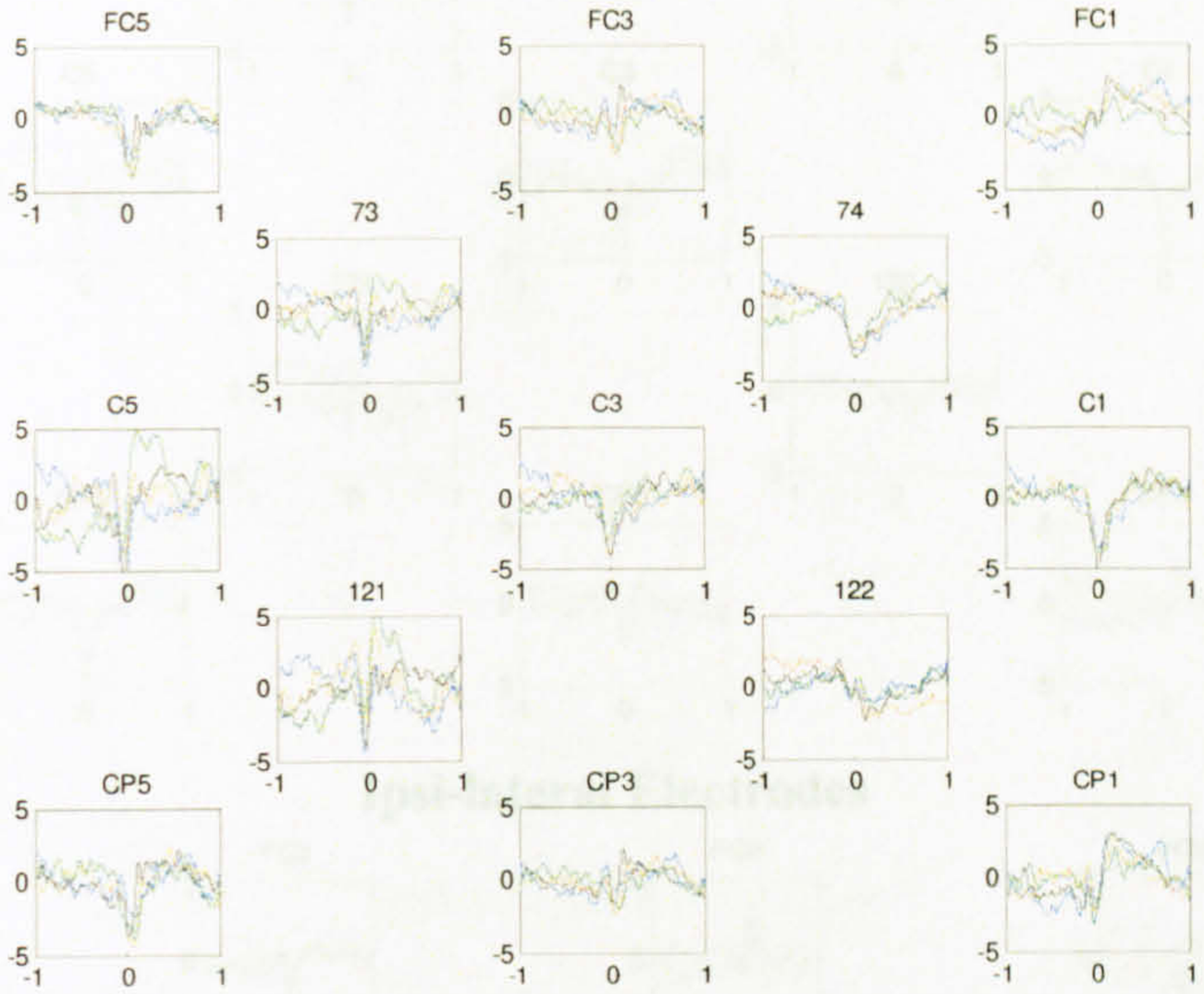
ERP

The figures in this section compare the MRCP for CAR EEG from the all electrodes in the montage during movements (actual and imagined) towards directions. (**Key: Blue - Three , Red- Six, Green – Nine** and **Black - Twelve**)

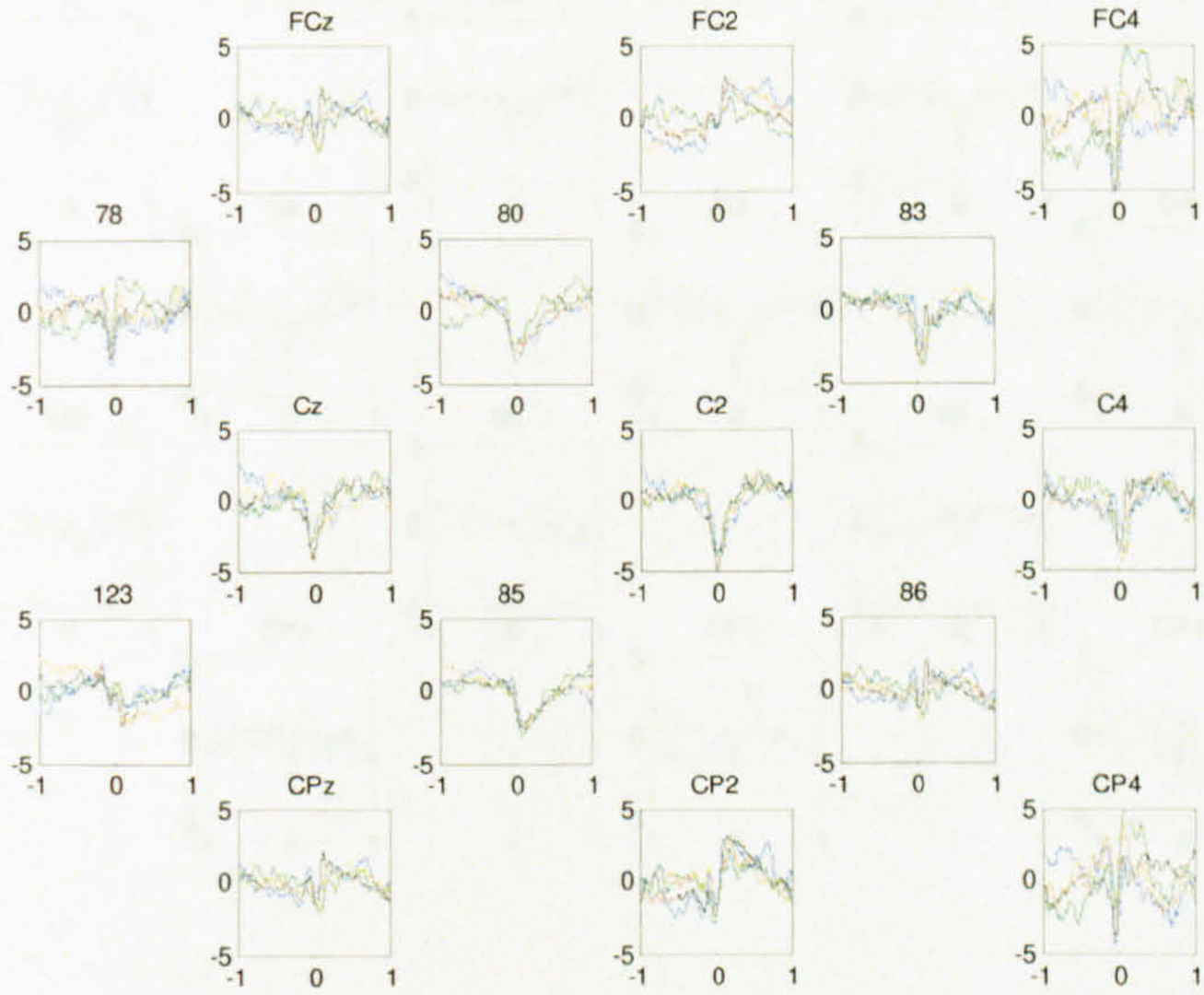
Externally Cued

Subject 1

Contra-lateral Electrodes



Ipsi-lateral Electrodes



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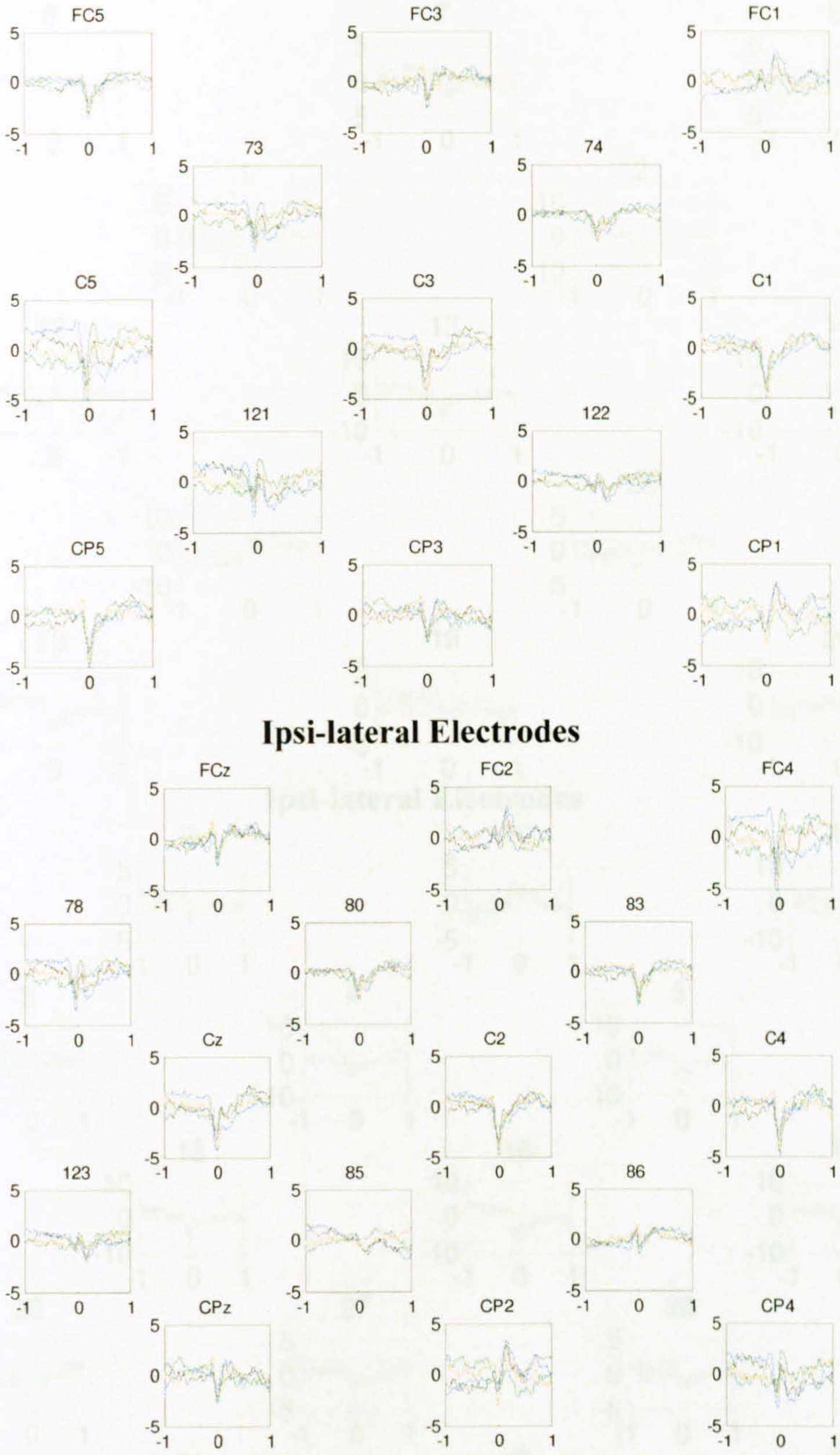
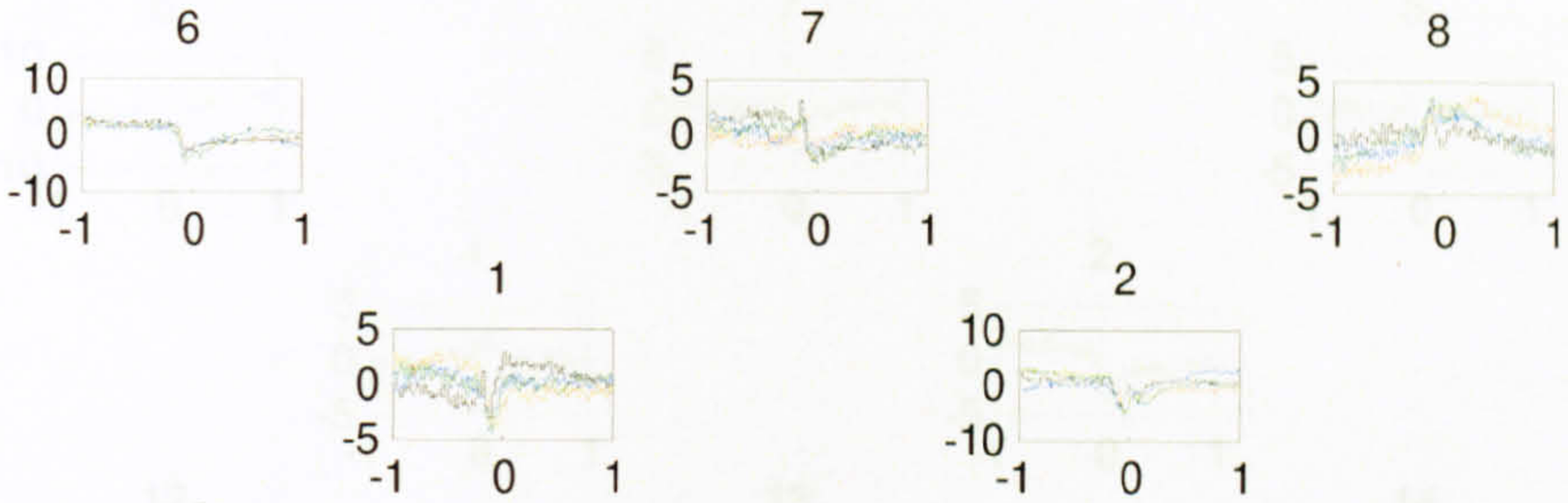
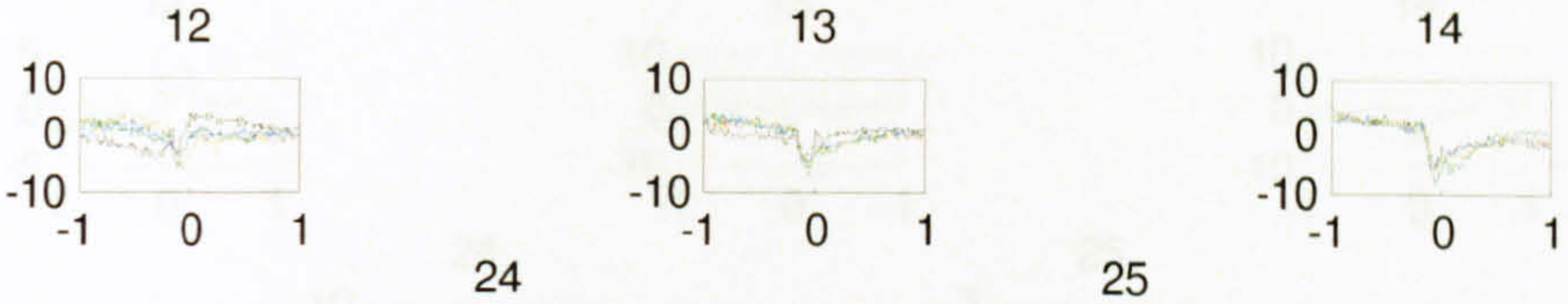

Contra-lateral Electrodes
FC5
FC3
FC1
73
74
C5
C3
C1
121
122
CP5
CP3
CP1
Ipsi-lateral Electrodes
FCz
FC2
FC4
78
80
83
Cz
C2
C4
123
85
86
CPz
CP2
CP4

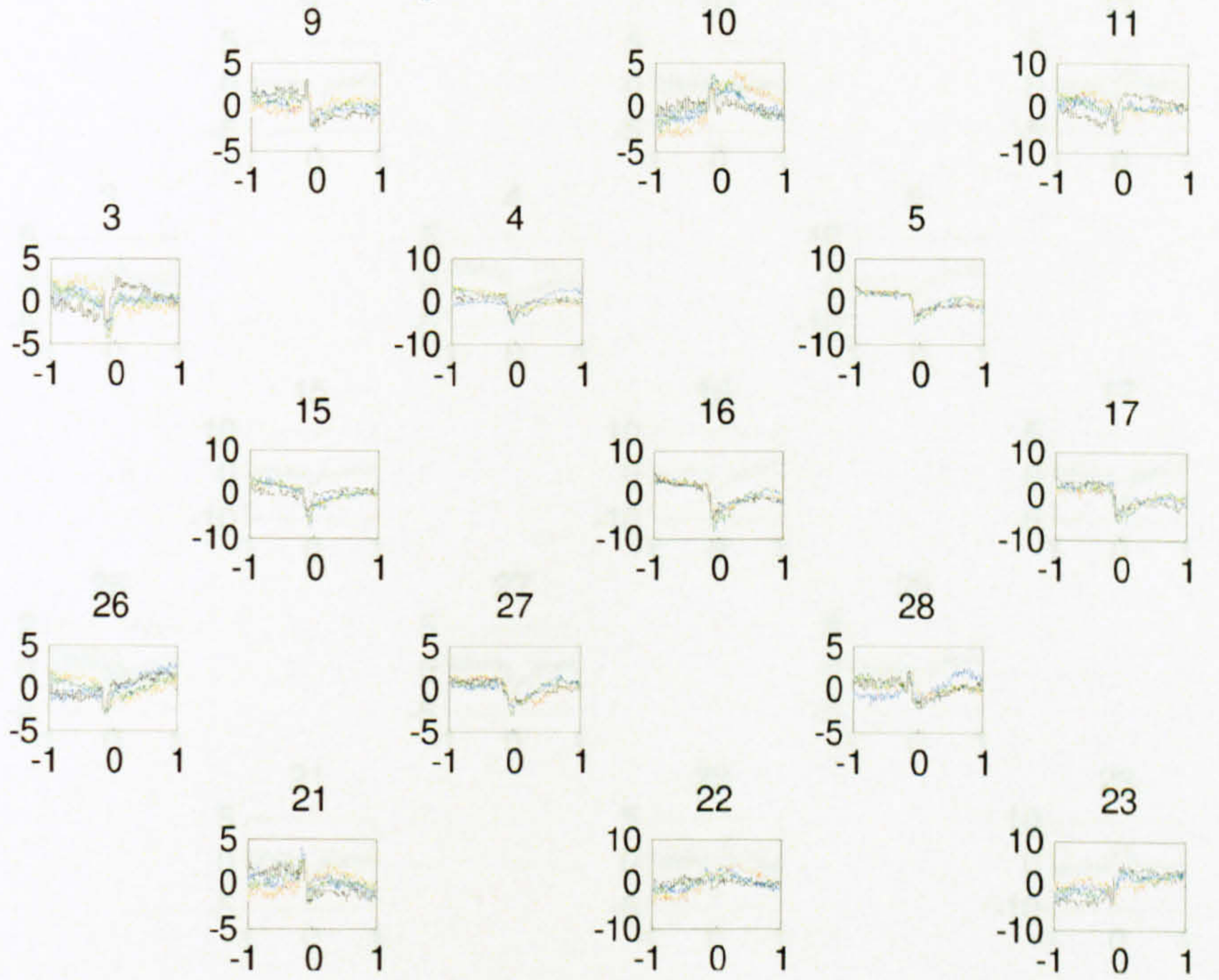
Subject 3

Contra-lateral Electrodes



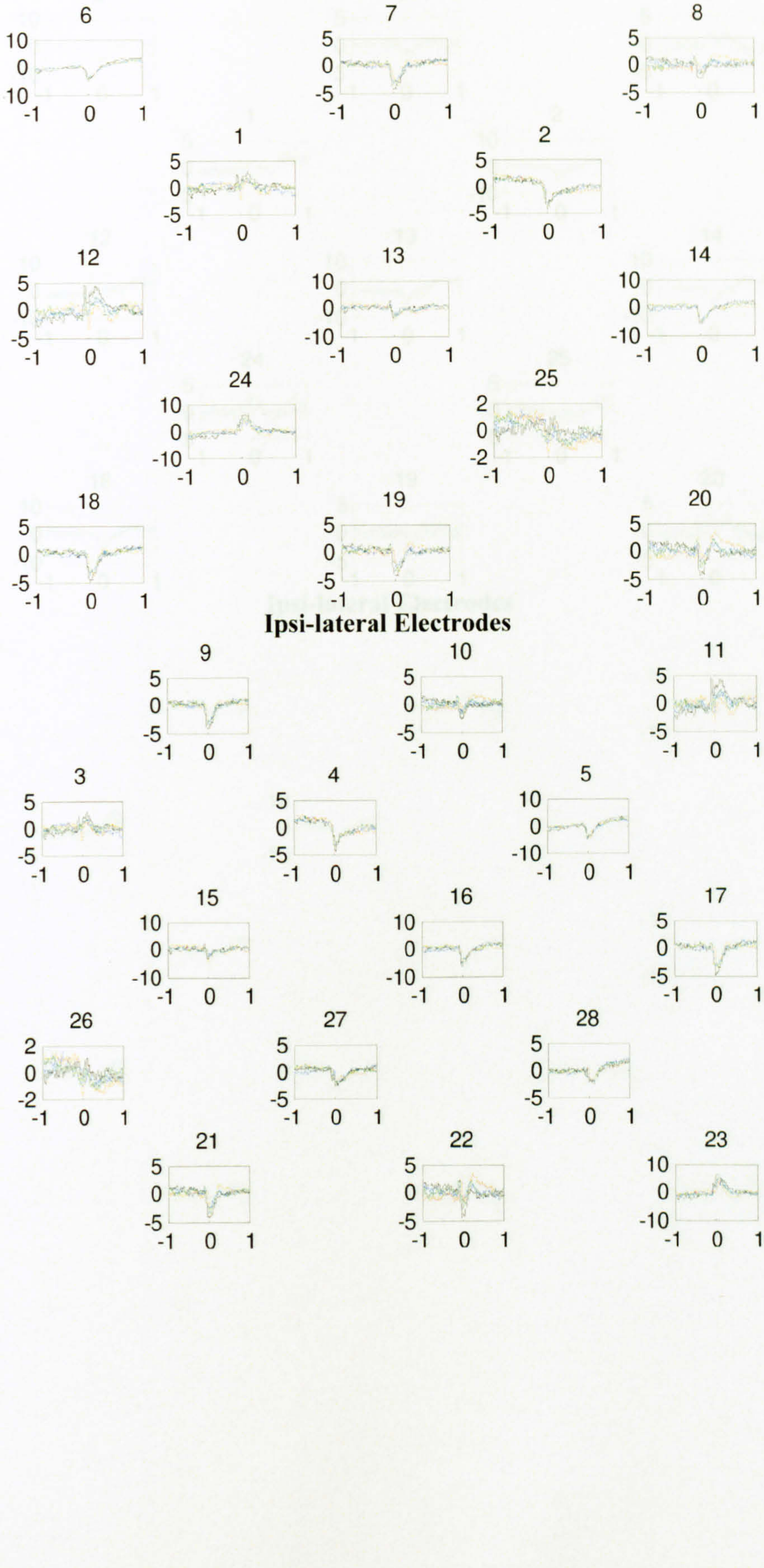


Ipsi-lateral Electrodes



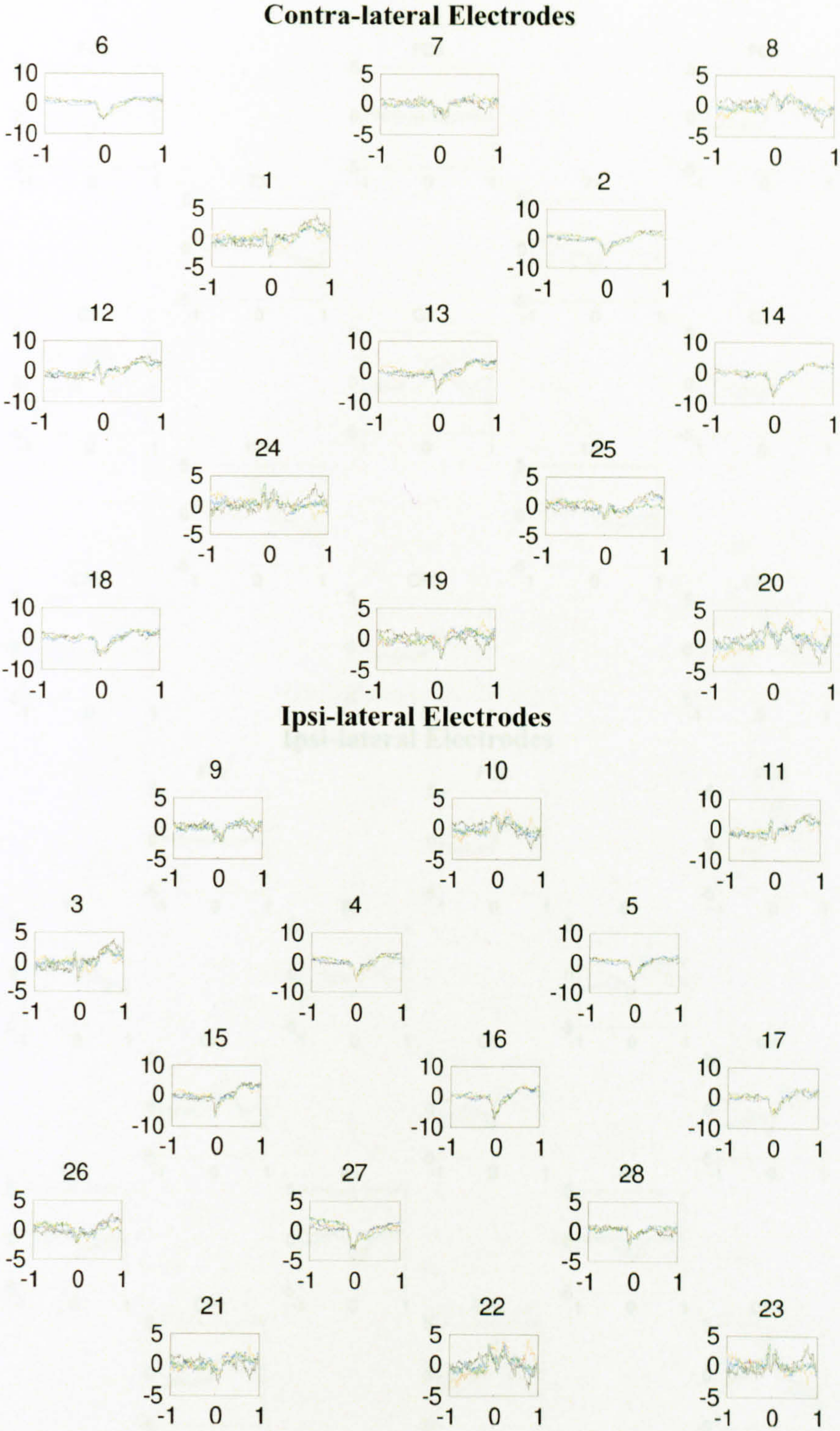
Subject 4

Contra-lateral Electrodes



Ipsi-lateral Electrodes

Subject 5


Contra-lateral Electrodes
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Ipsi-lateral Electrodes
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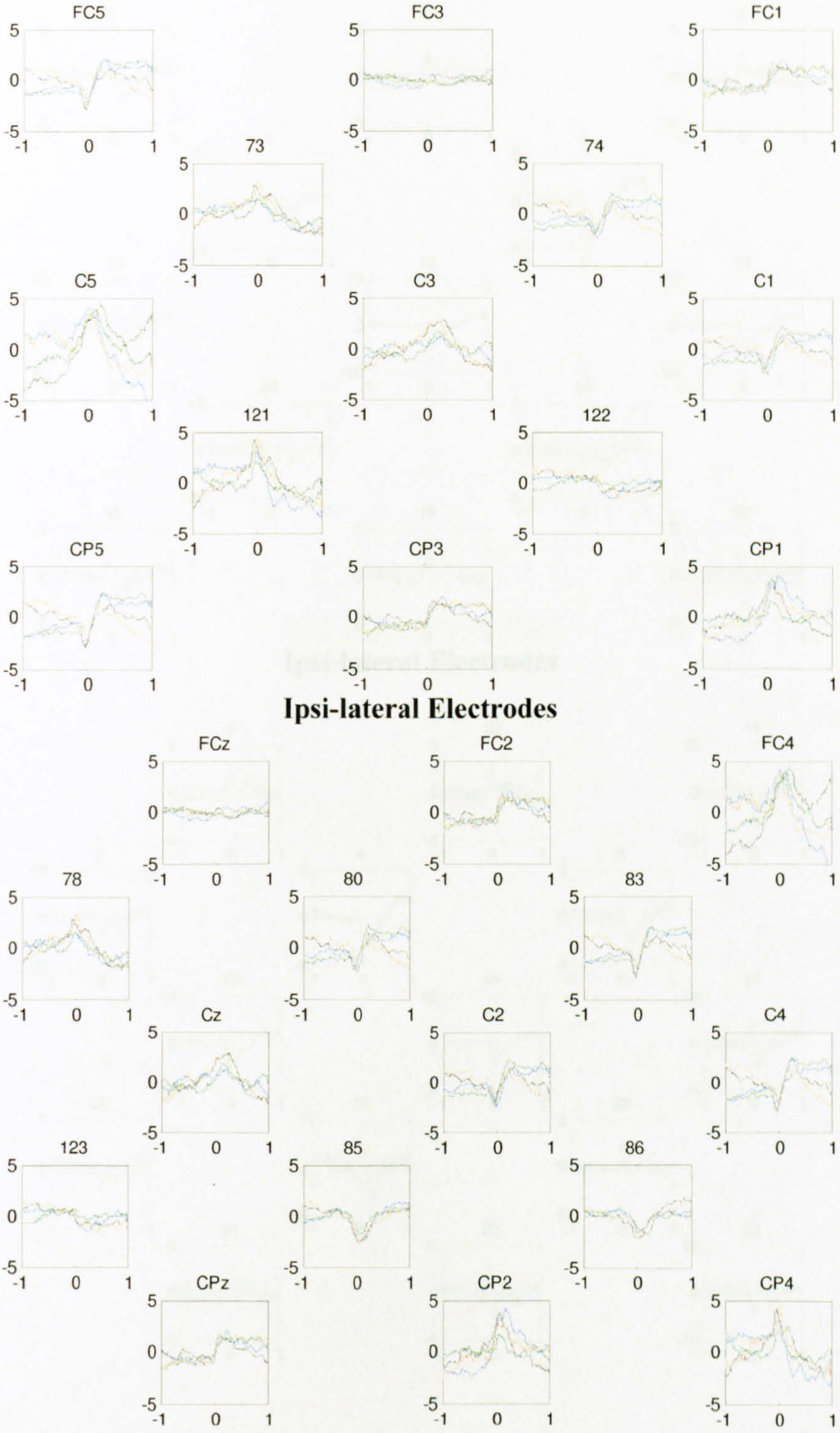
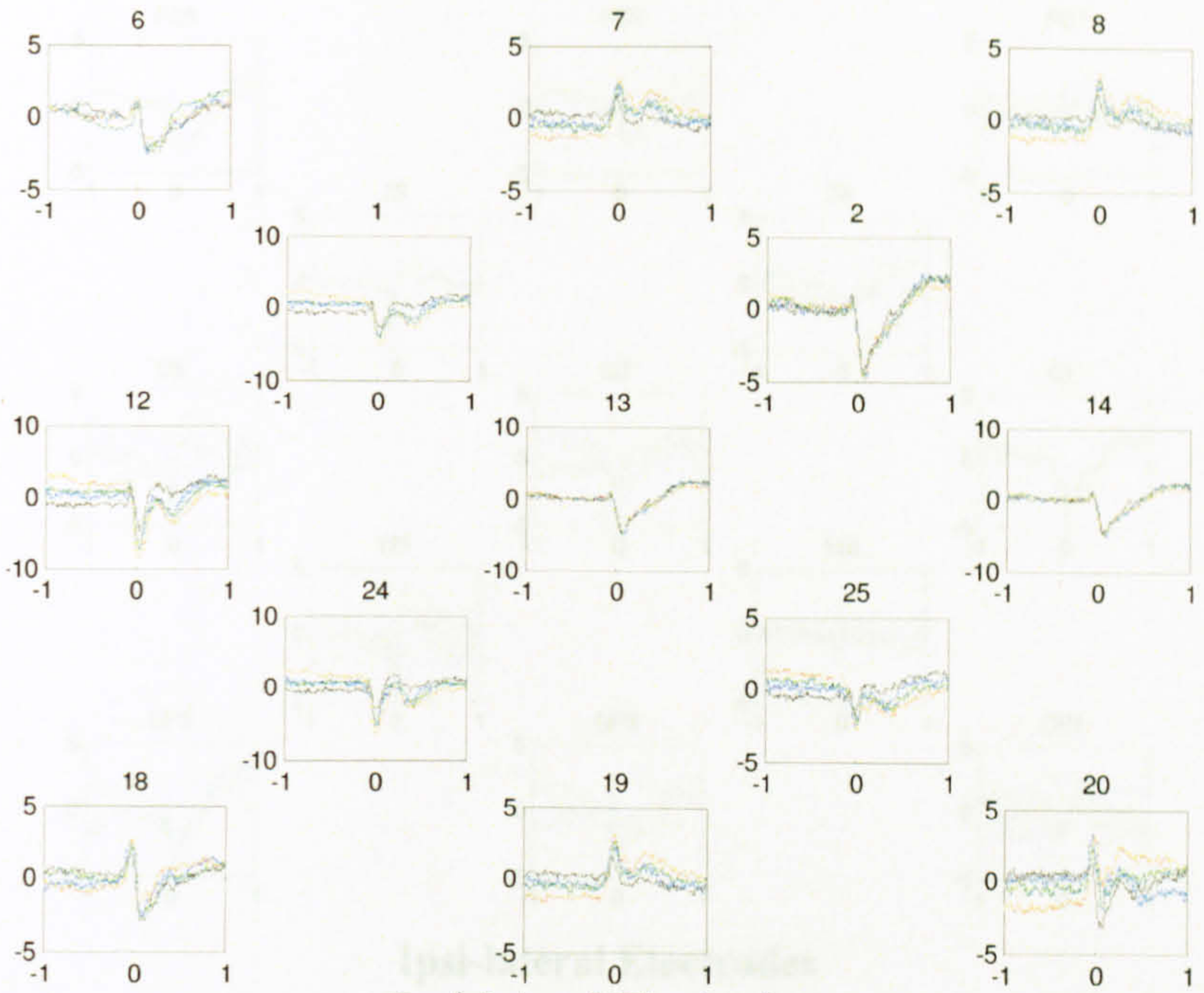
Subject 6


Contra-lateral Electrodes
FC5
FC3
FC1
73
74
C5
C3
C1
121
122
CP5
CP3
CP1
Ipsi-lateral Electrodes
FCz
FC2
FC4
78
80
83
Cz
C2
C4
123
85
86
CPz
CP2
CP4

Subject 7


Contra-lateral Electrodes
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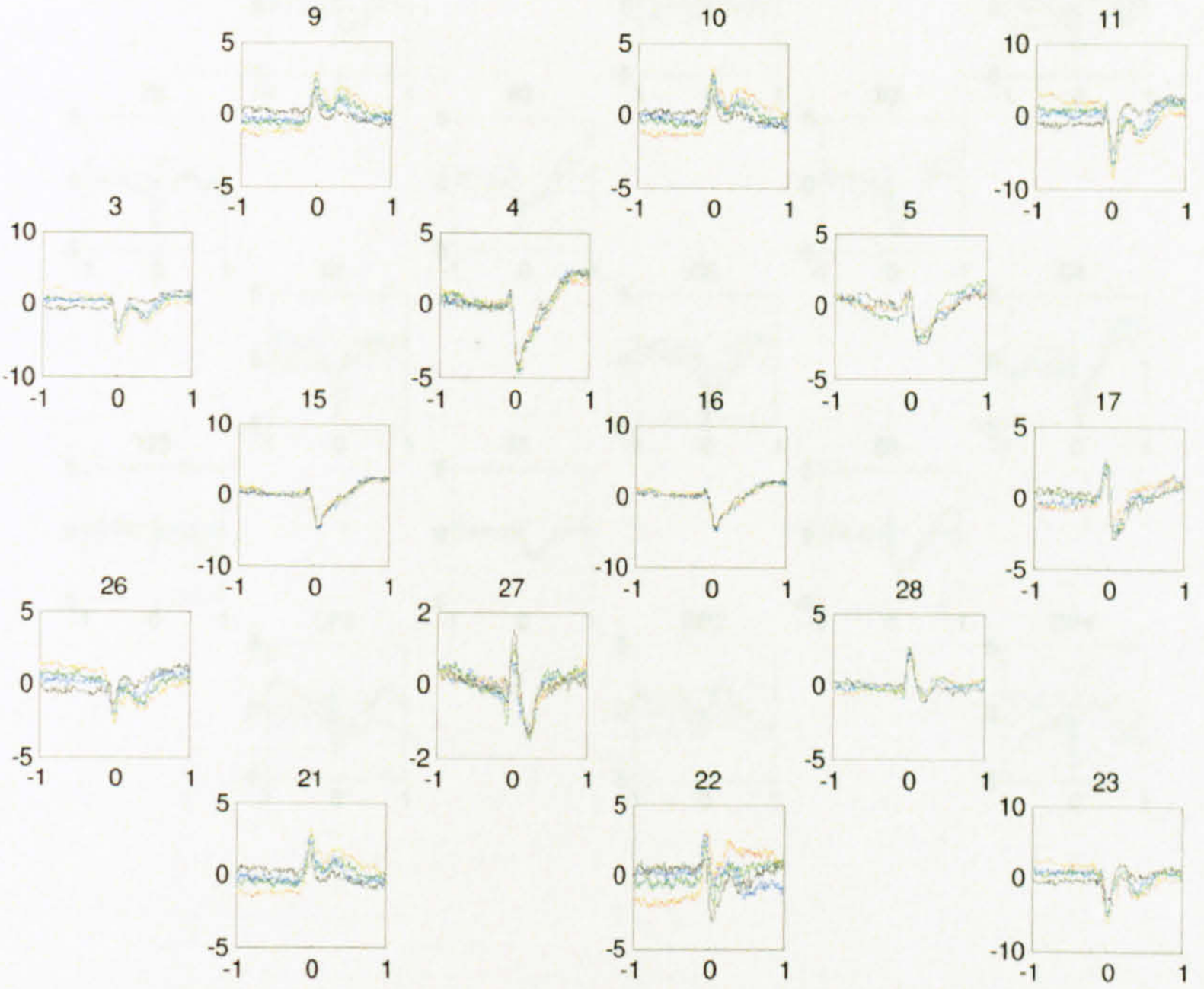
Ipsi-lateral Electrodes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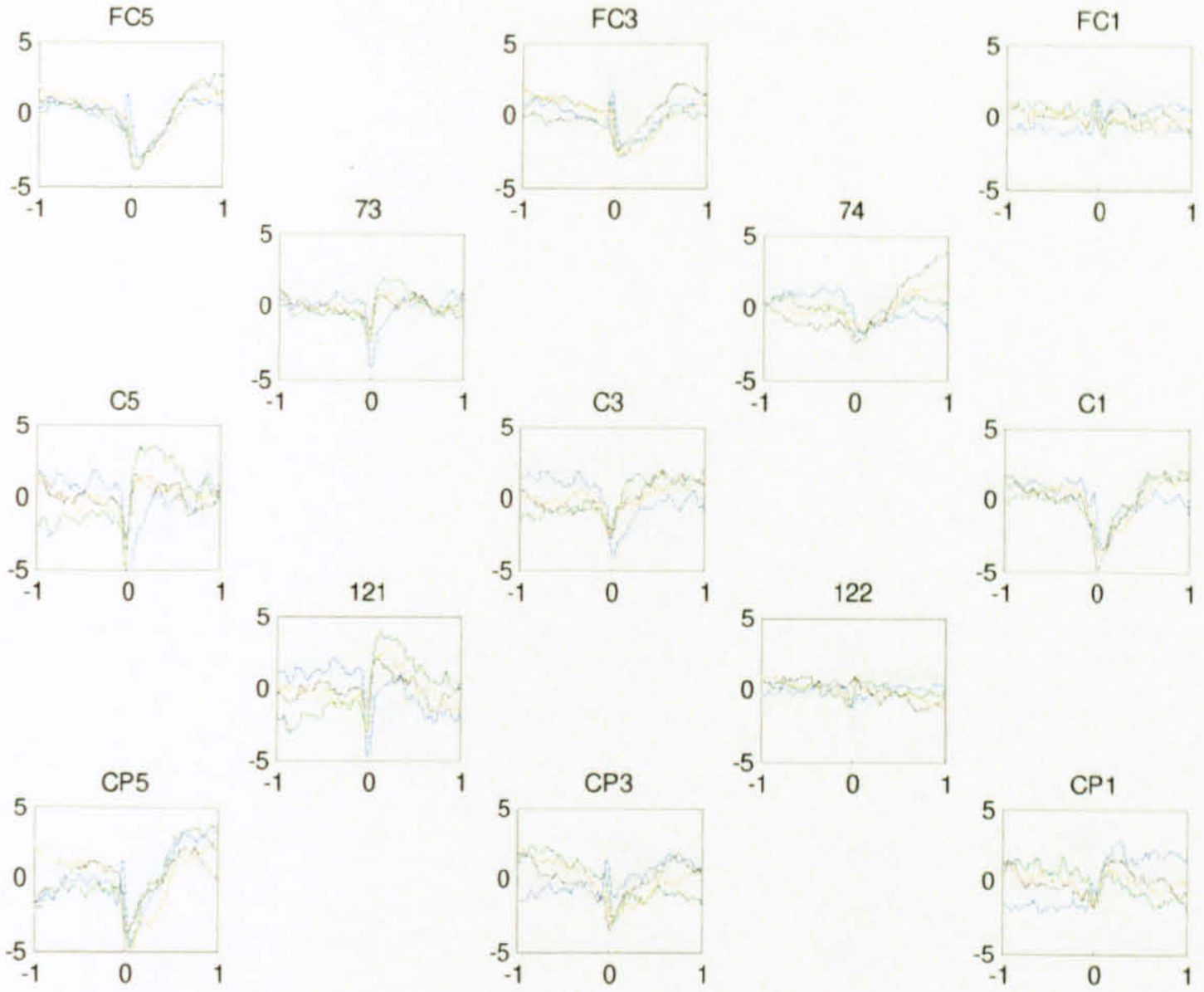
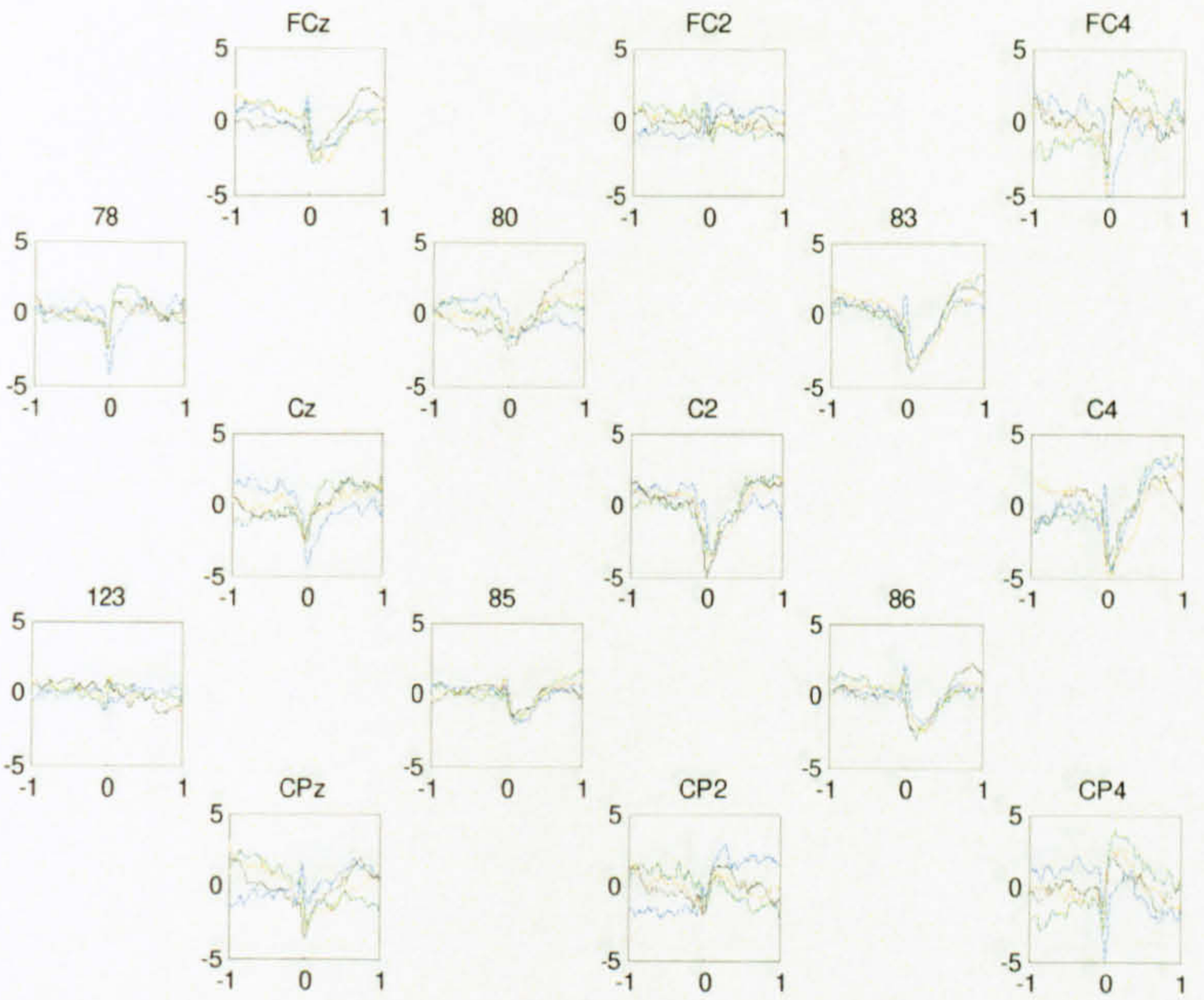
Subject 8

Contra-lateral Electrodes

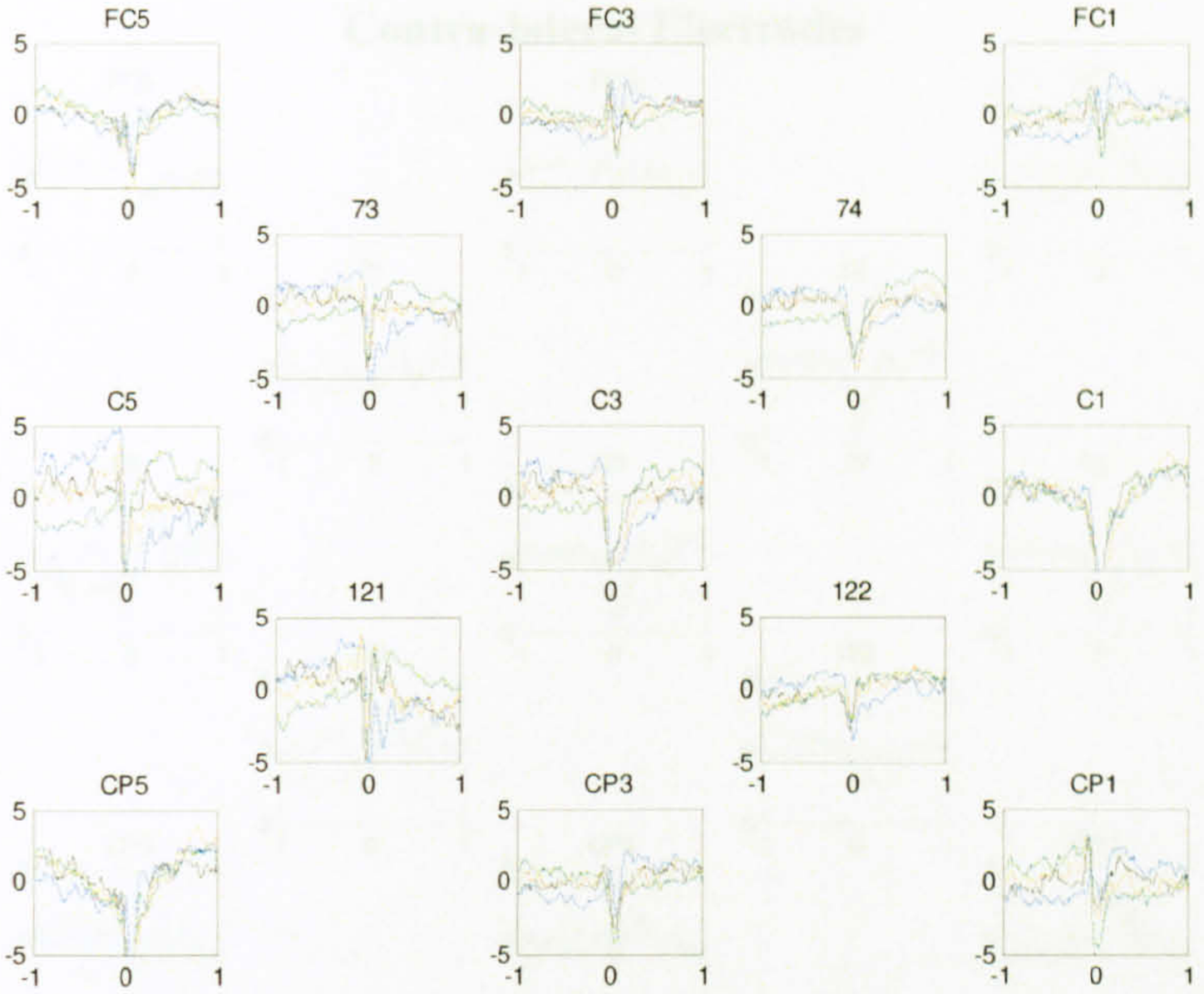


Ipsi-lateral Electrodes

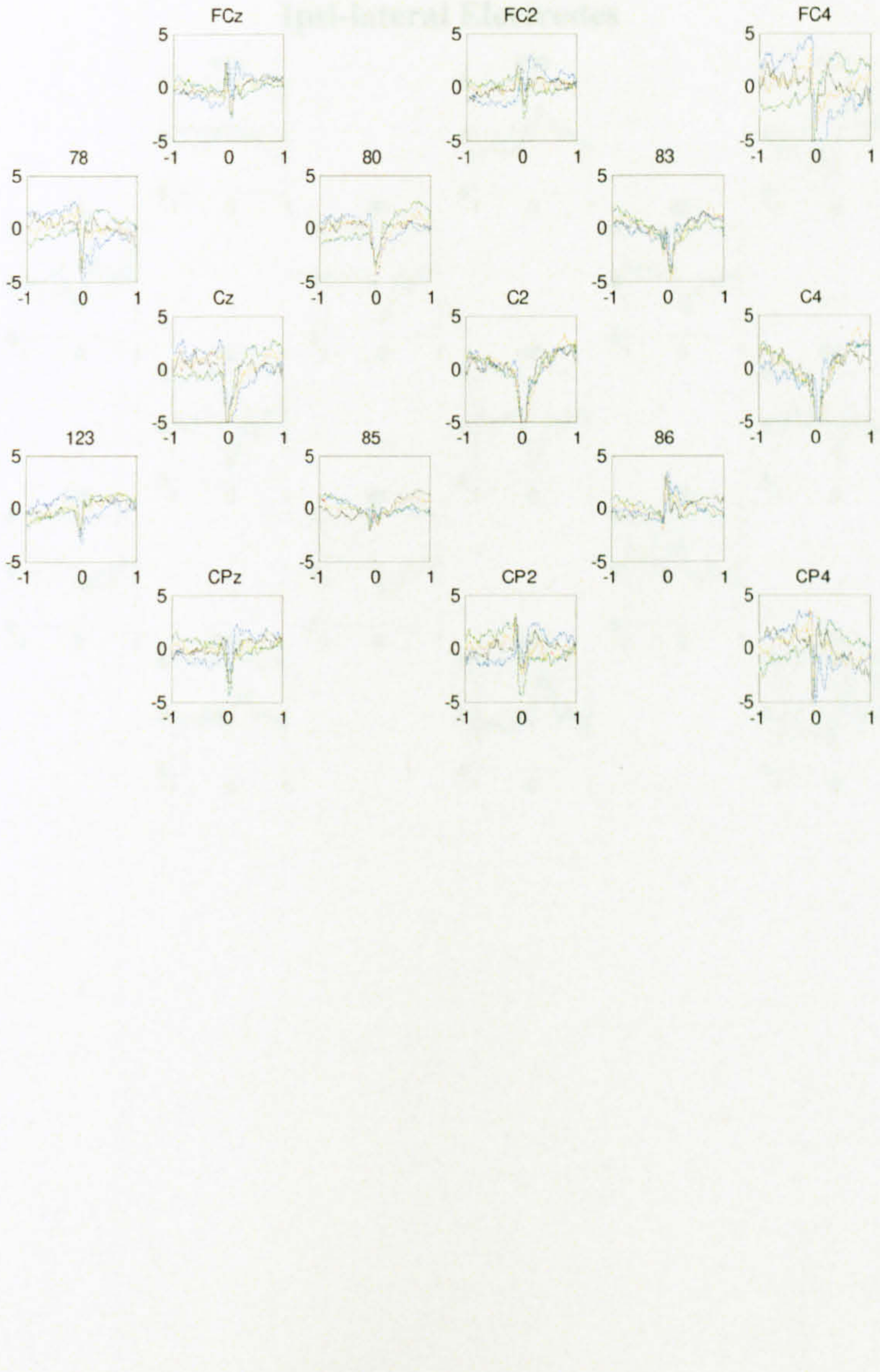


Subject 10

Contra-lateral Electrodes



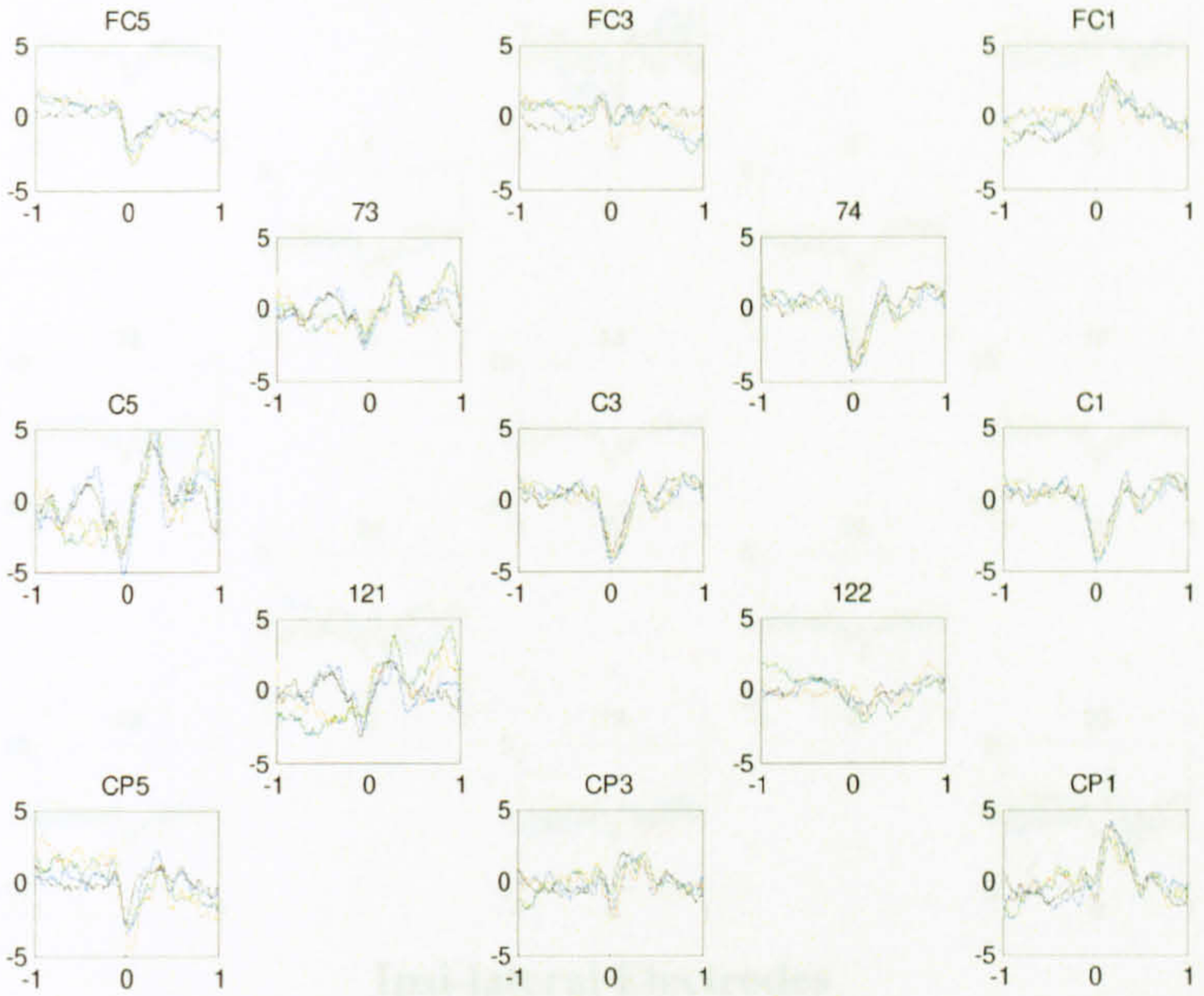
Ipsi-lateral Electrodes



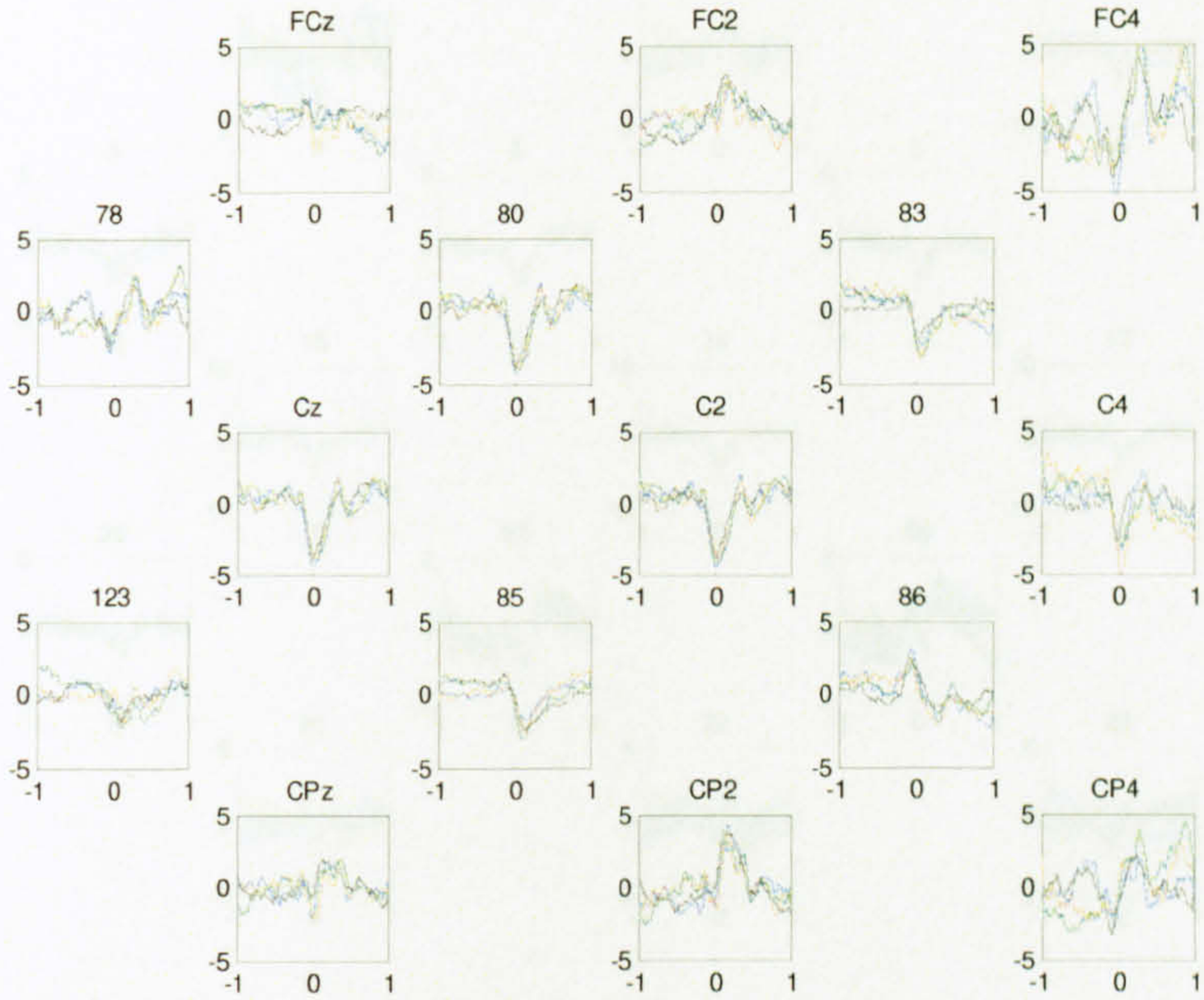
Forced Choice Trials

Subject 1

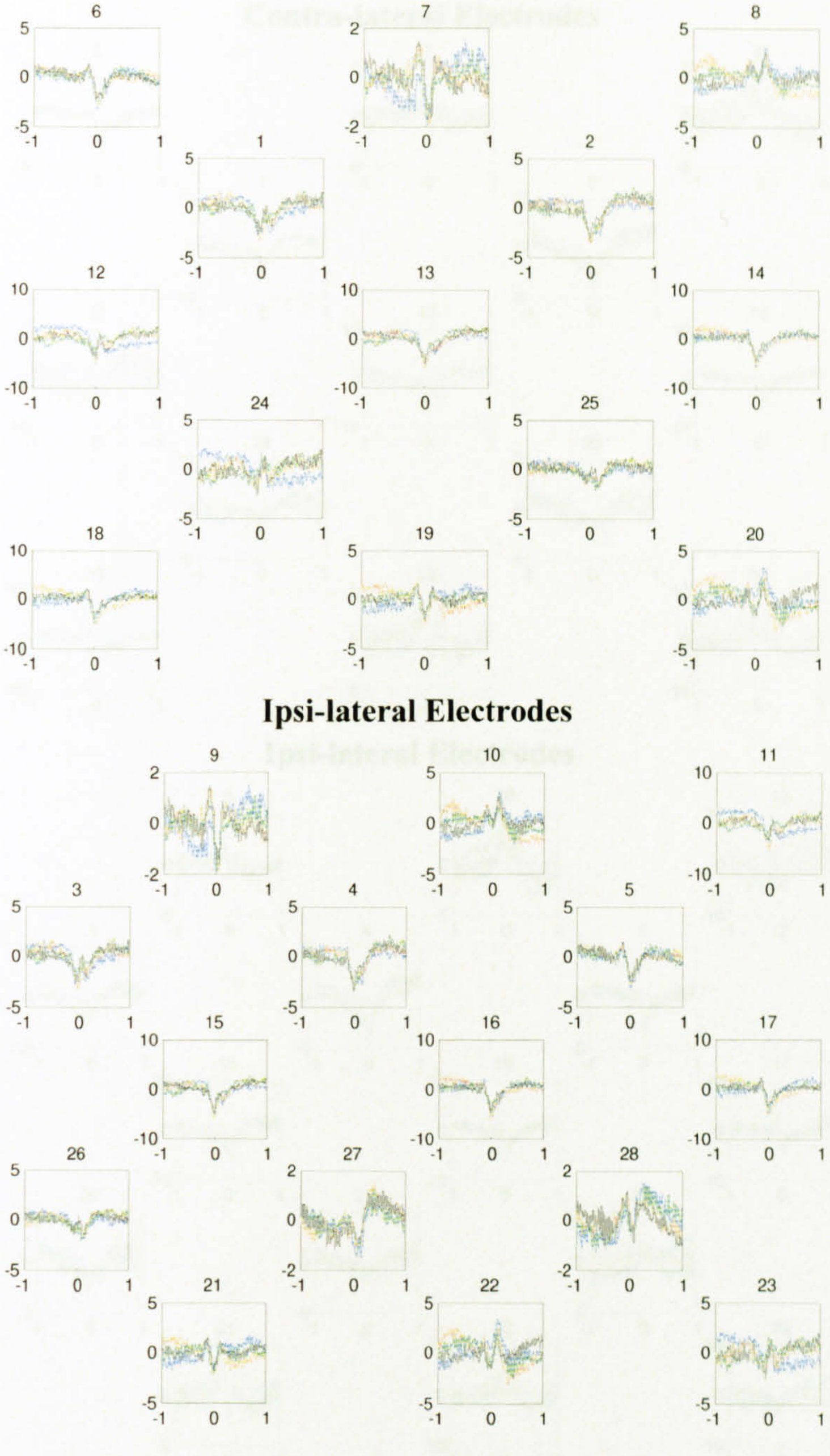
Contra-lateral Electrodes



Ipsi-lateral Electrodes



Subject 2


Contra-lateral Electrodes
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Ipsi-lateral Electrodes
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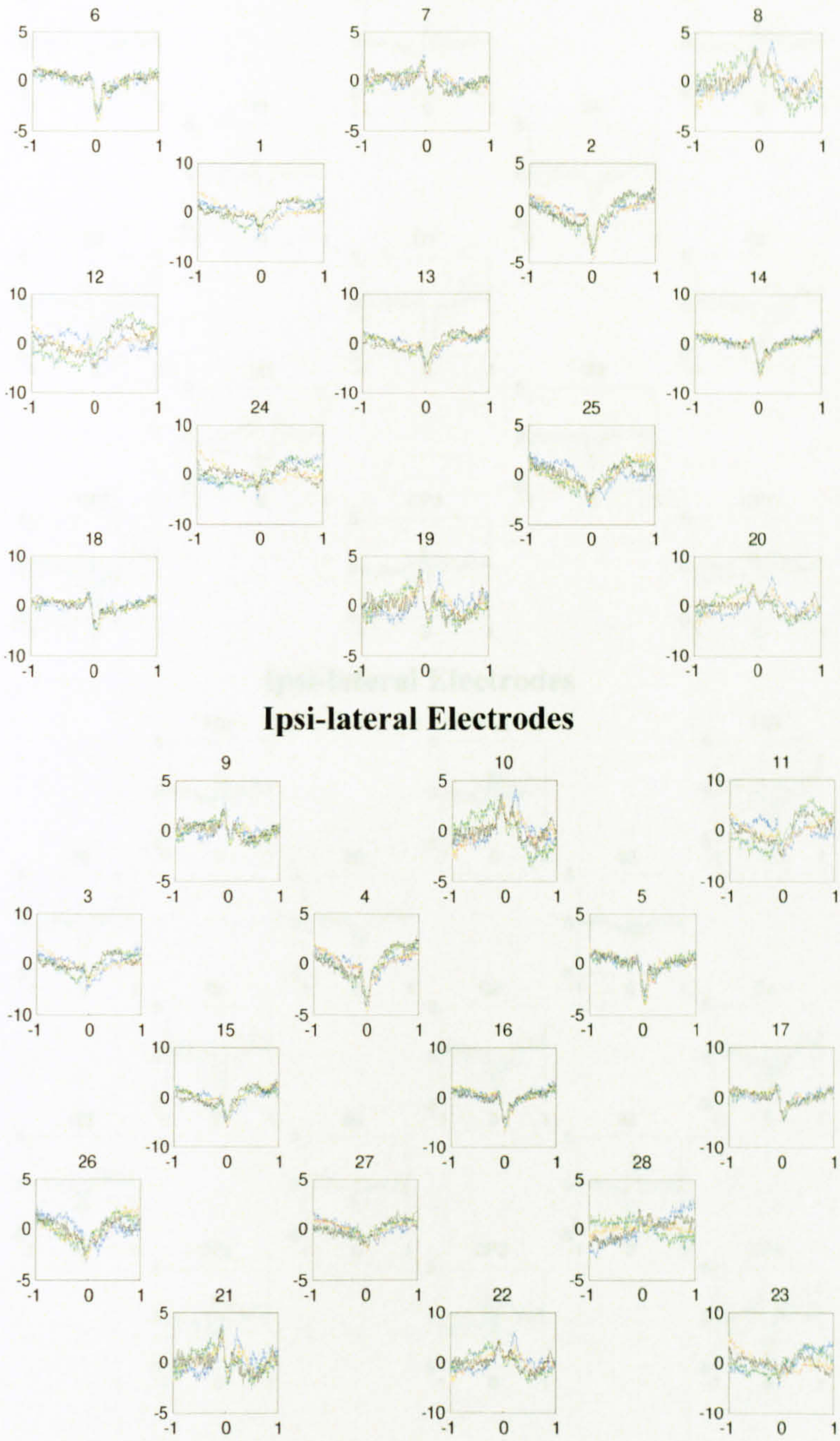
Subject 3


Contra-lateral Electrodes
6
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Ipsi-lateral Electrodes
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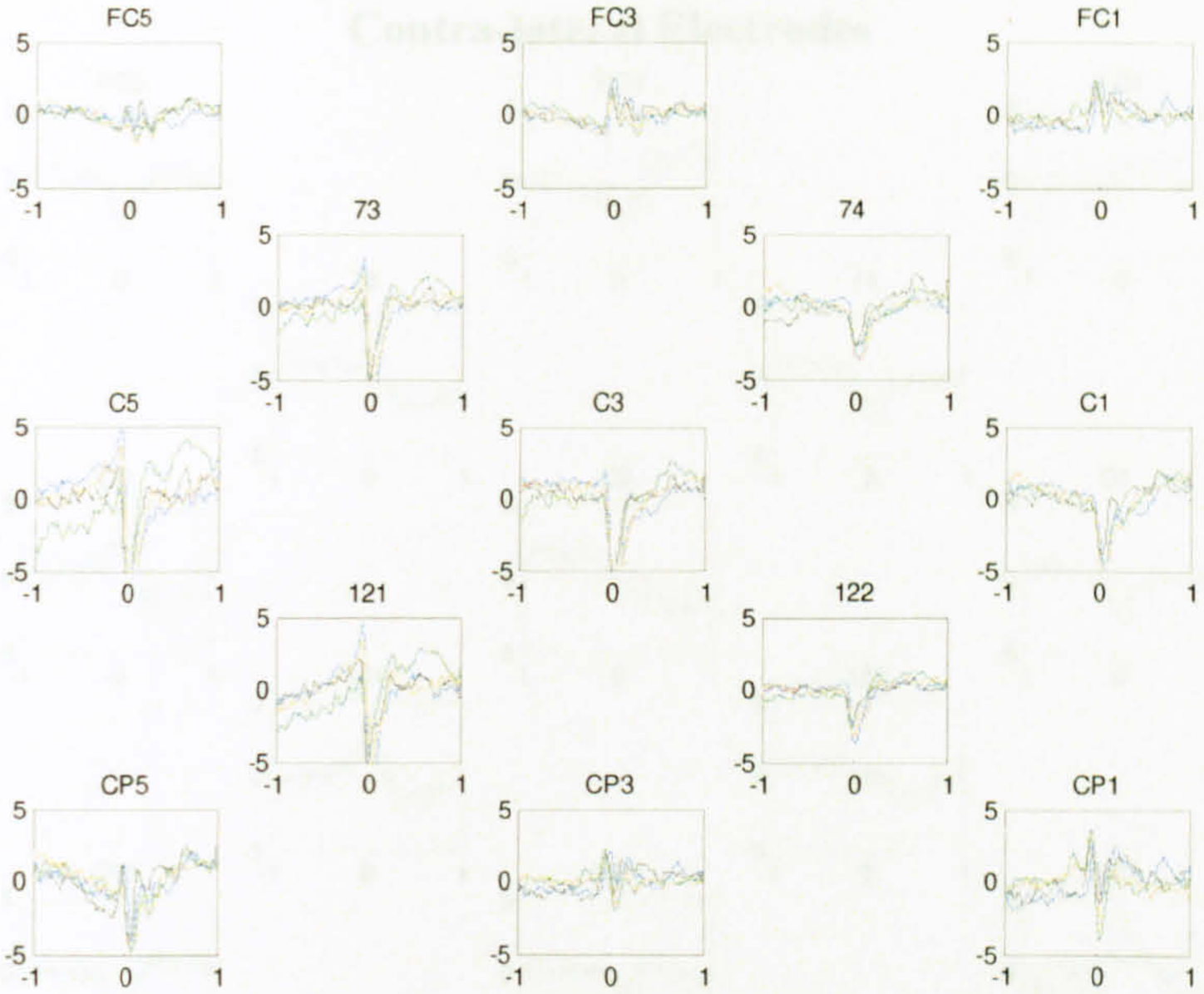
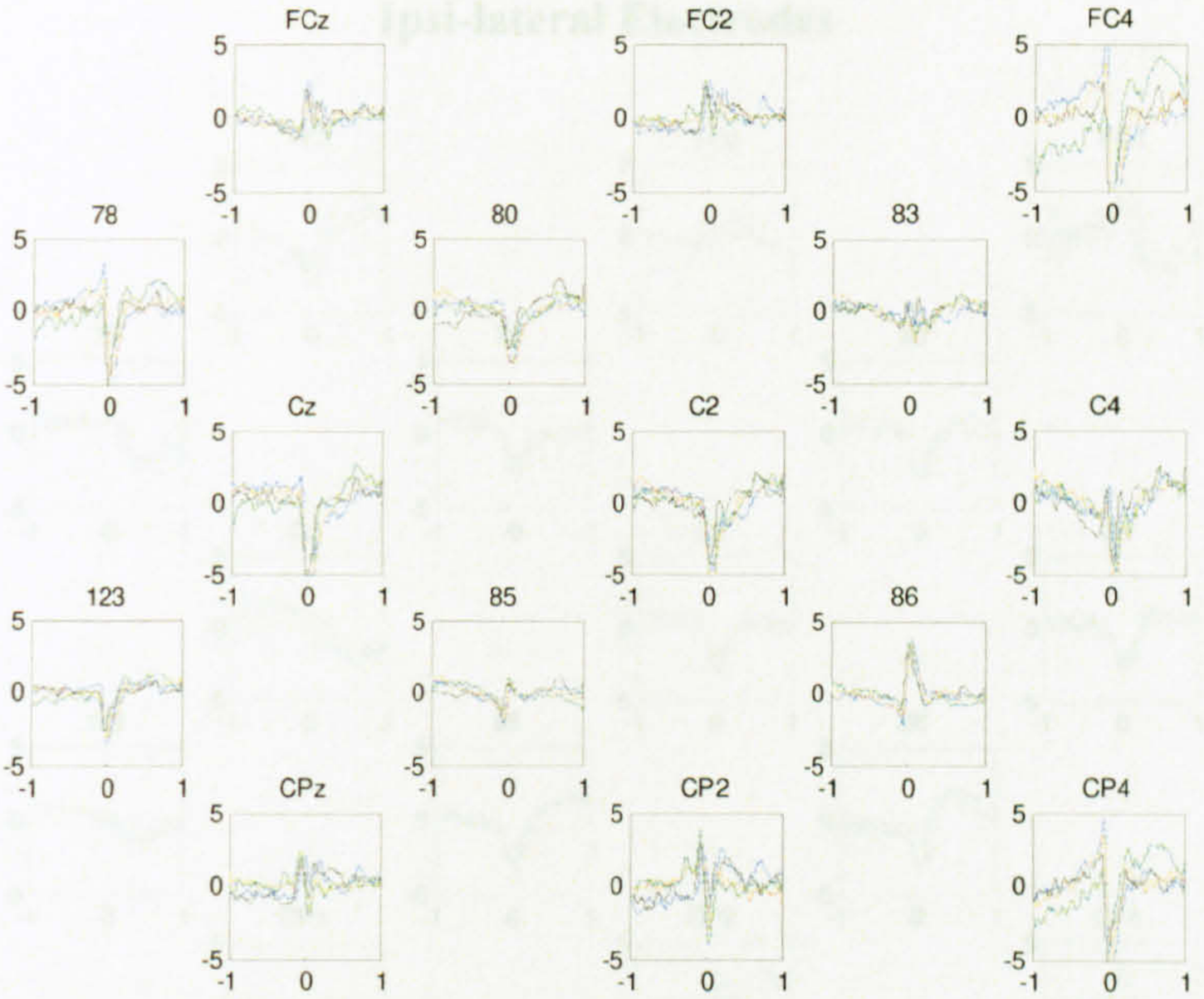
Subject 10

Contra-lateral Electrodes

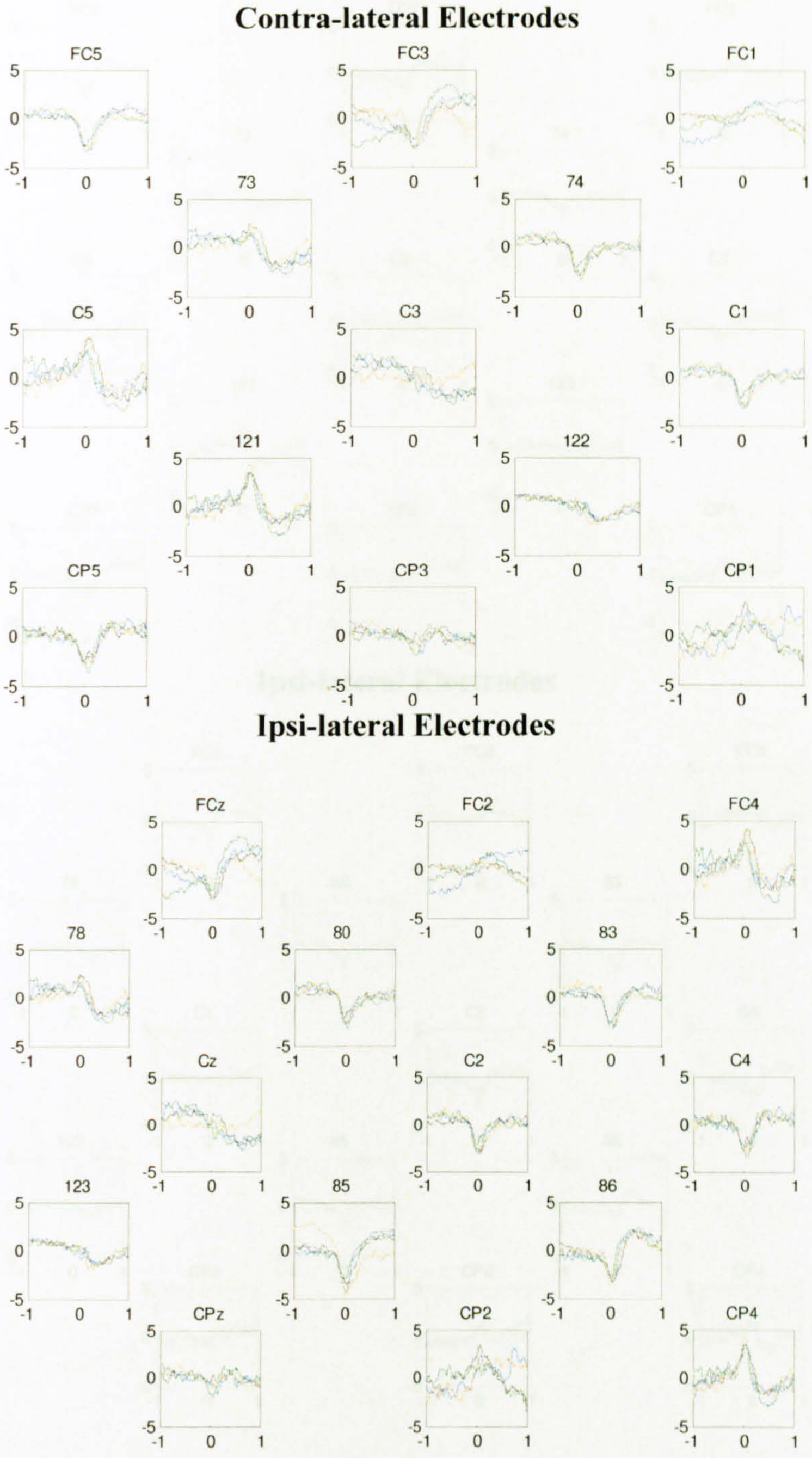


Ipsi-lateral Electrodes

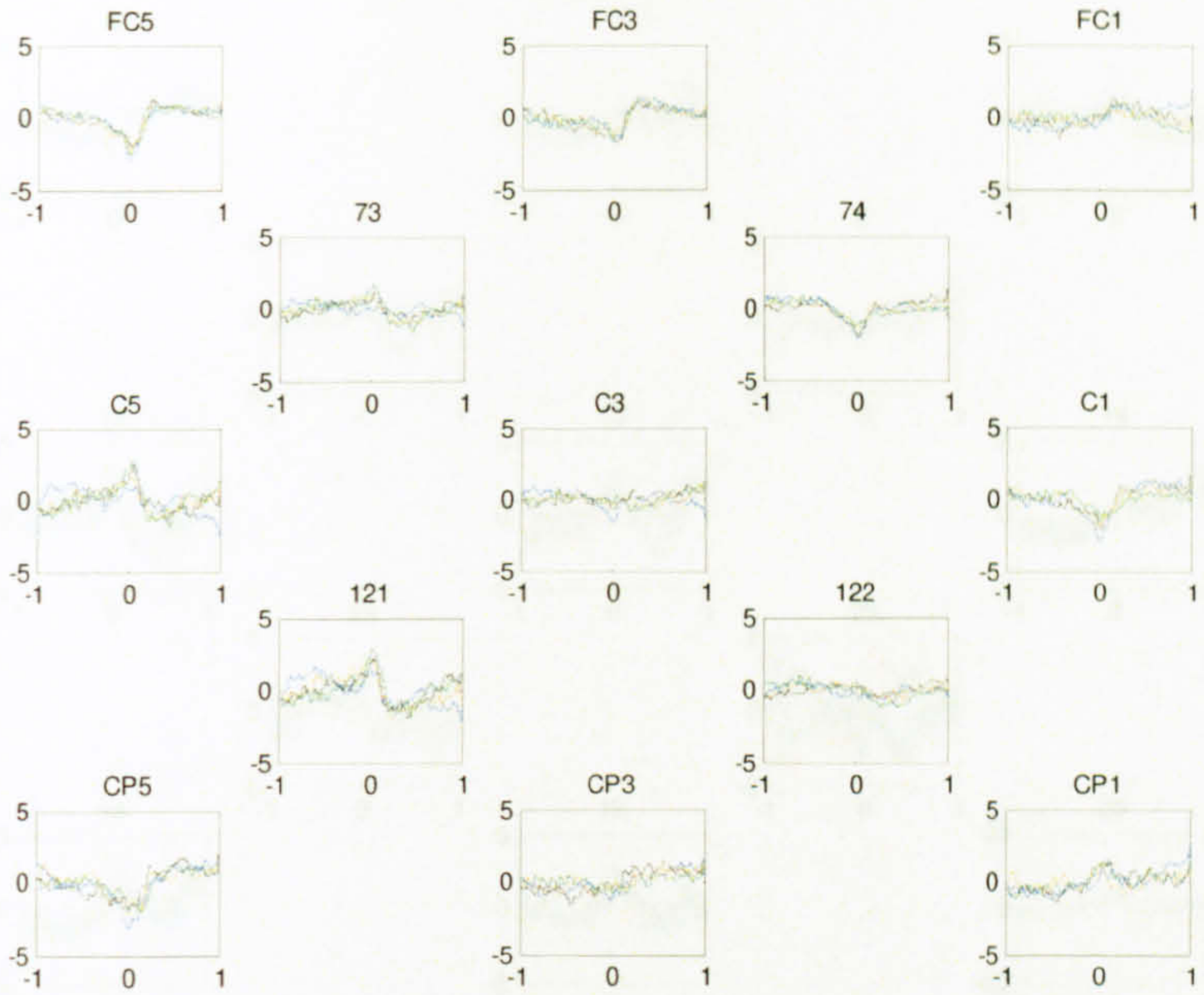


Self Determined

Subject 1



Subject 2


Contra-lateral Electrodes
FC5
FC3
FC1
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74
C5
C3
C1
121
122
CP5
CP3
CP1
Ipsi-lateral Electrodes
FCz
FC2
FC4
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Cz
C2
C4
123
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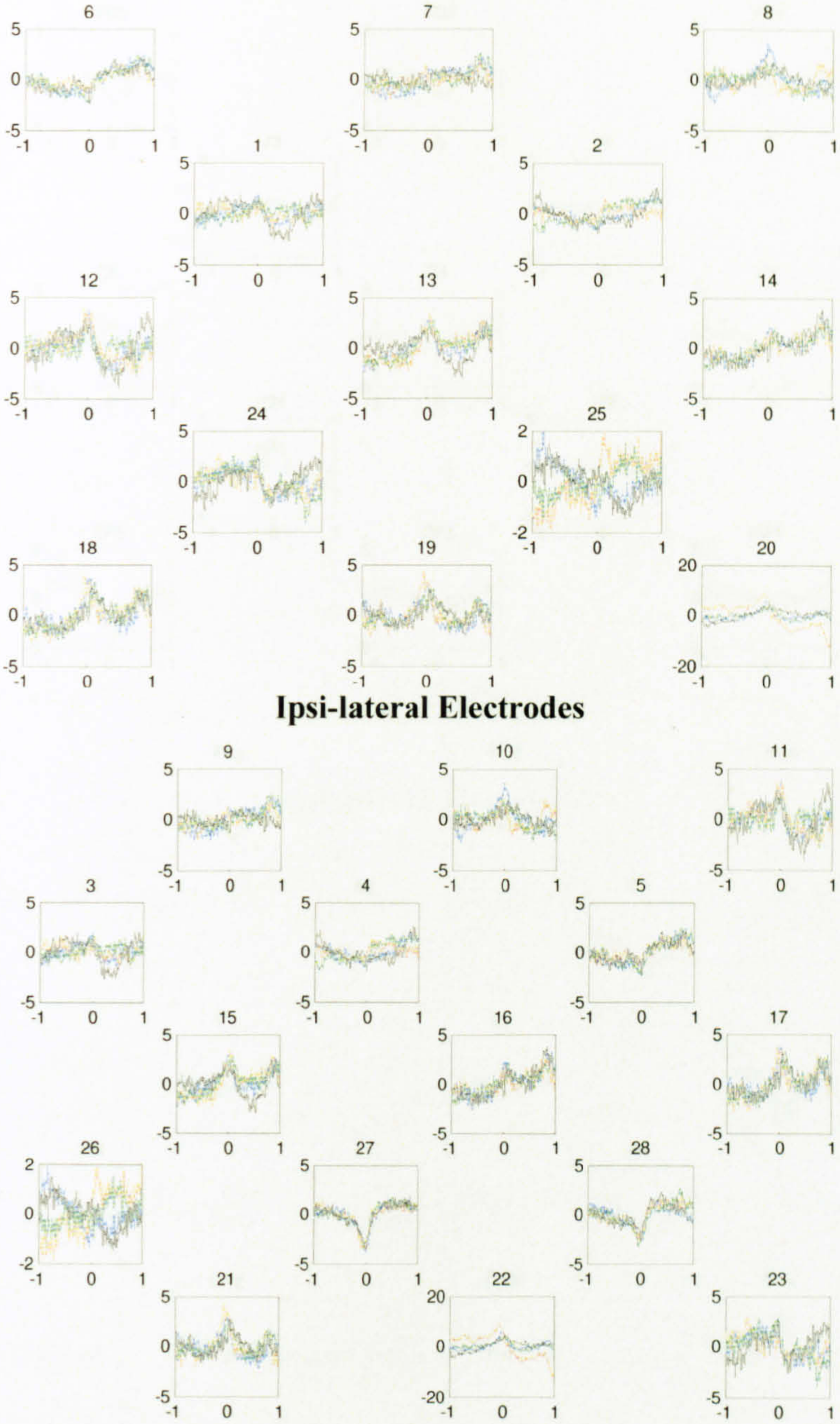
CPz
CP2
CP4

Subject 3


Contra-lateral Electrodes
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Ipsi-lateral Electrodes
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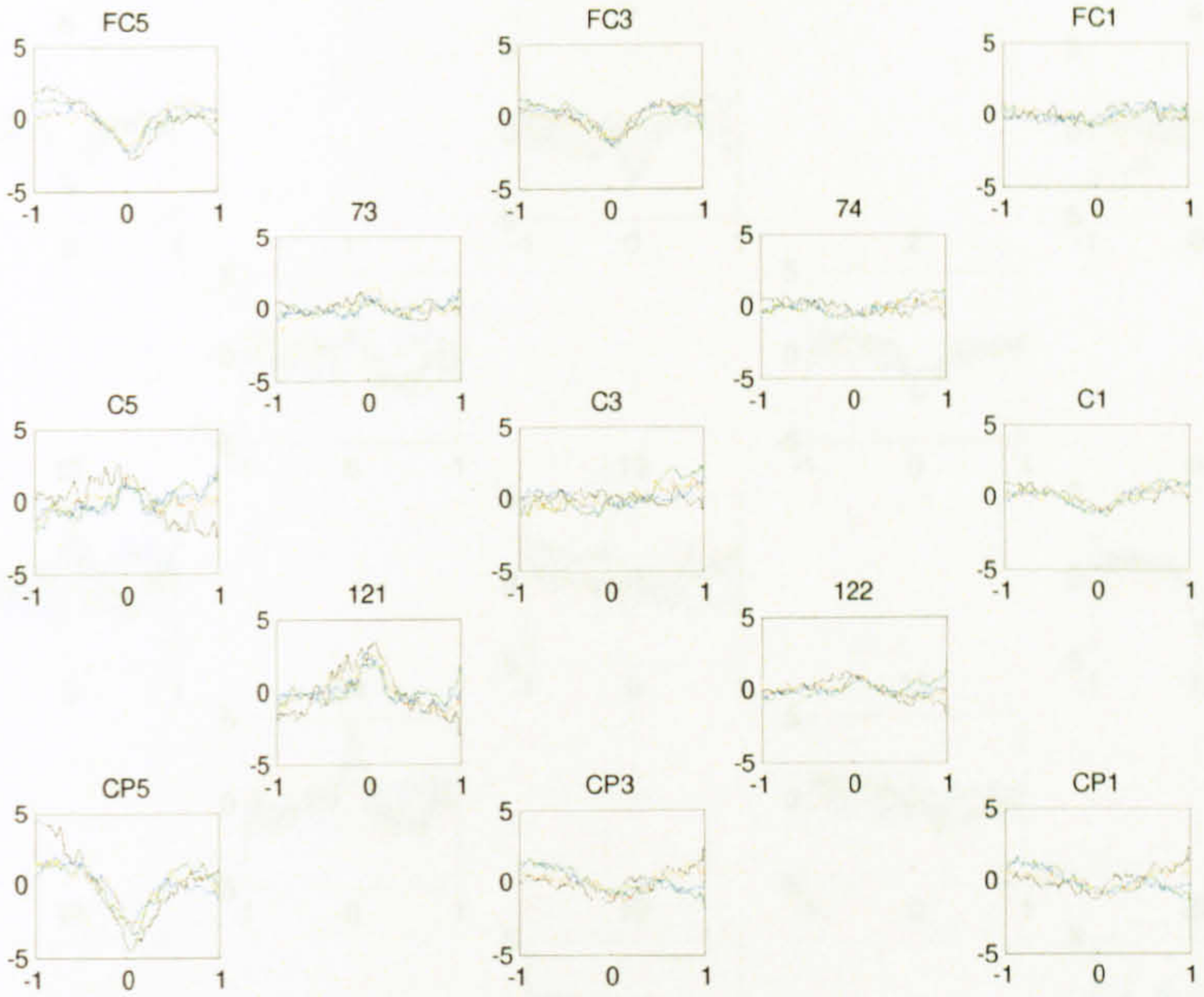
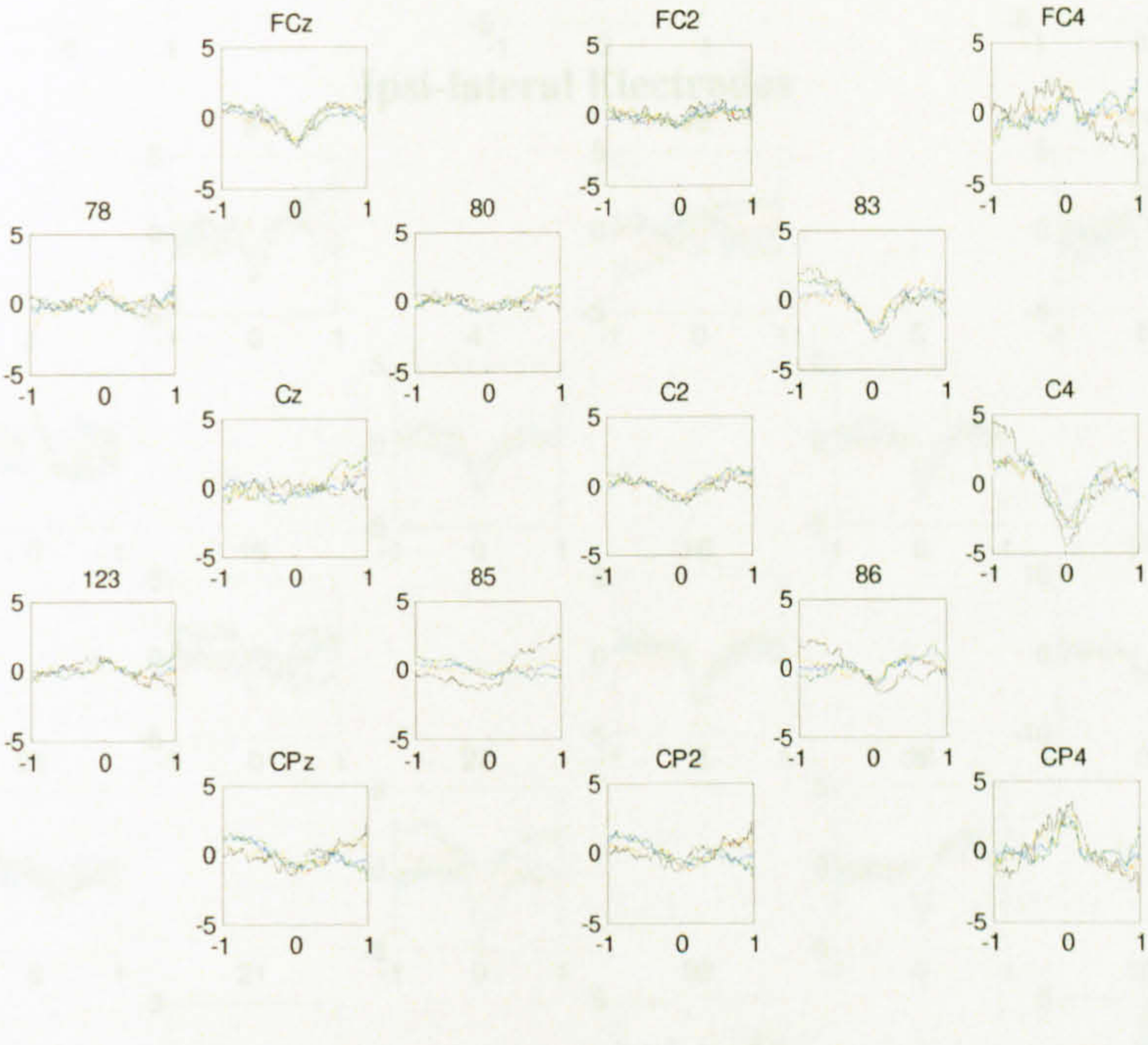
Subject 8

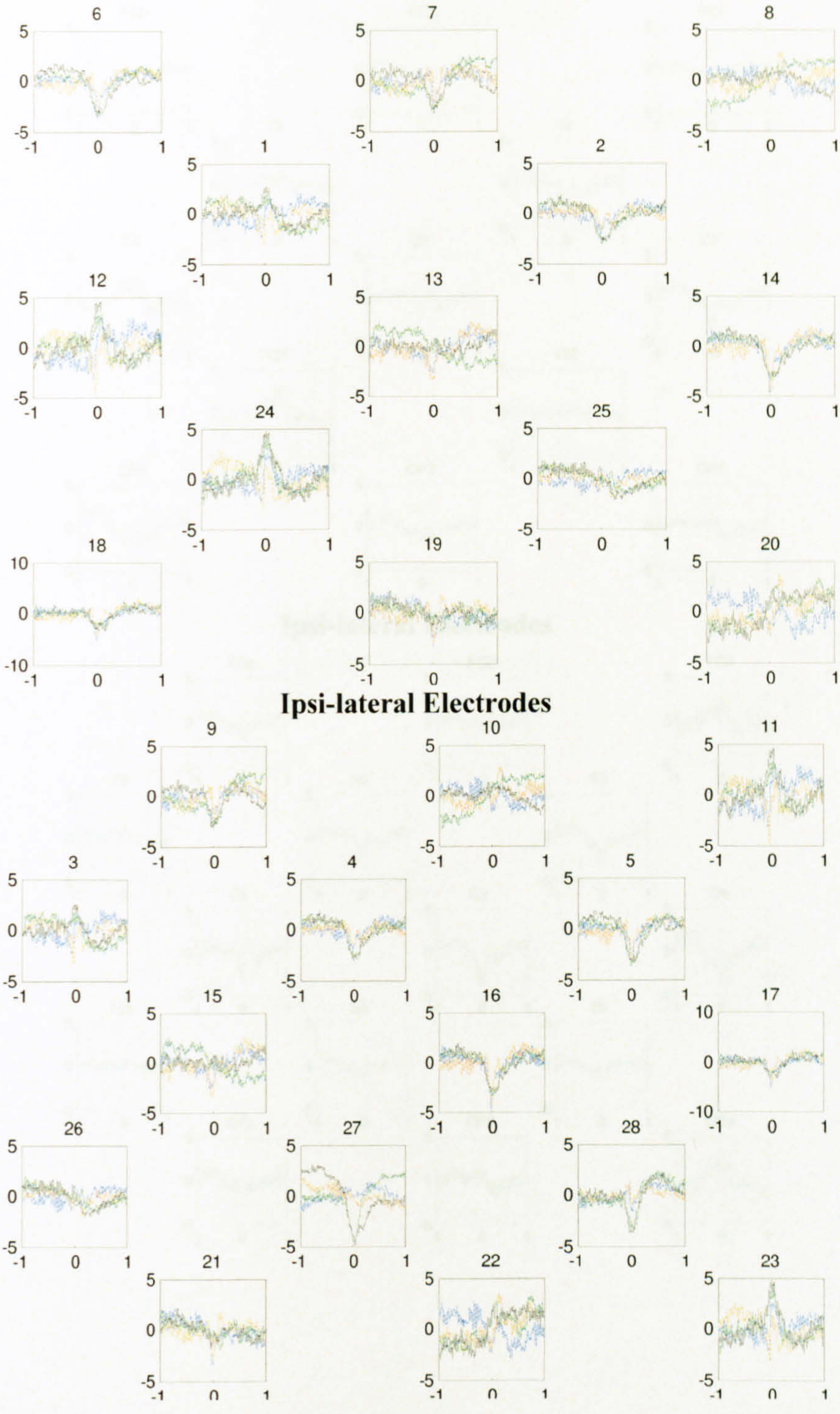
Contra-lateral Electrodes



Ipsi-lateral Electrodes



Subject 9


Contra-lateral Electrodes
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Ipsi-lateral Electrodes
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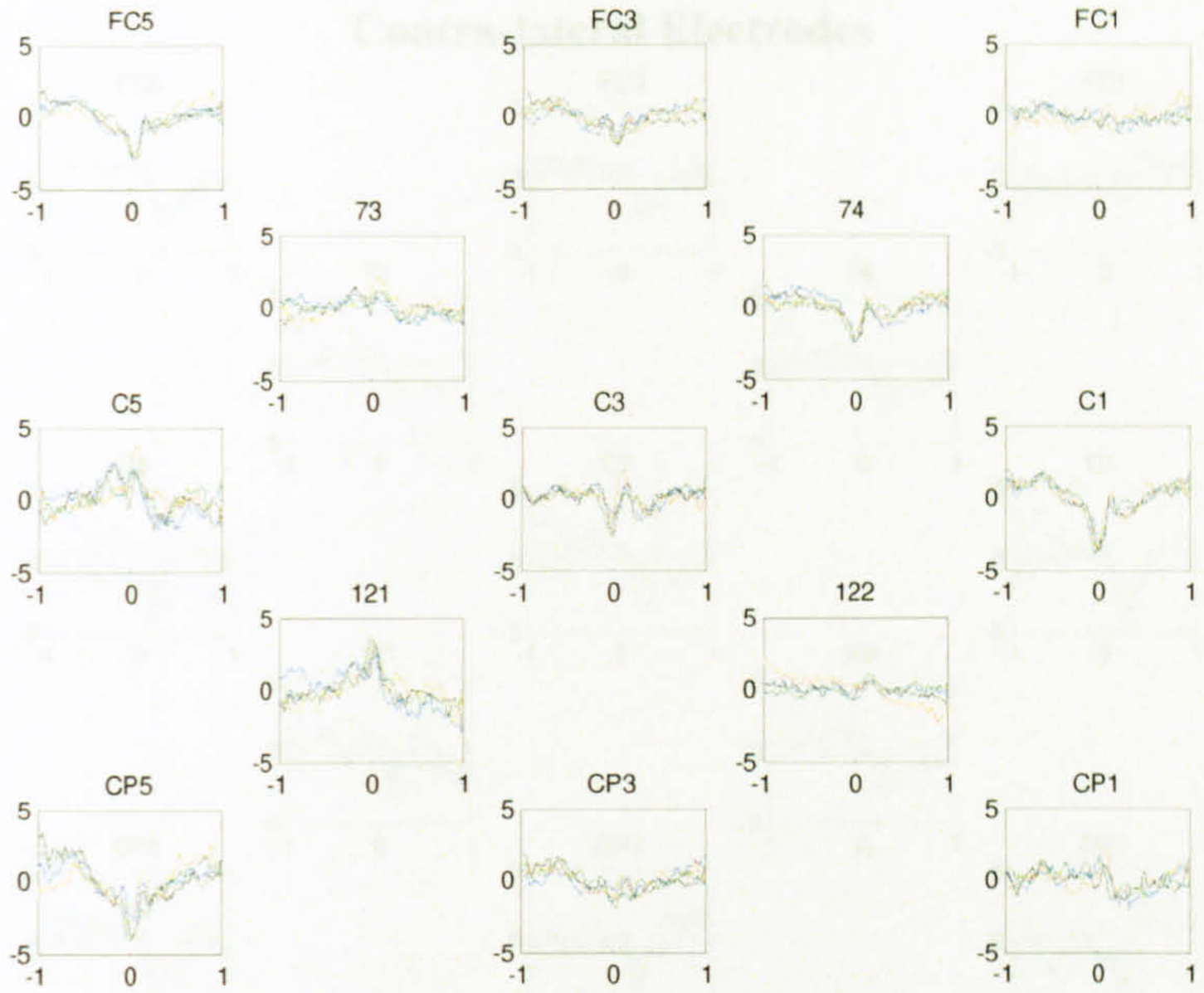
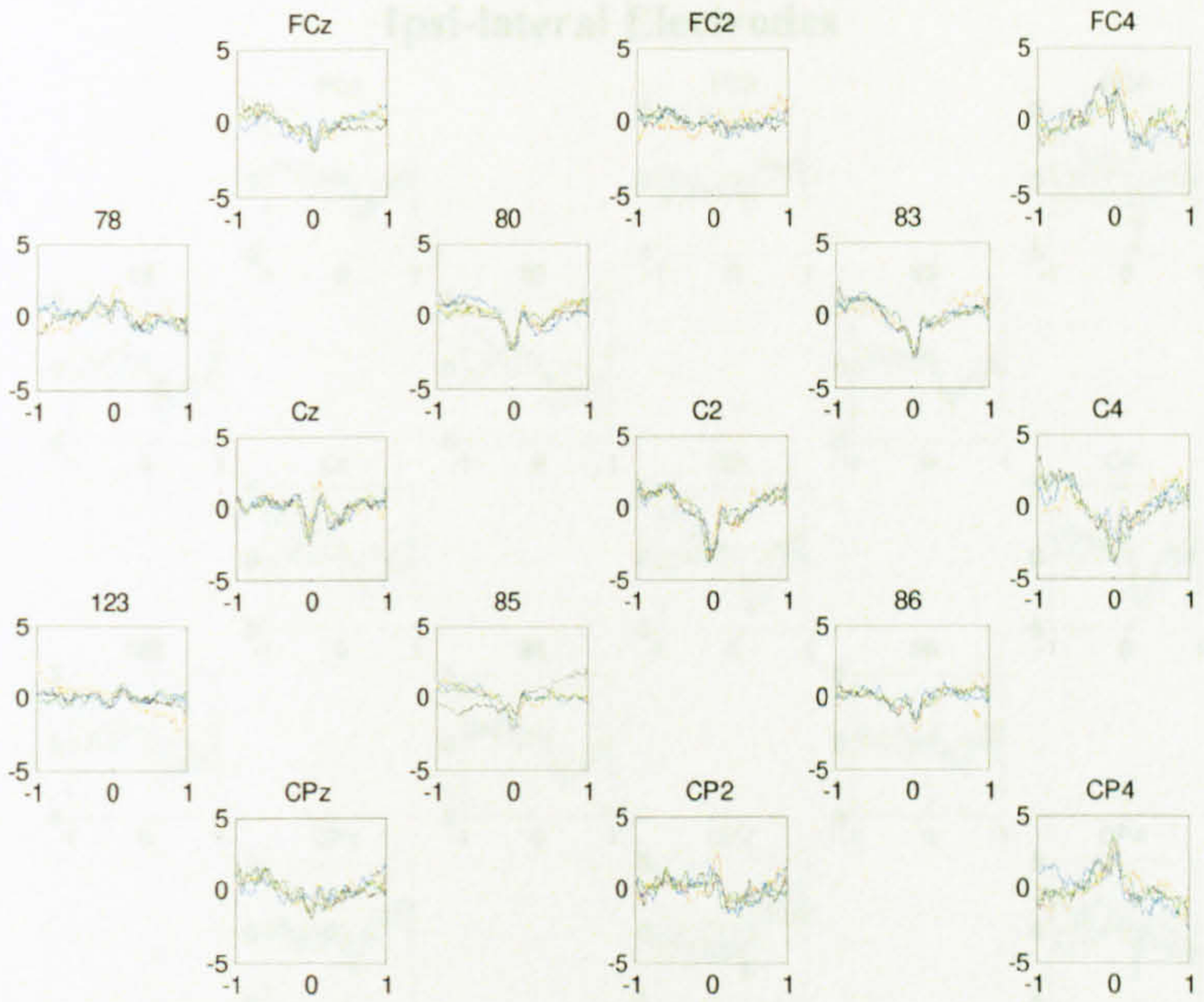
Subject 10

Contra-lateral Electrodes



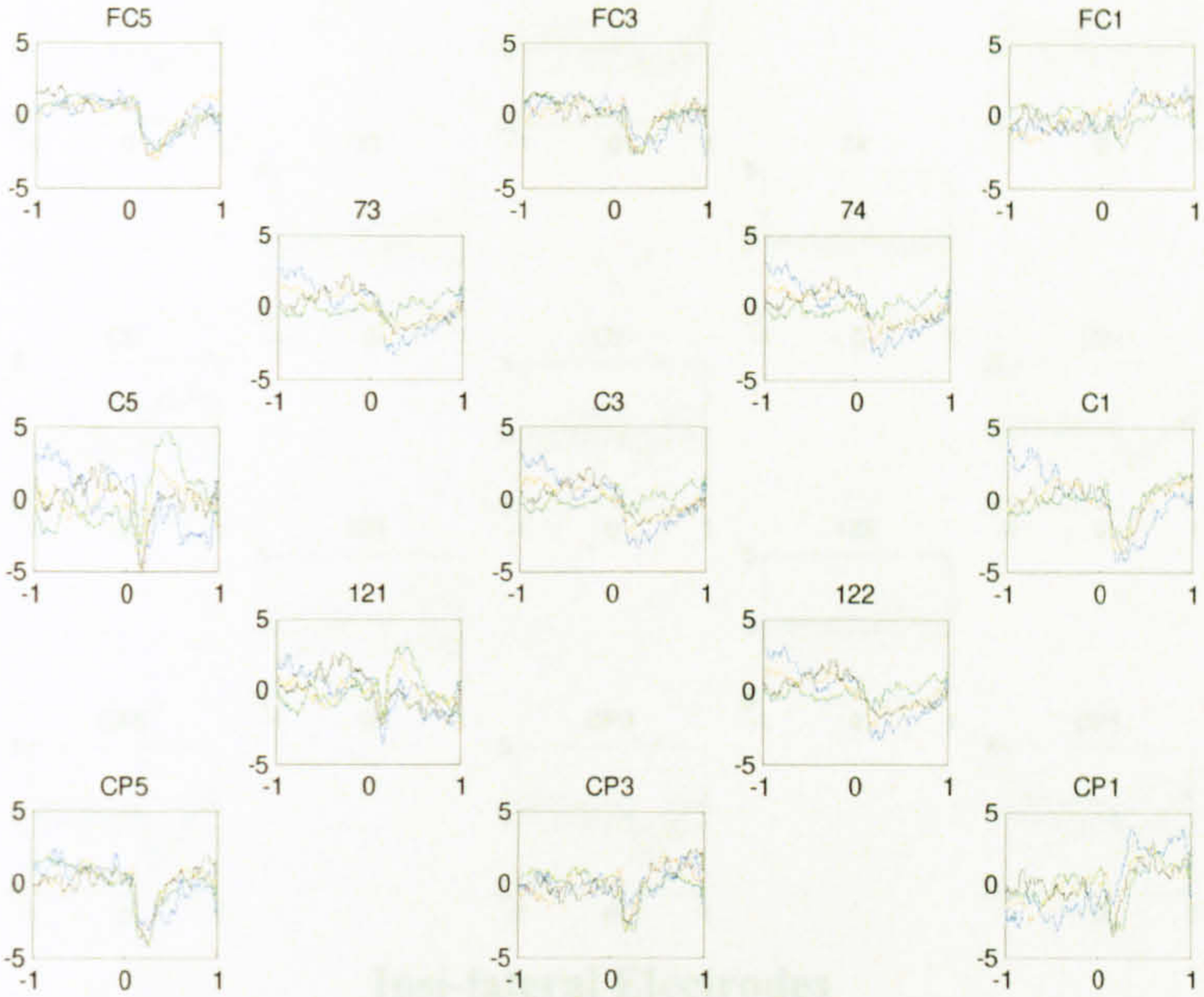
Ipsi-lateral Electrodes



Imagination

Subject 1

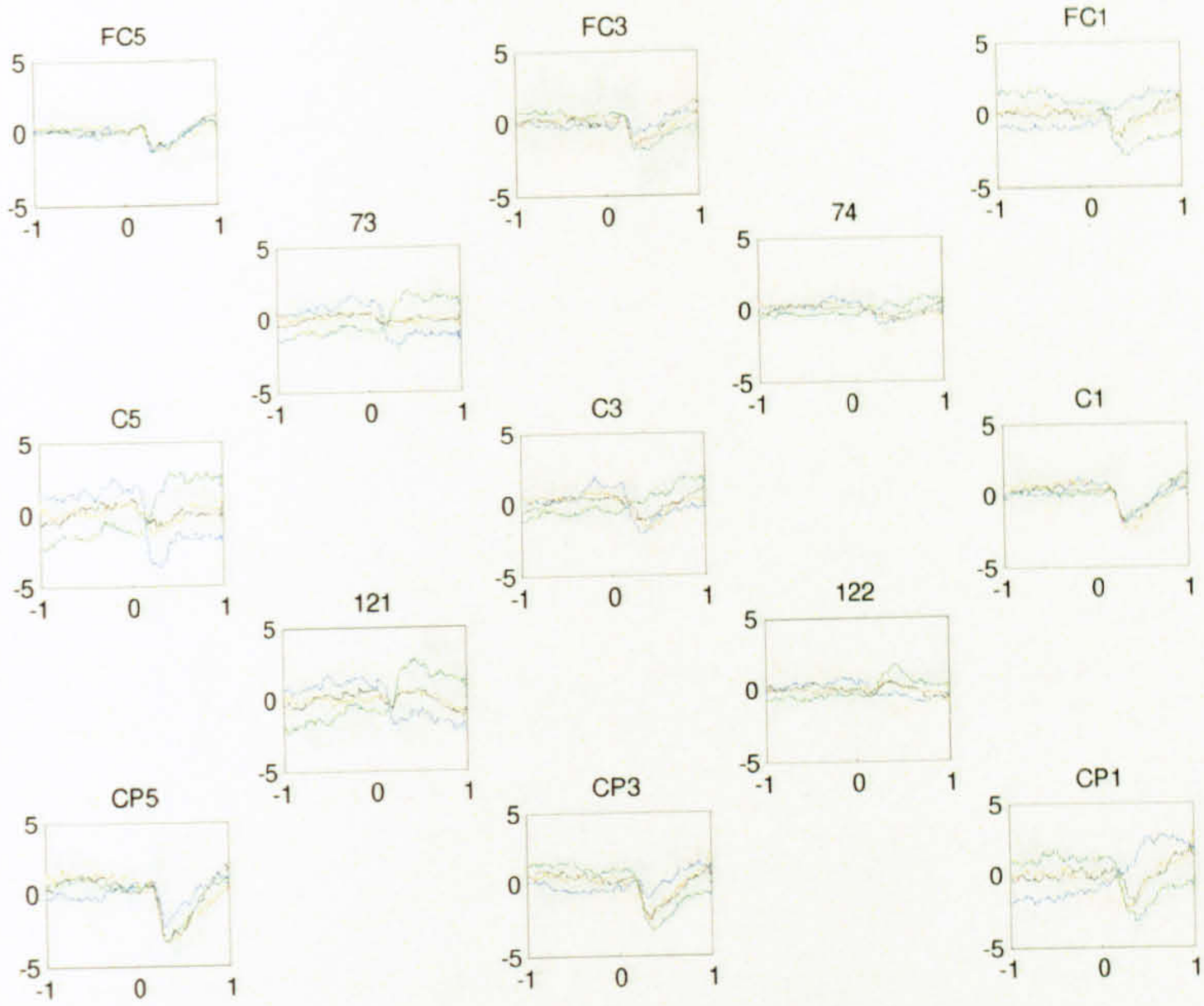
Contra-lateral Electrodes



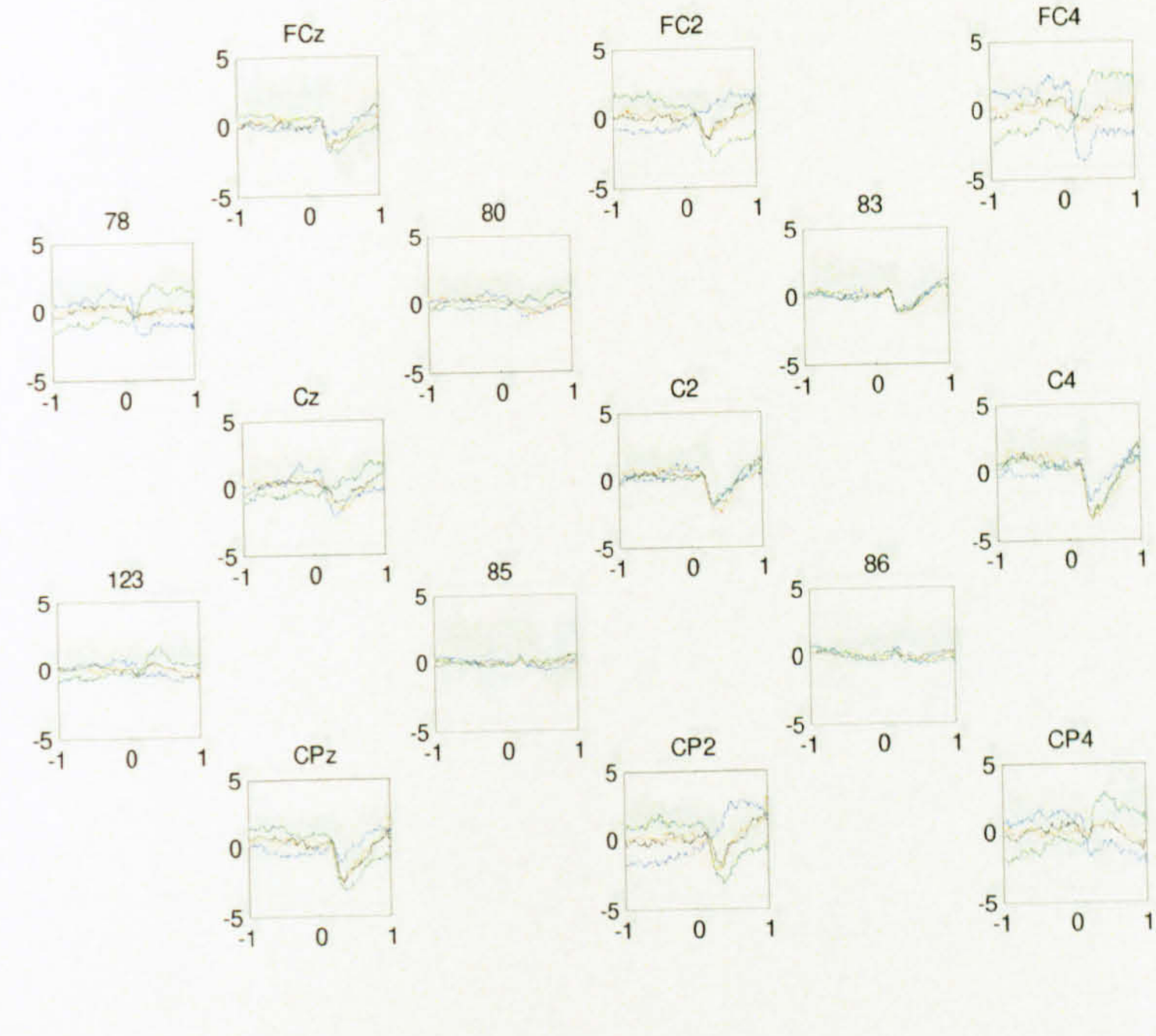
Ipsi-lateral Electrodes

Subject 2

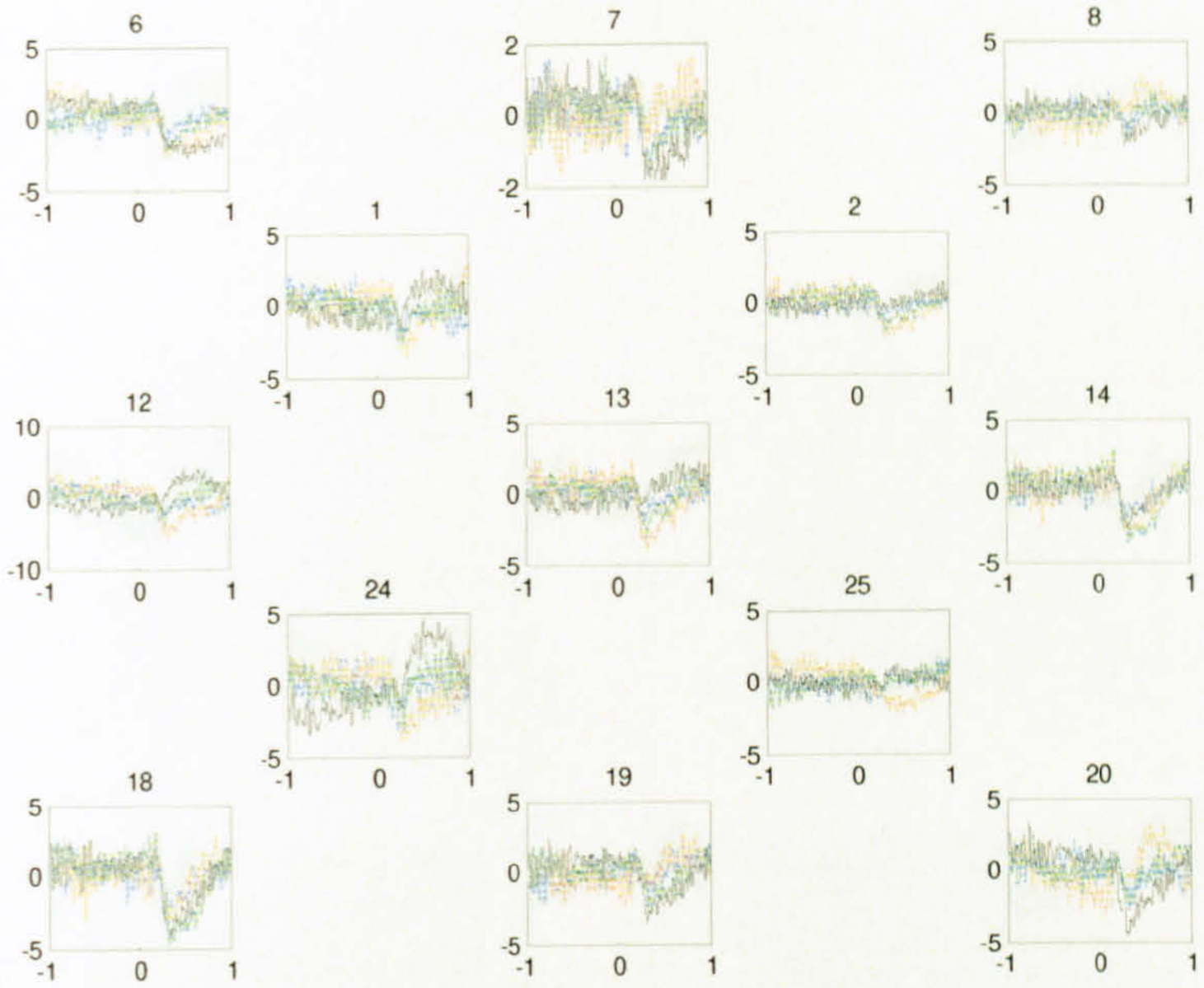
Contra-lateral Electrodes



Ipsi-lateral Electrodes



Subject 3


Contra-lateral Electrodes
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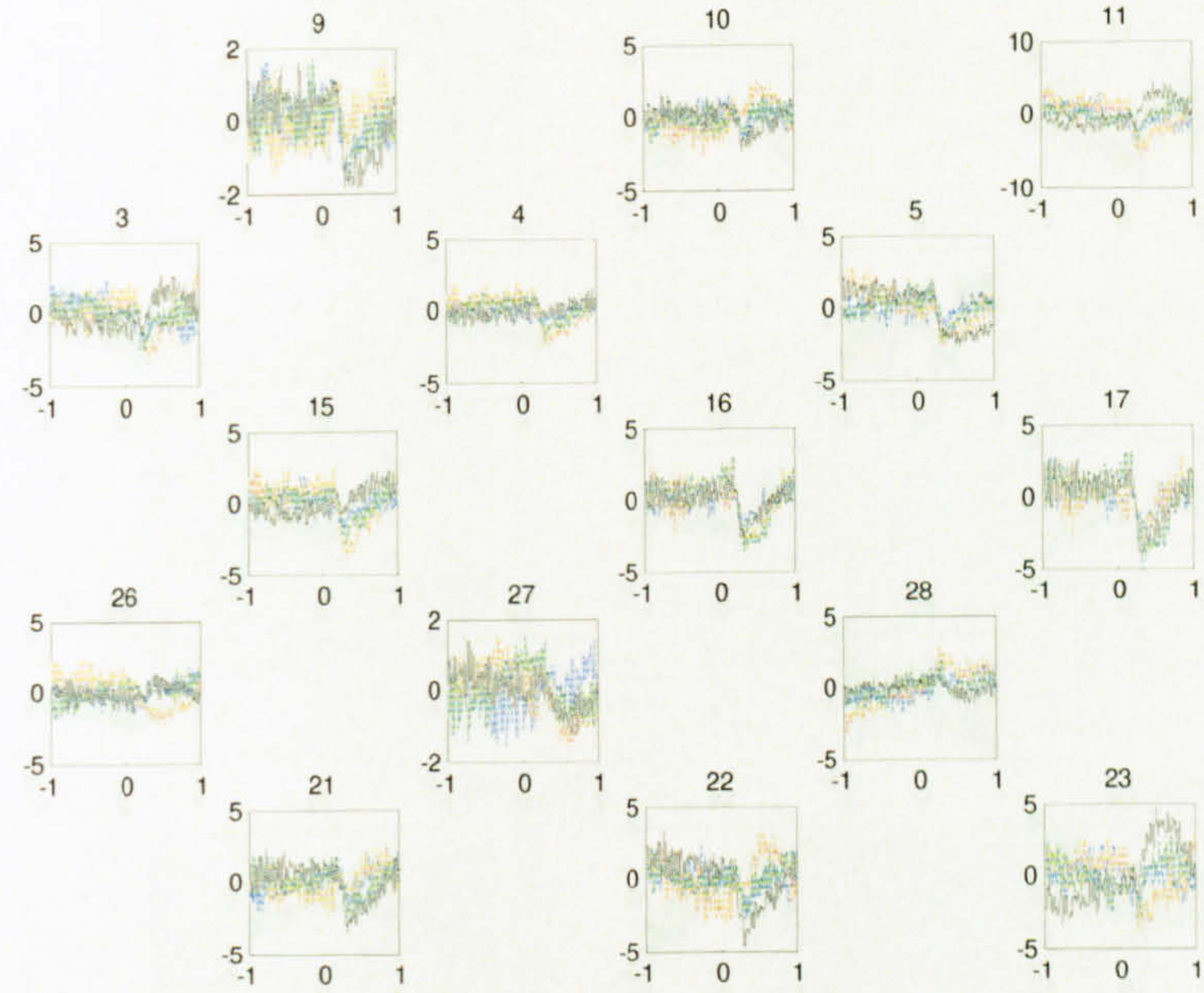
Ipsi-lateral Electrodes
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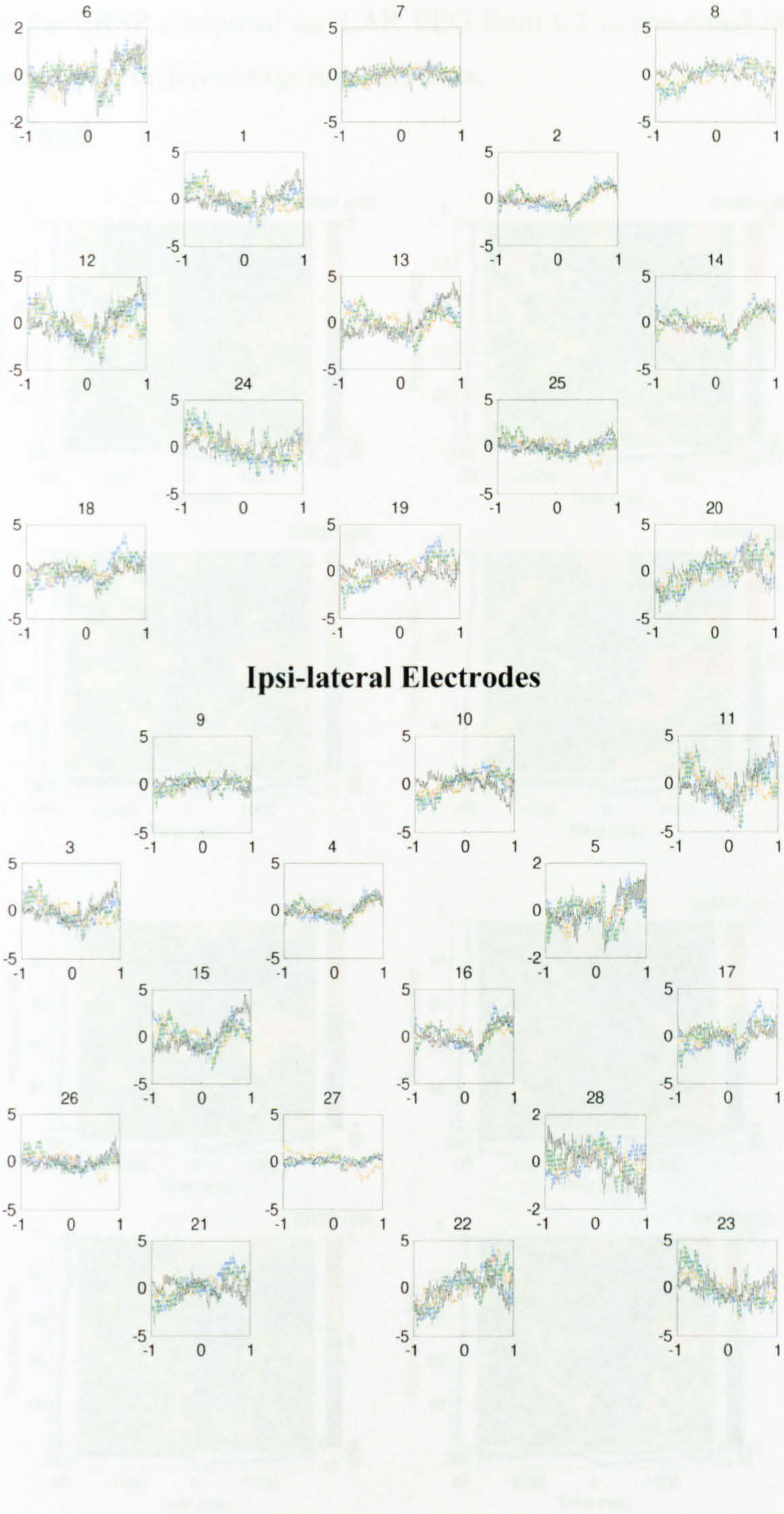
Subject 5


Contra-lateral Electrodes
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Ipsi-lateral Electrodes
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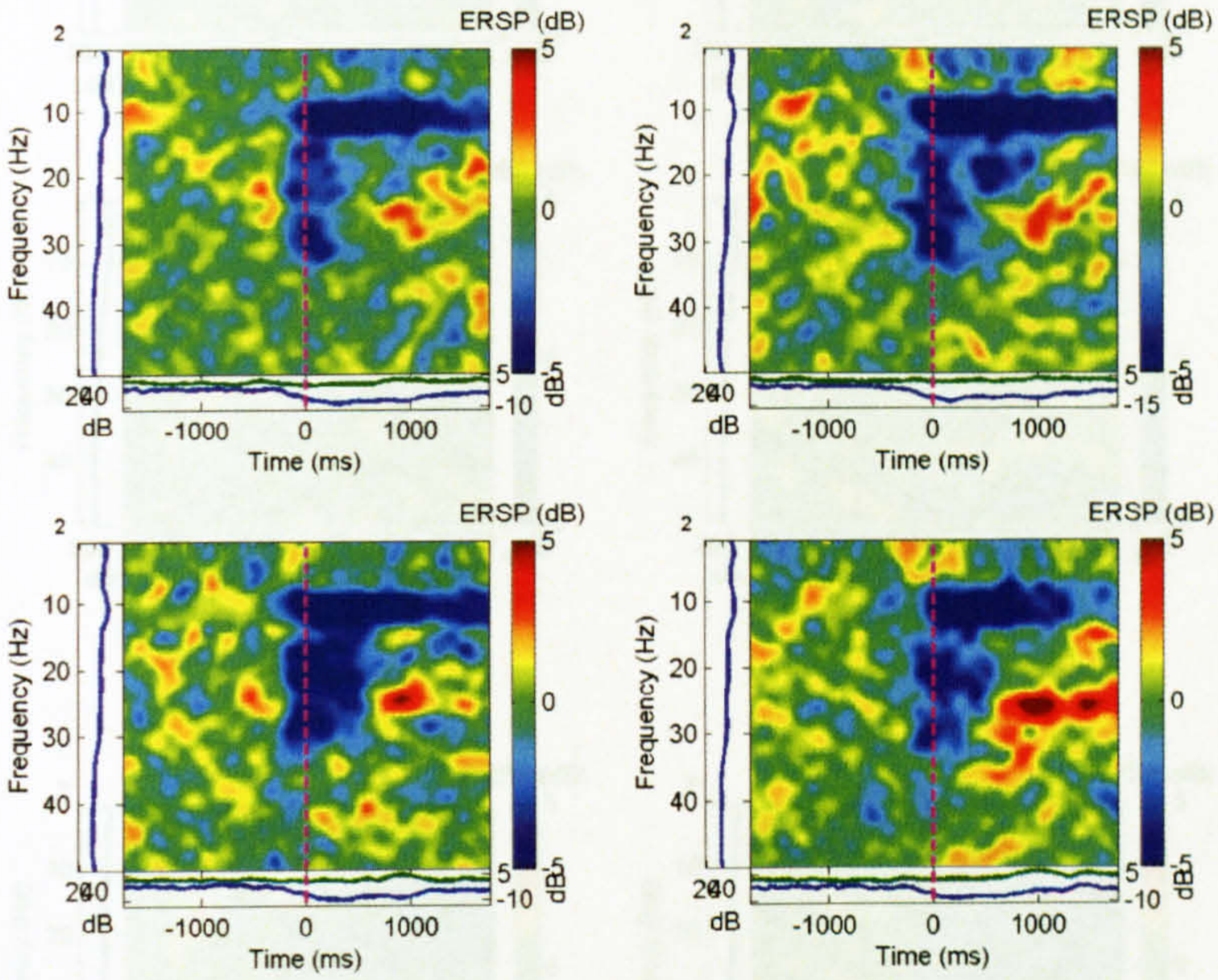
ERSP

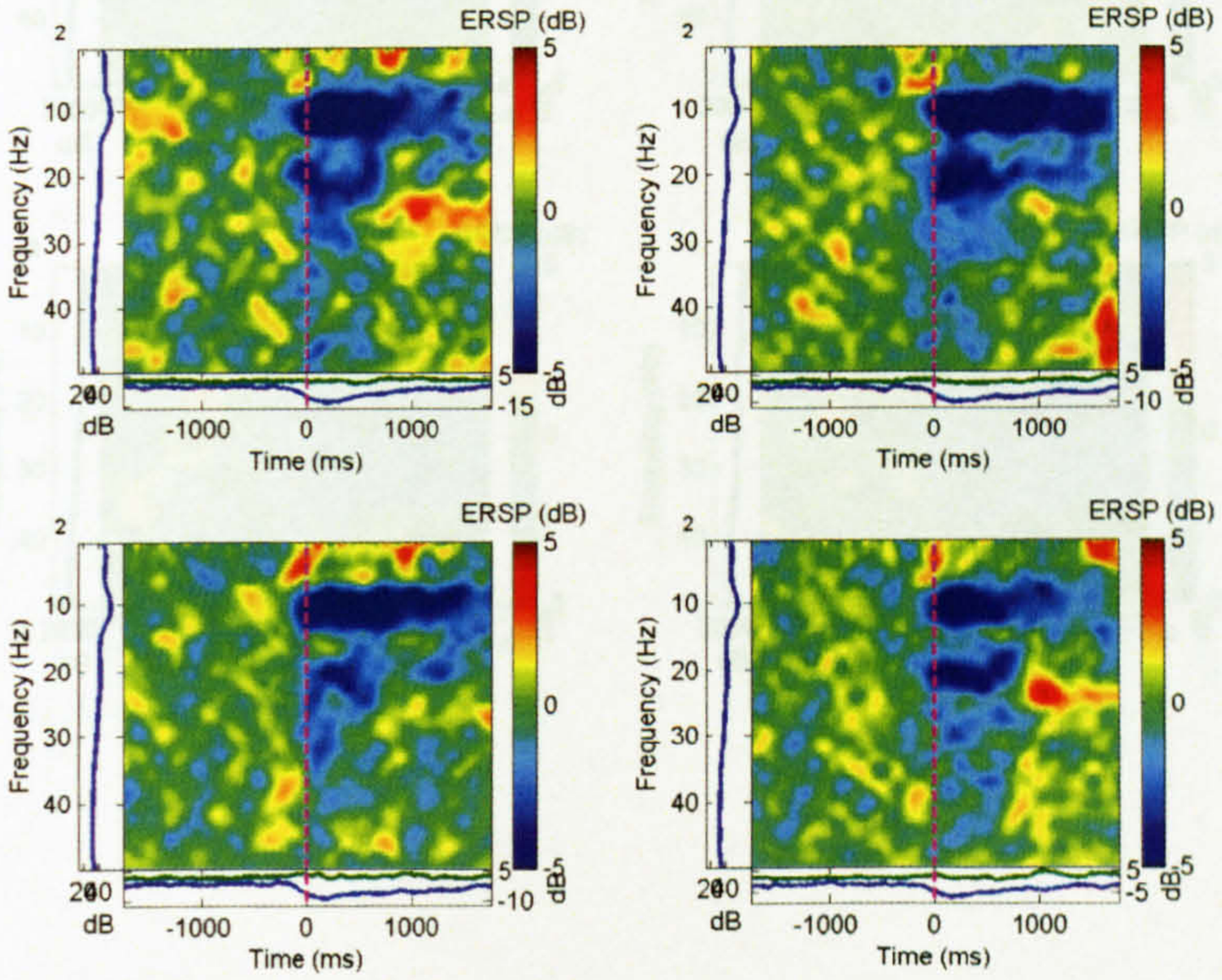
In this section the ERSP computed for CAR EEG from C3 is presented for all subjects who participated in the different experimental tasks.

Externally Cued

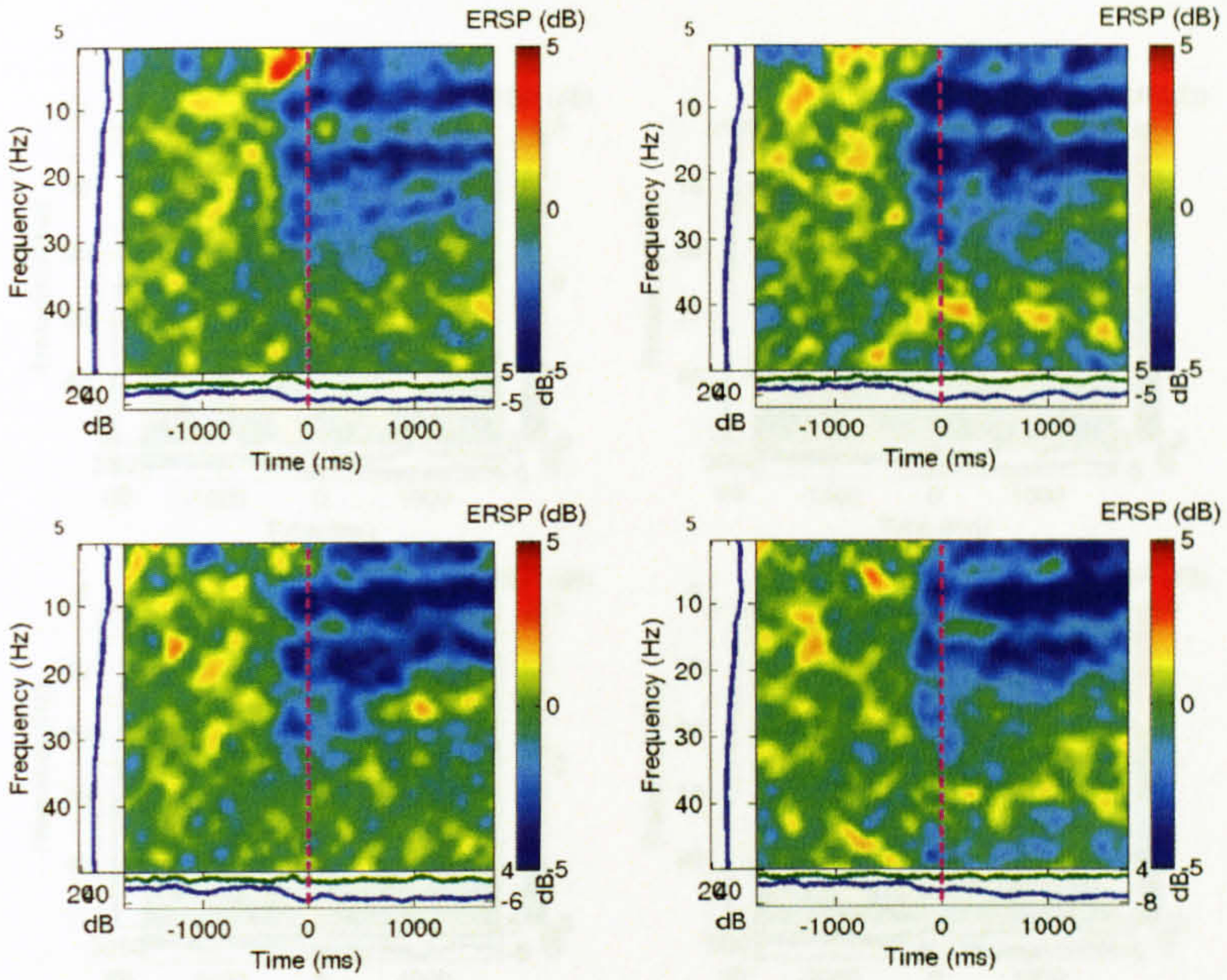
Subject 1



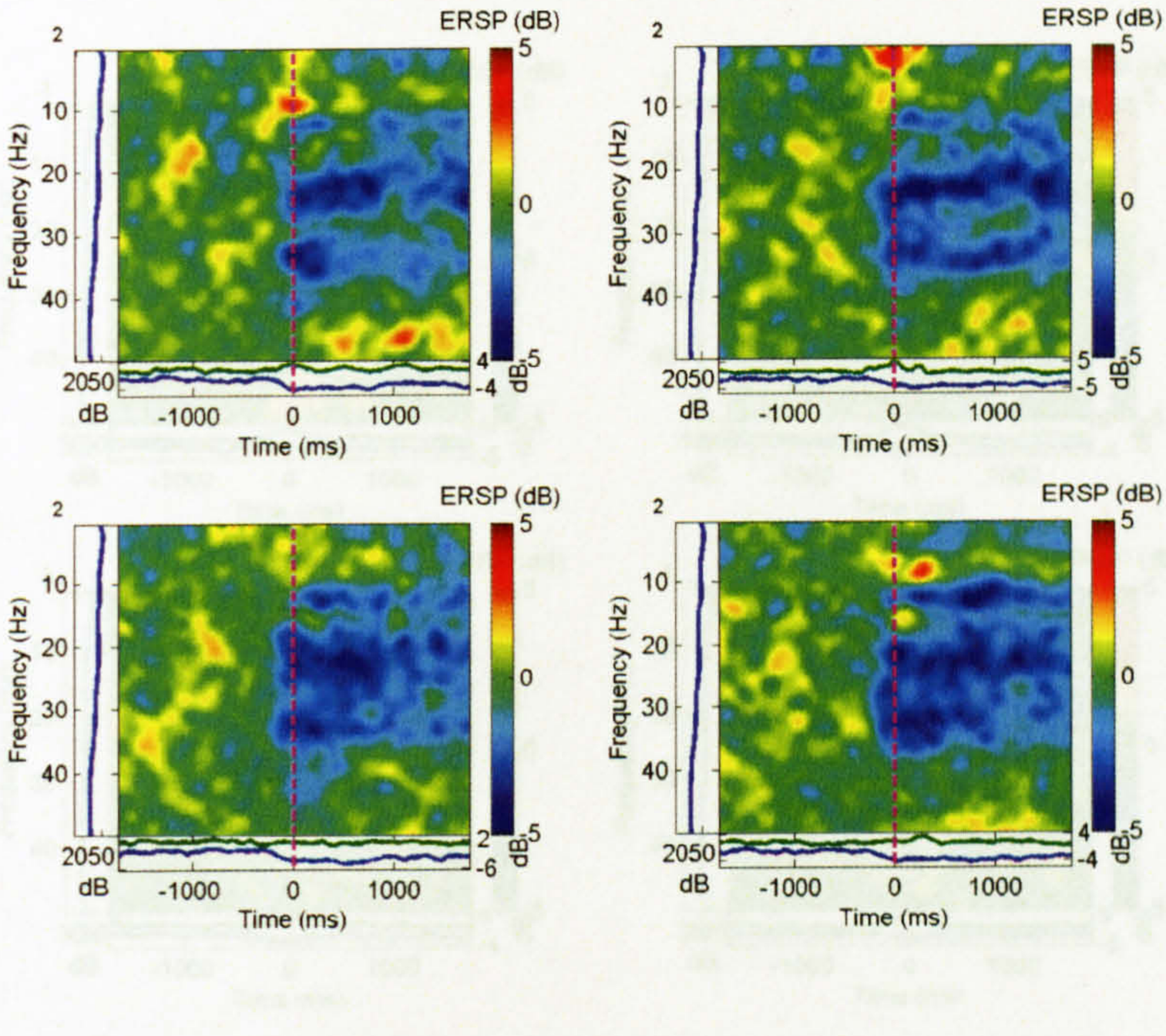
Subject 2



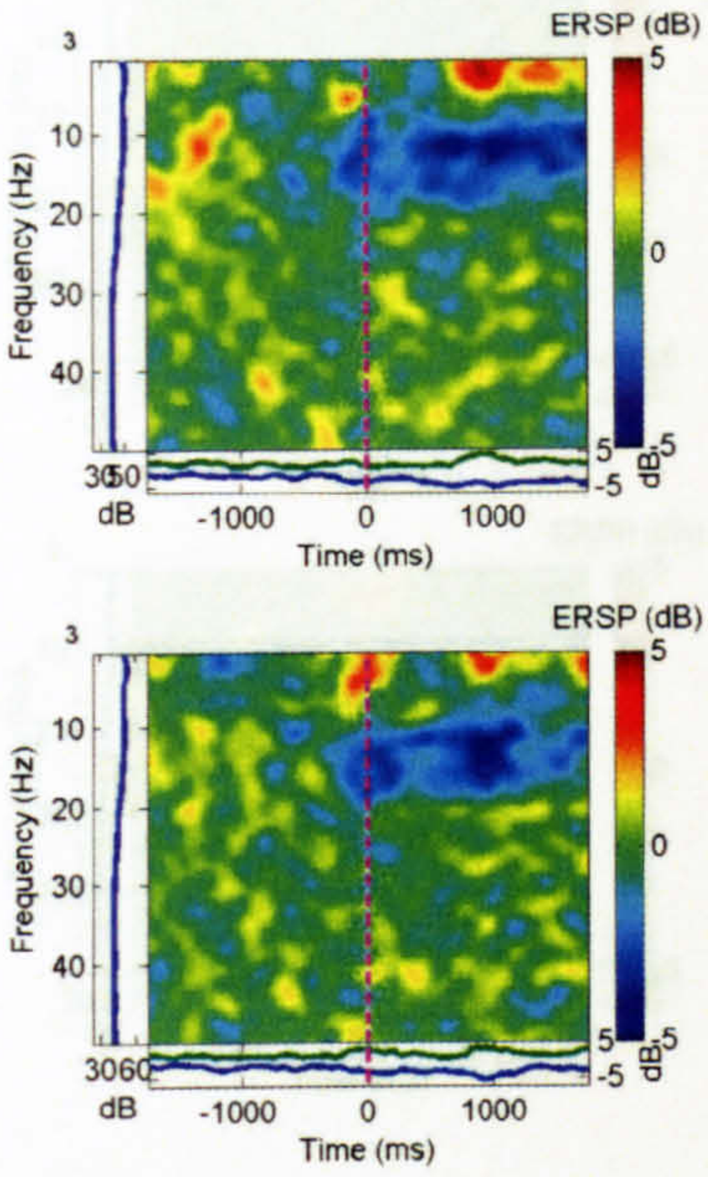
Subject 3

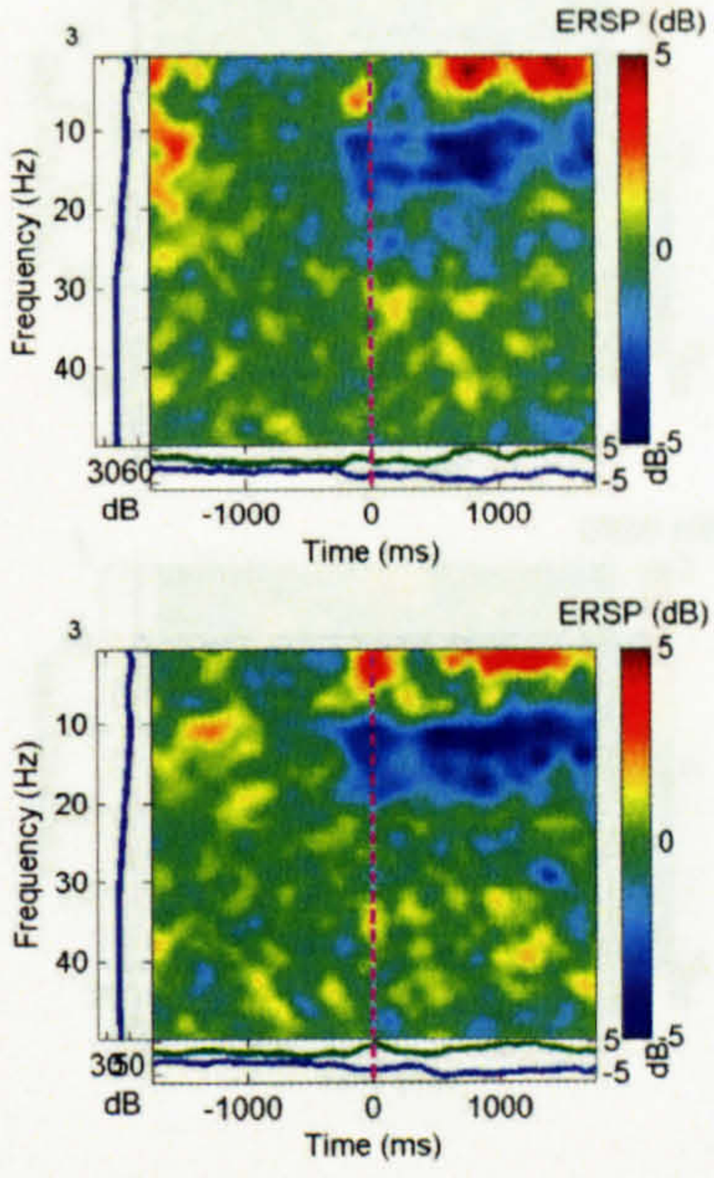


Subject 4

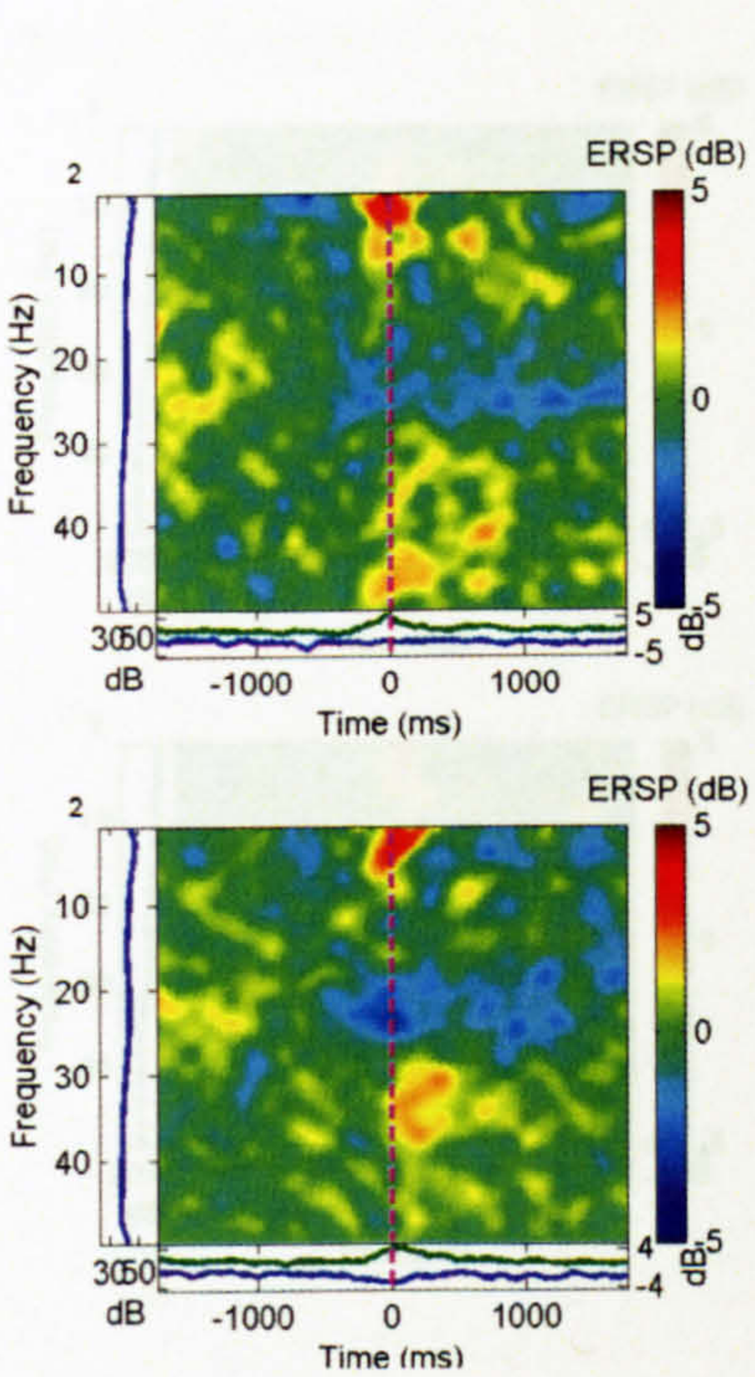


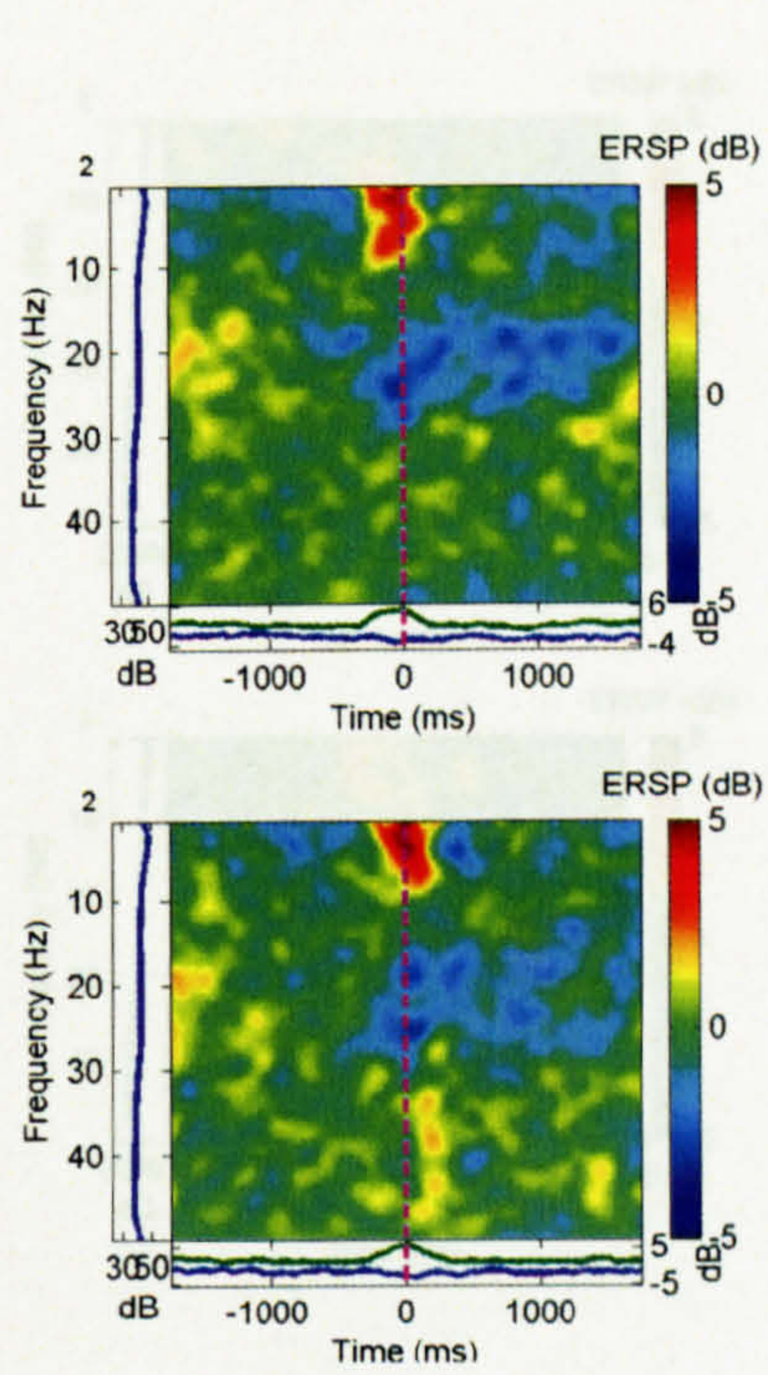
Subject 5



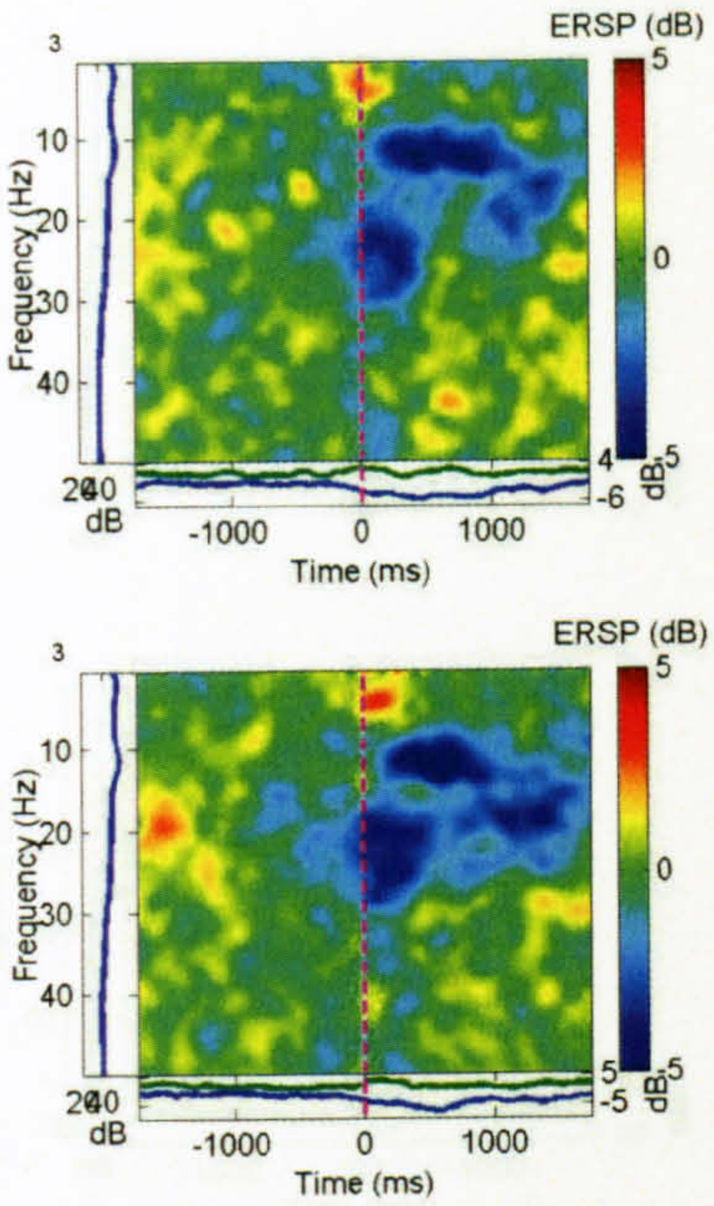


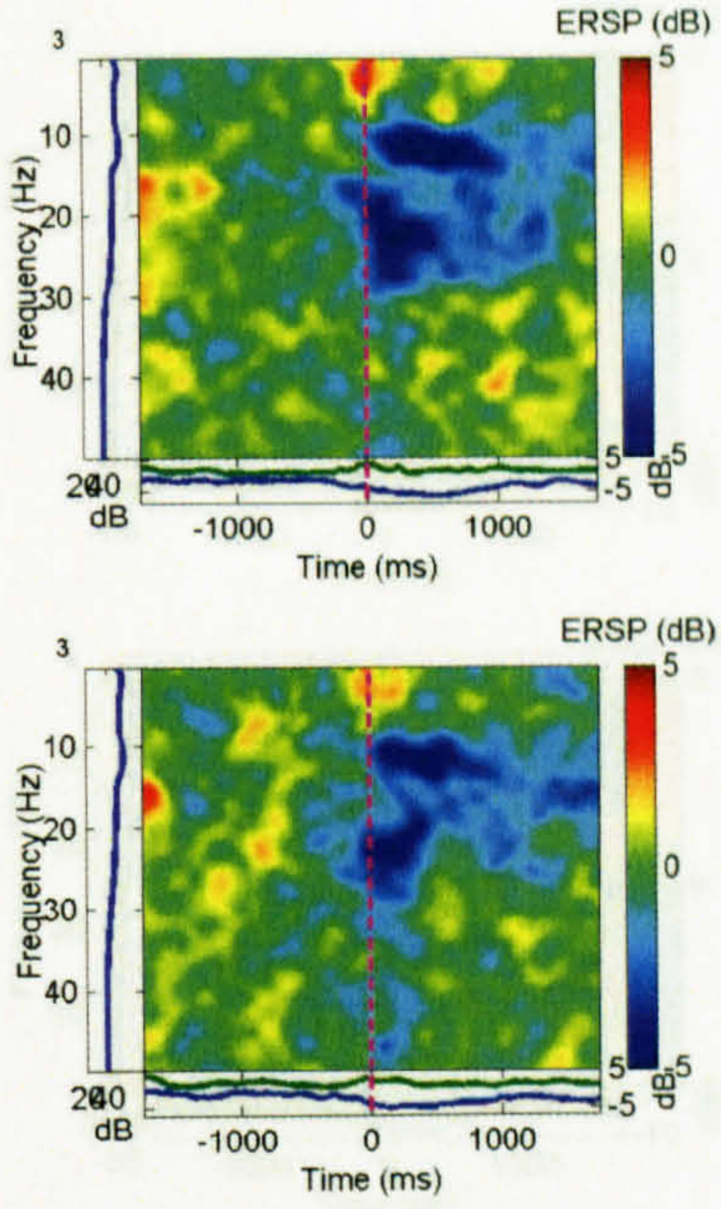
Subject 6



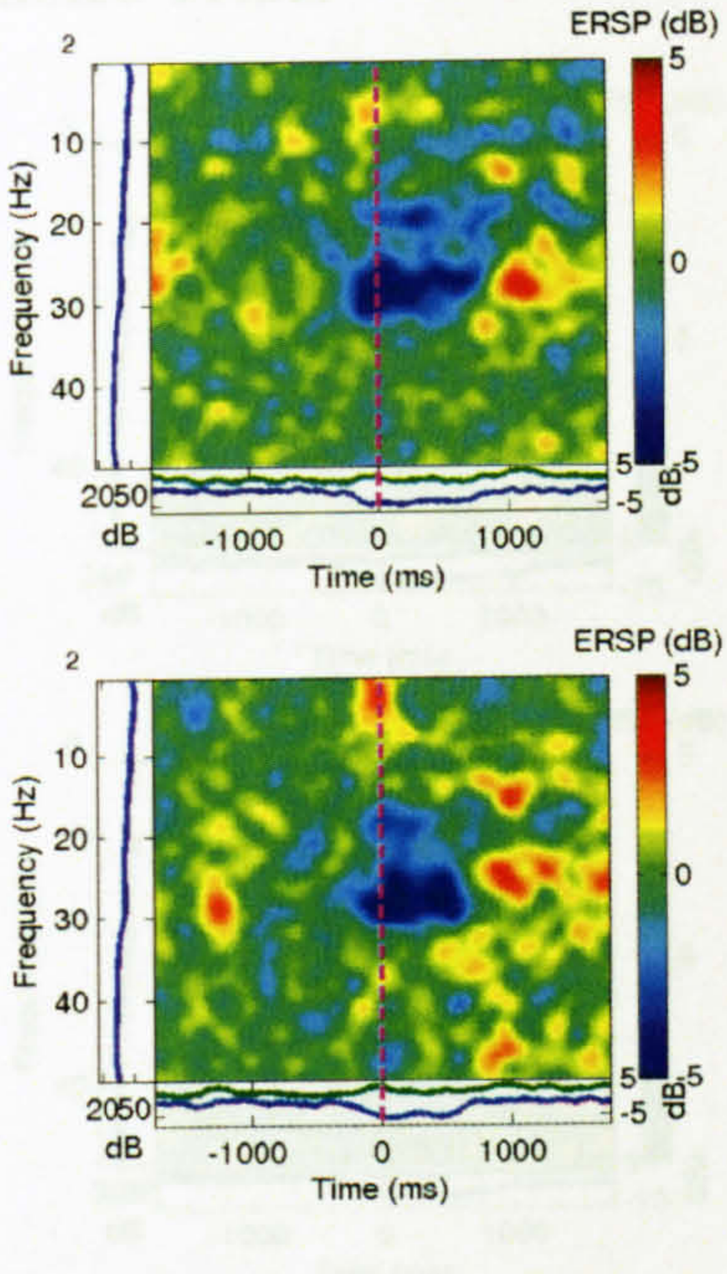


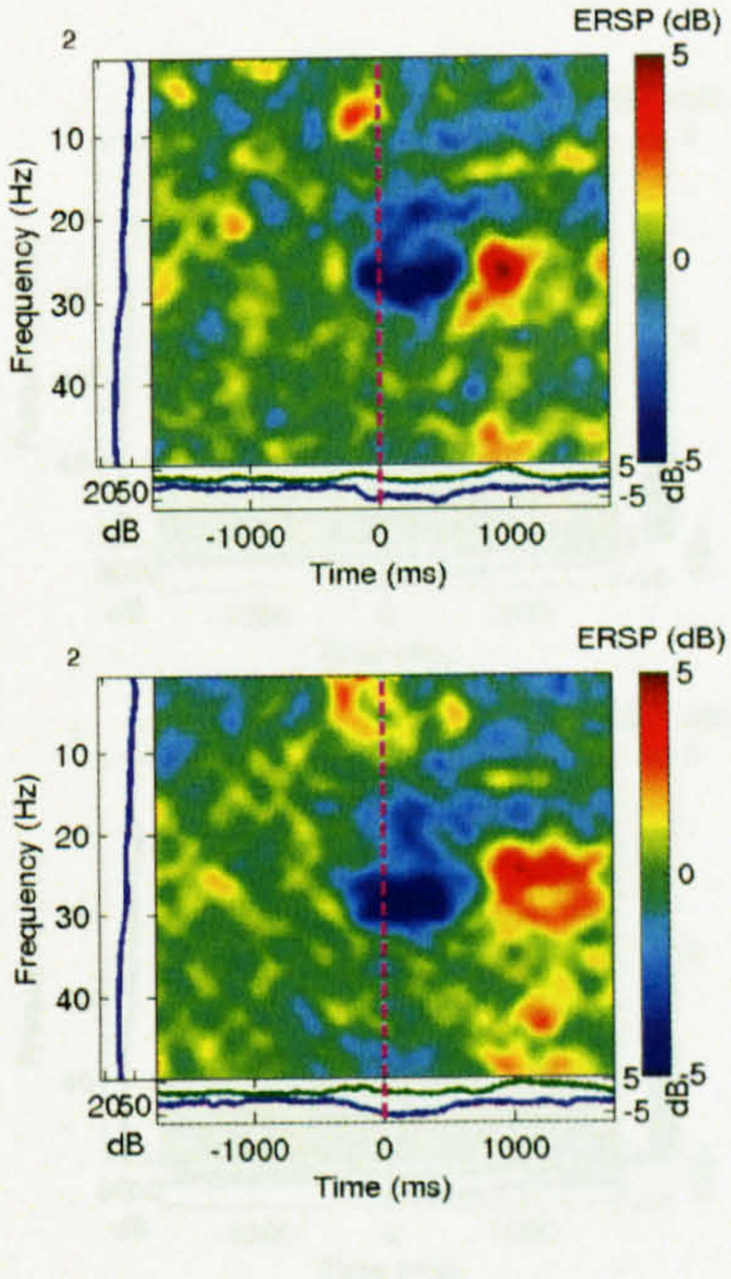
Subject 7



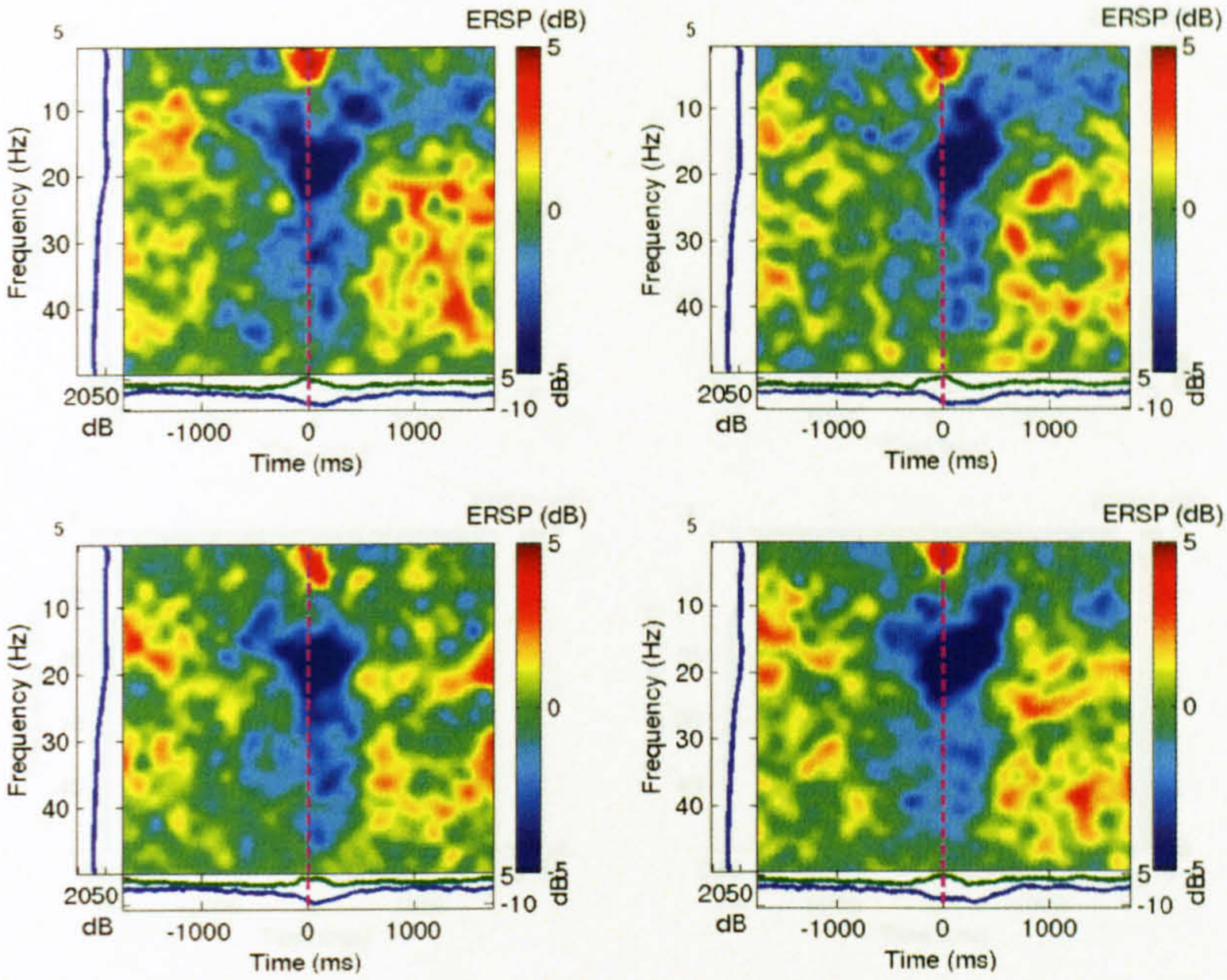


Subject 8



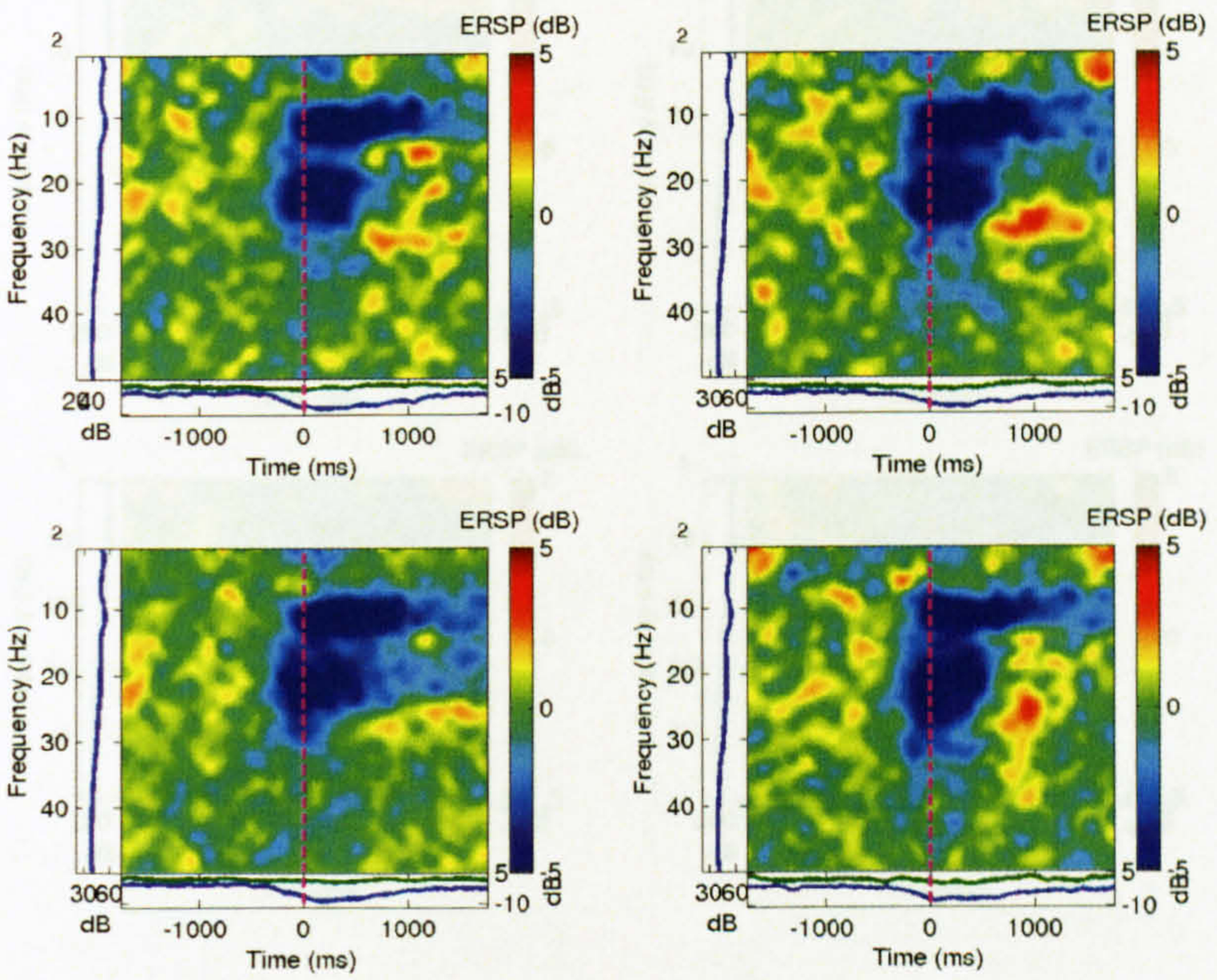


Subject 10

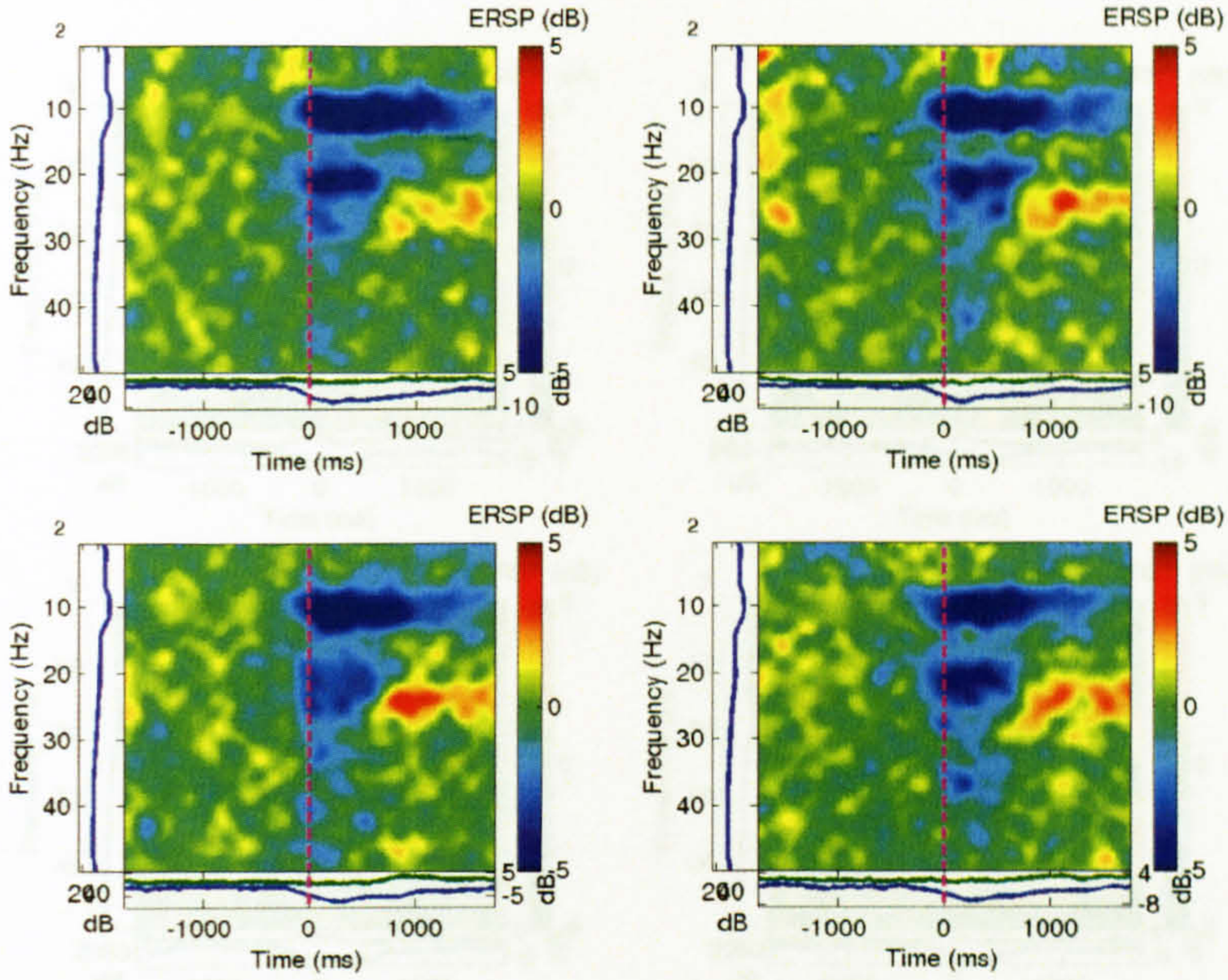


Forced Choice Trials

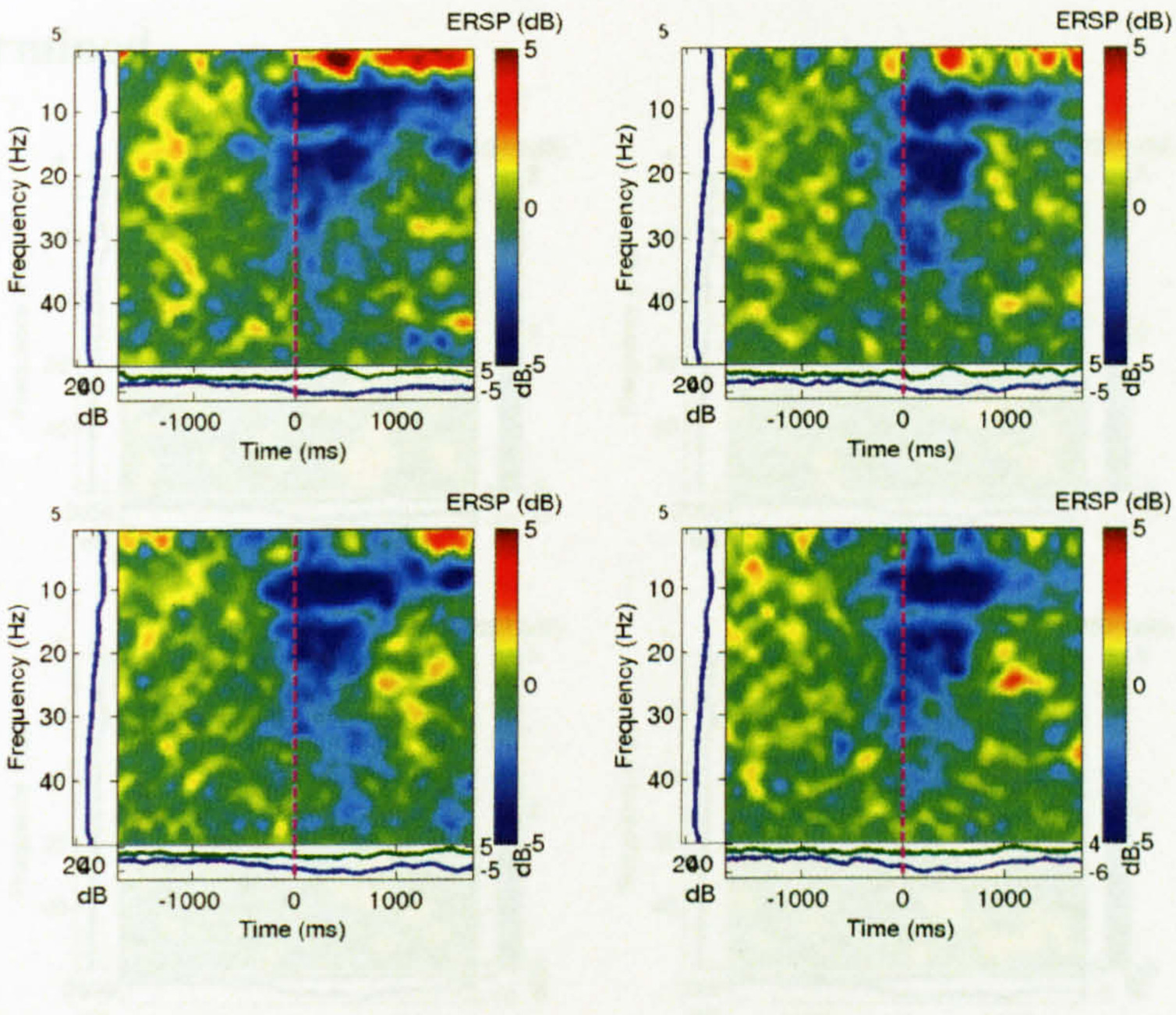
Subject 1



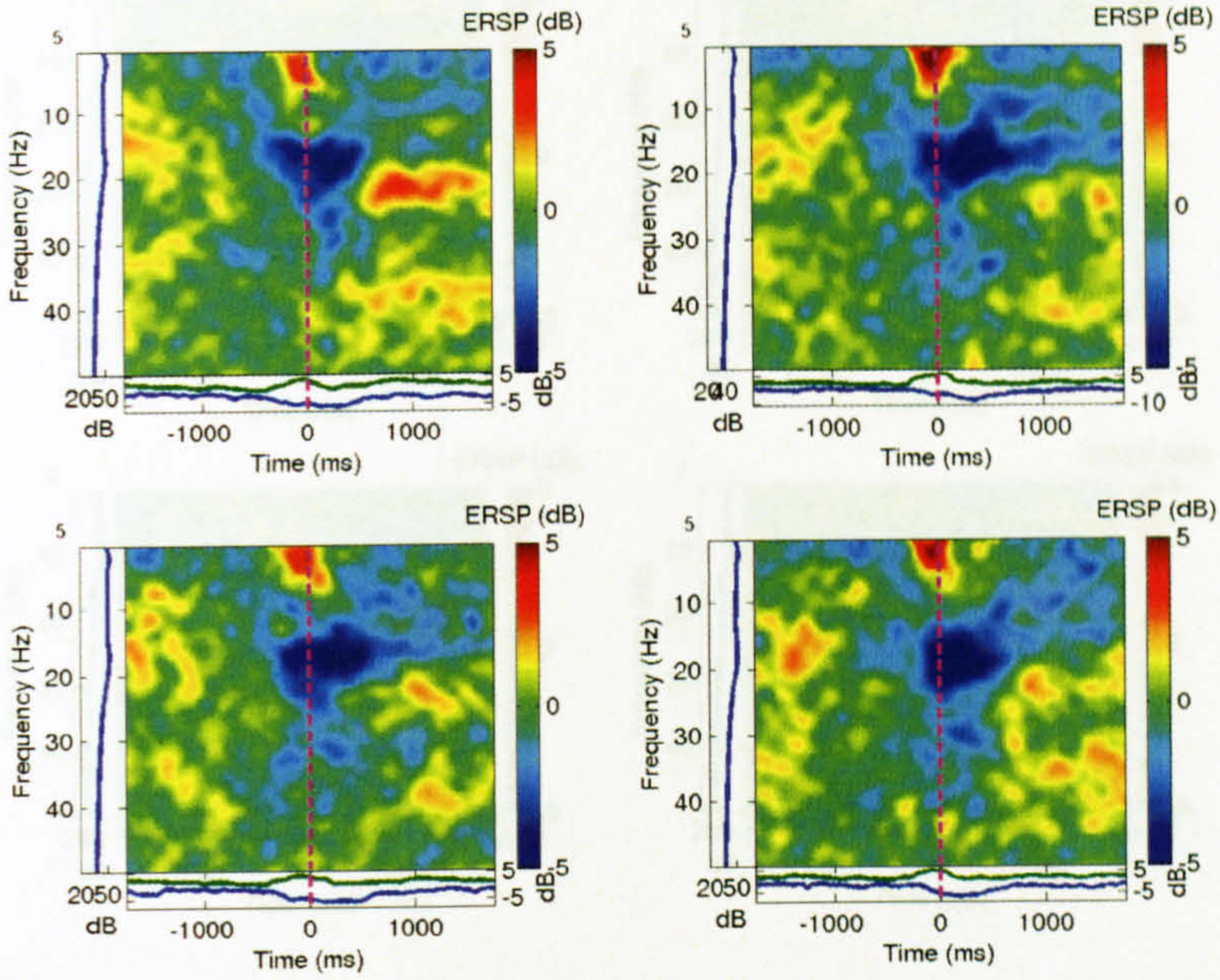
Subject 2



Subject 3



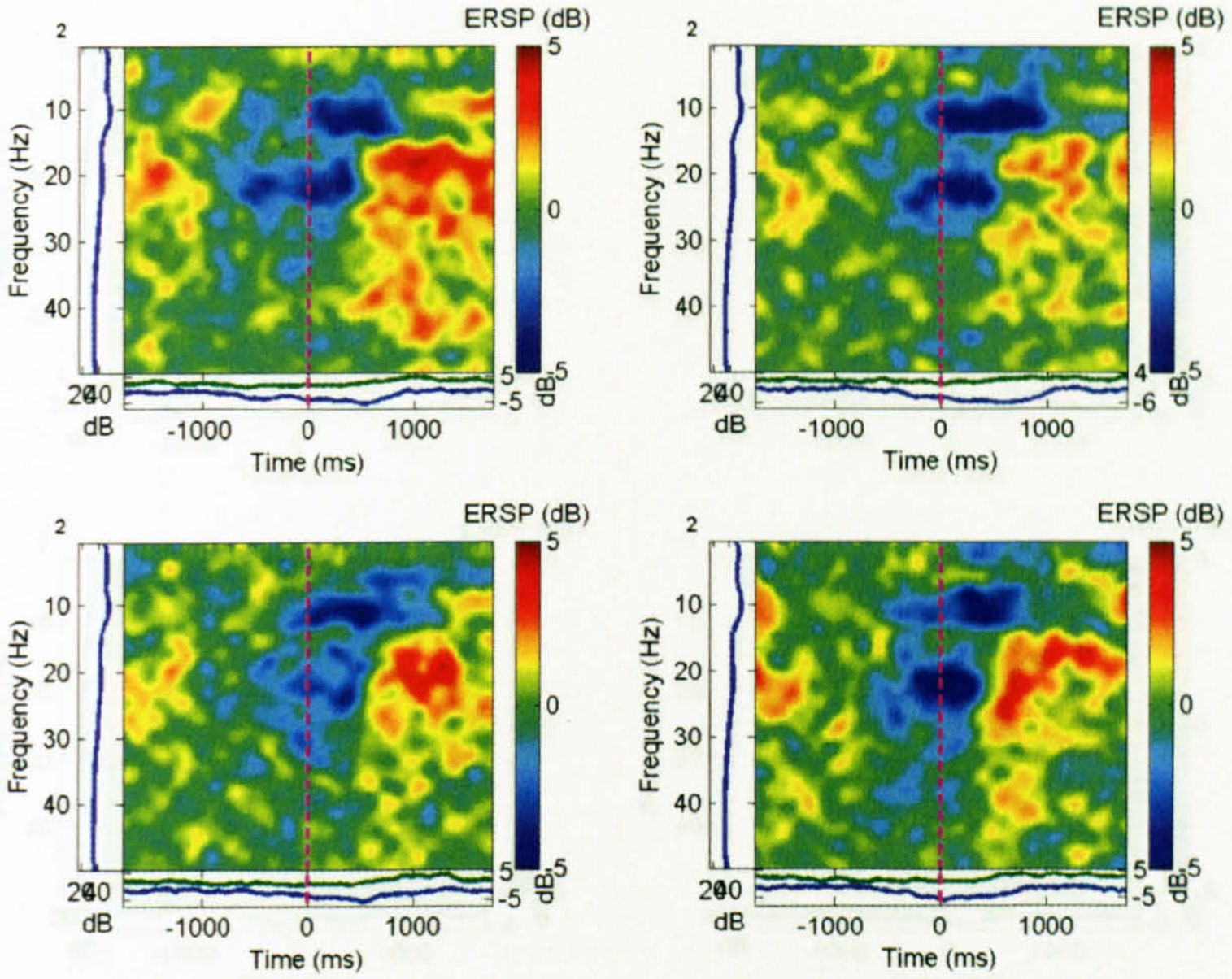
Subject 10



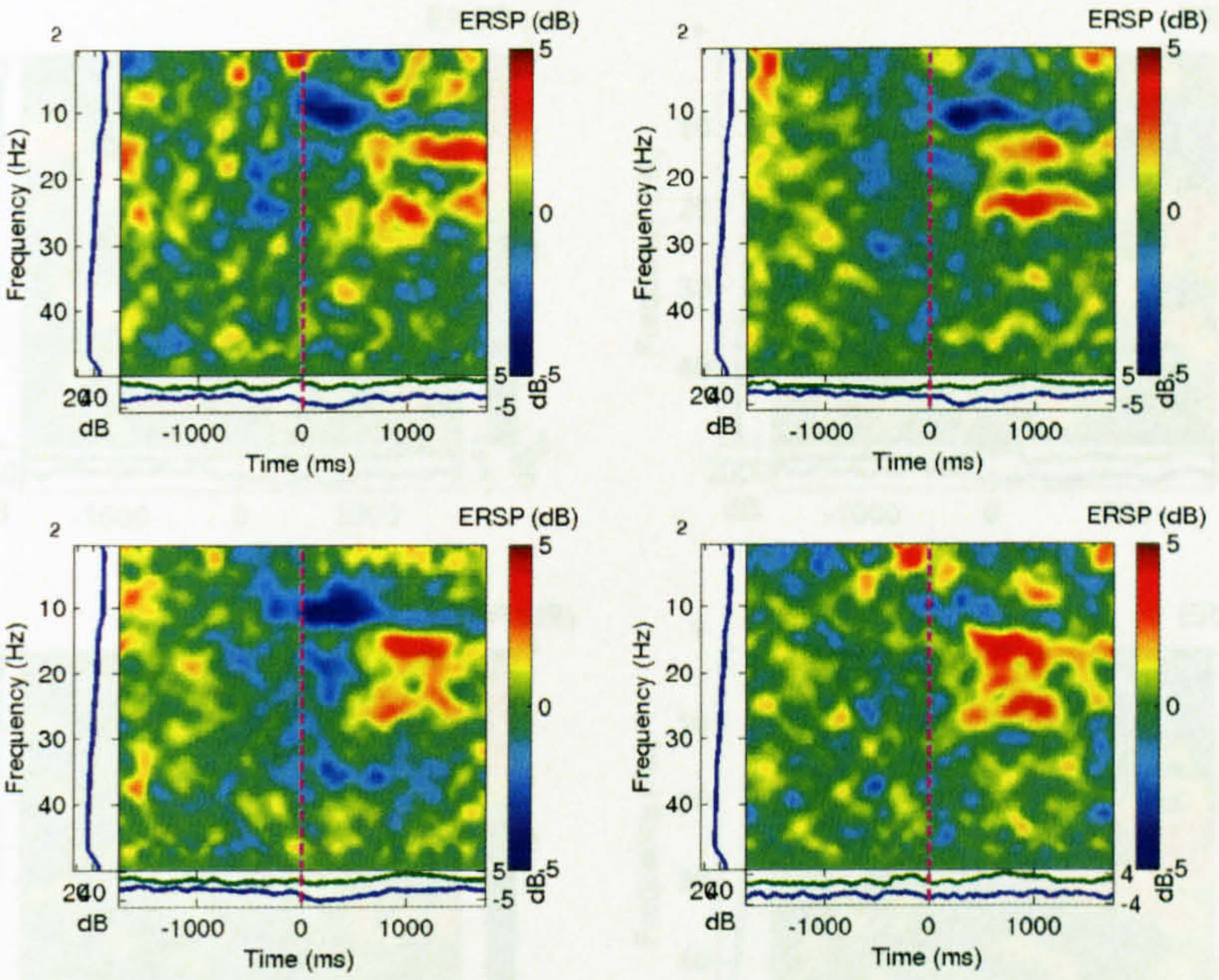
Self Determined

Subject 1

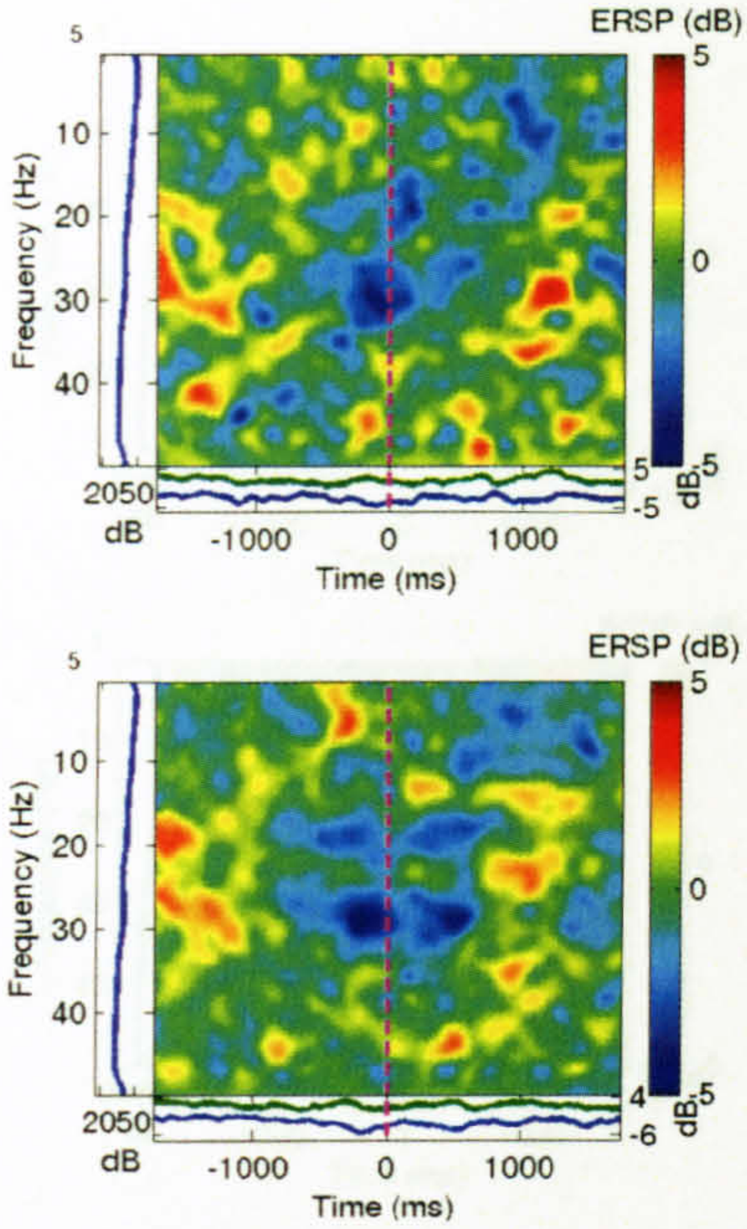
Subject 2

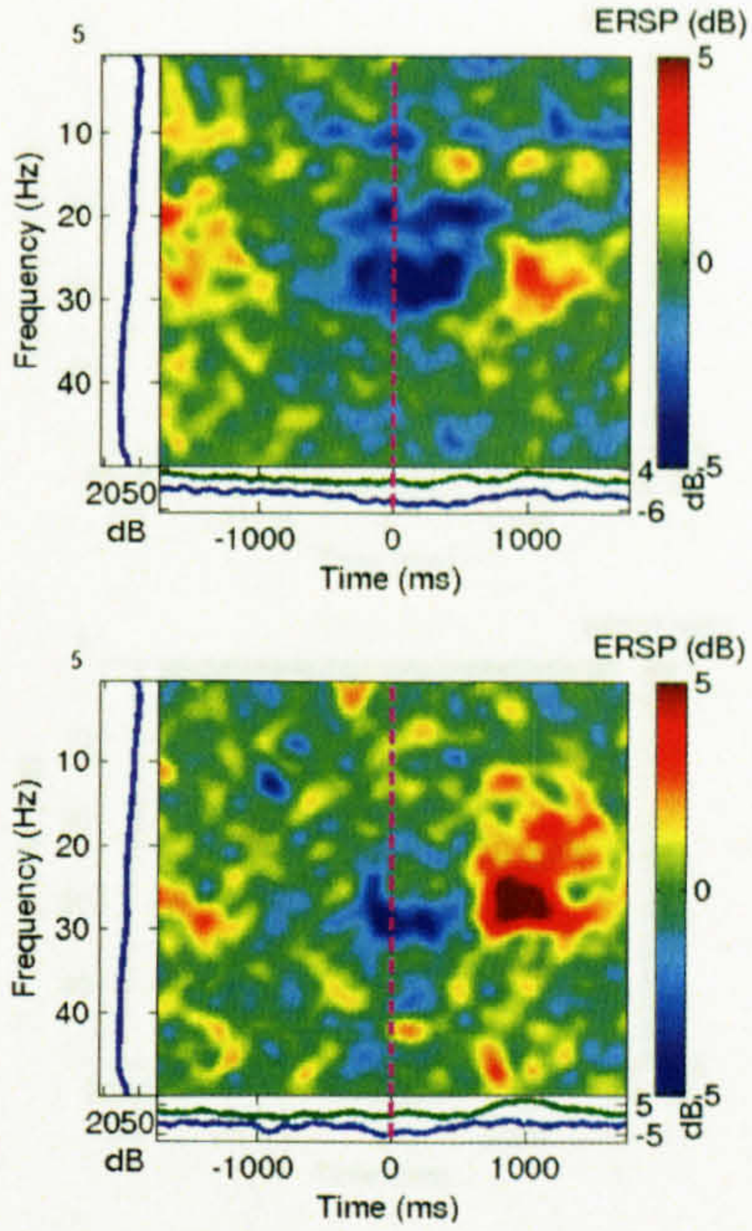


Subject 3

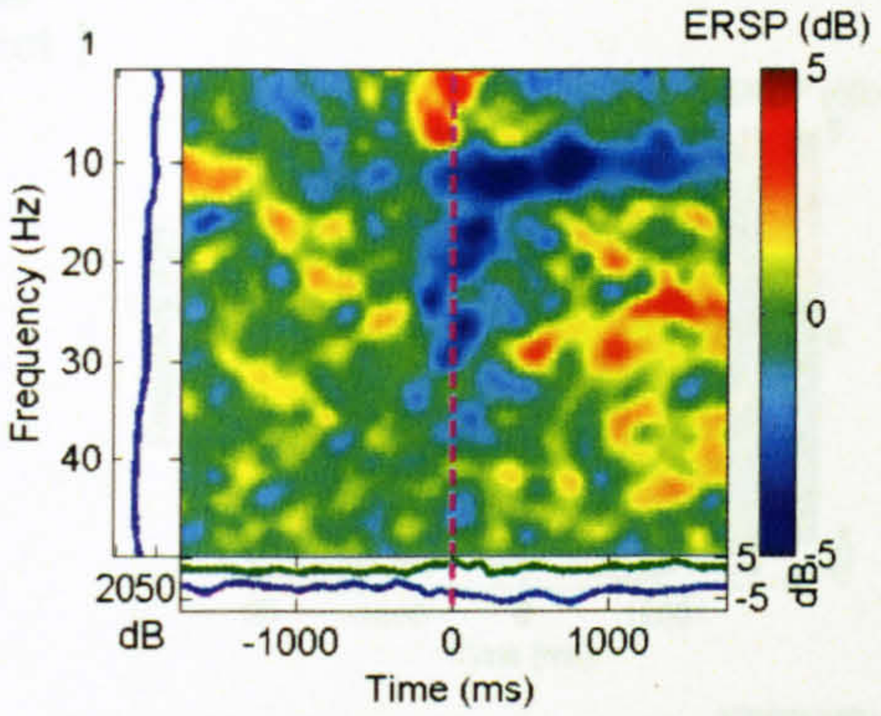


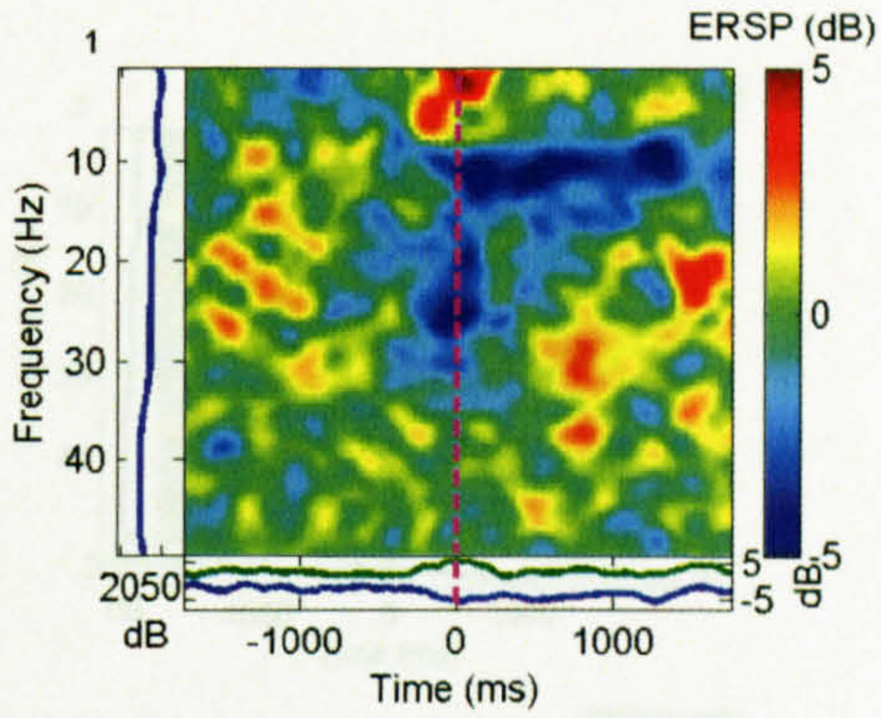
Subject 8

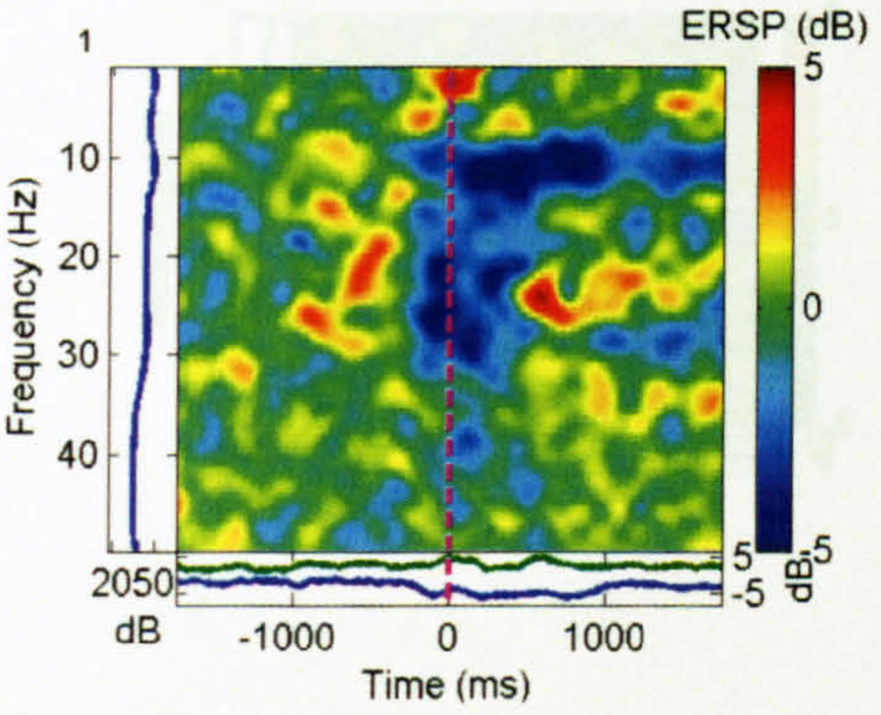


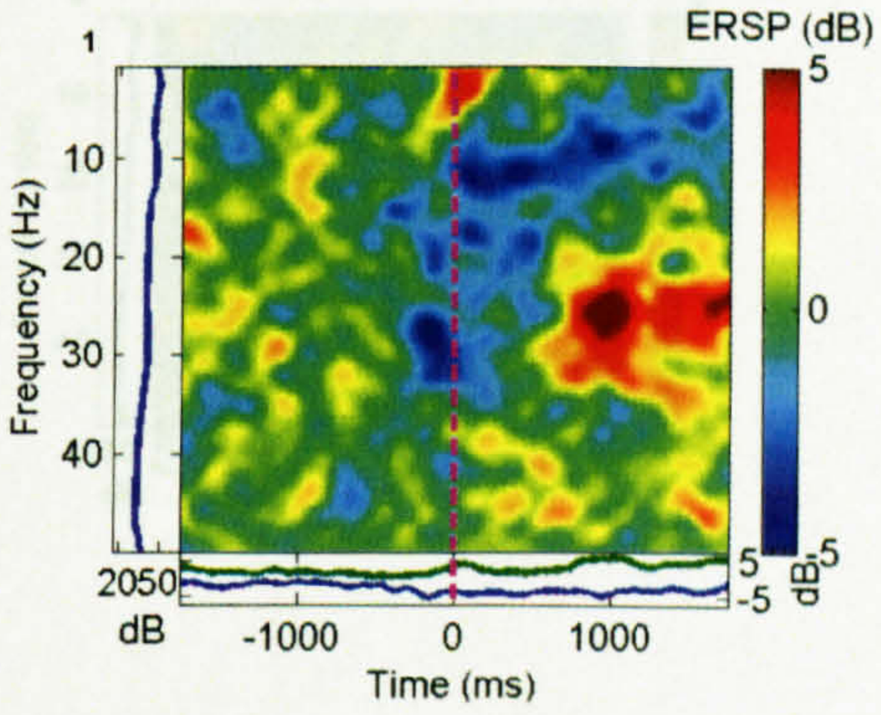


Subject 9

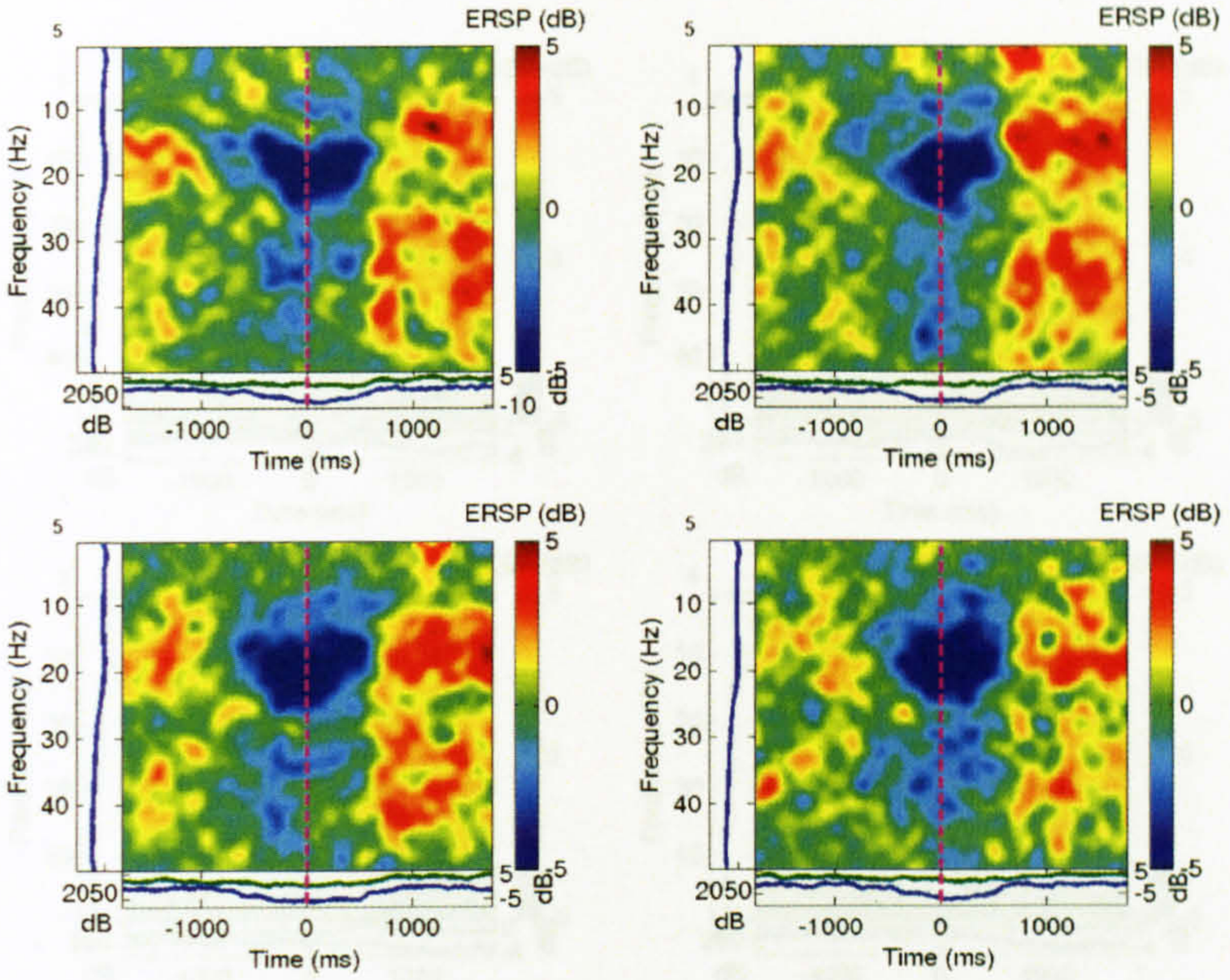






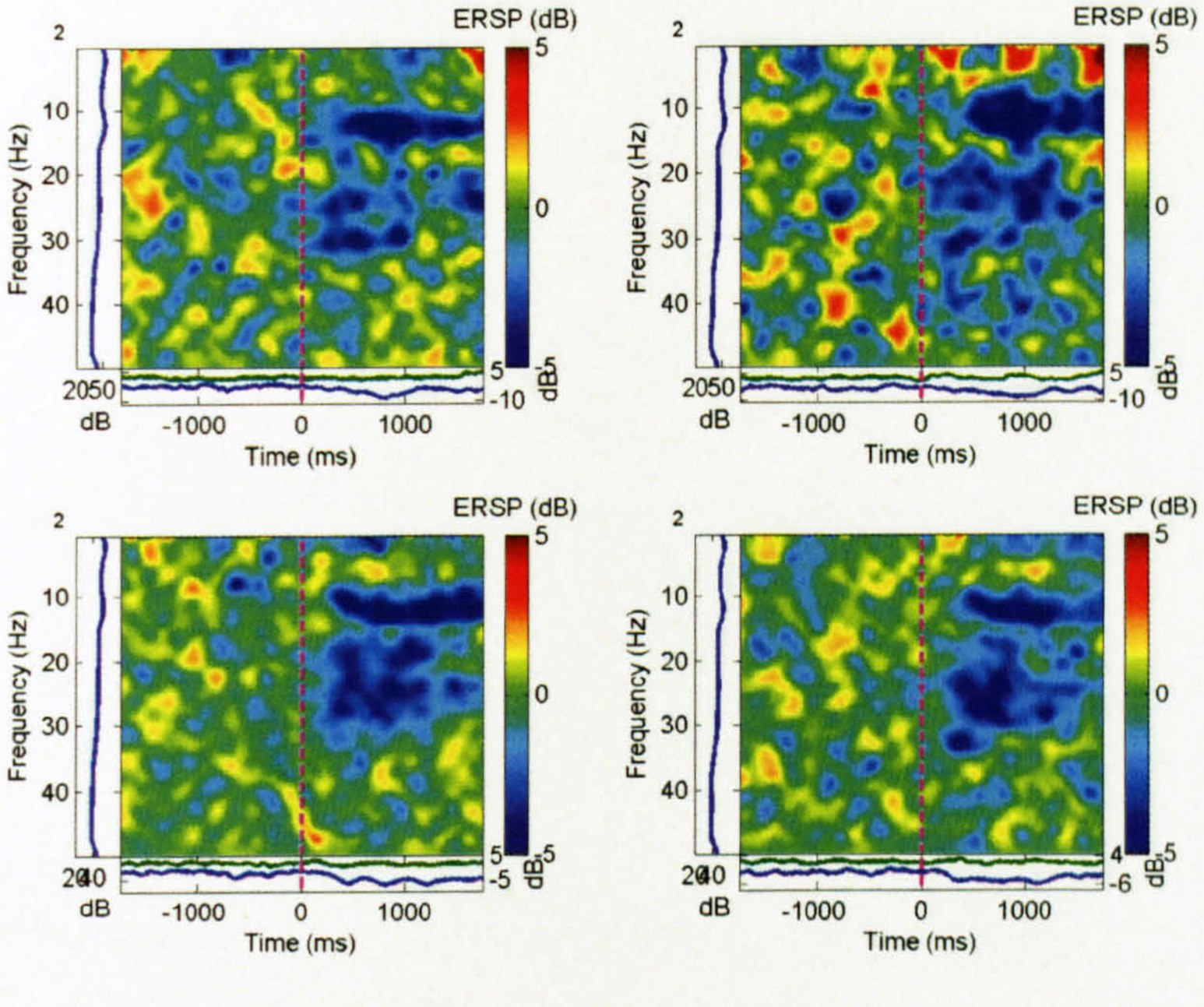


Subject 10

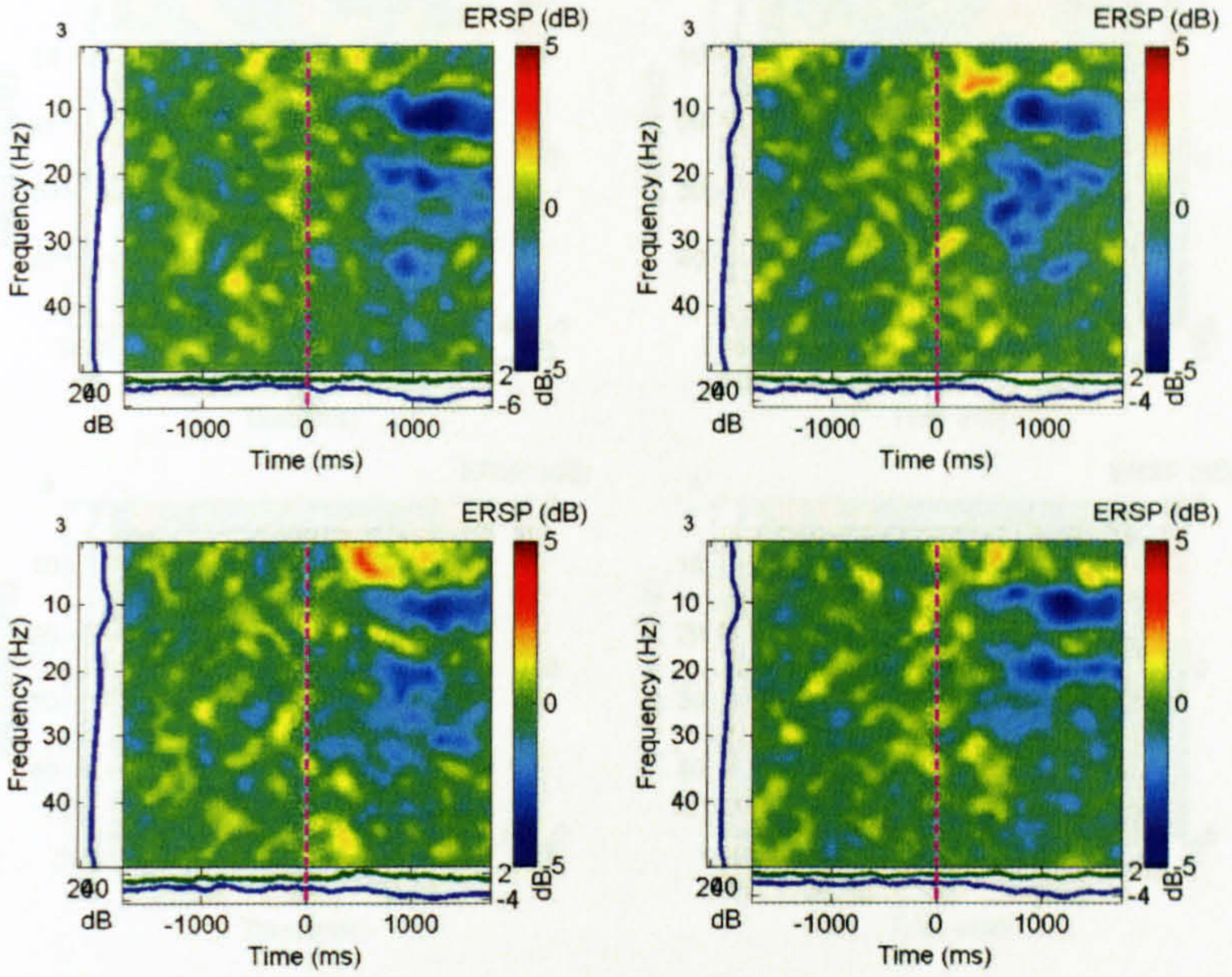


Imagination

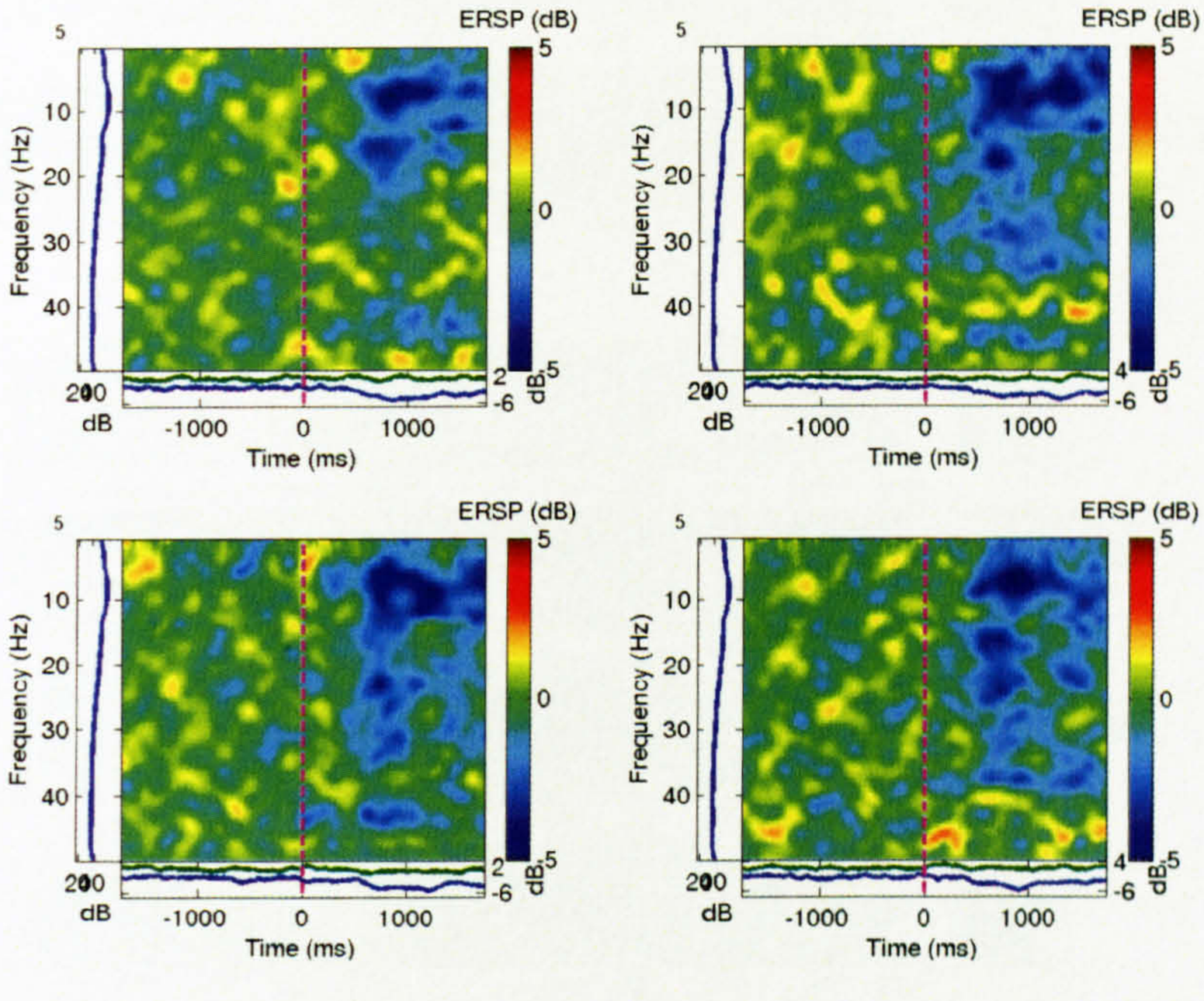
Subject 1



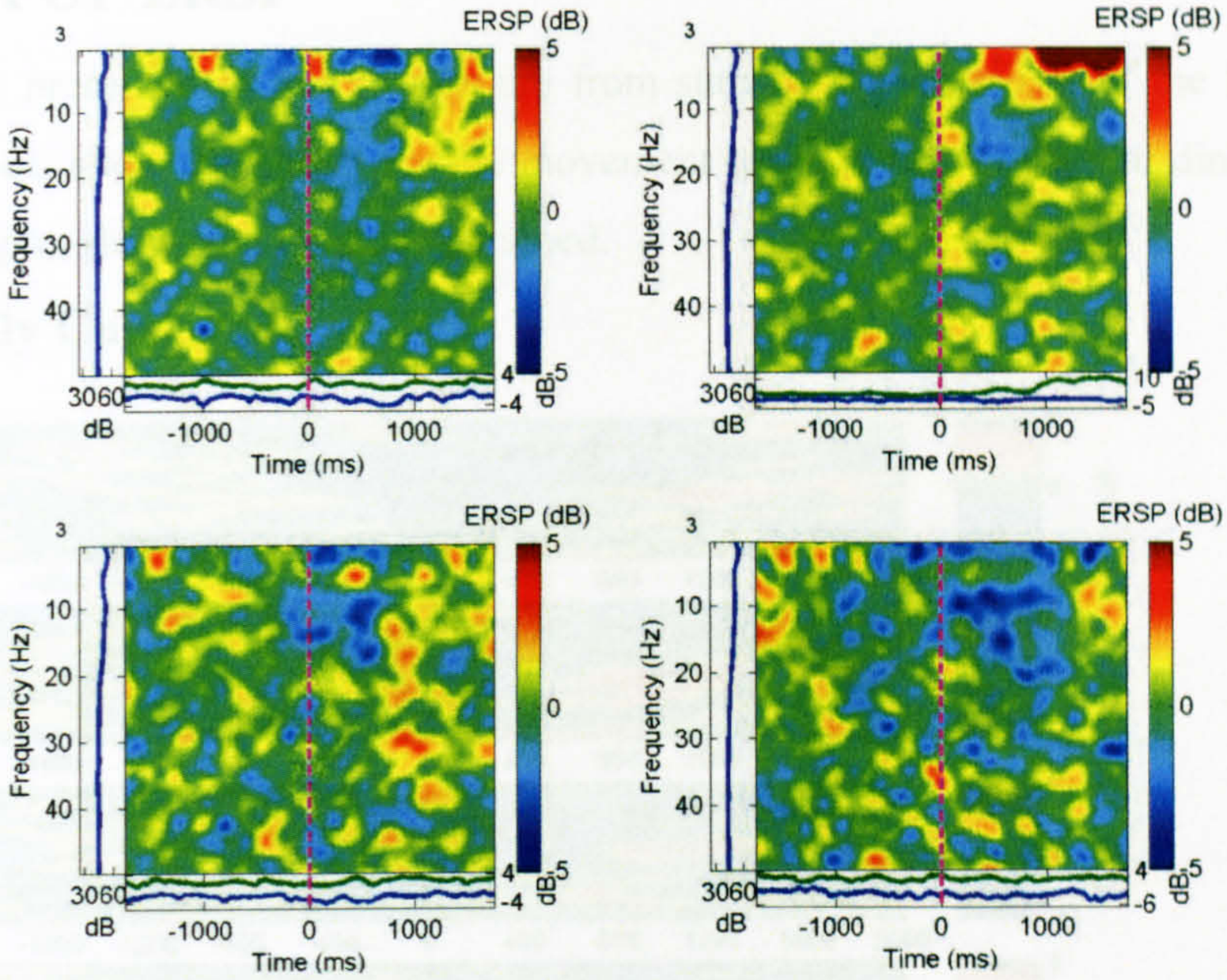
Subject 2



Subject 3



Subject 5

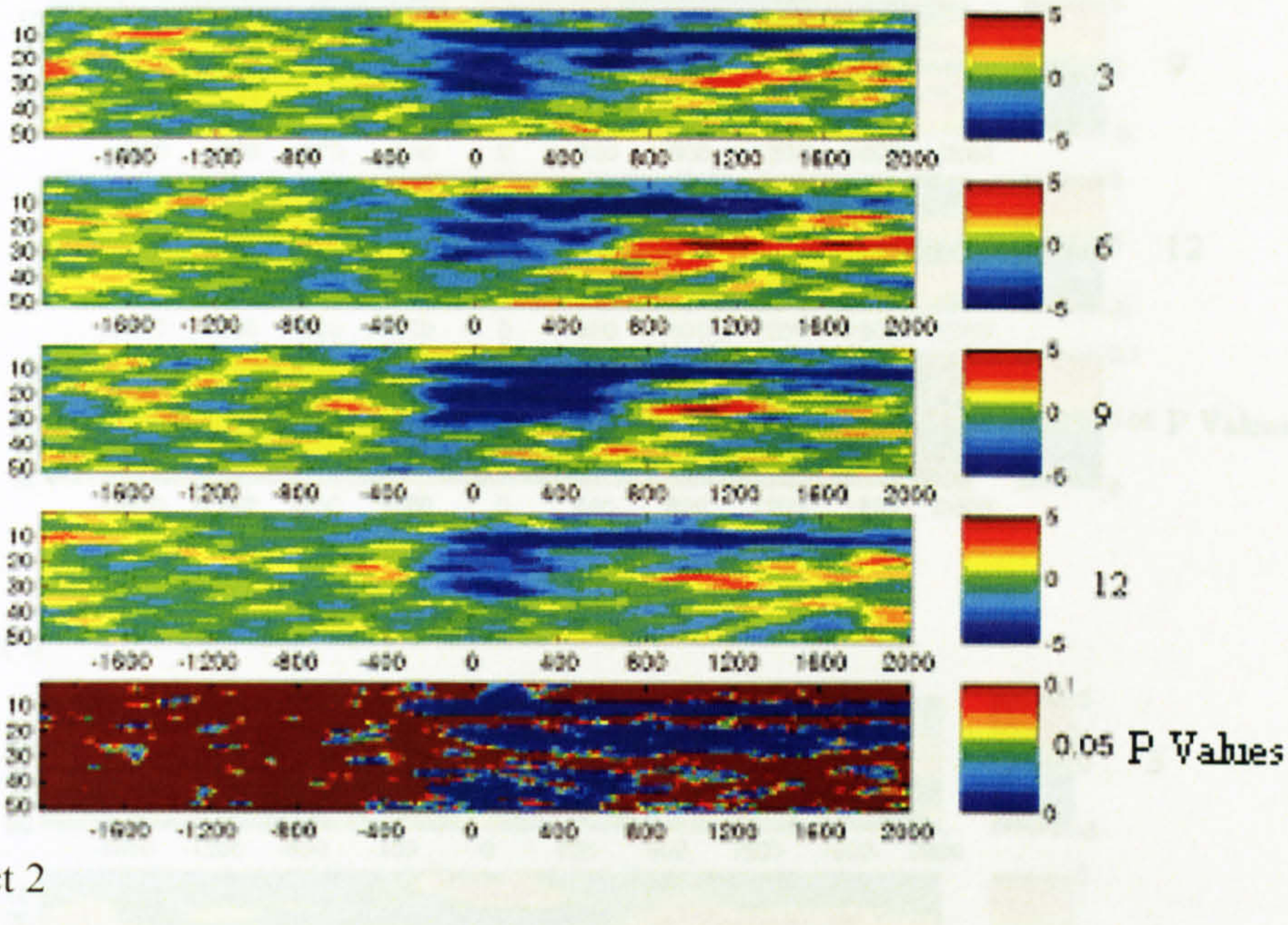


ANOVA OF ERSP

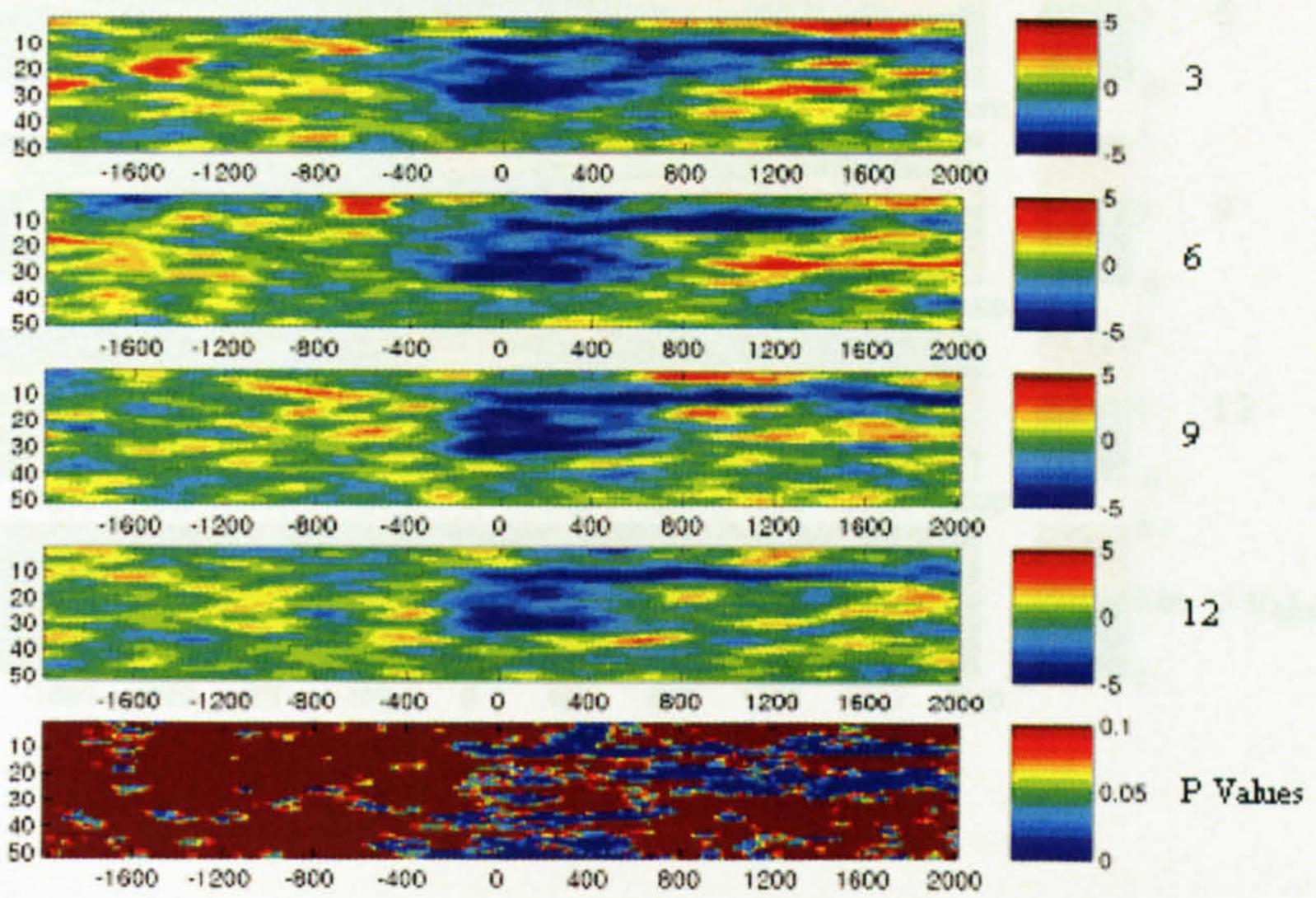
The results presented in this section are from statistical comparison of the ERSP. The top four plots show the ERSP for the movement towards the 4 different directions and the lowest plot shows the P values obtained.

Externally Cued

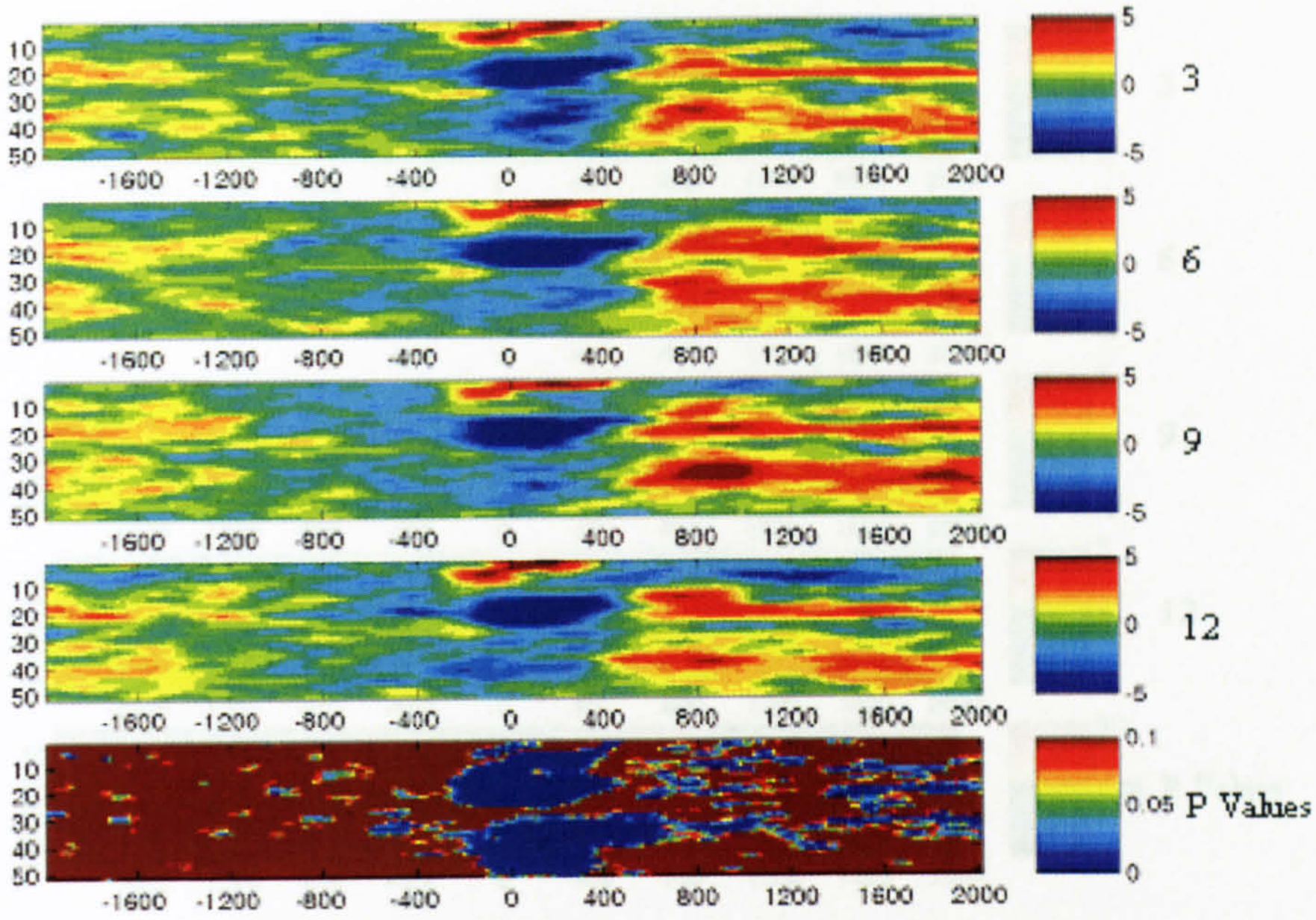
Subject 1



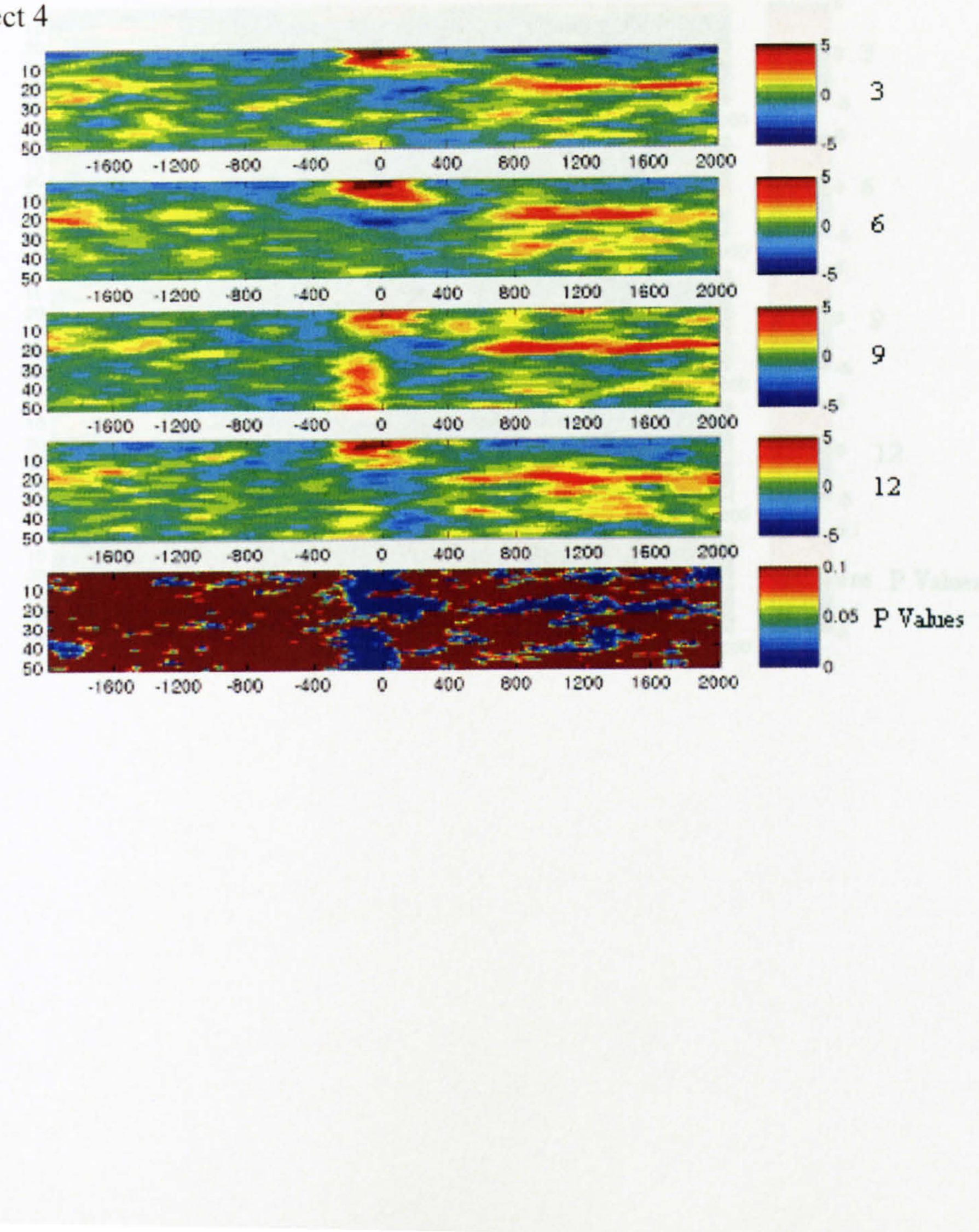
Subject 2



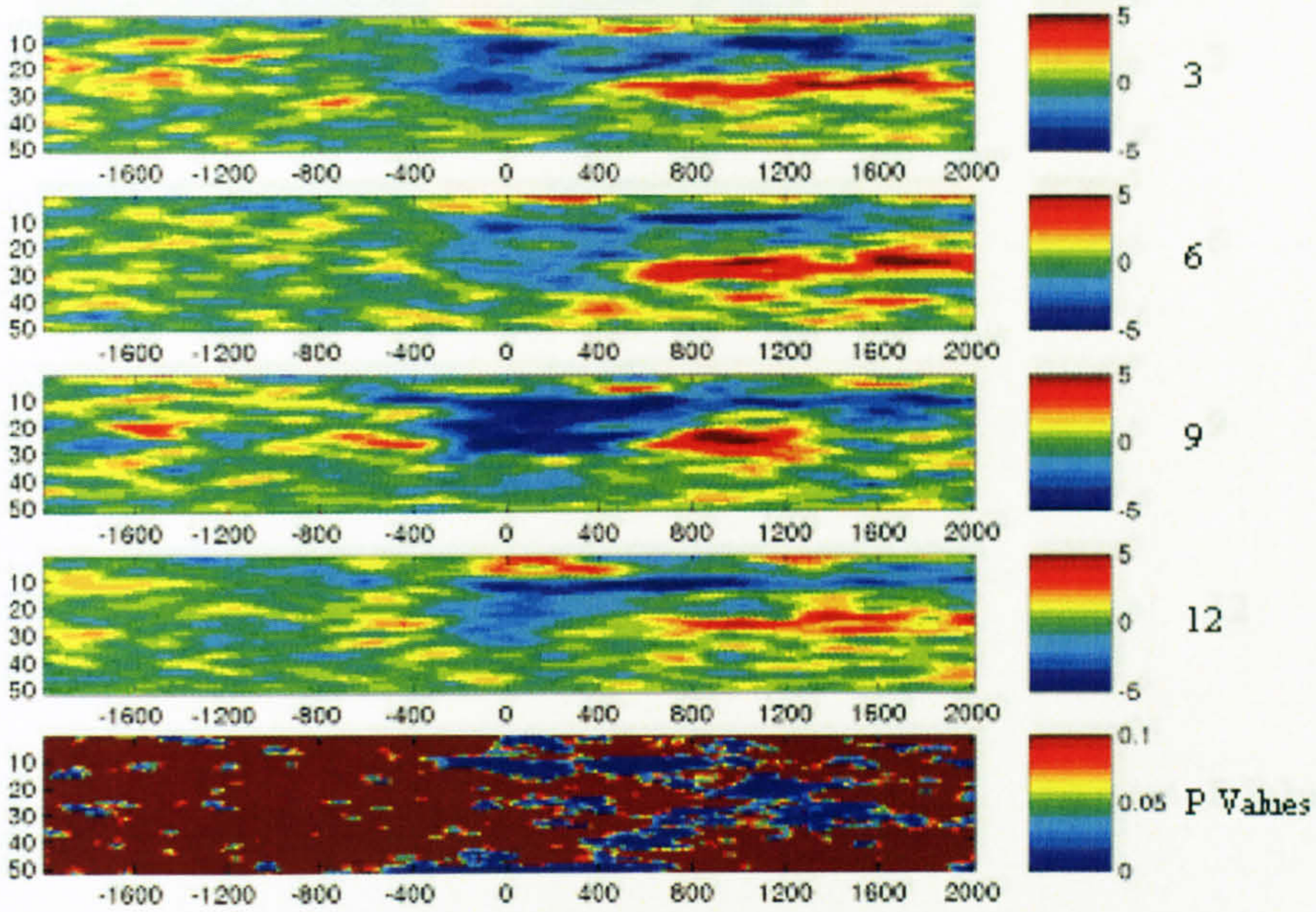
Subject 3



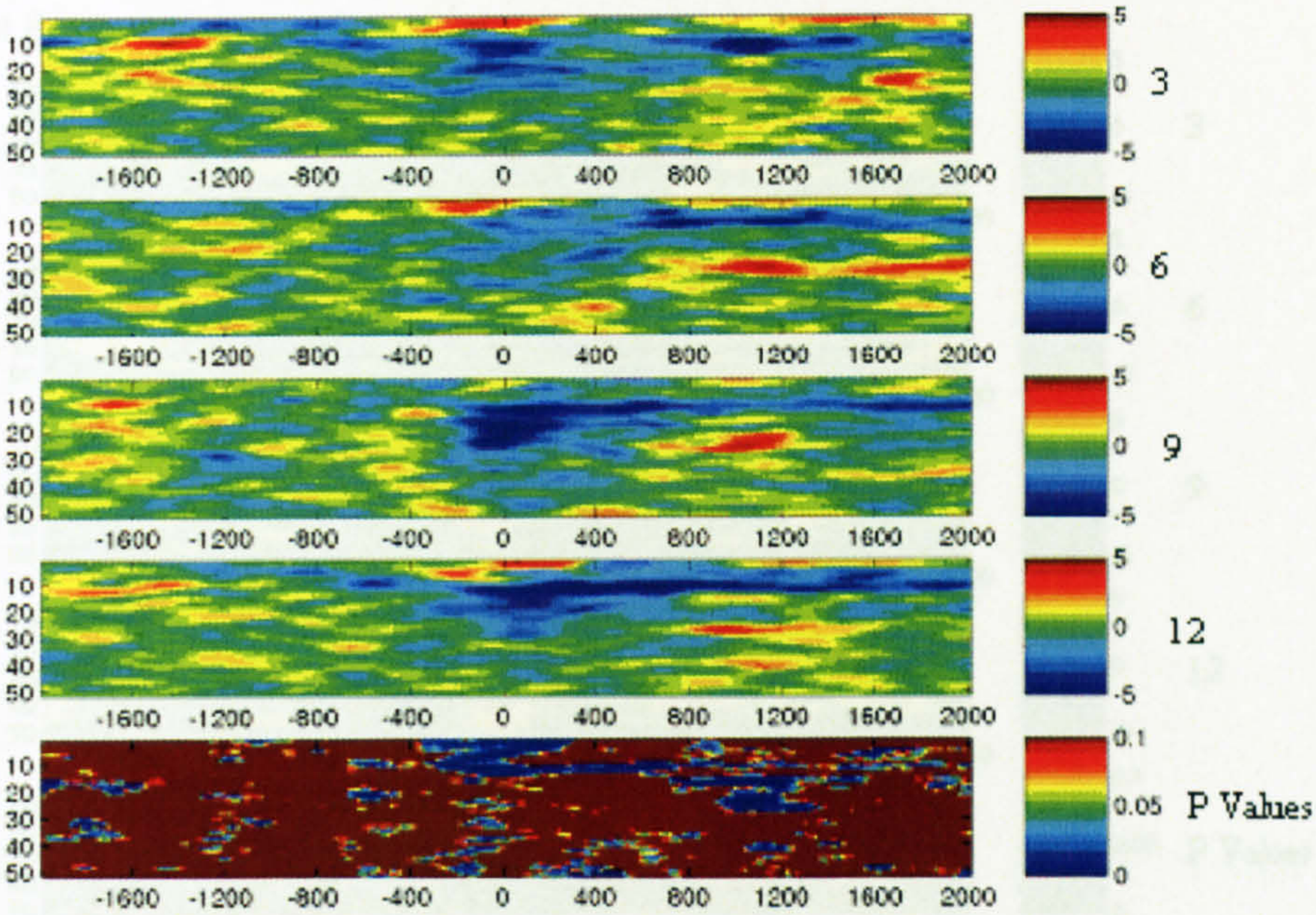
Subject 4



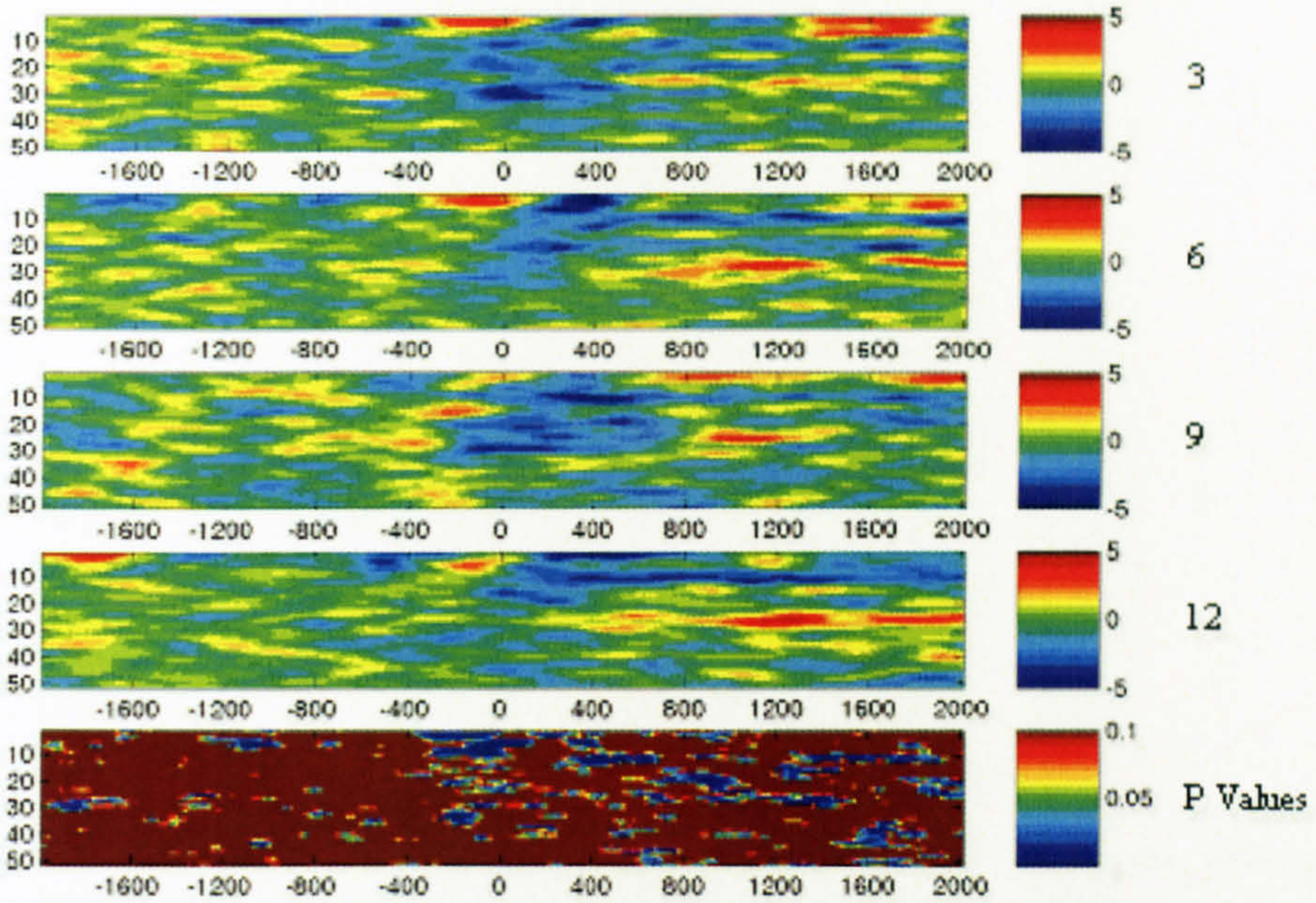
Subject 5



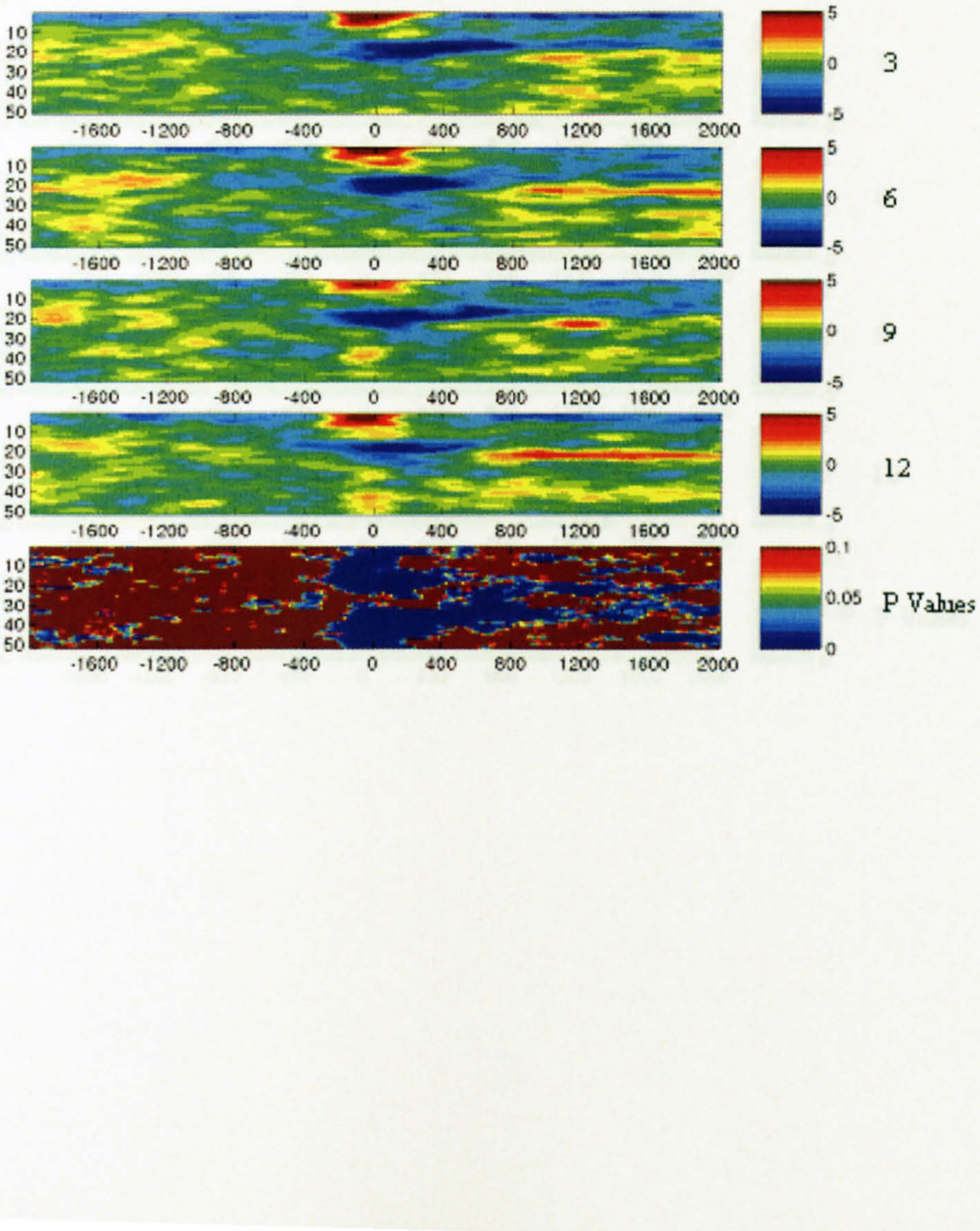
Subject 6



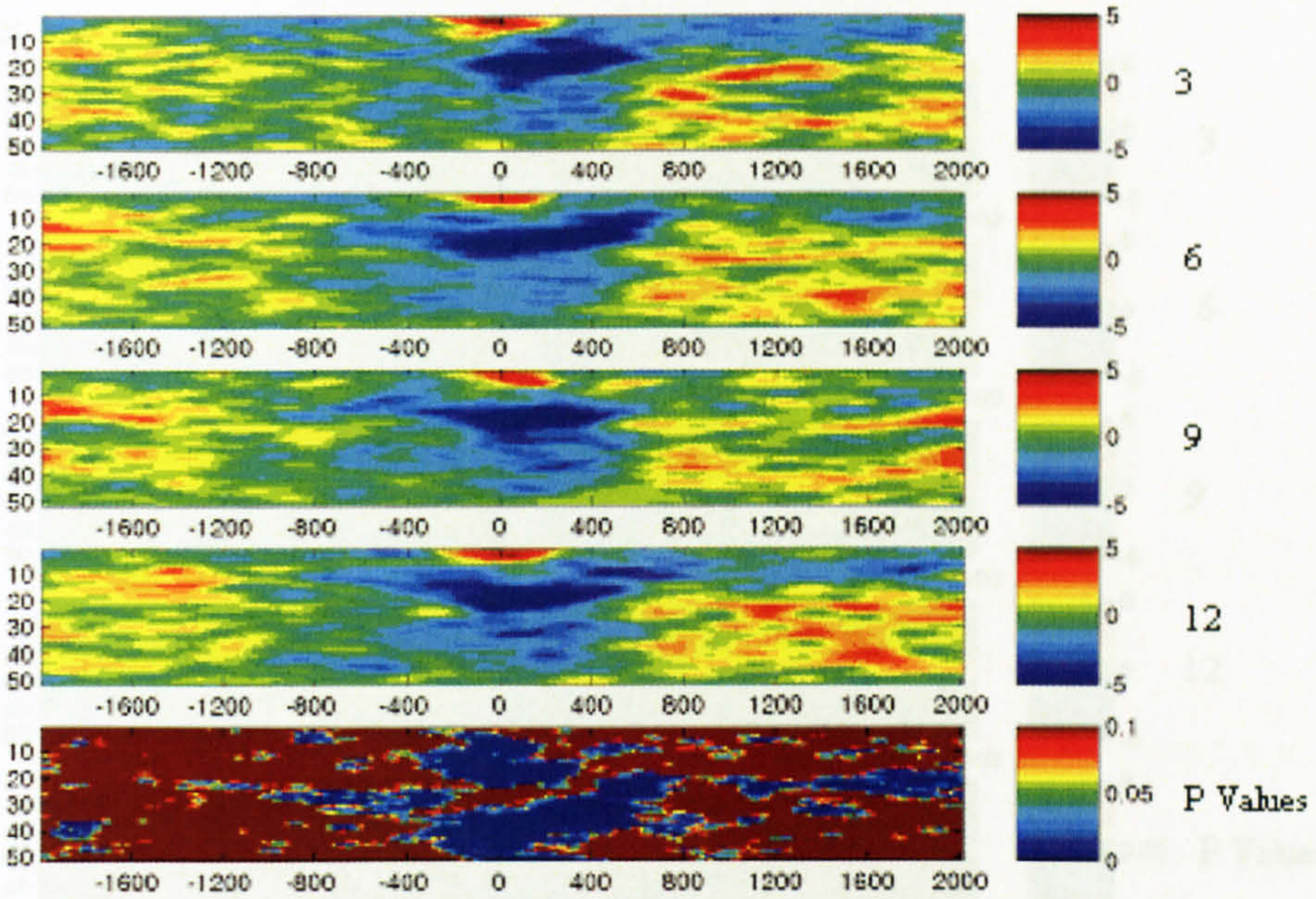
Subject 7



Subject 8

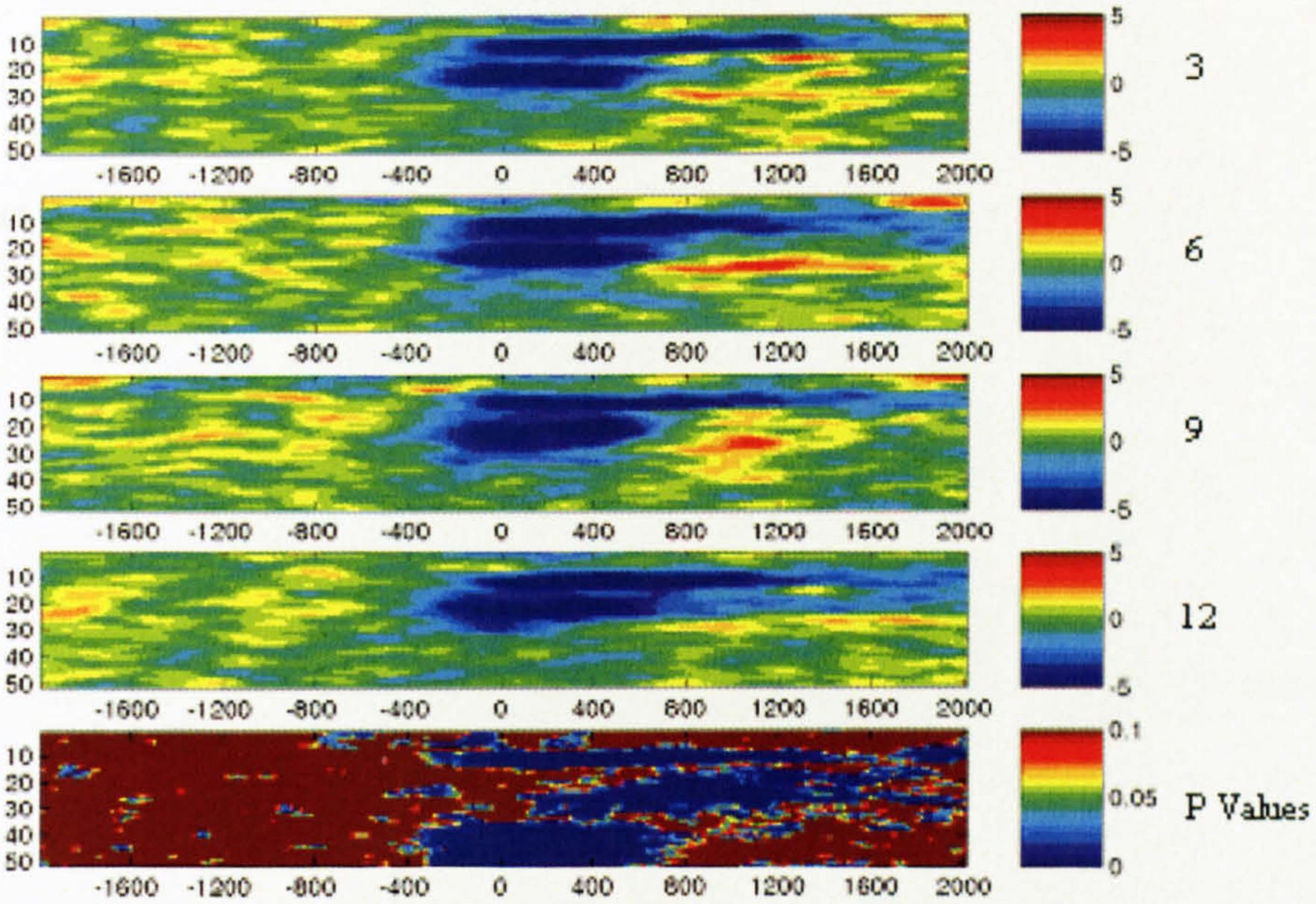


Subject 10

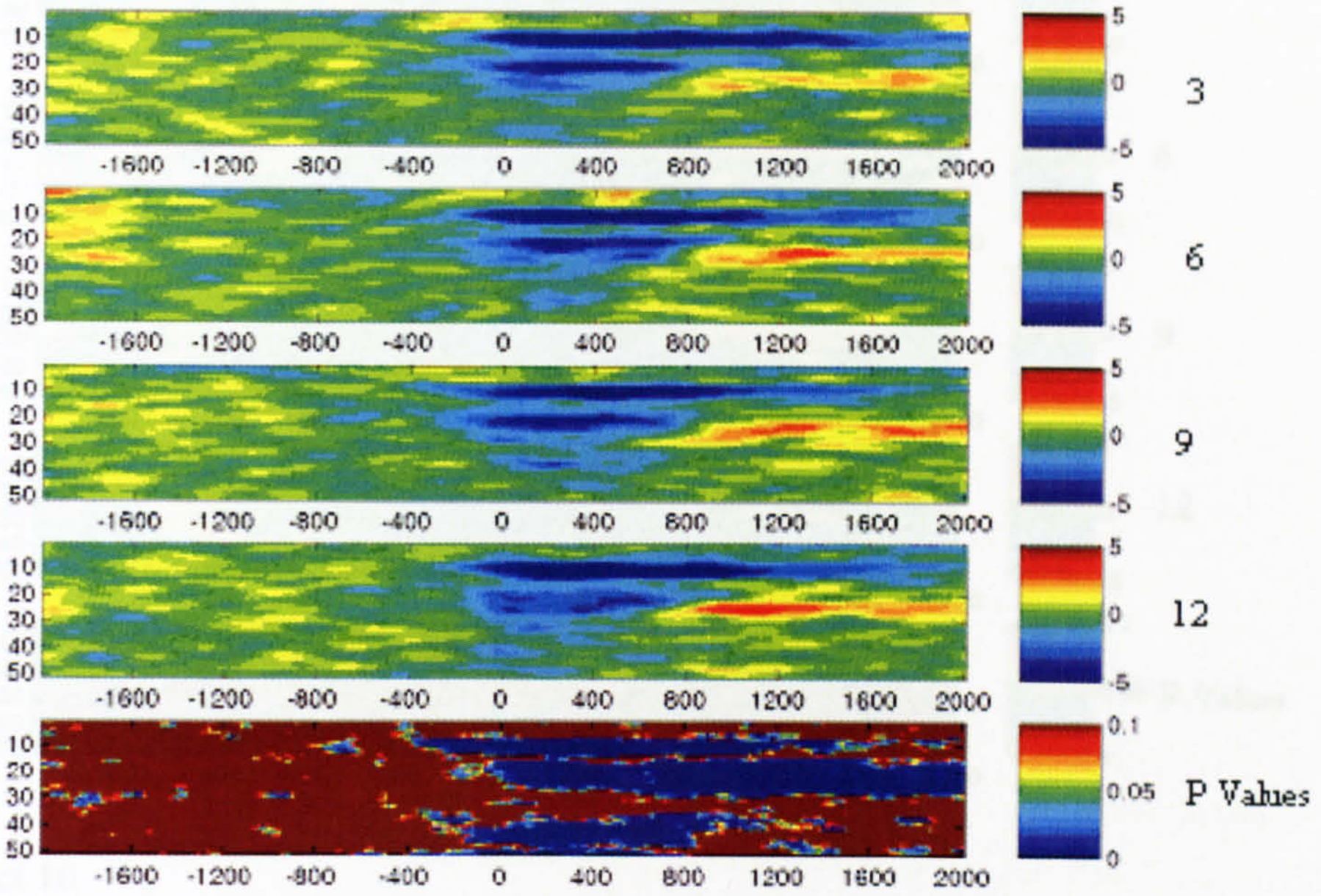


Forced Choice Trials

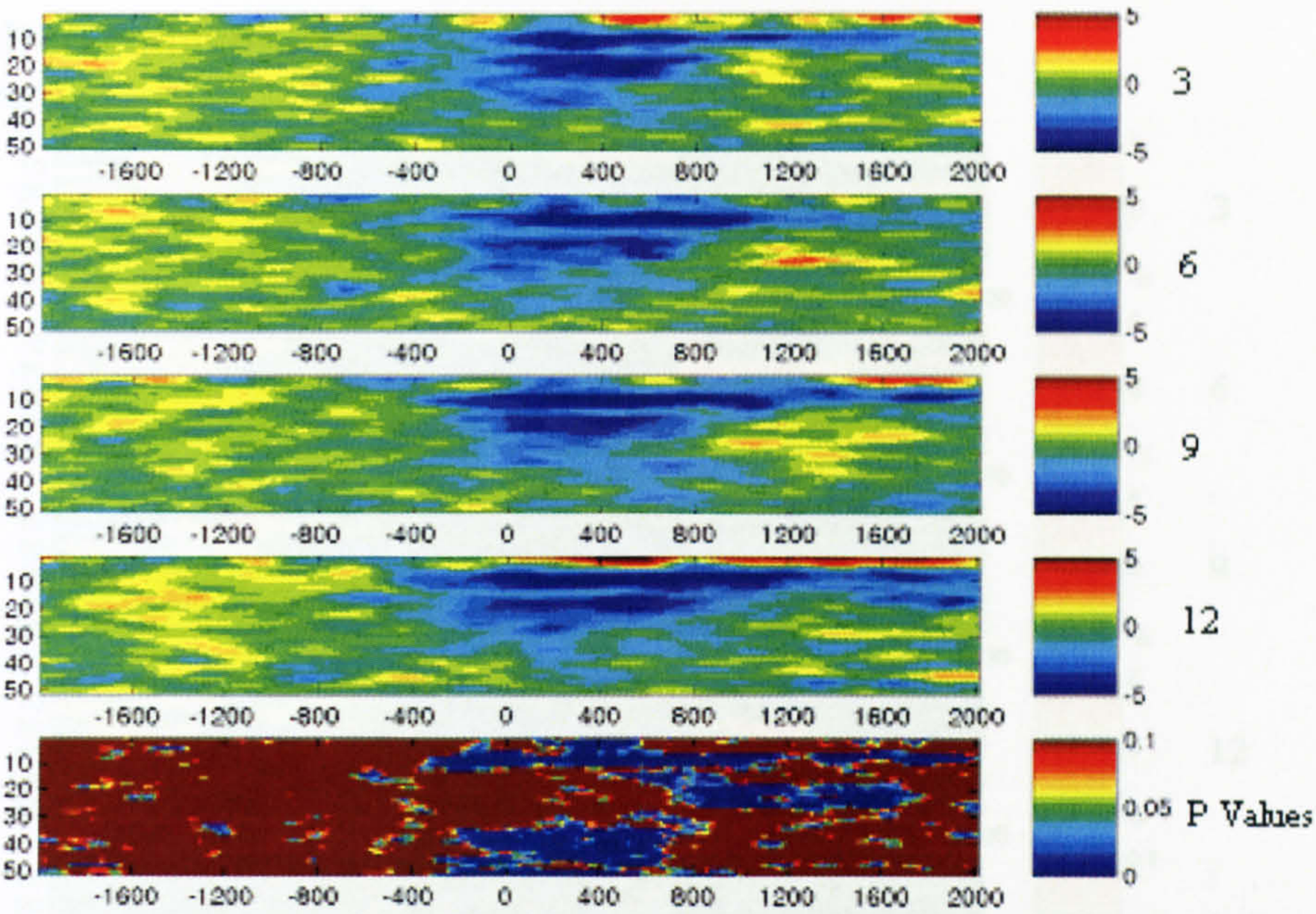
Subject 1



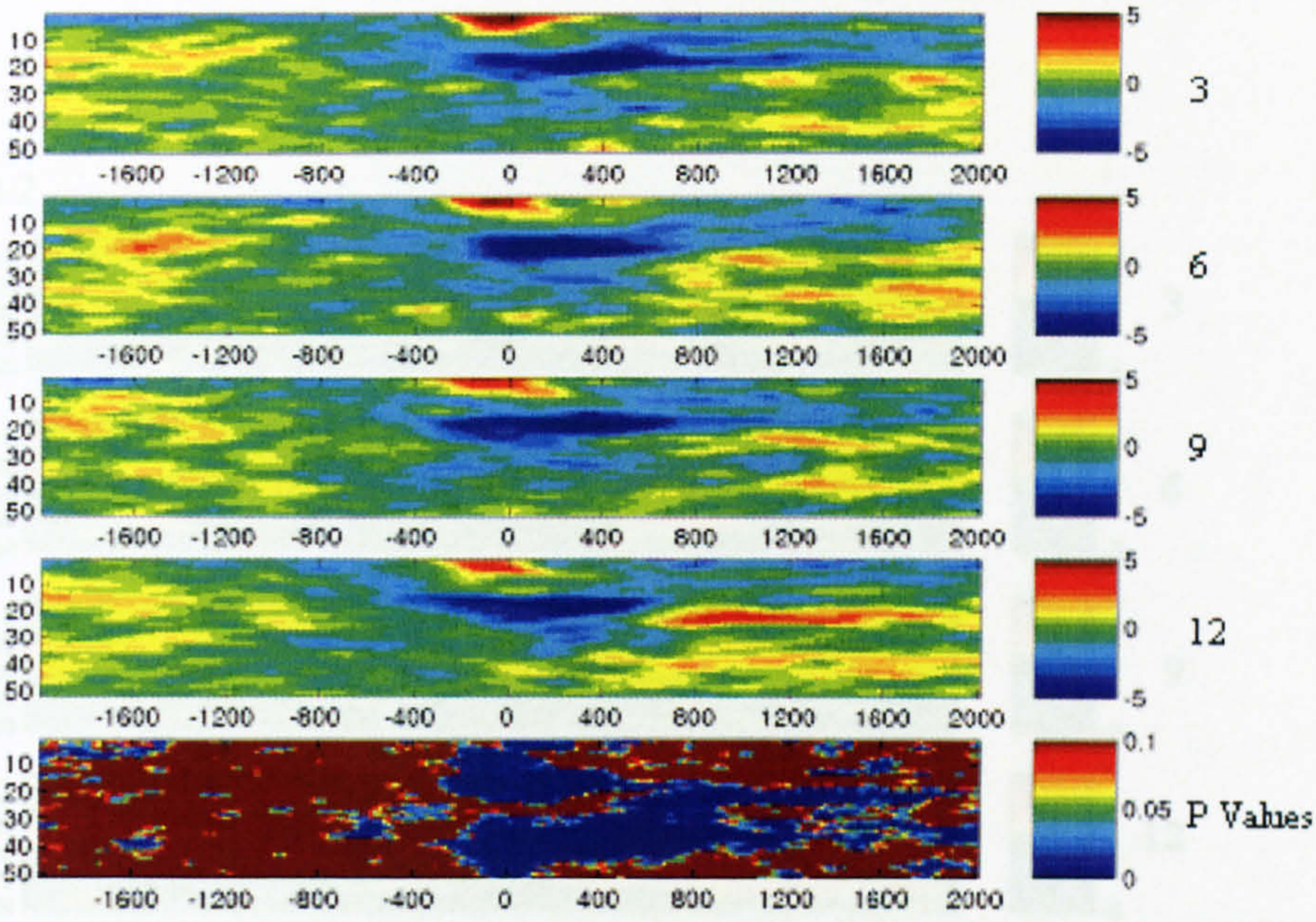
Subject 2



Subject 3

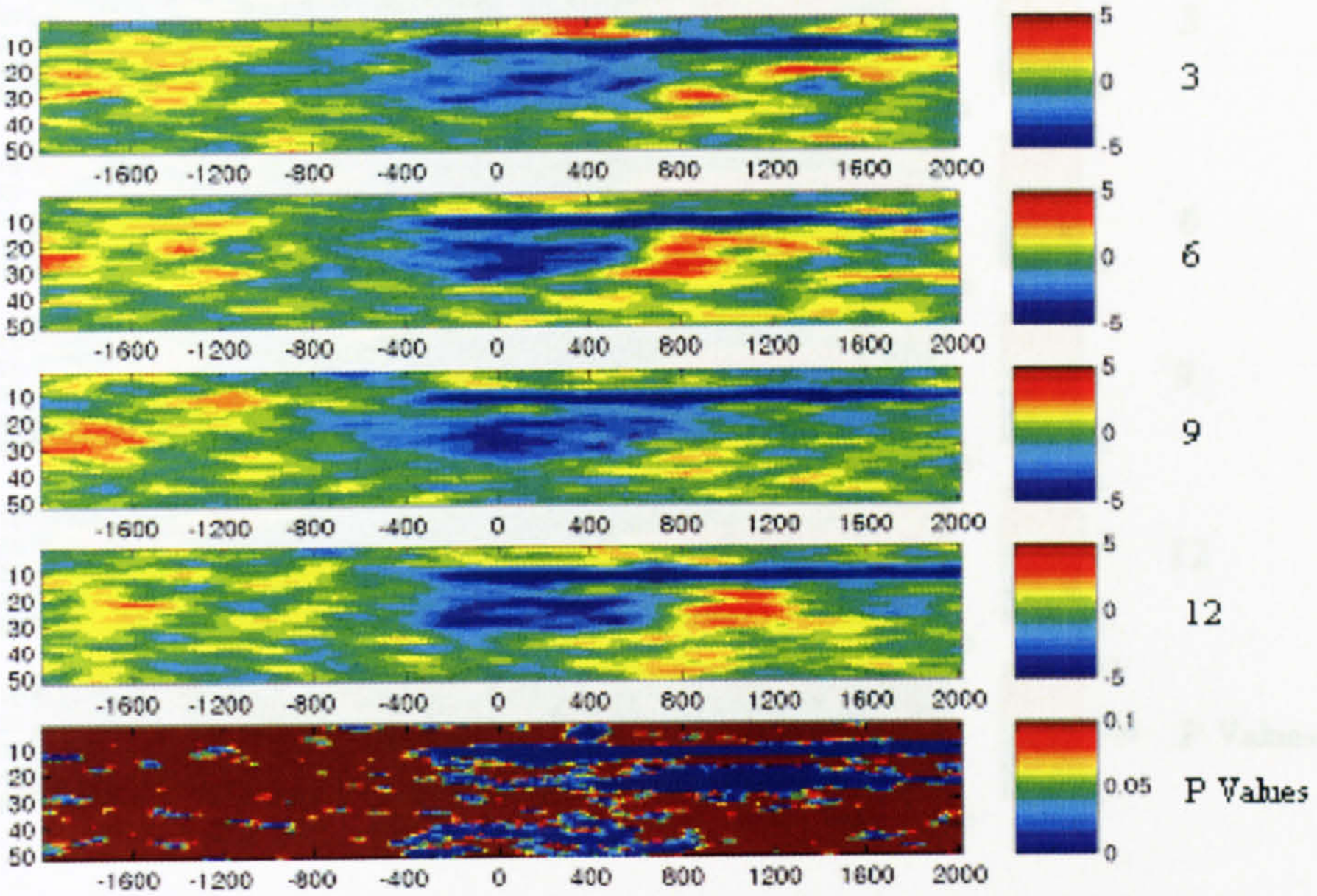

10
20
30
40
50
-1600 -1200 -800 -400 0 400 800 1200 1600 2000
5
0
-5
3
6
9
12
0.1
0.05
0
P Values

Subject 10

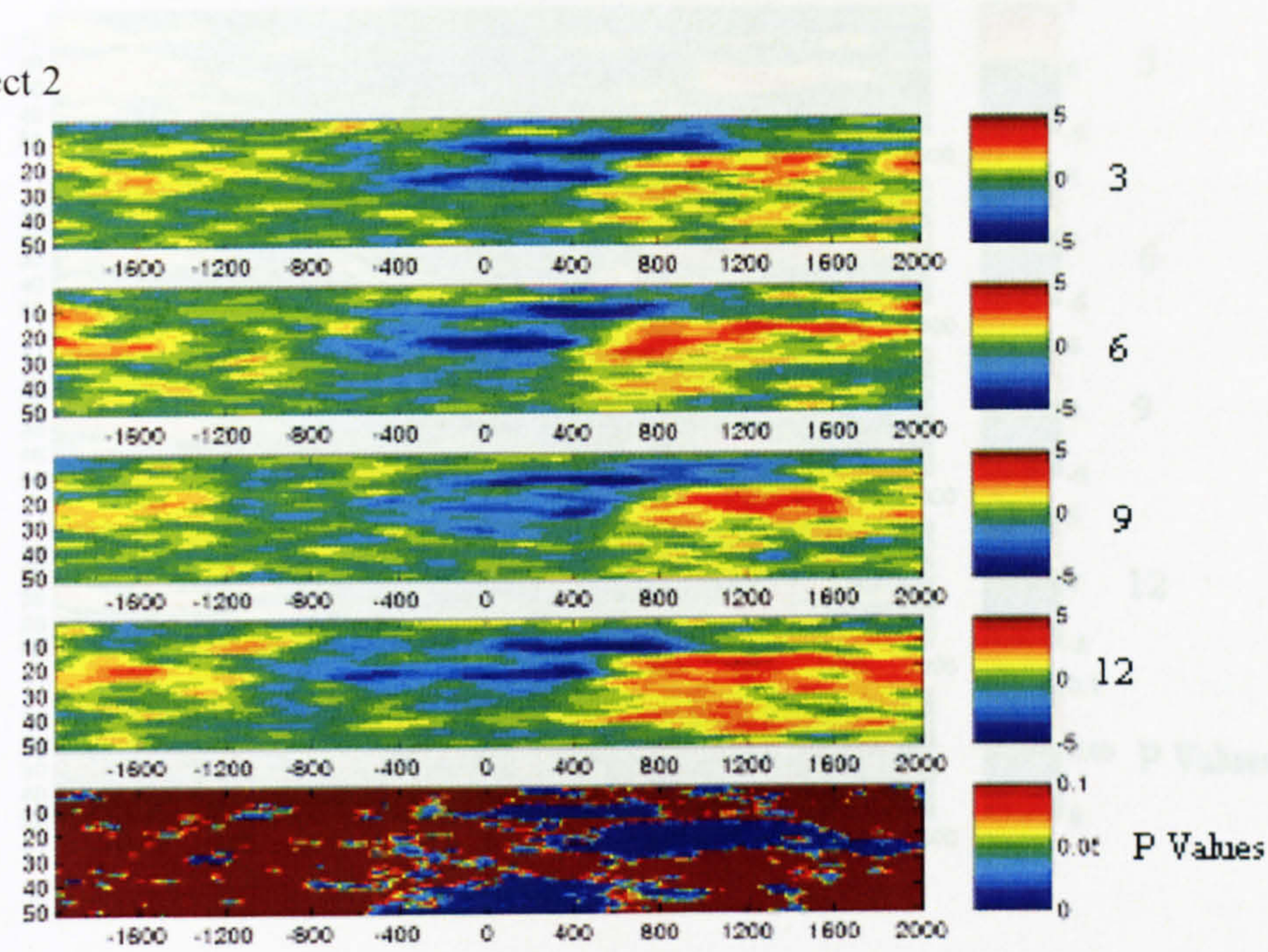

10
20
30
40
50
-1600 -1200 -800 -400 0 400 800 1200 1600 2000
5
0
-5
3
6
9
12
0.1
0.05
0
P Values

Self Determined

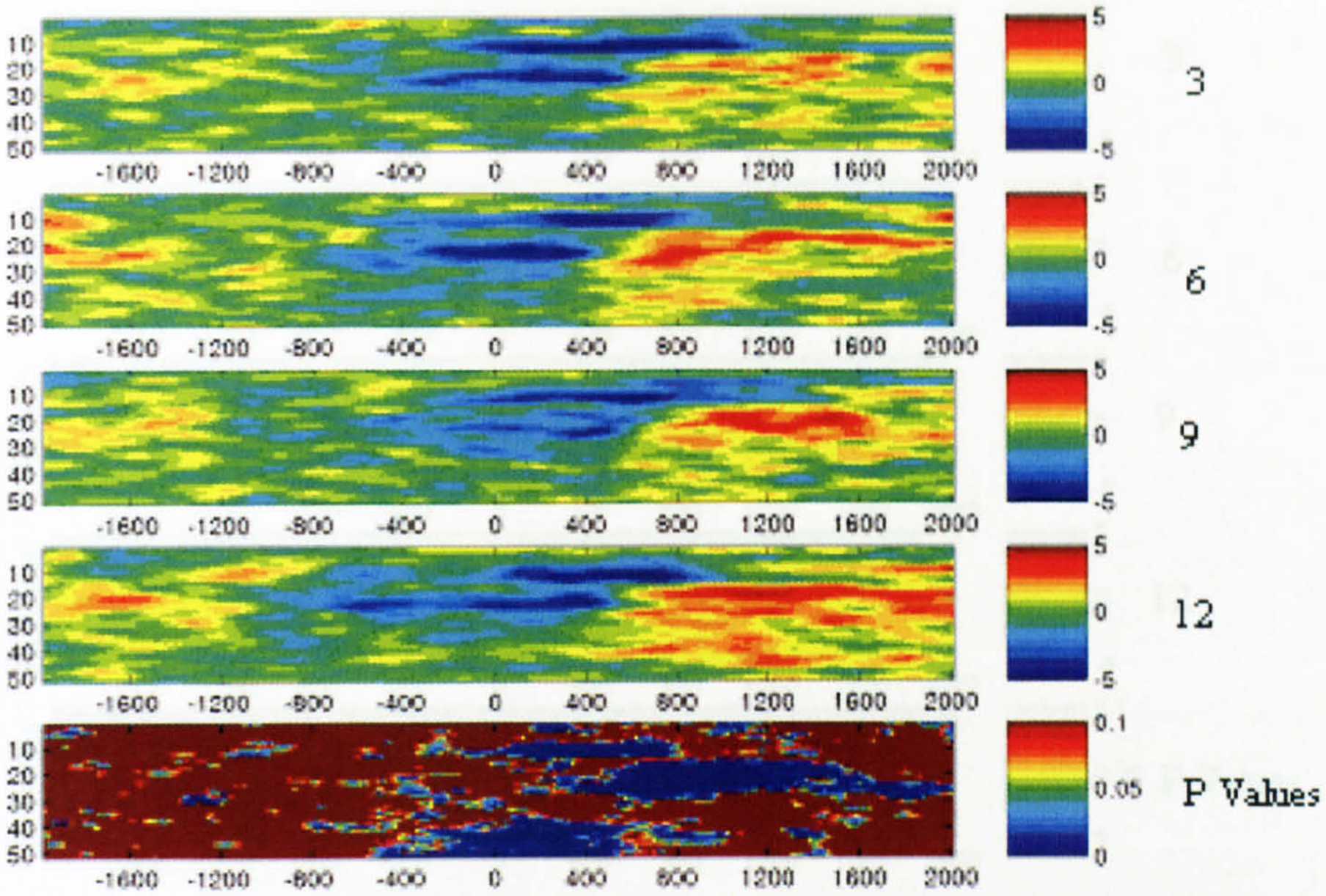
Subject 1



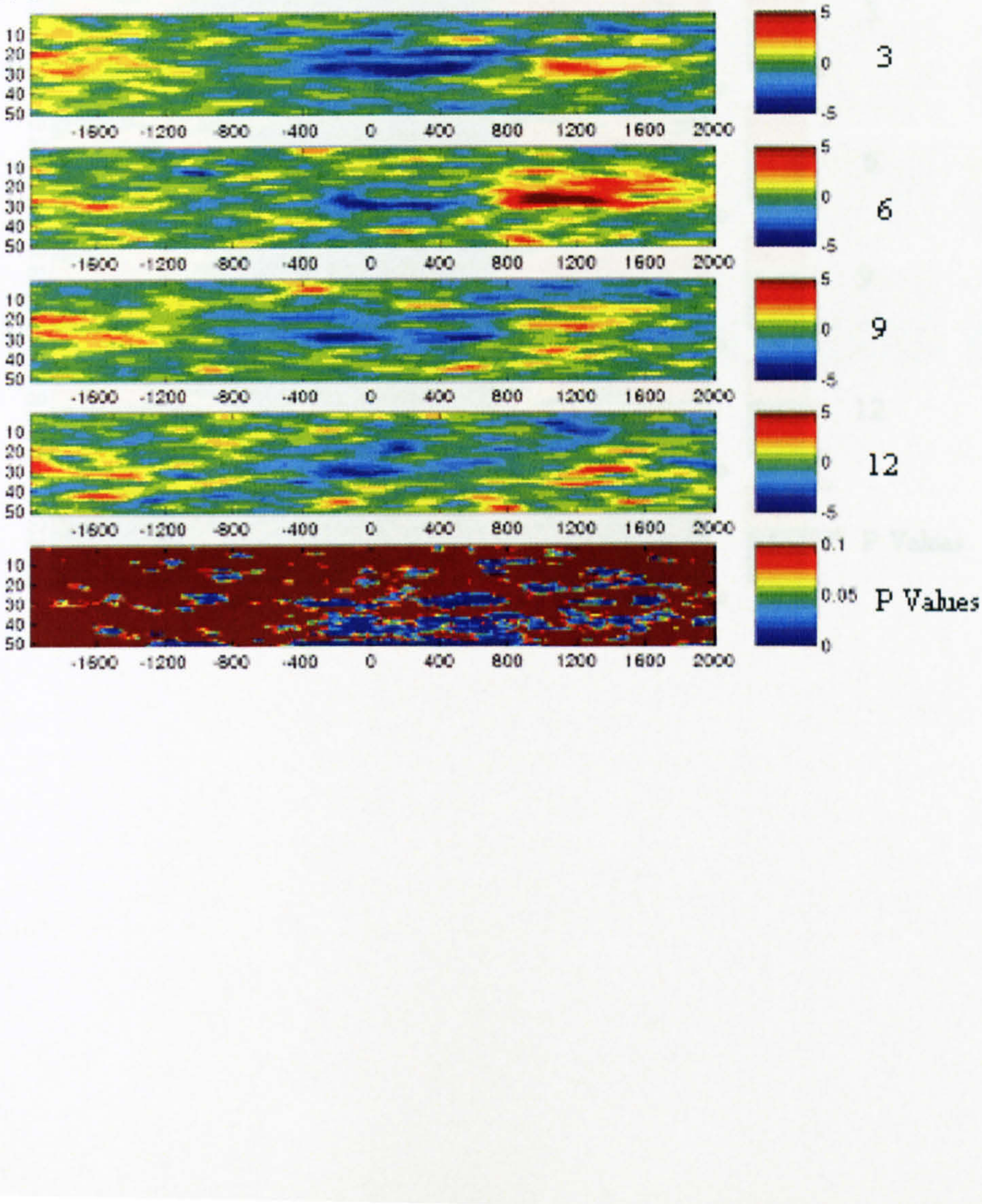
Subject 2



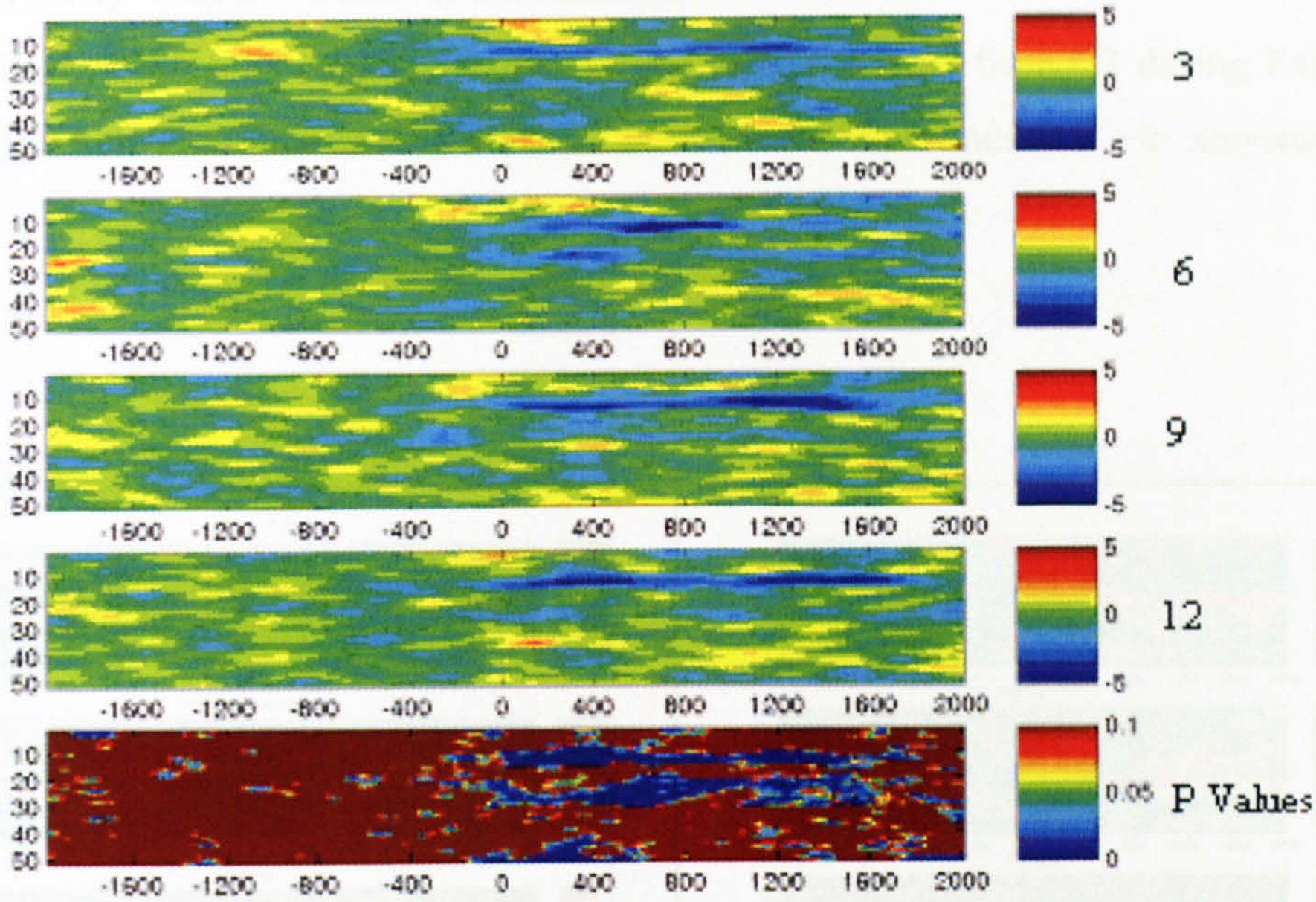
Subject 3



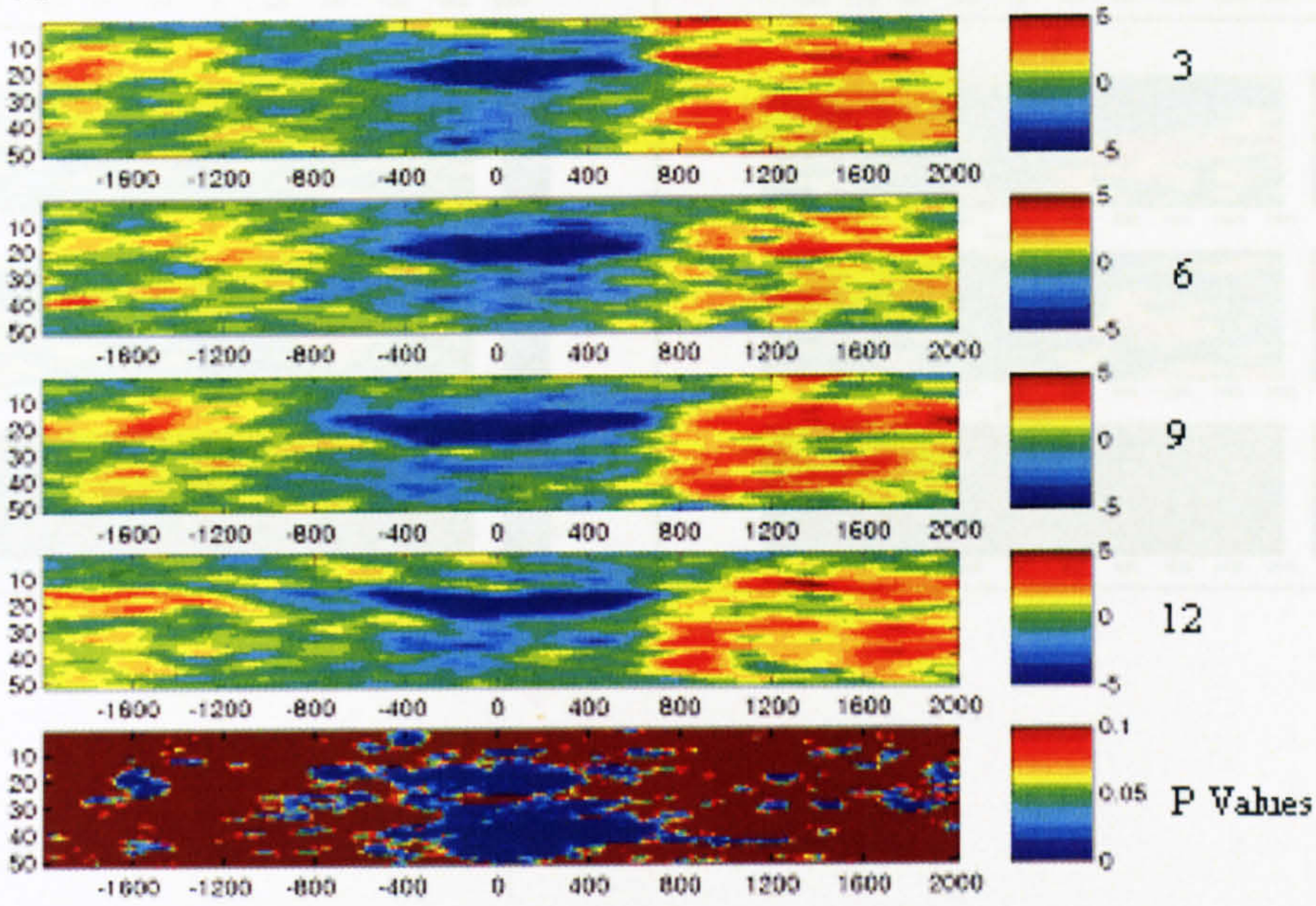
Subject 8



Subject 9



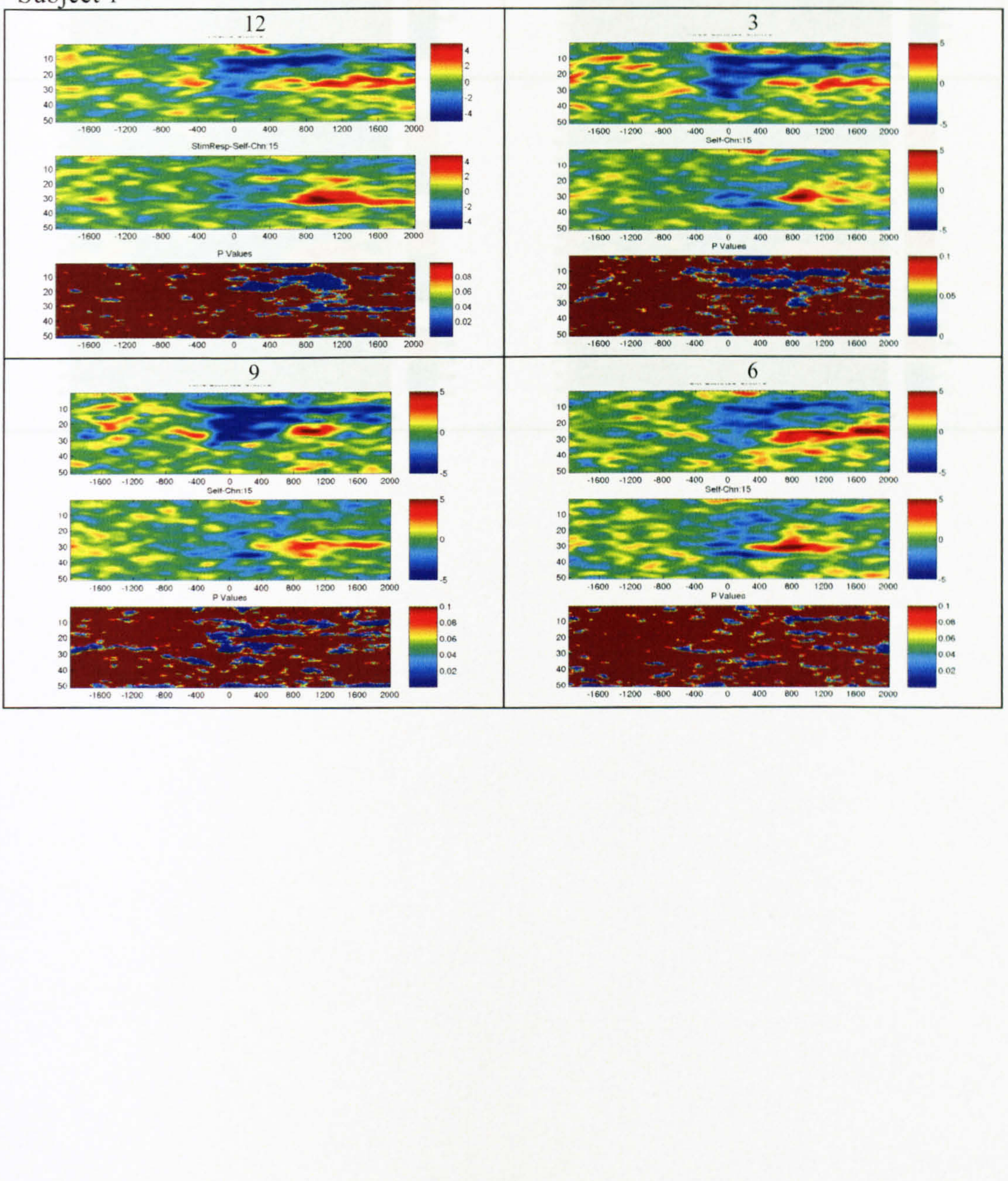
Subject 10



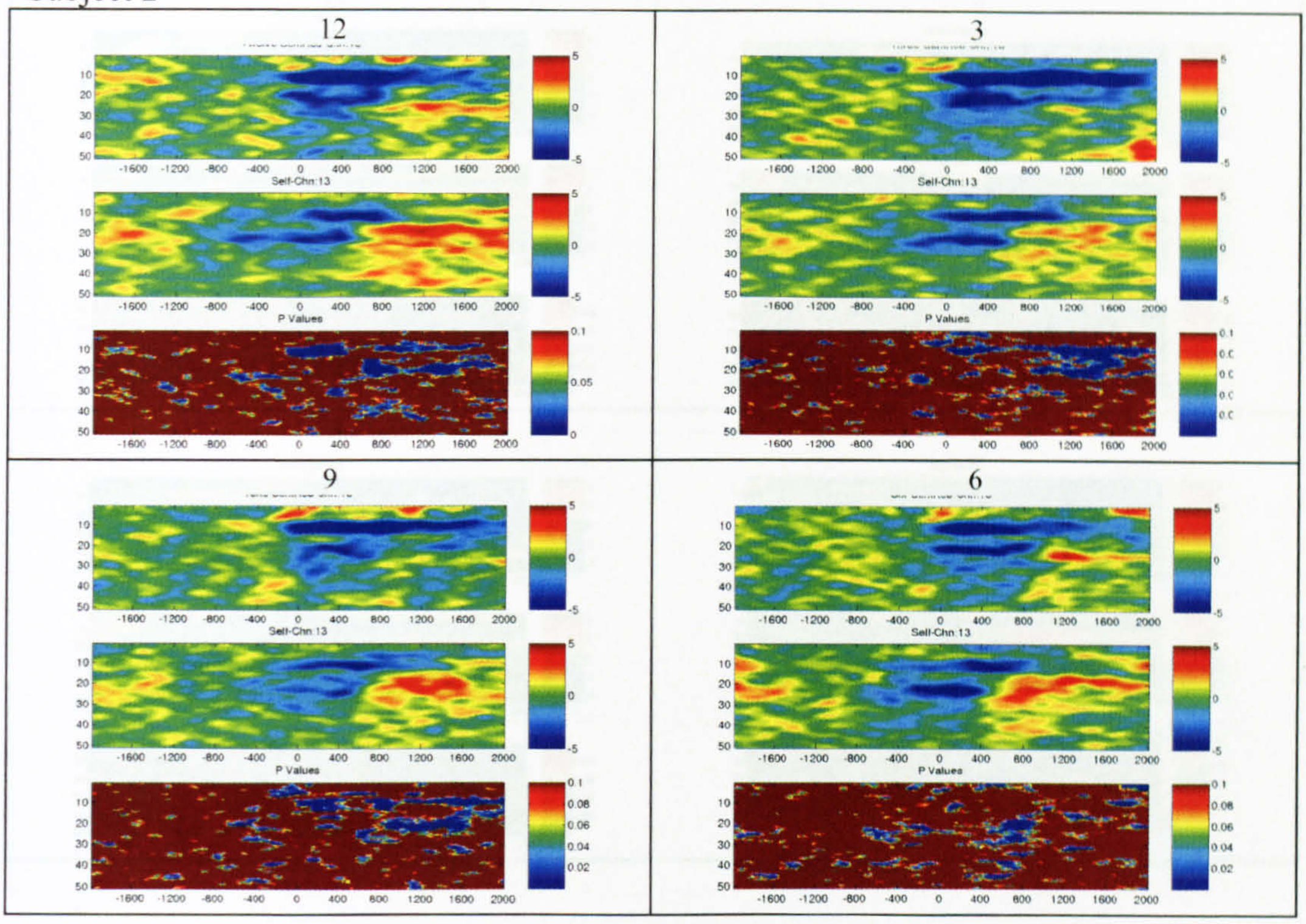
Externally Cued Vs Self Determined

The following results compare the ERSP for the CAR EEG from C3 during Externally cued and Self-Paced movement trials for the different experiments. (t = 0: movement init)

Subject 1

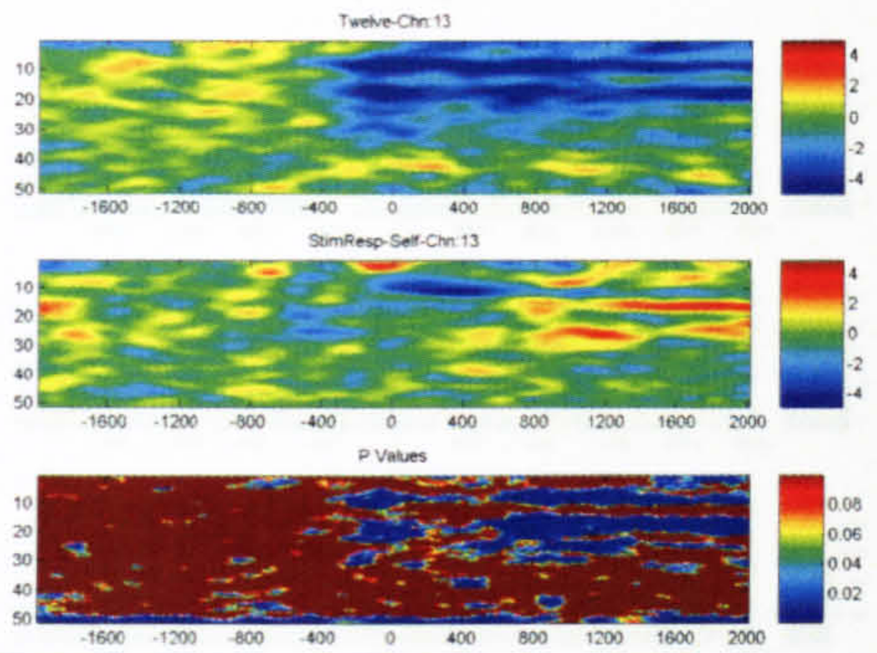


Subject 2

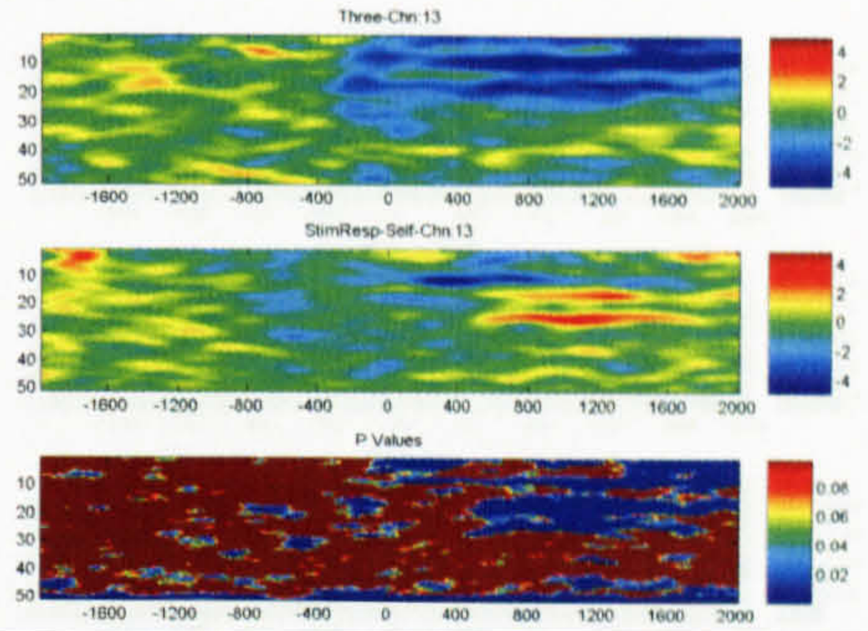

12
Self-Chn:13
P Values
3
Self-Chn:13
P Values
9
Self-Chn:13
P Values
6
Self-Chn:13
P Values

Subject 3

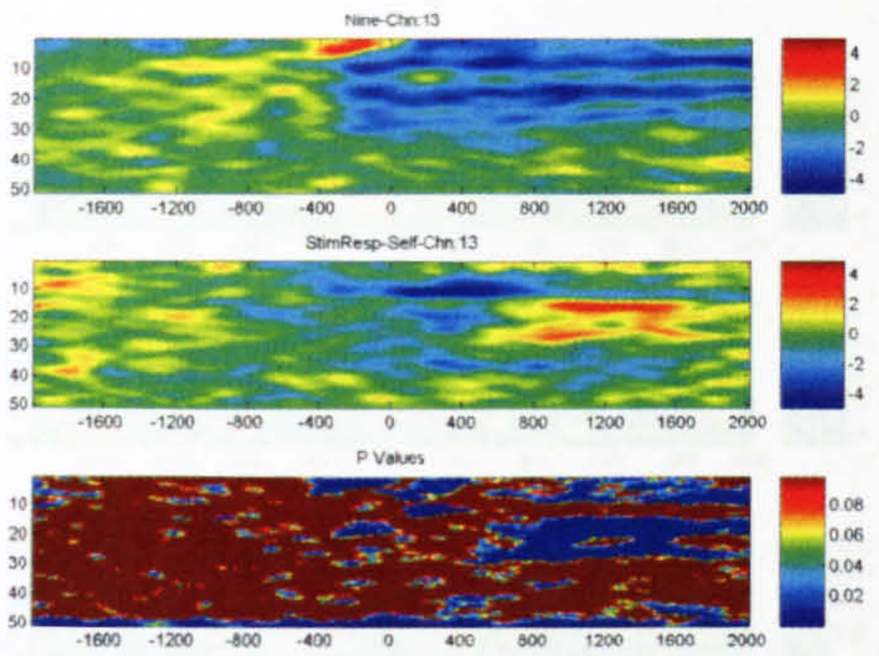
12



3



9



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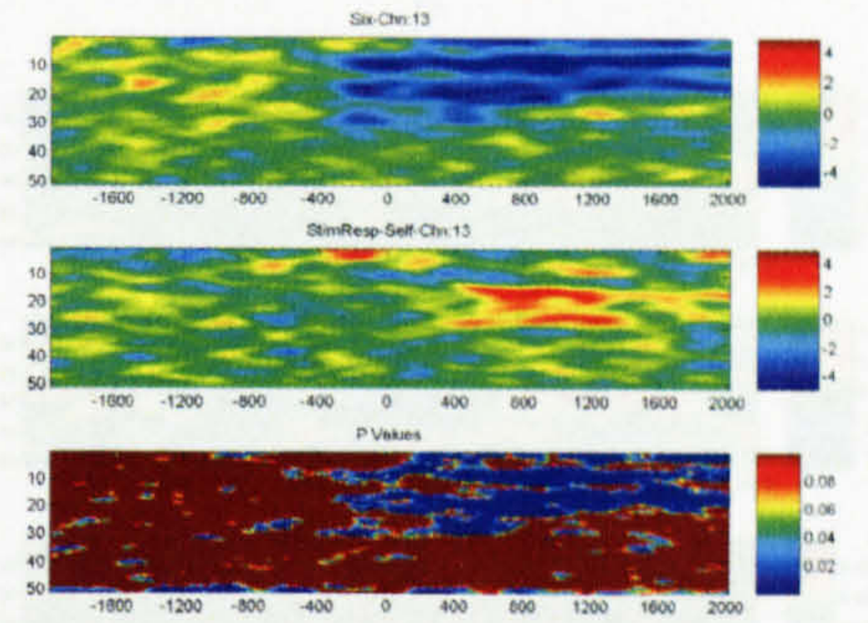
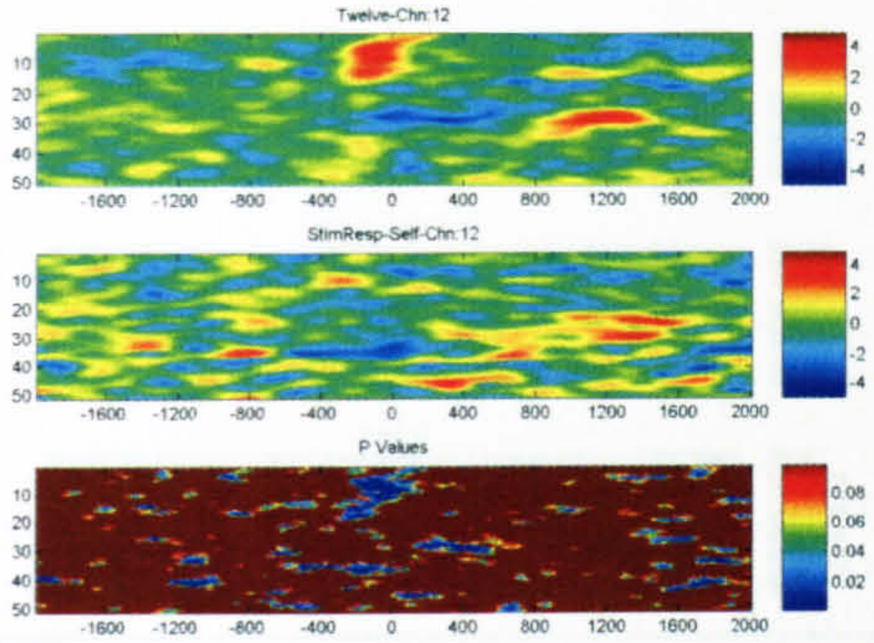
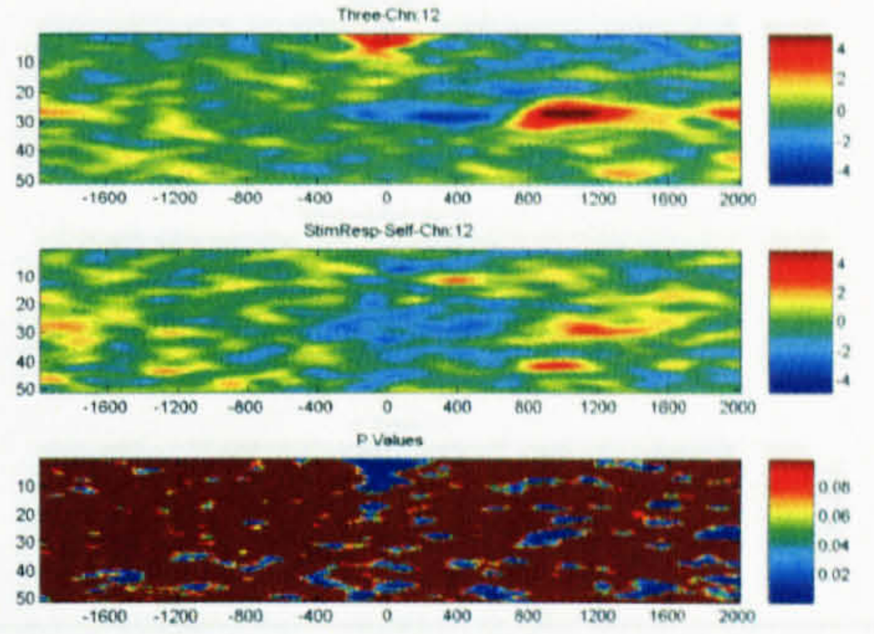


Subject 8

12



3



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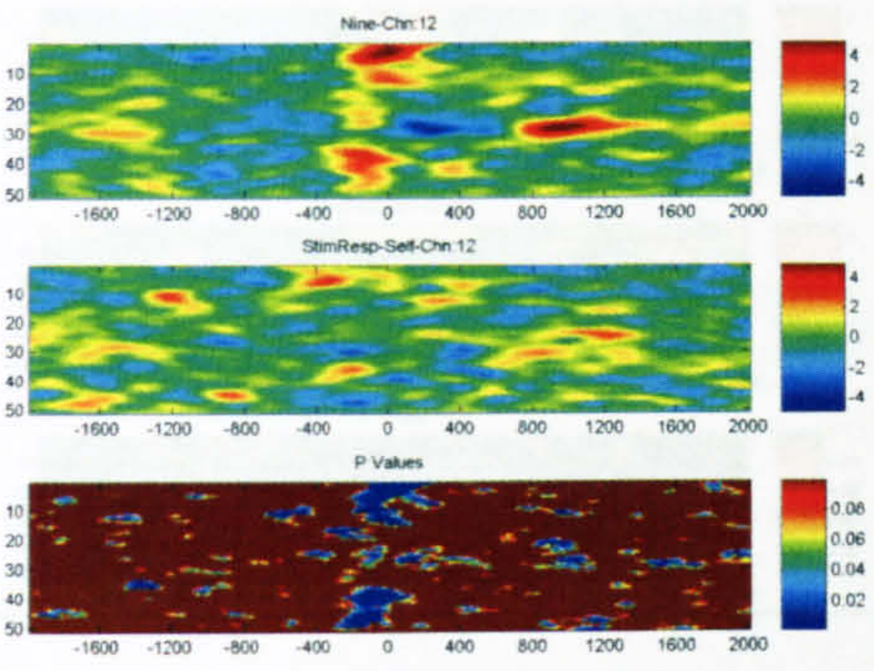

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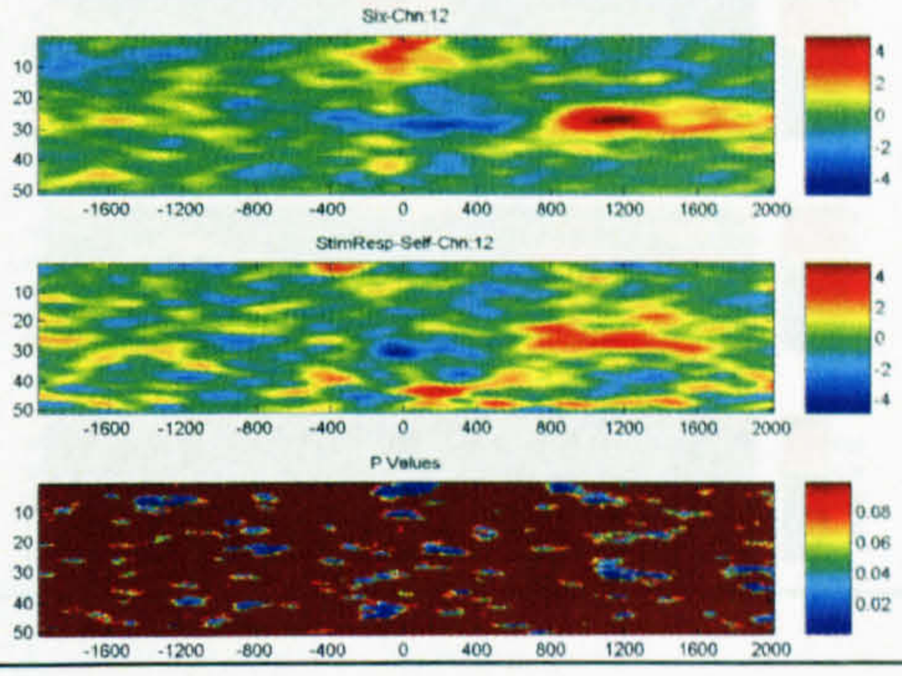
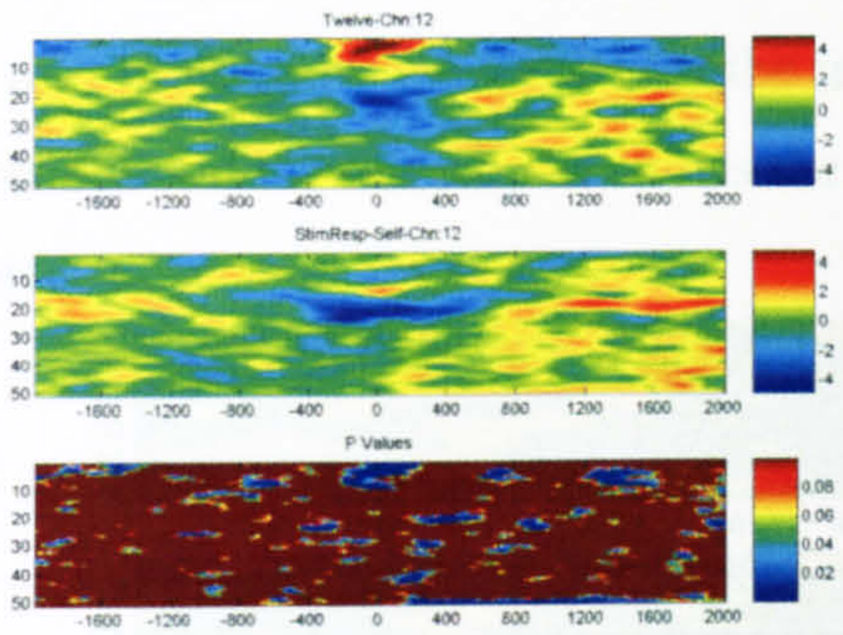


Subject 10

12



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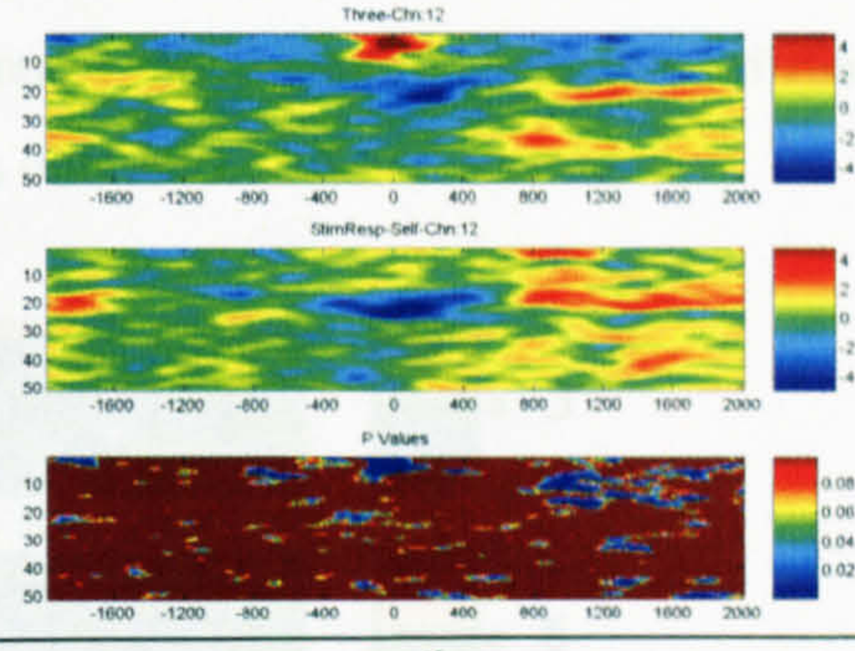
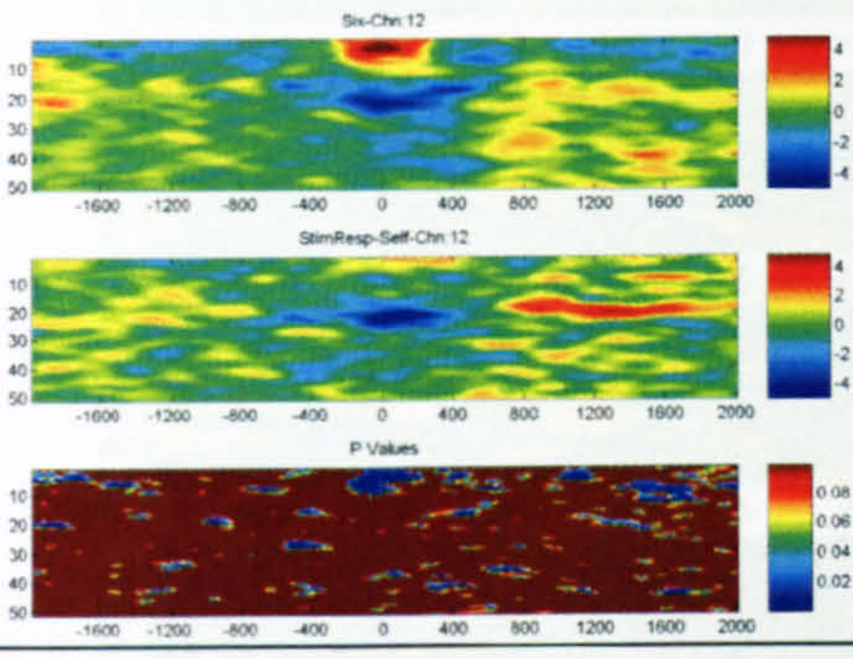
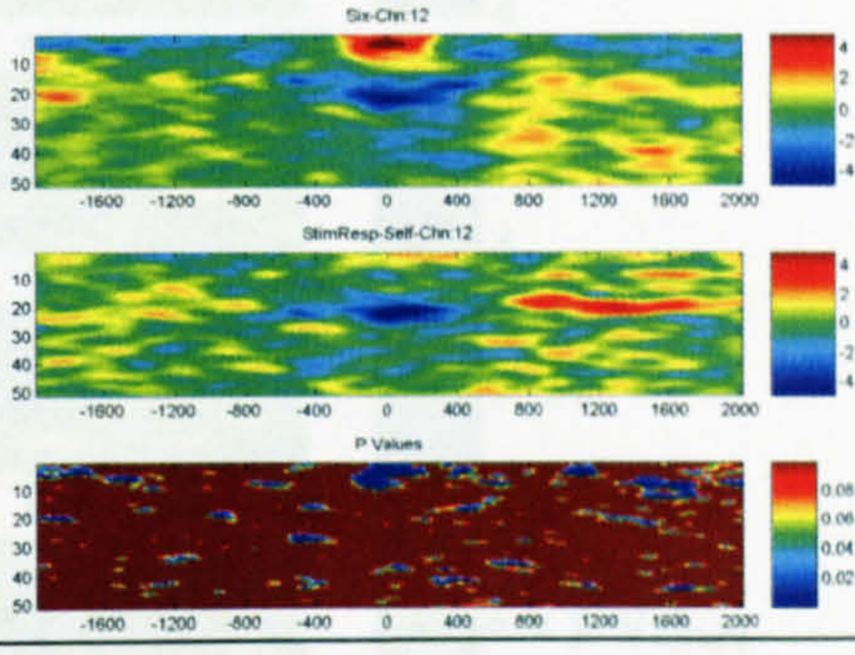


9



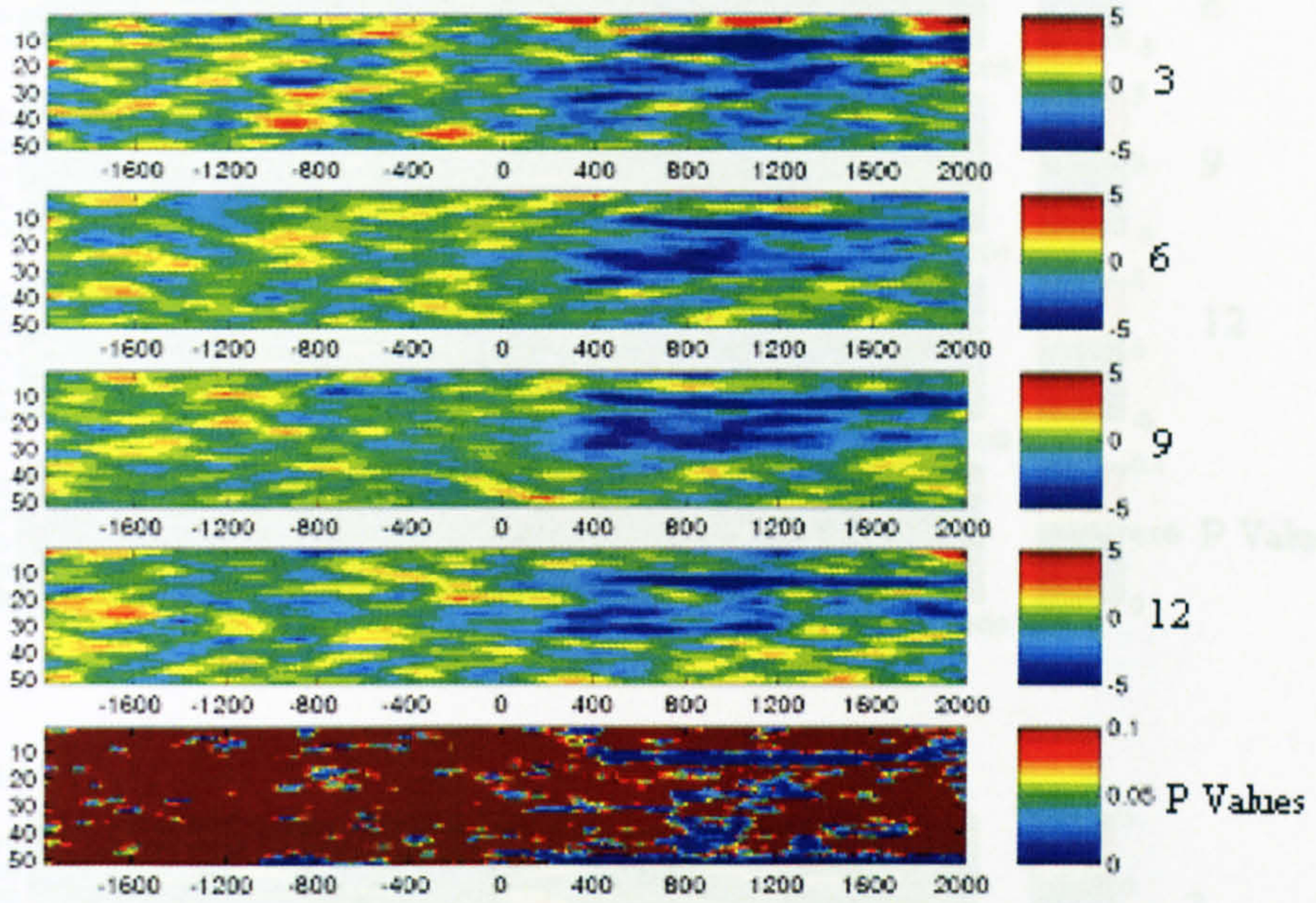
6



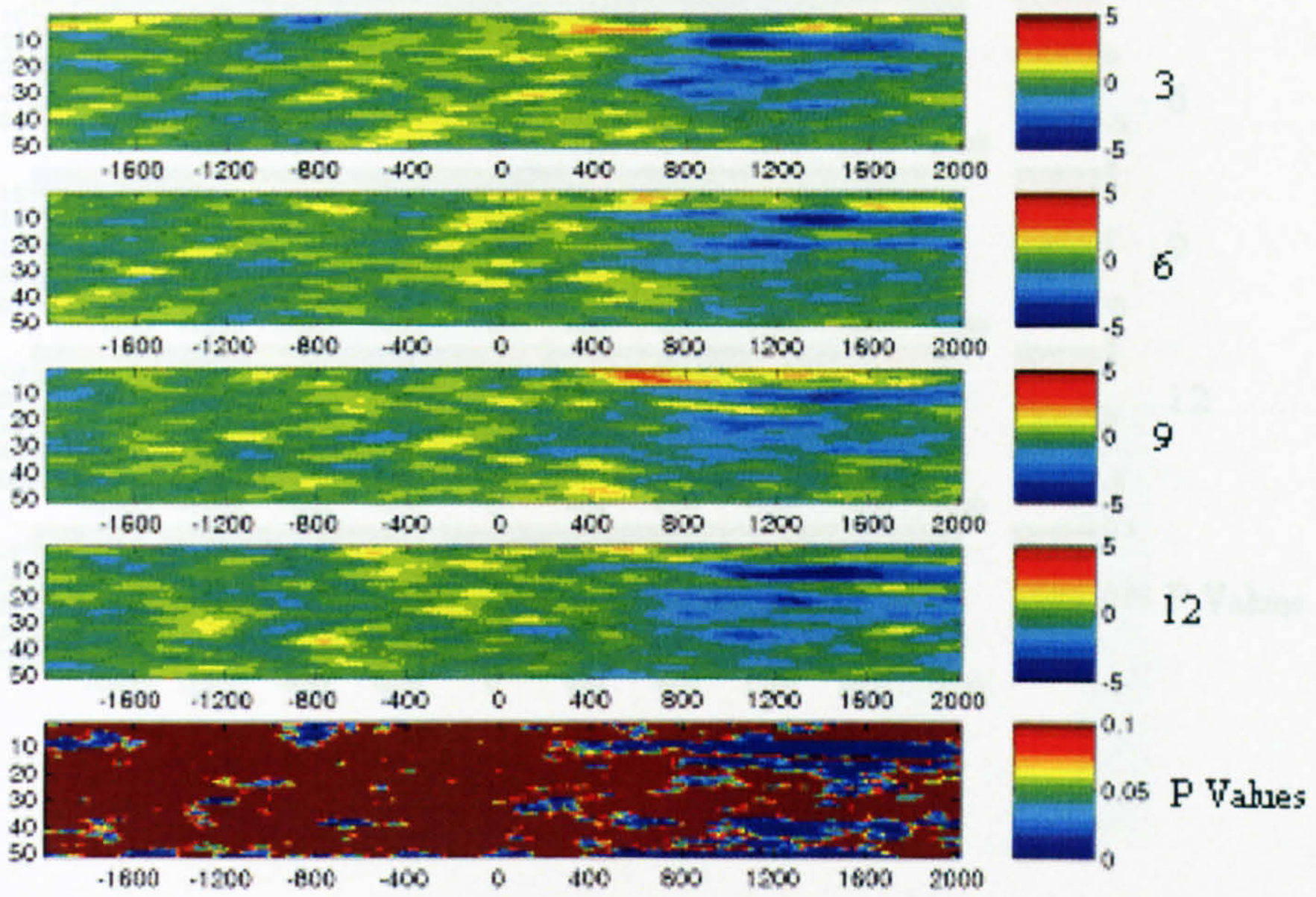
Imagination

The results presented in this section are from statistical comparison of the ERSP. The top four plots show the ERSP for the imagination of movement towards the 4 different directions and the lowest plot shows the P values obtained.

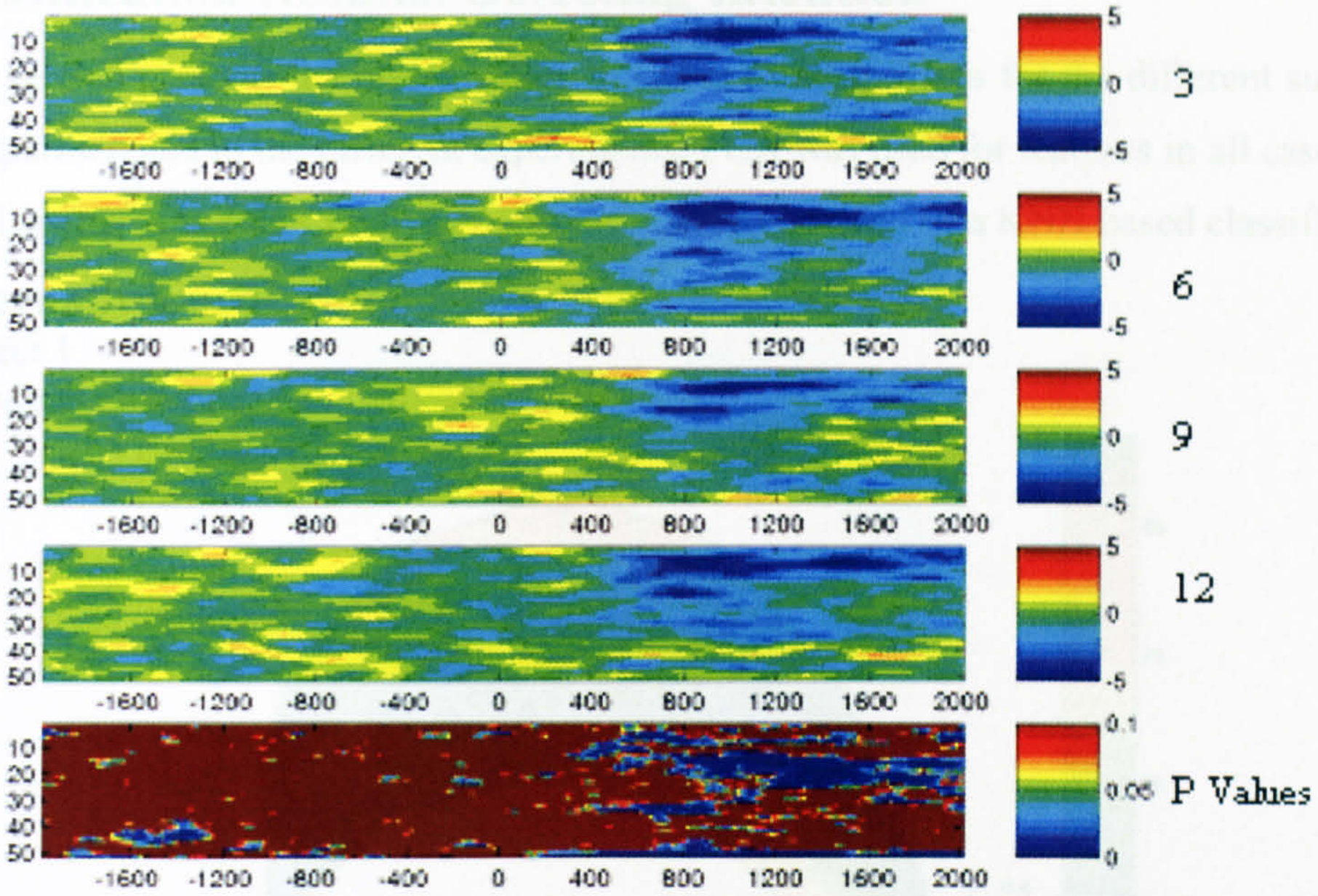
Subject 1



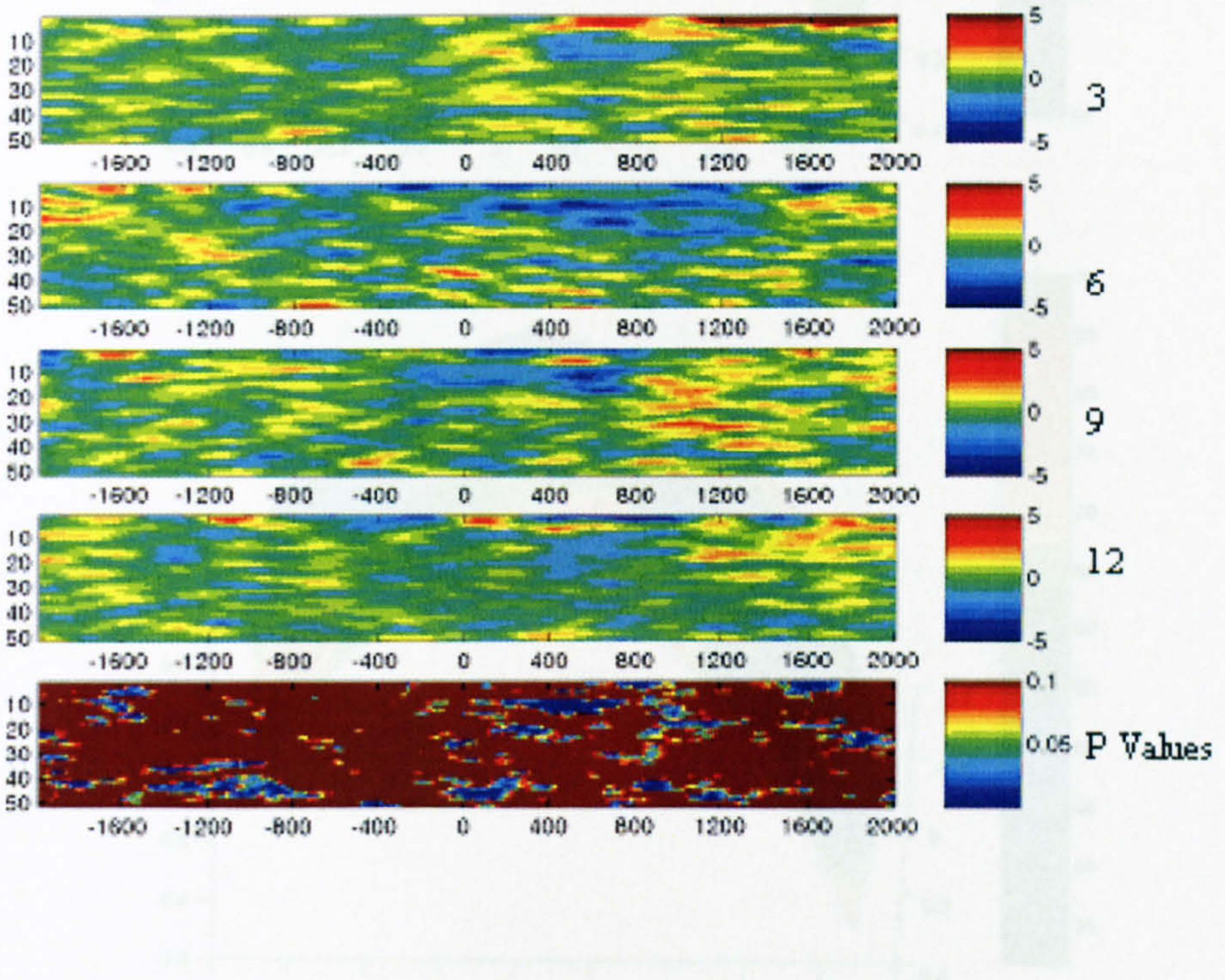
Subject 2



Subject 3



Subject 5



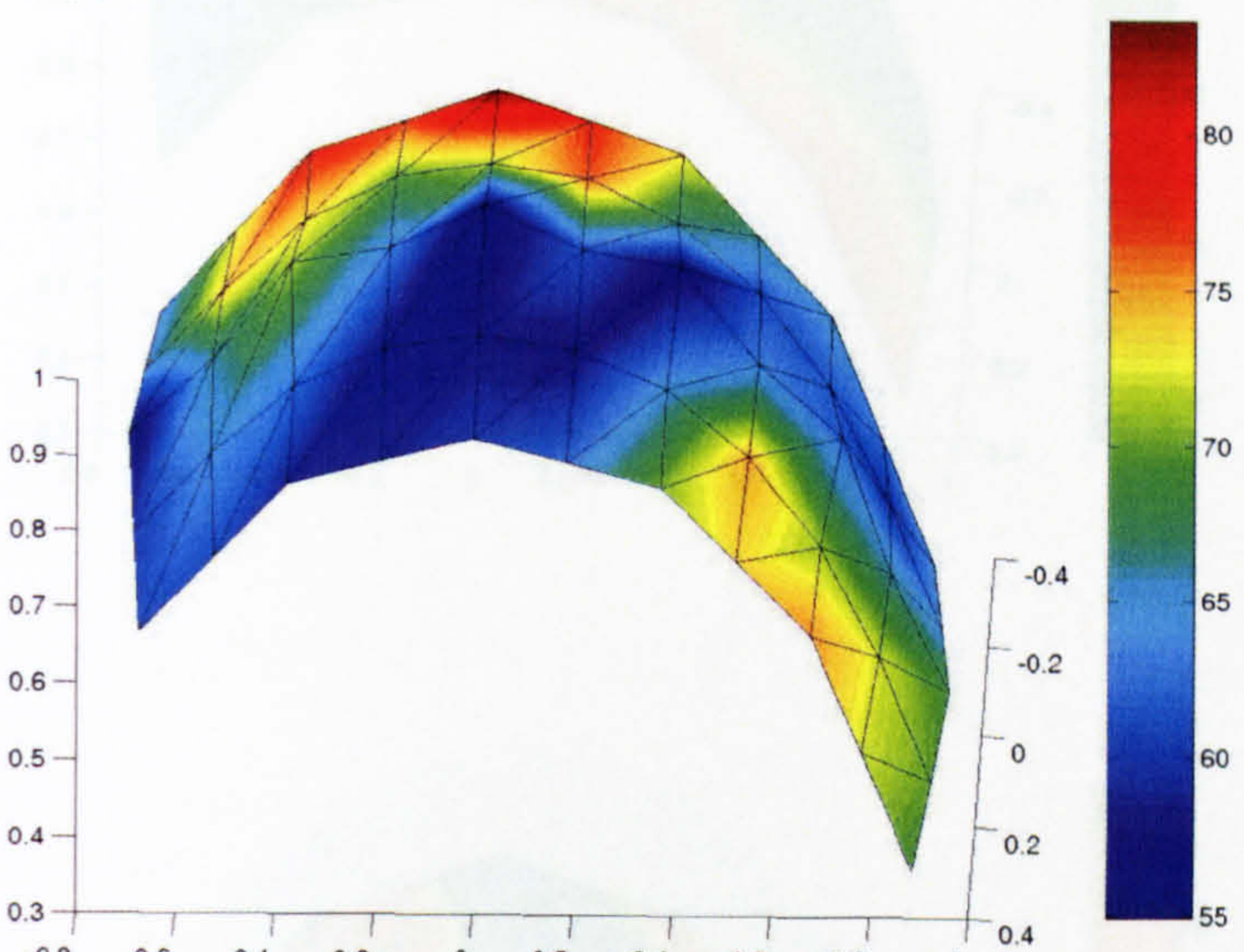
Classification Results: Detecting Intention

This section presents the classification attempts as scalp maps for the different subjects who participated in the different experiments. PCA was used for features in all cases and the classifier was either Euclidean distance based classifier or a KNN based classifier.

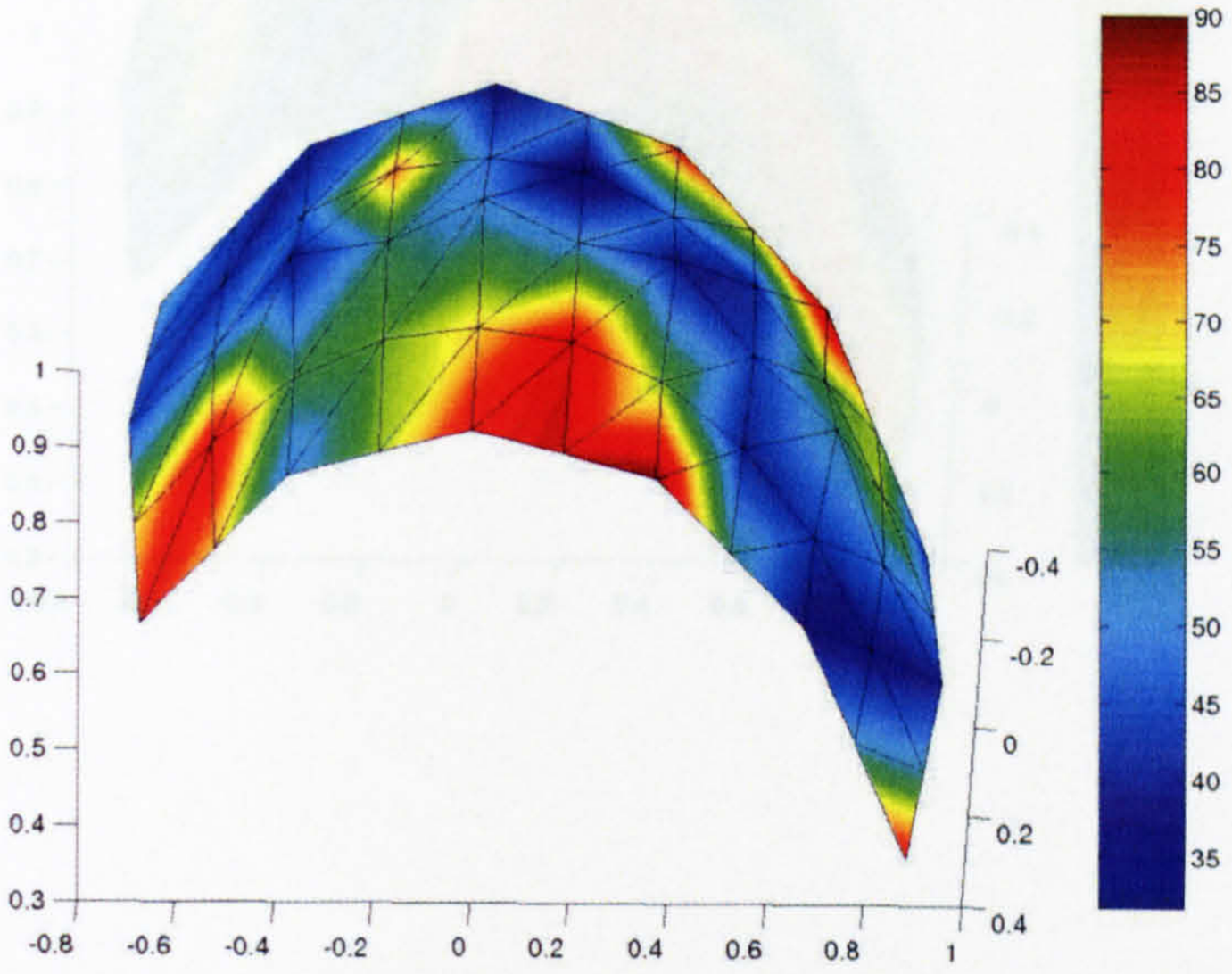
Externally Cued

Subject 1

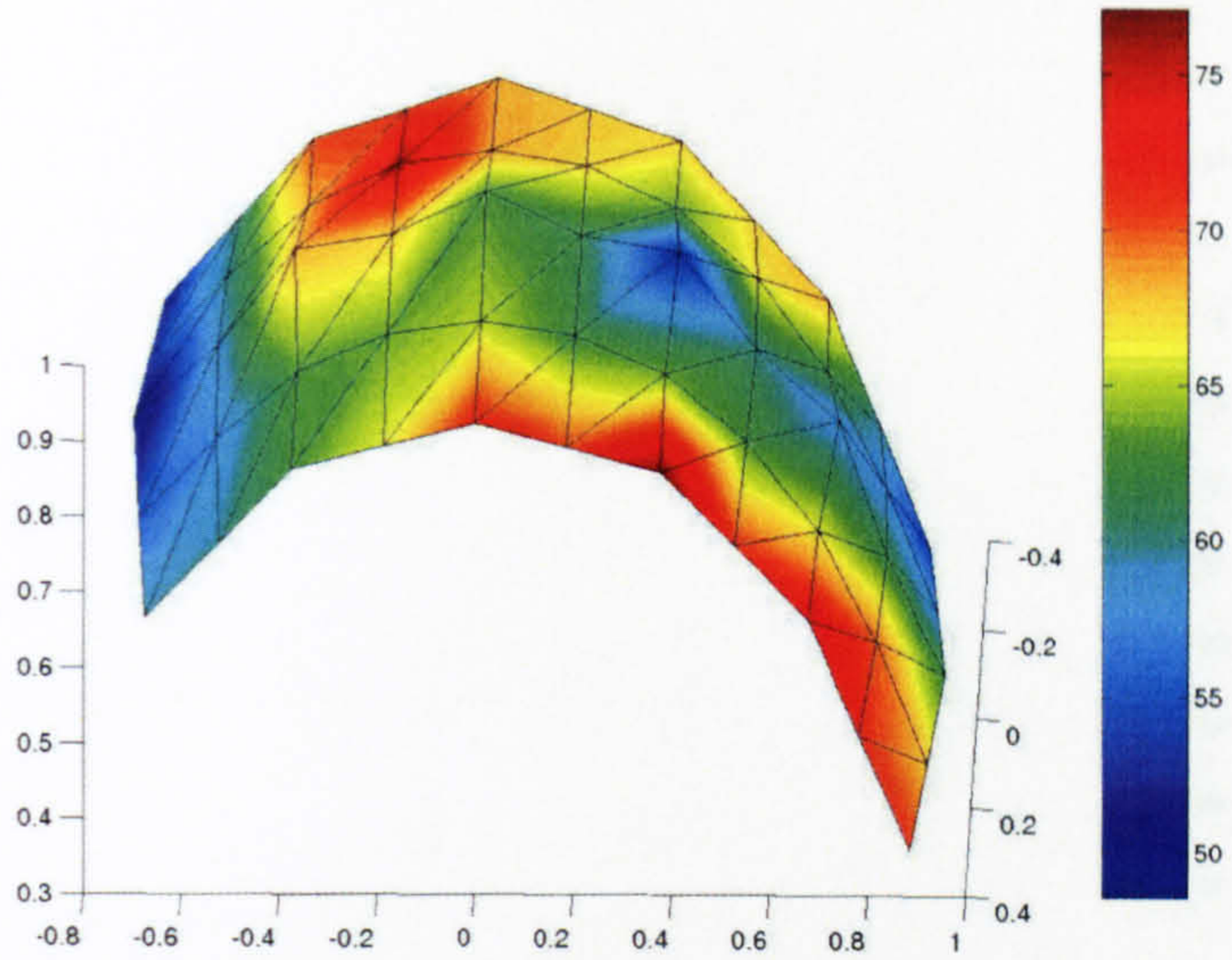
Euclidean Distance



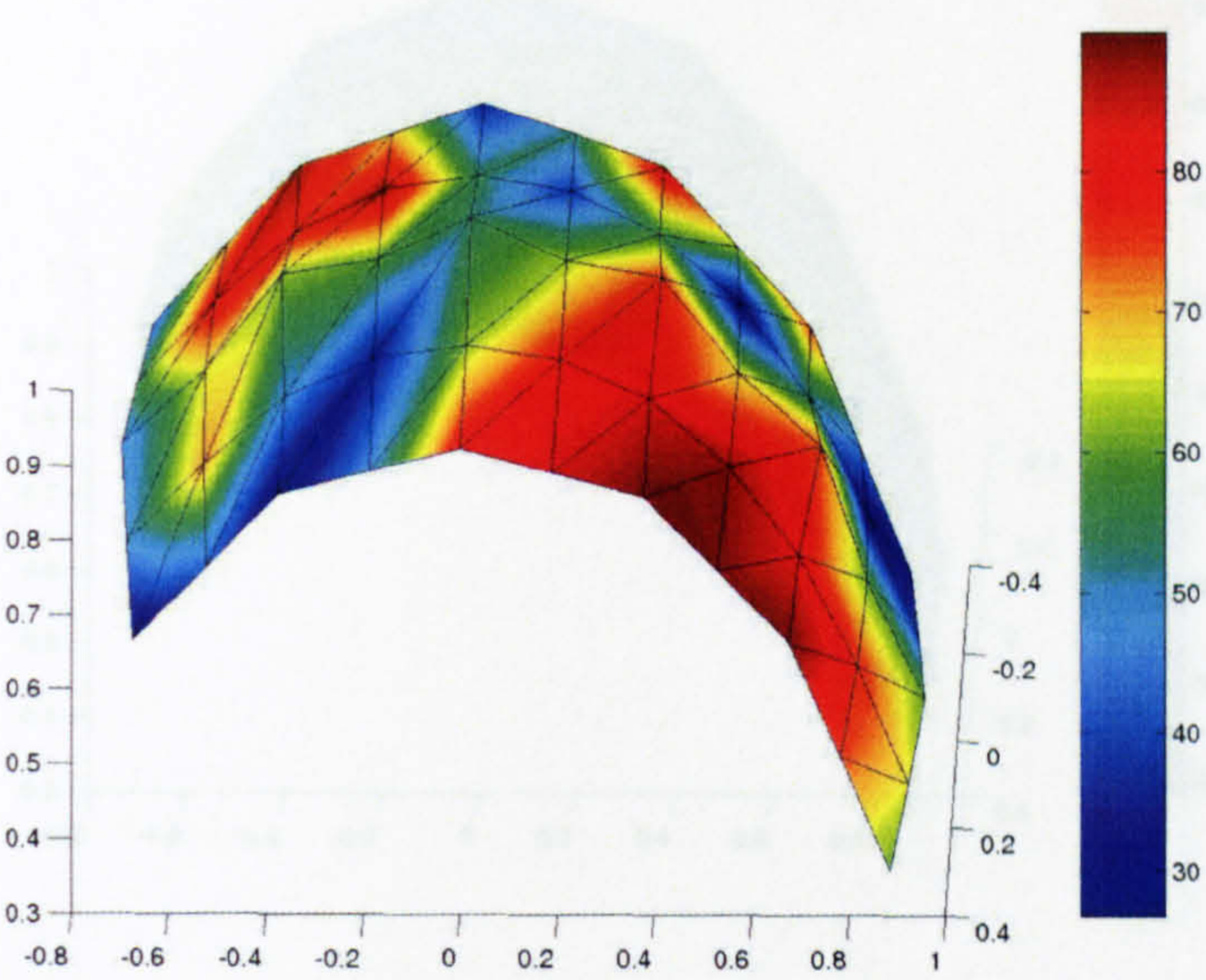
KNN



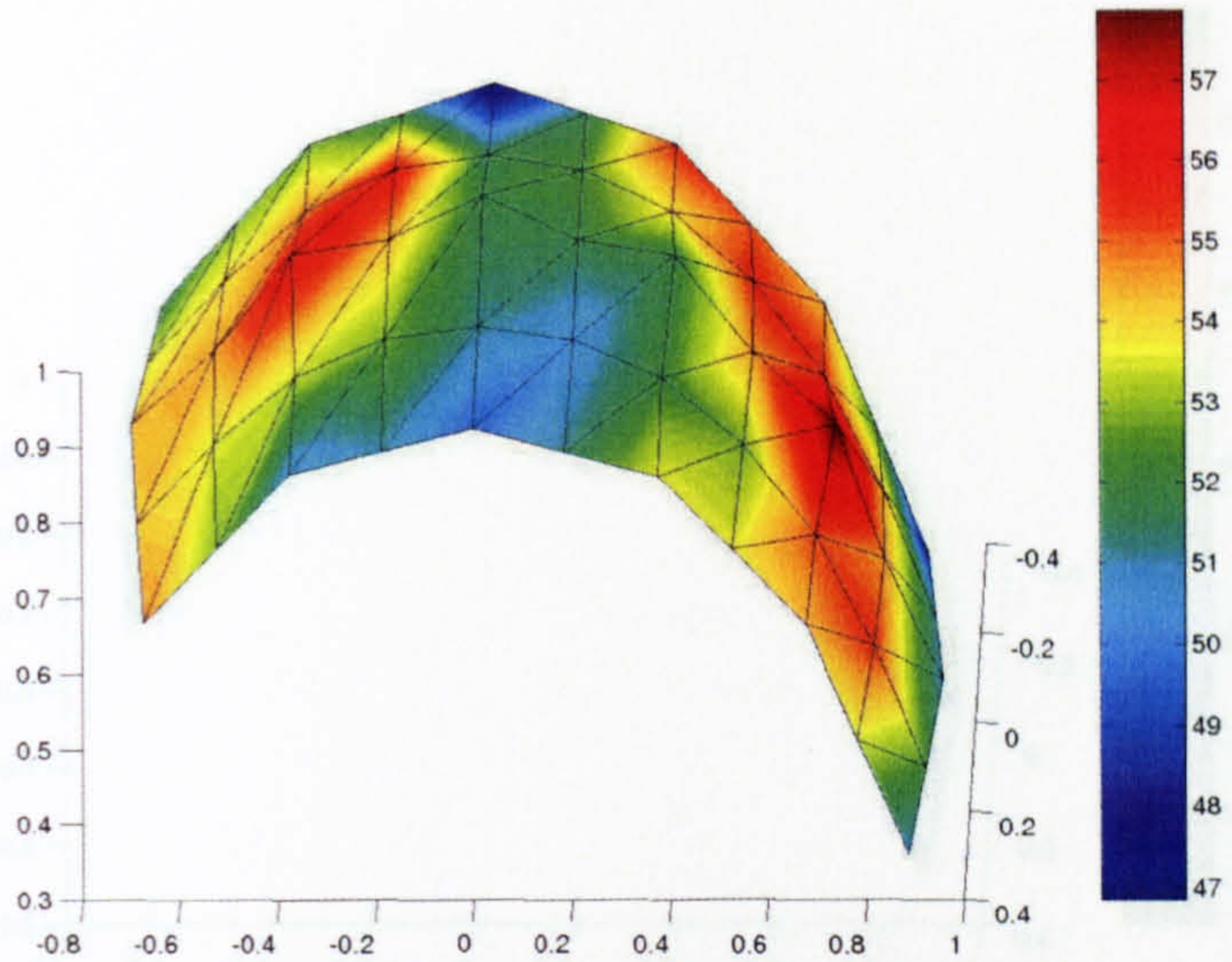
Subject 2
Euclidean Distance



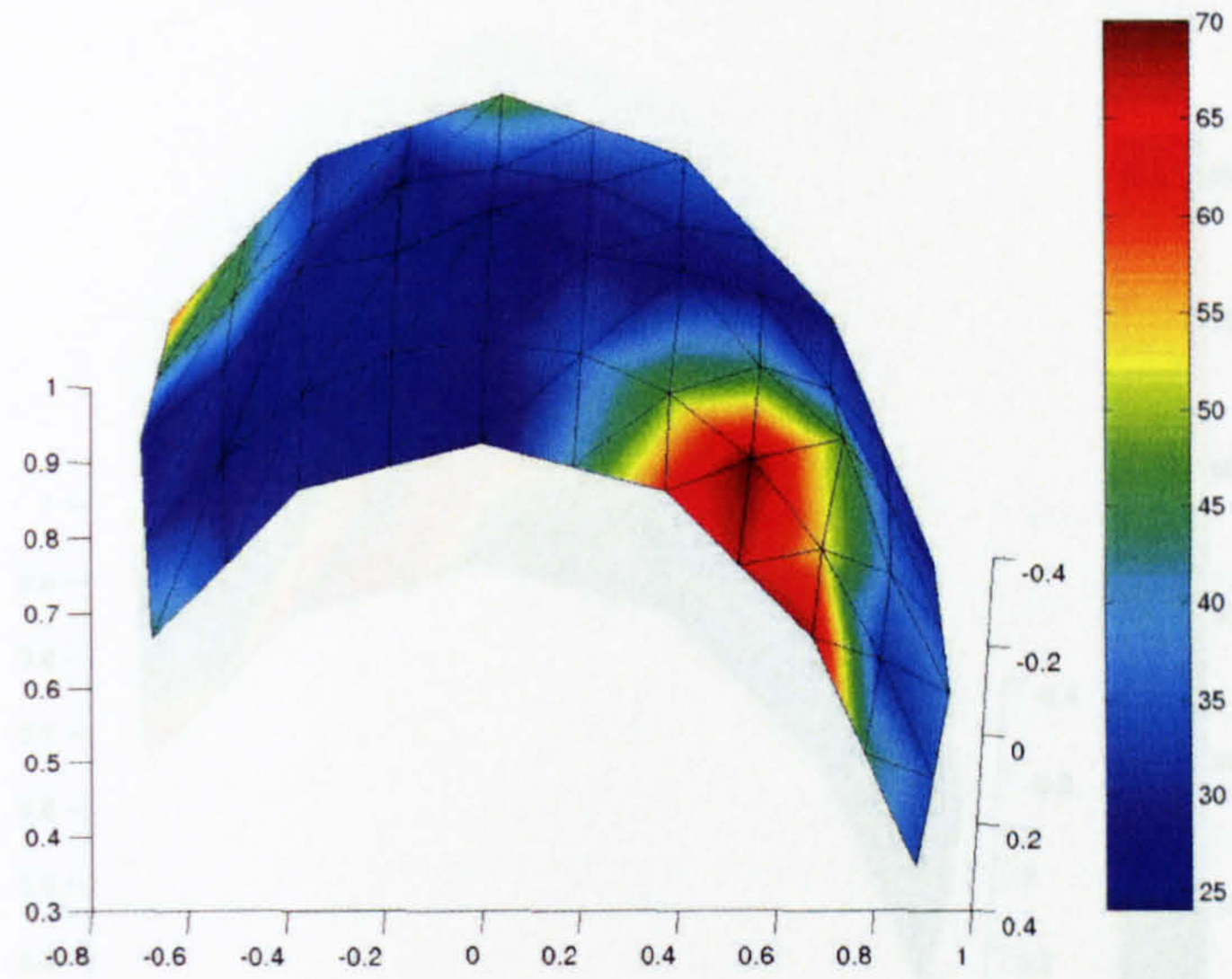
KNN



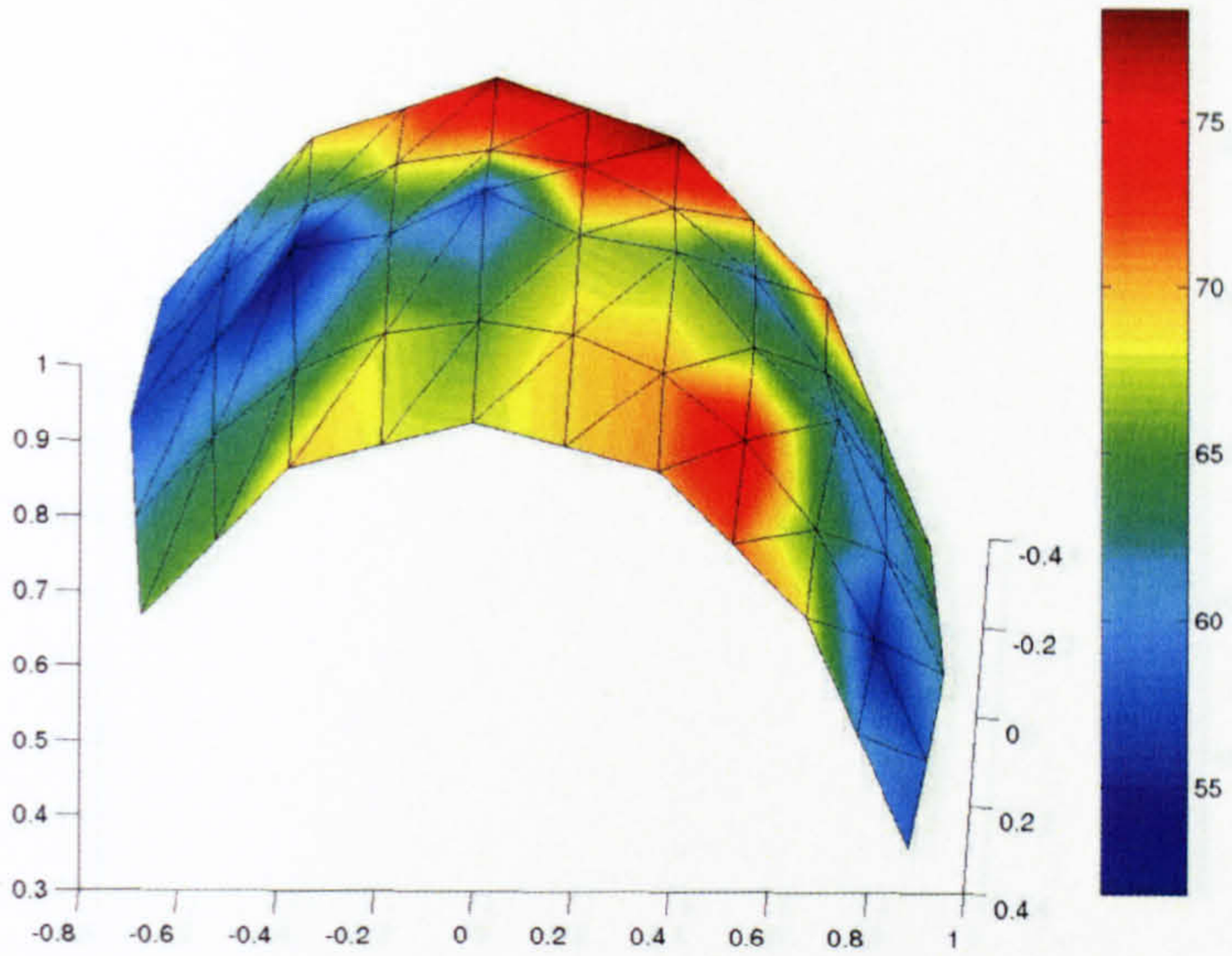
Subject 3
Euclidean Distance



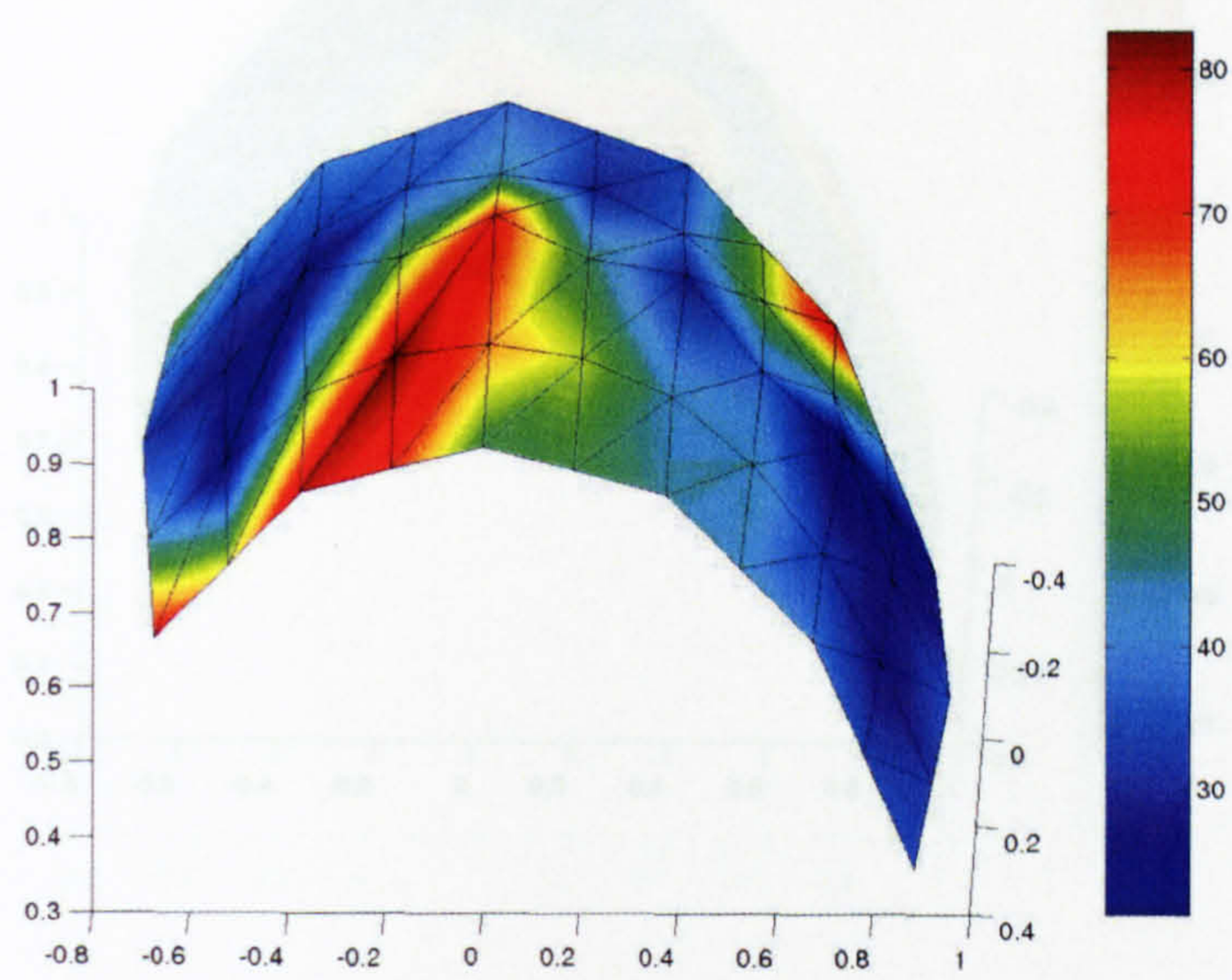
KNN



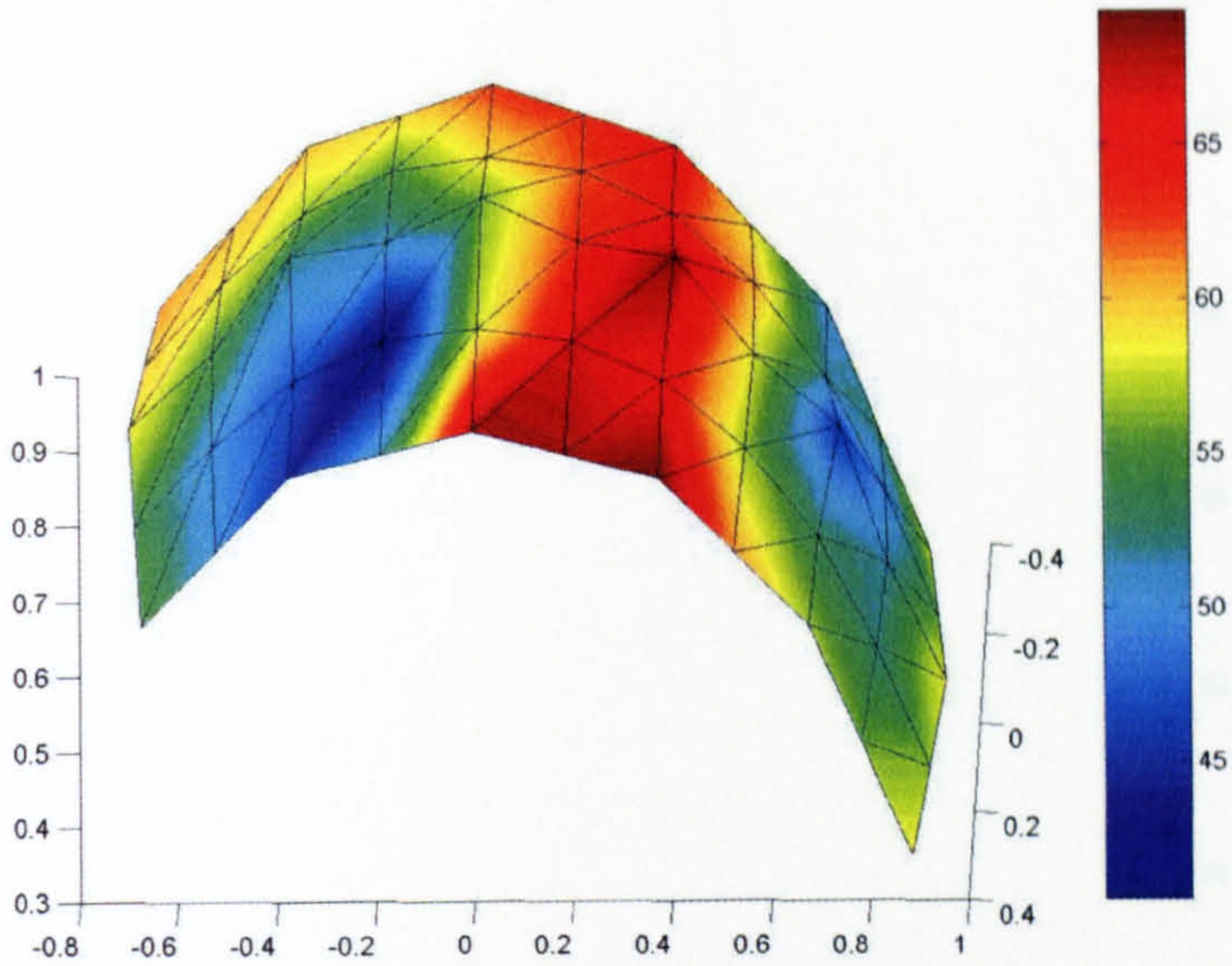
Subject 4
Euclidean Distance



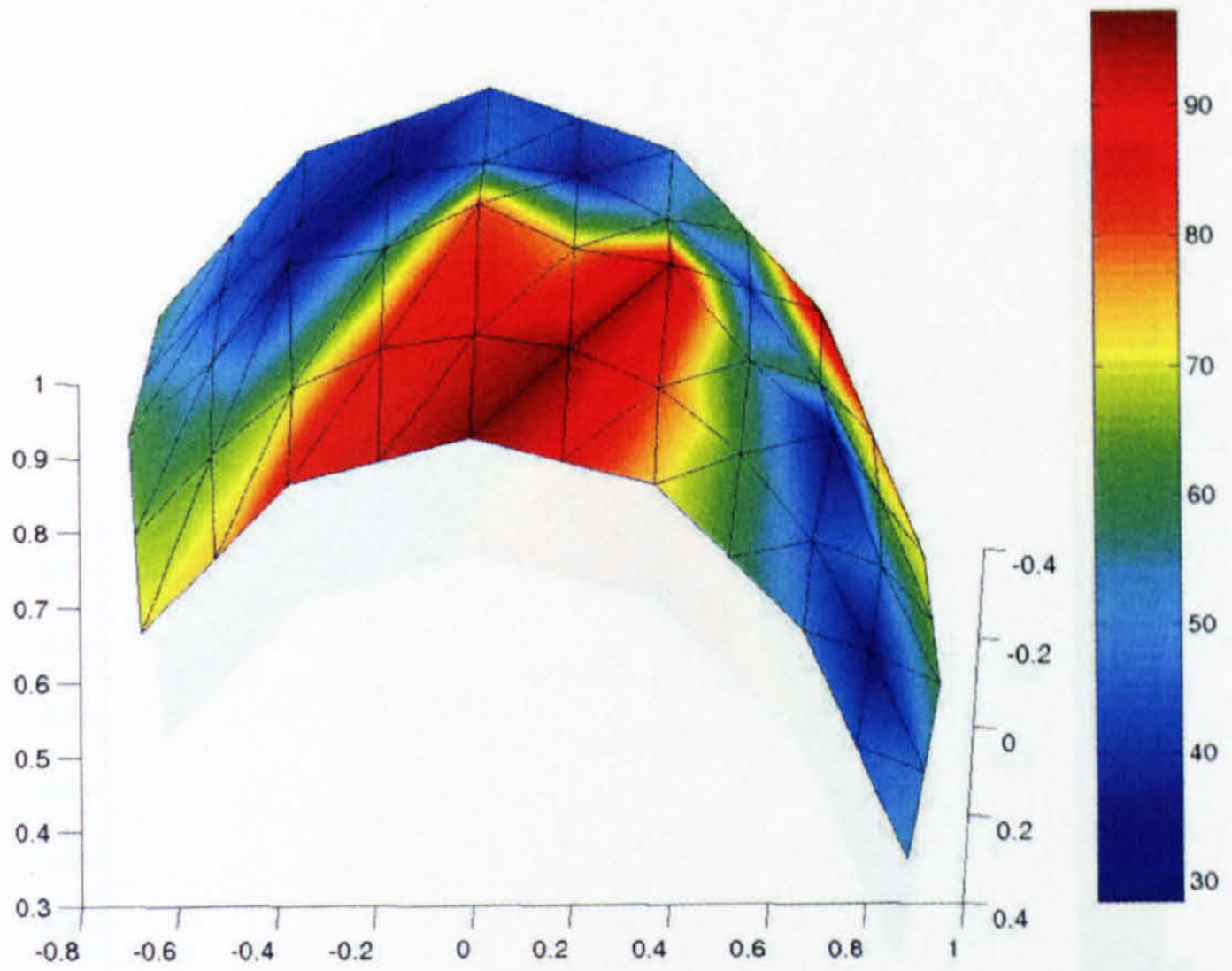
KNN



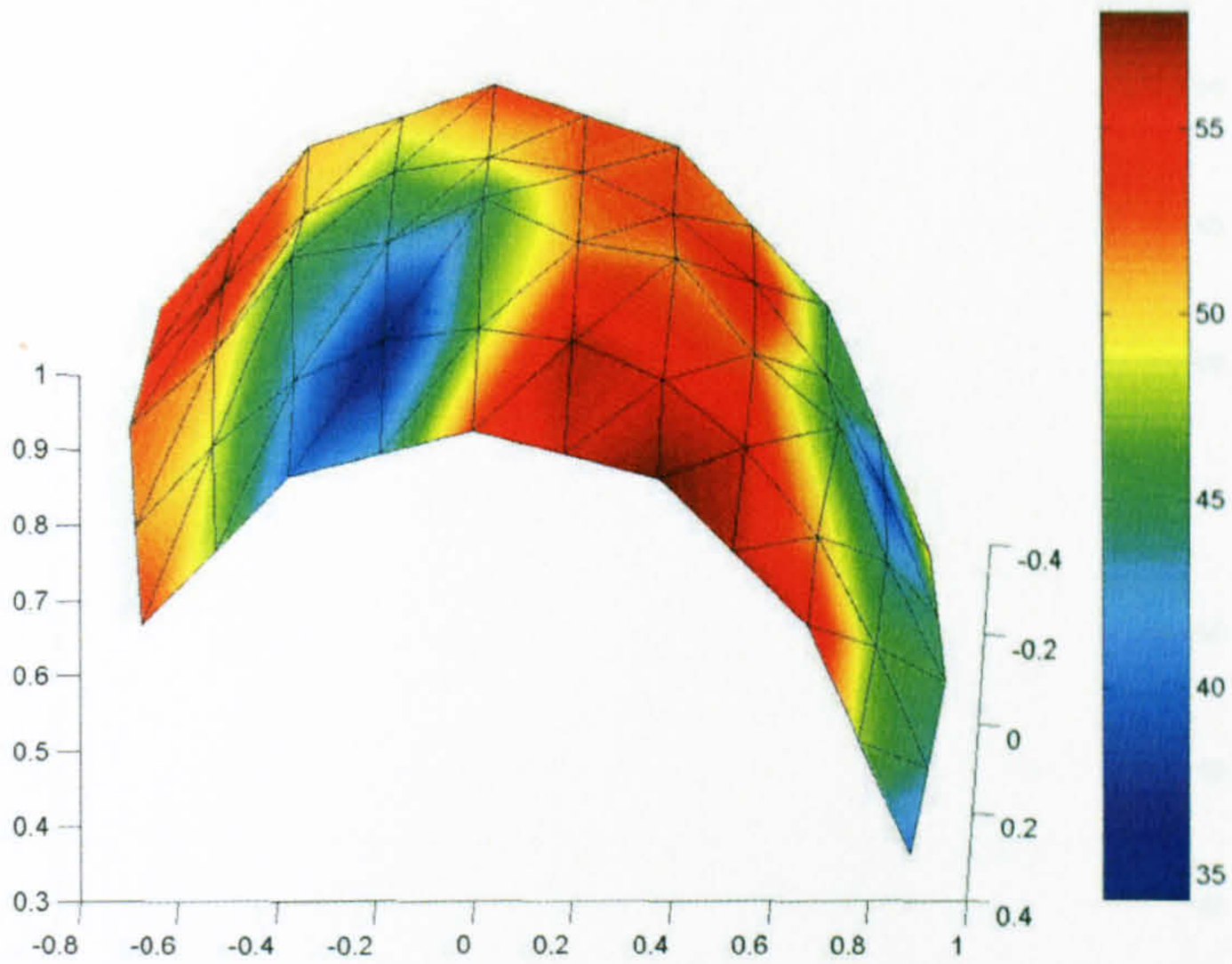
Subject 5
Euclidean Distance



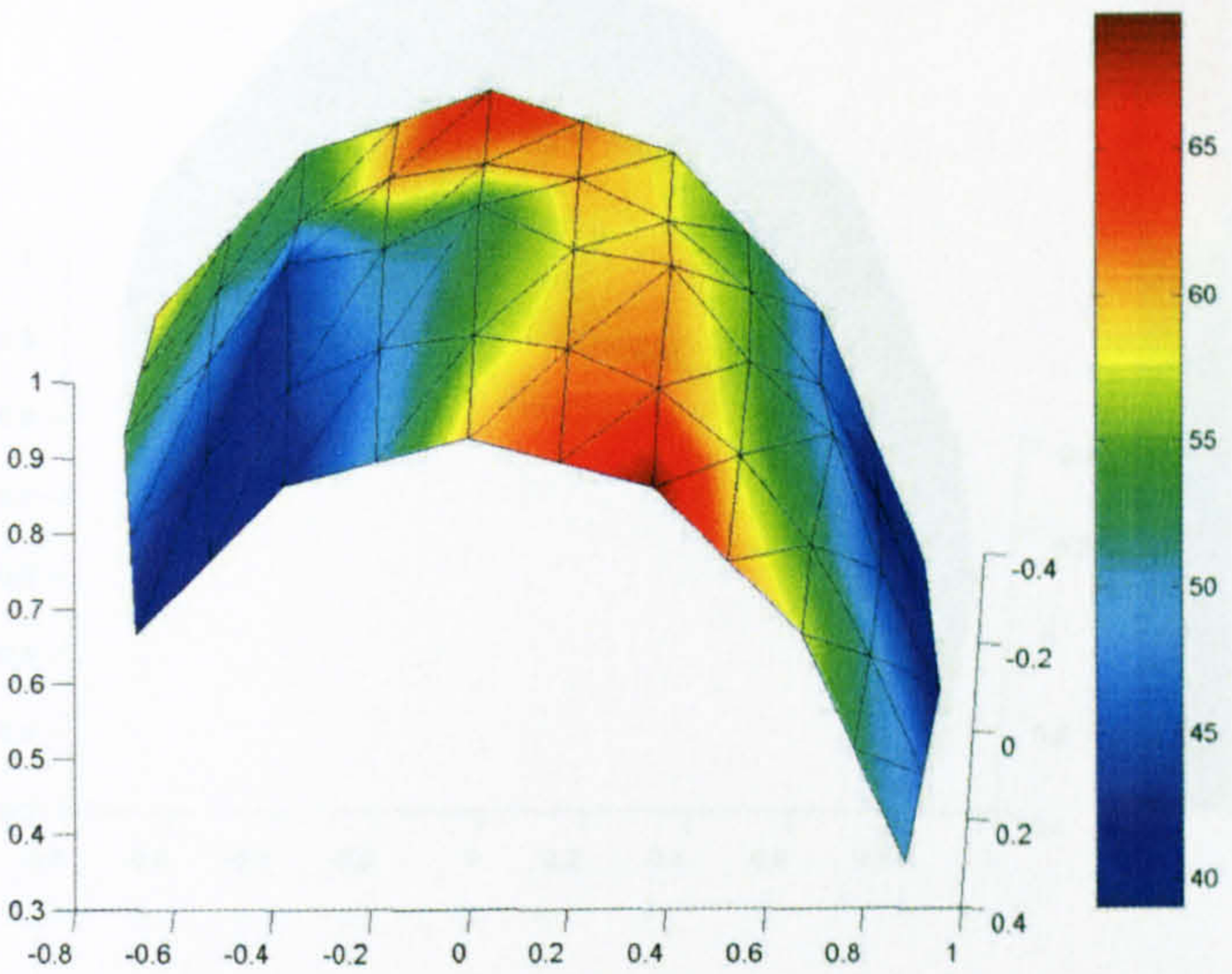
KNN



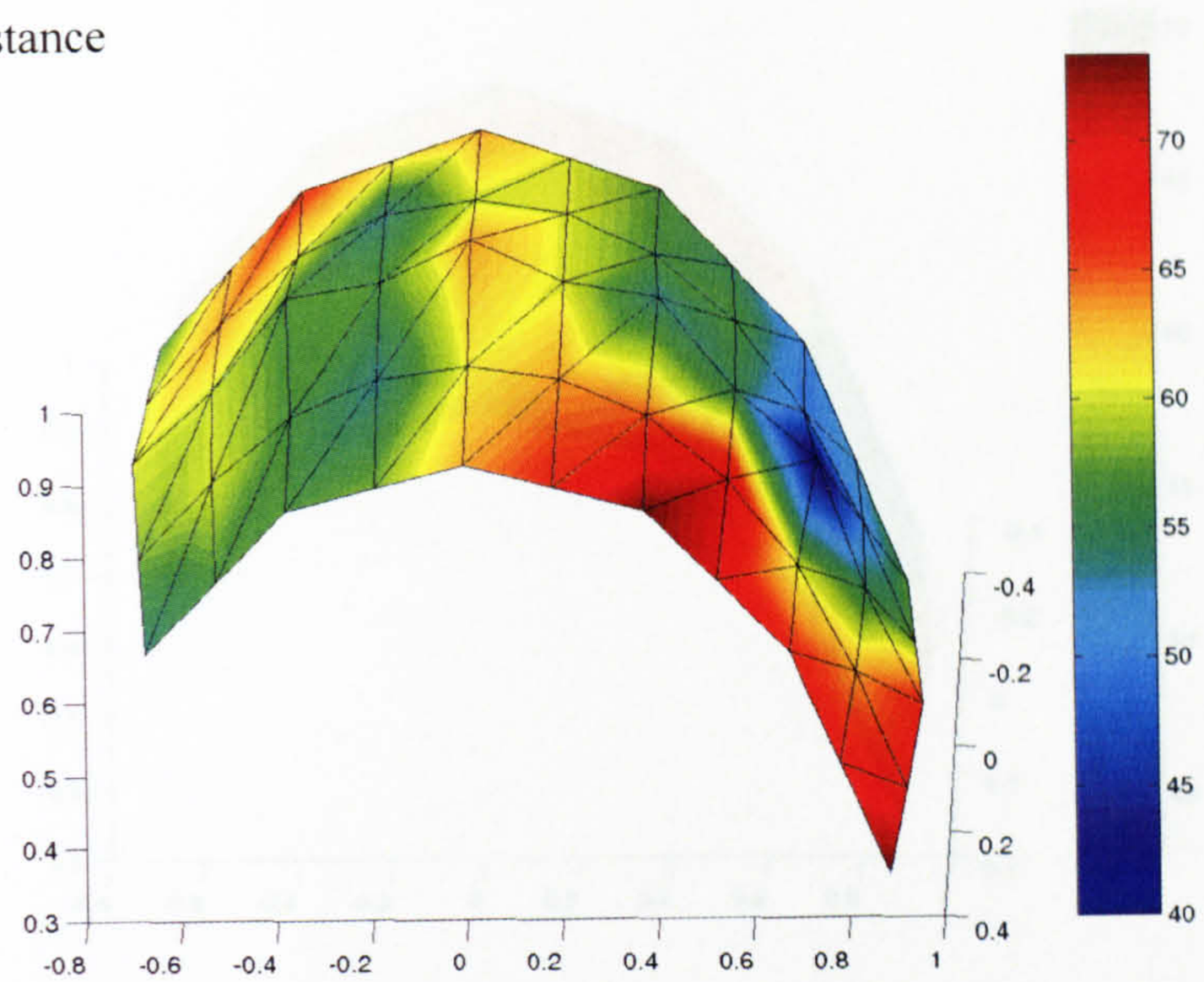
Subject 6
Euclidean Distance



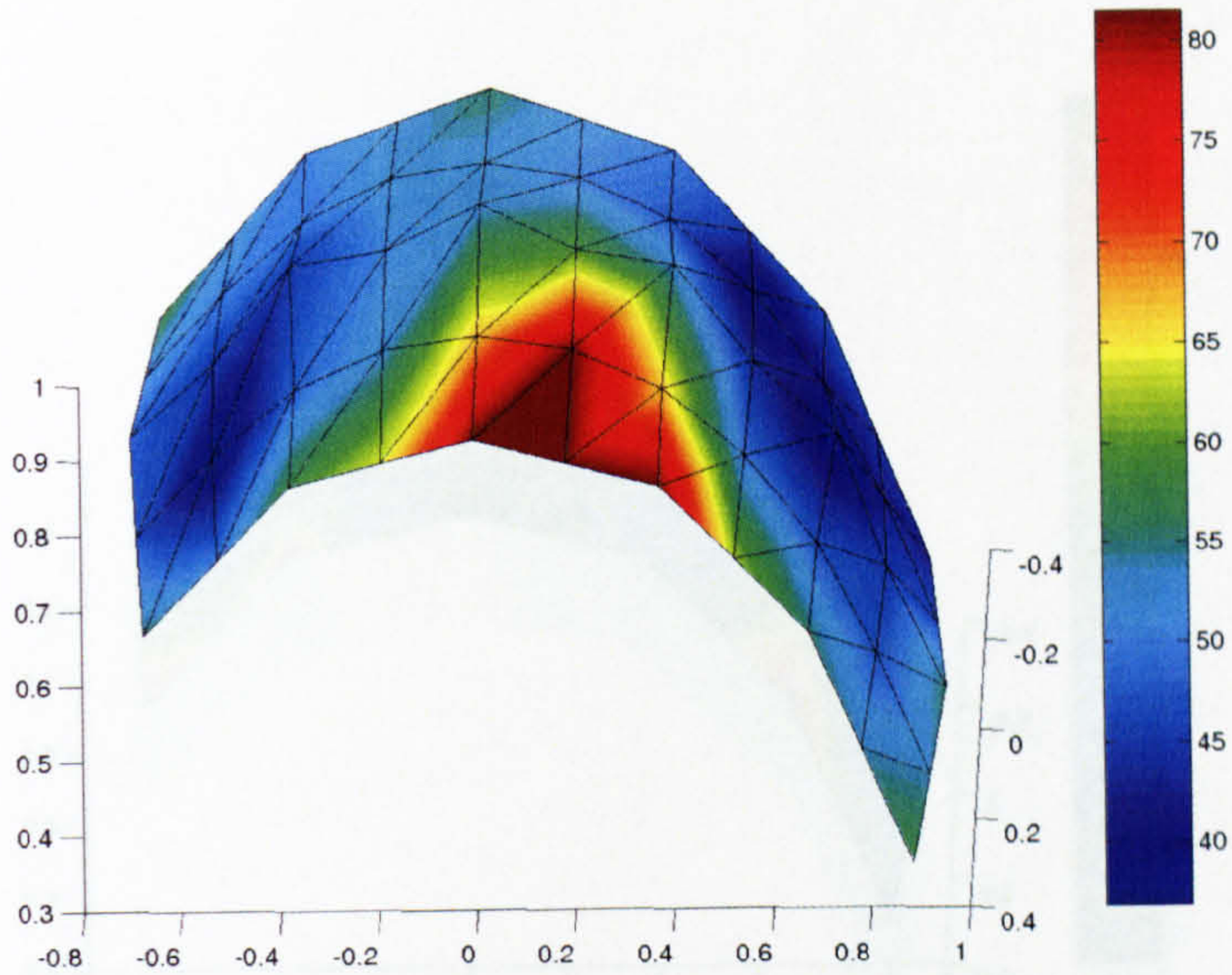
KNN



Subject 7
Euclidean Distance

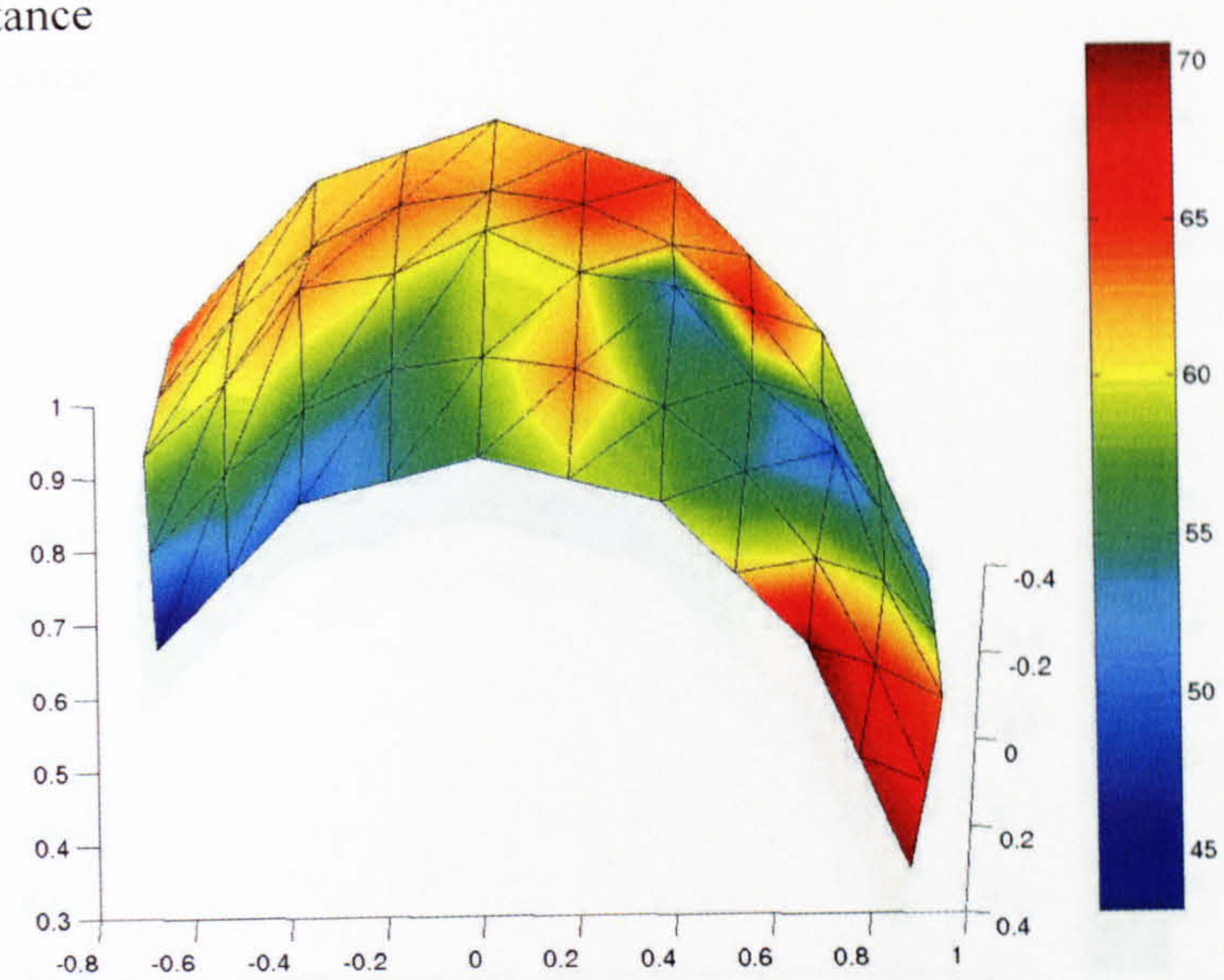


KNN

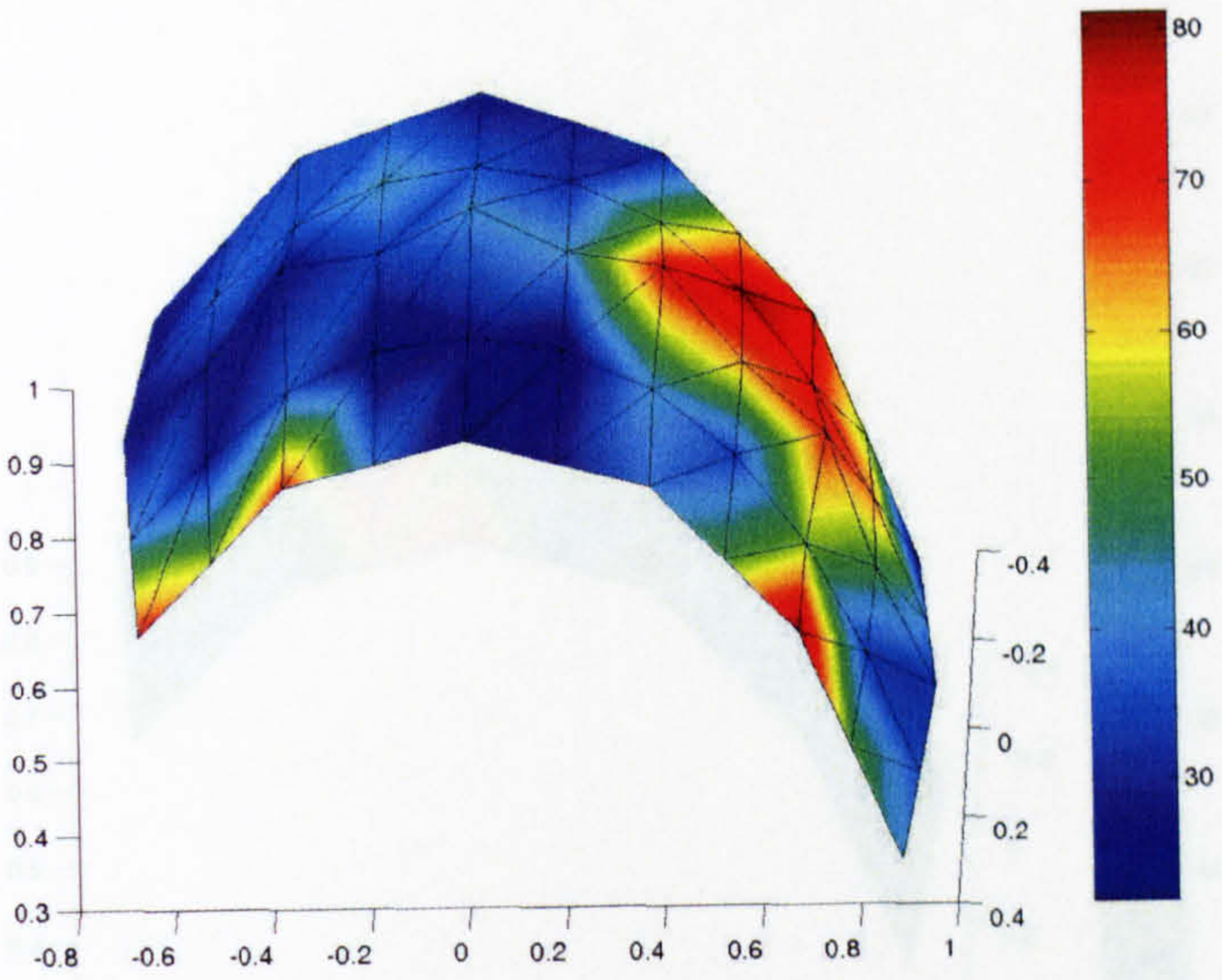


Subject 8

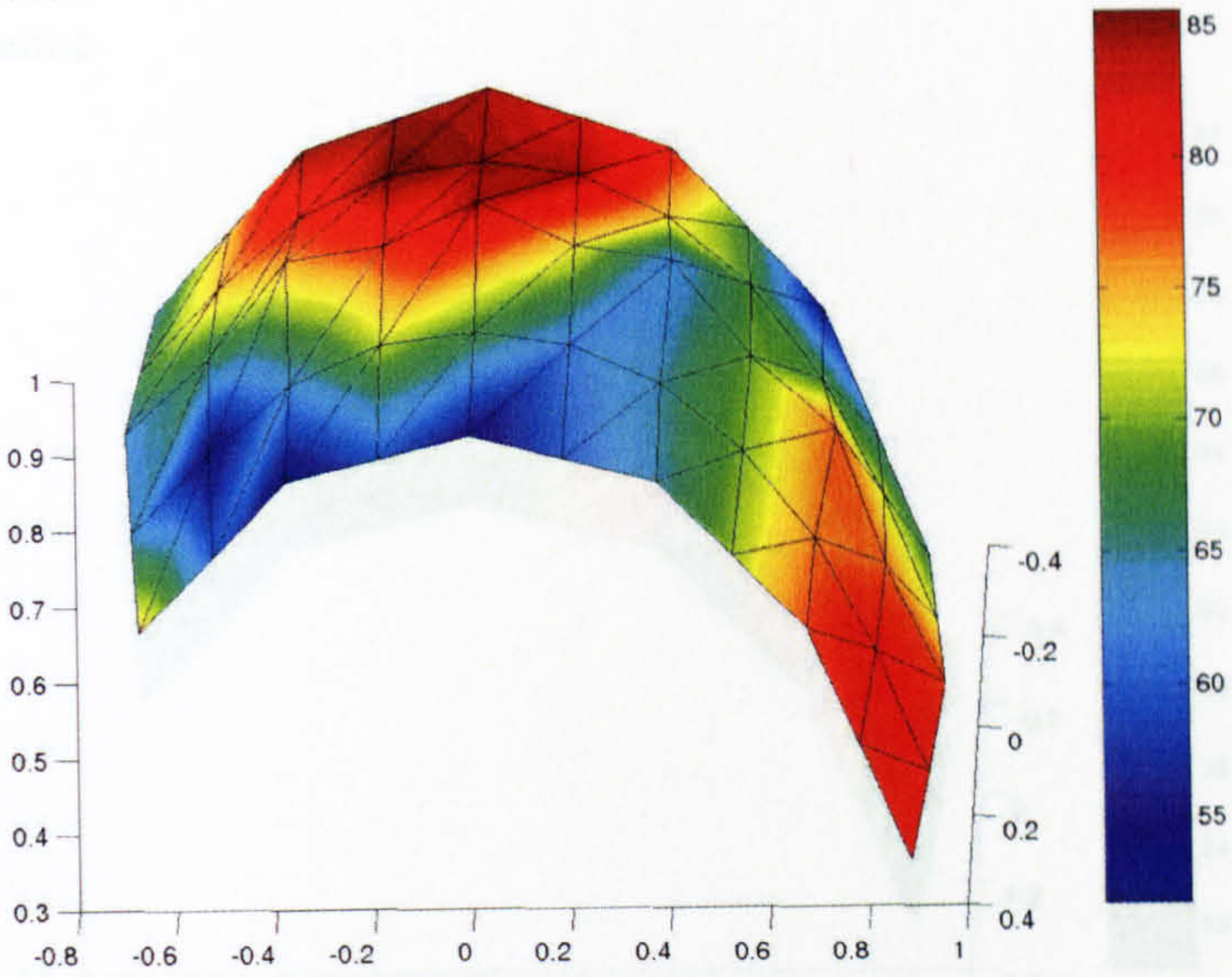
Euclidean Distance



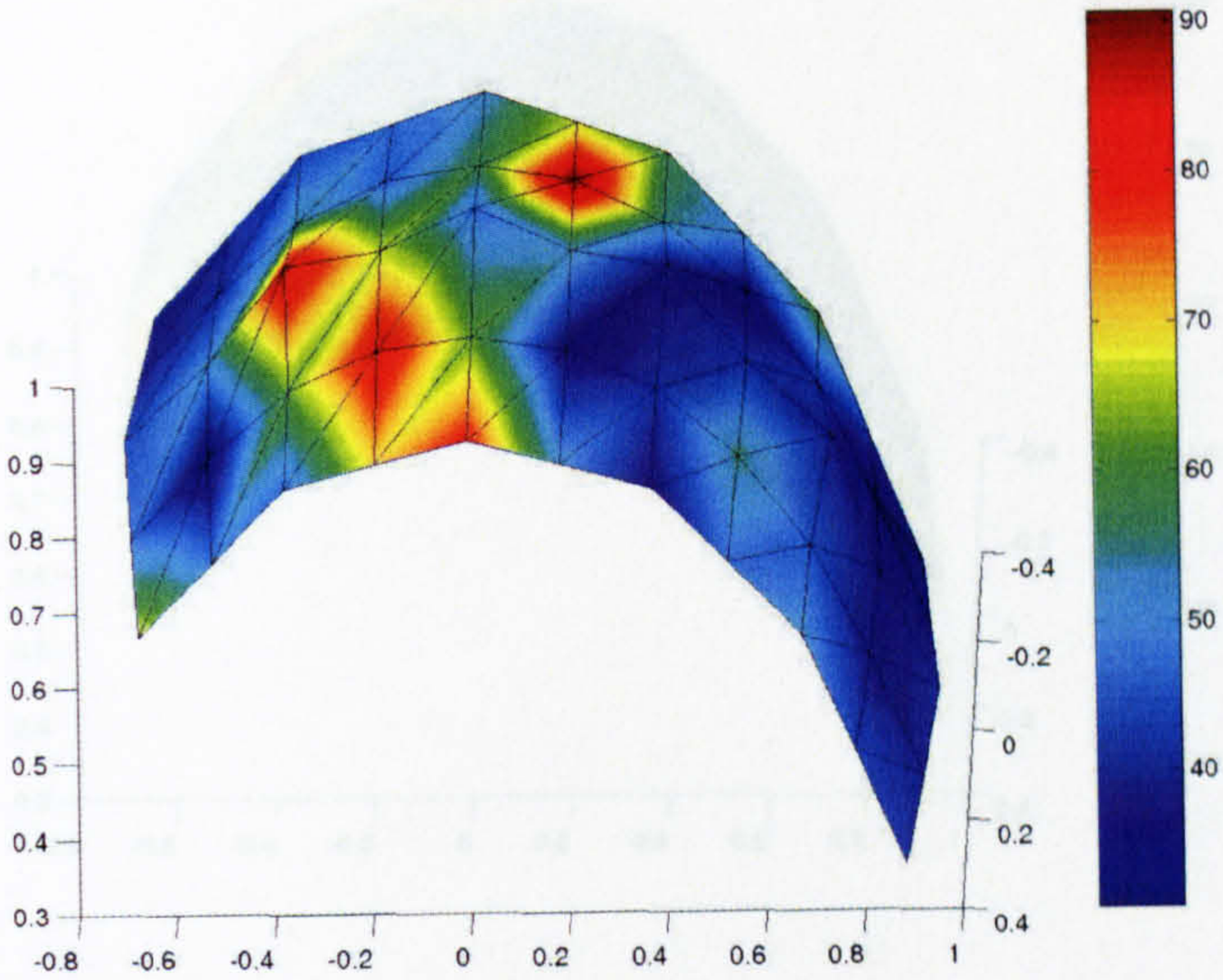
KNN



Subject 10
Euclidean Distance



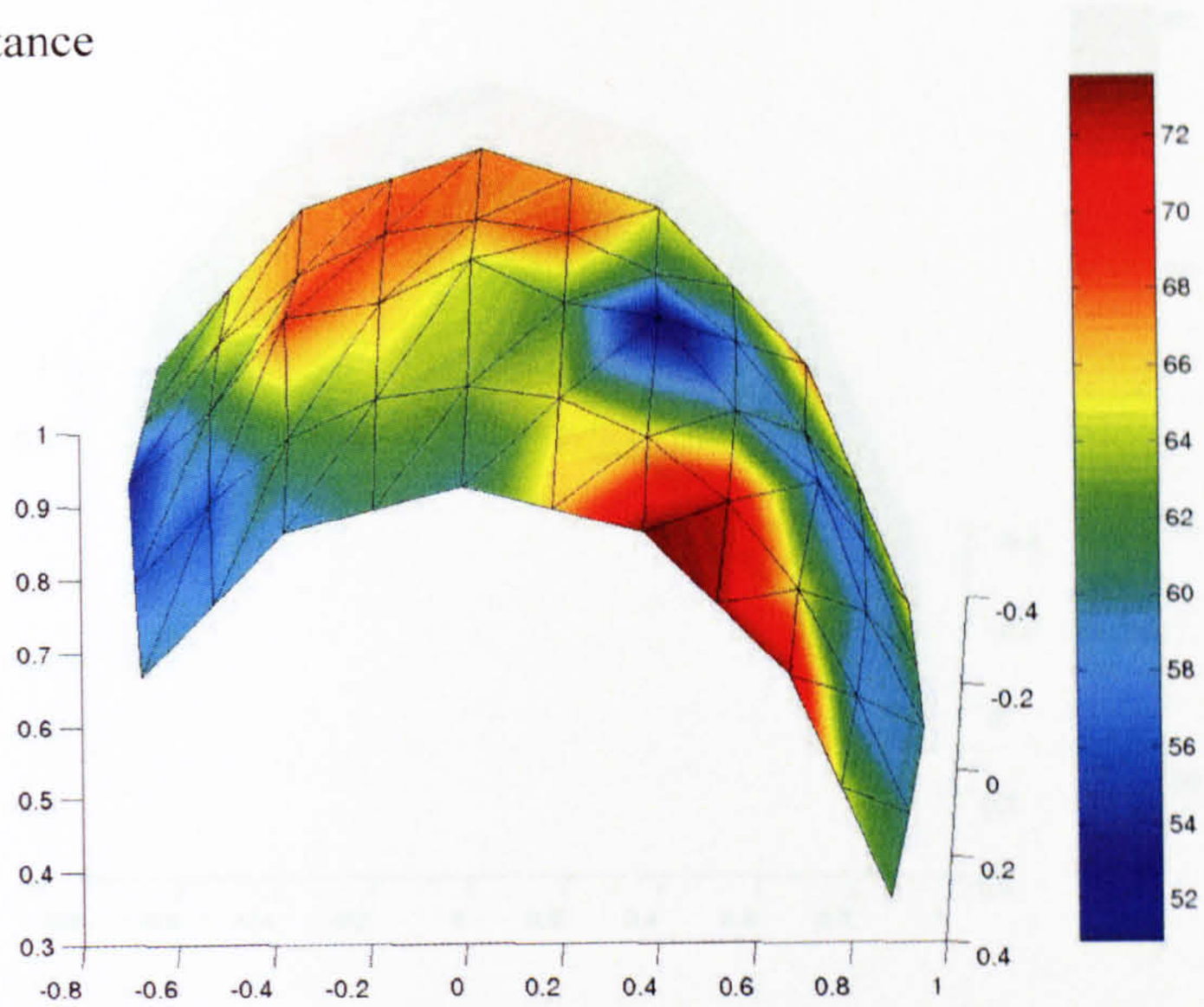
KNN



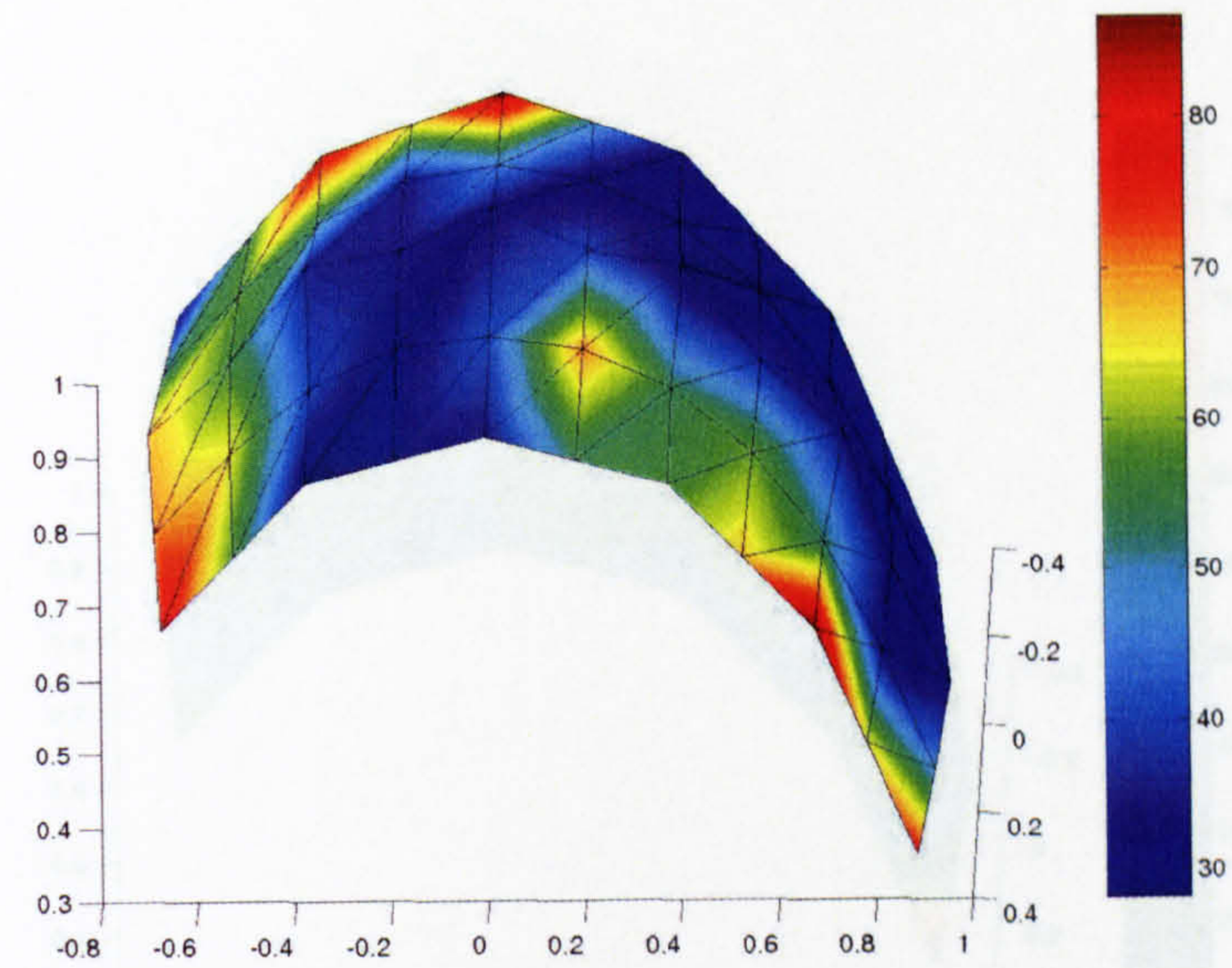
Forced Choice Trials

Subject 1

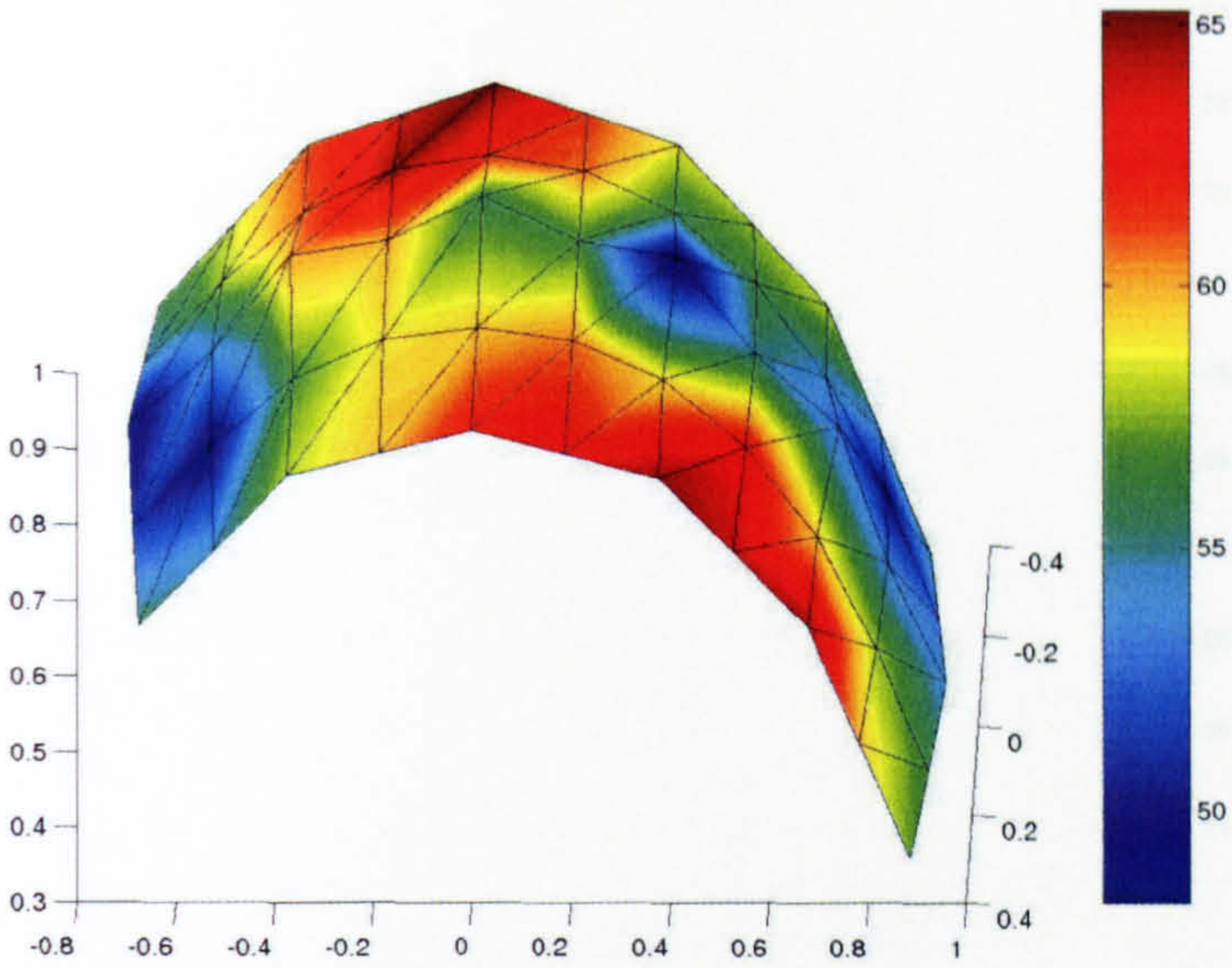
Euclidean Distance



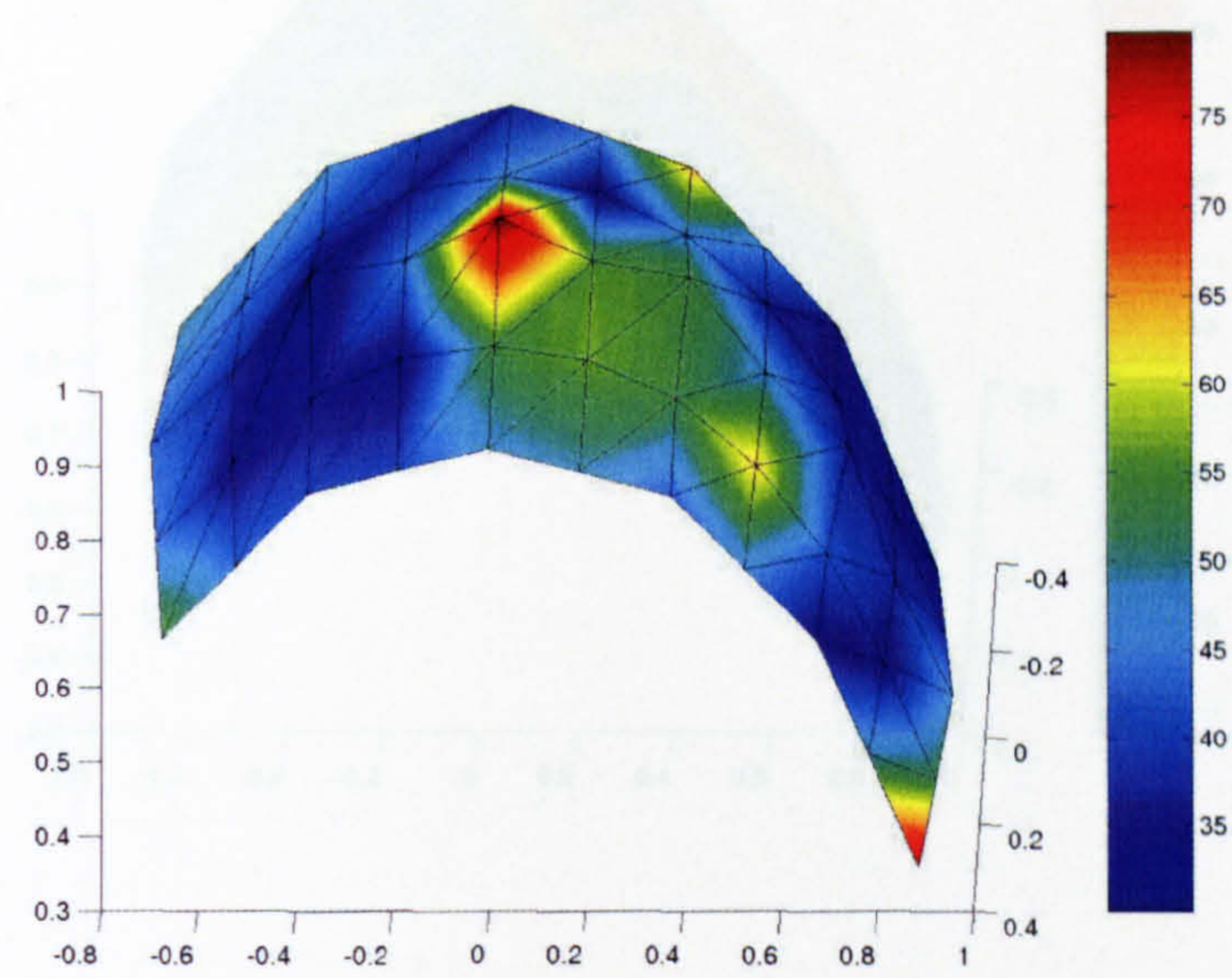
KNN



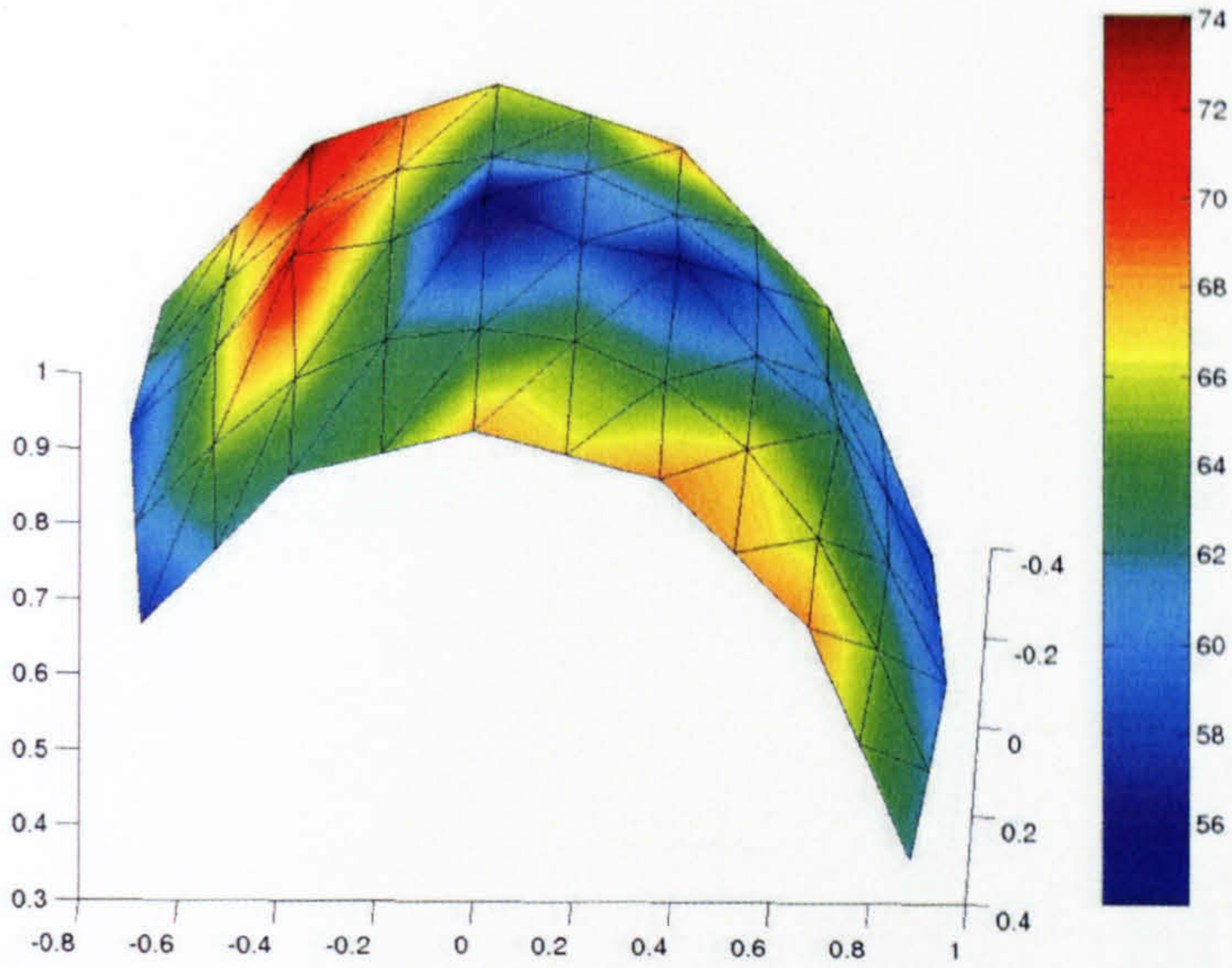
Subject 2
Euclidean Distance



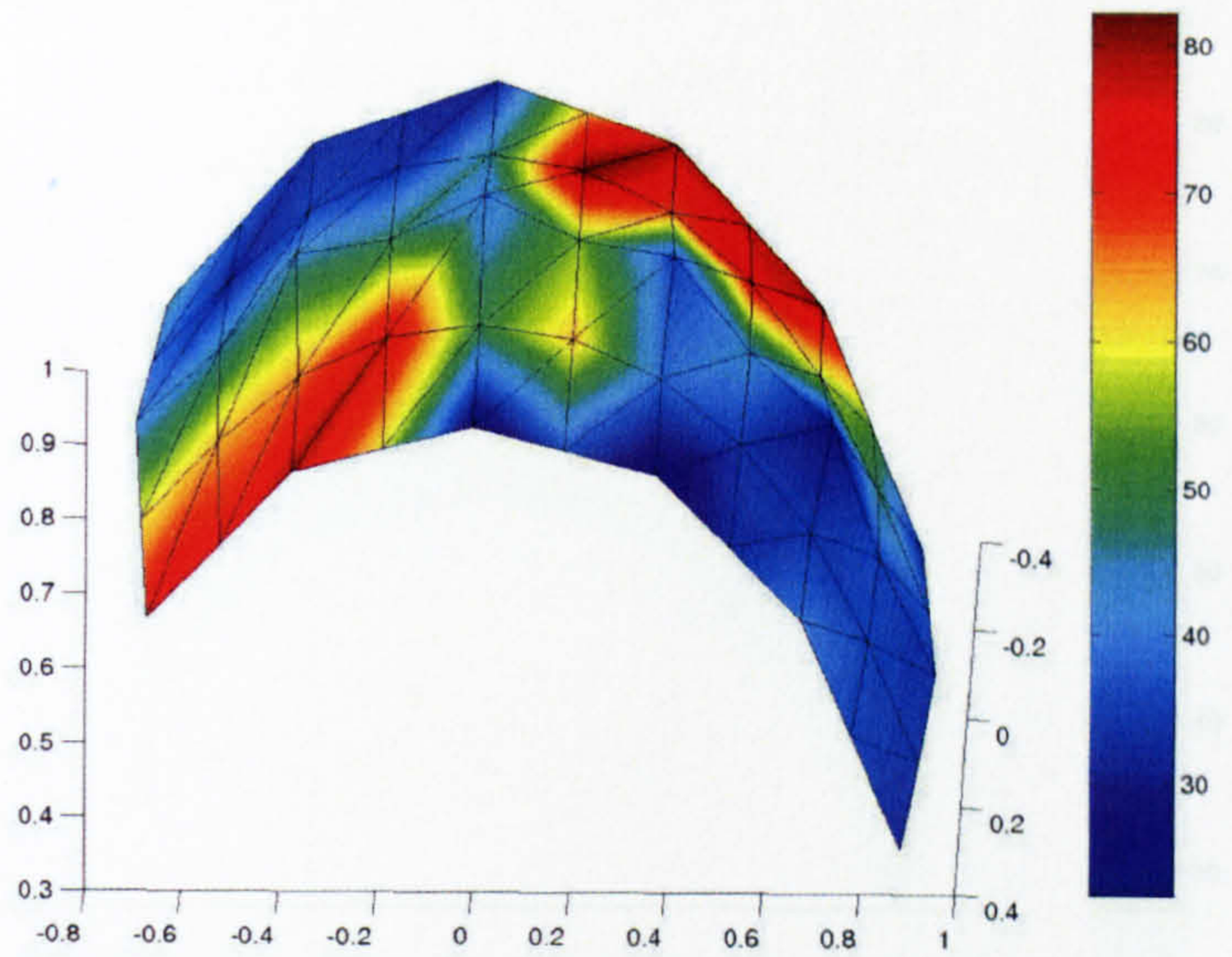
KNN



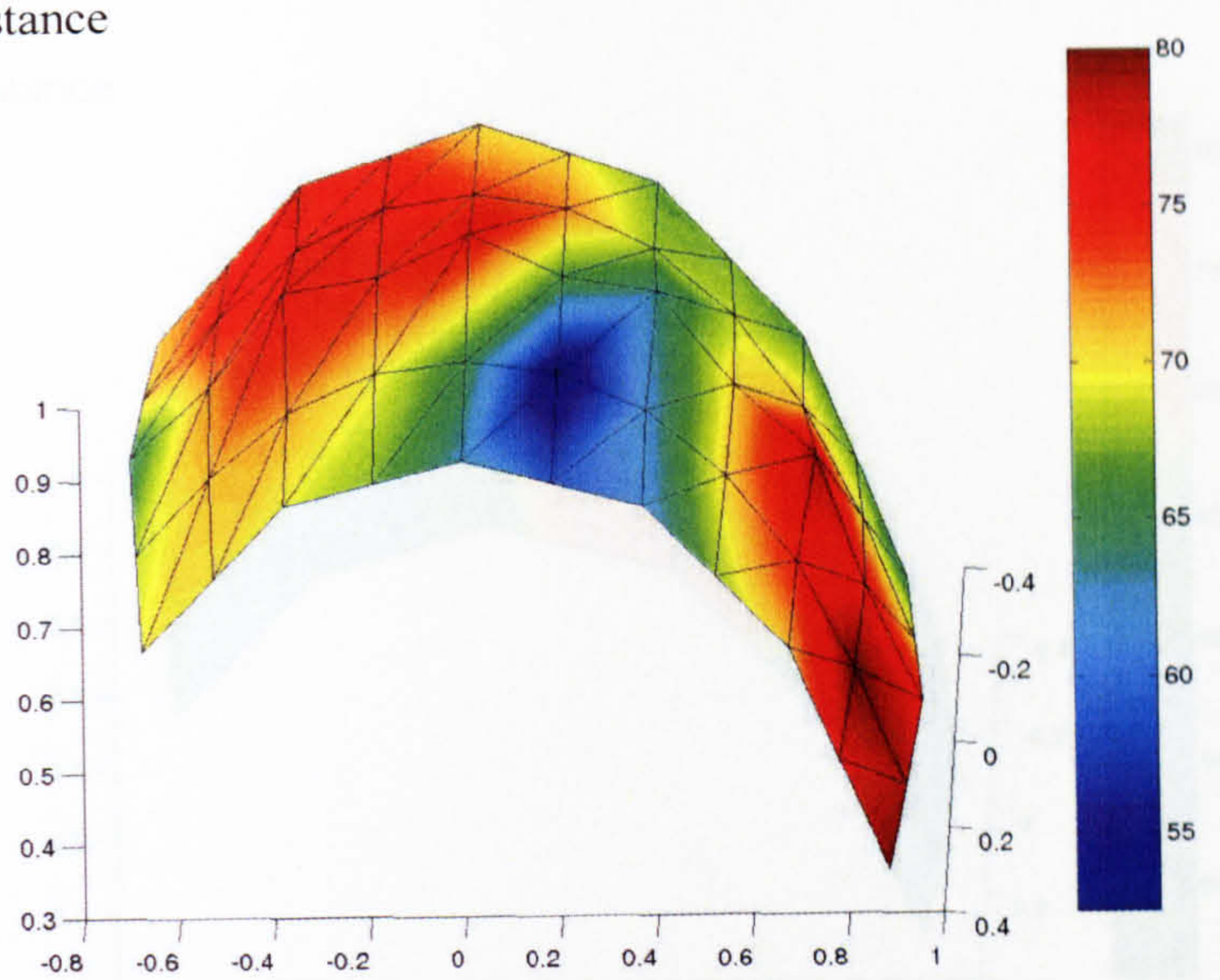
Subject 3
Euclidean Distance



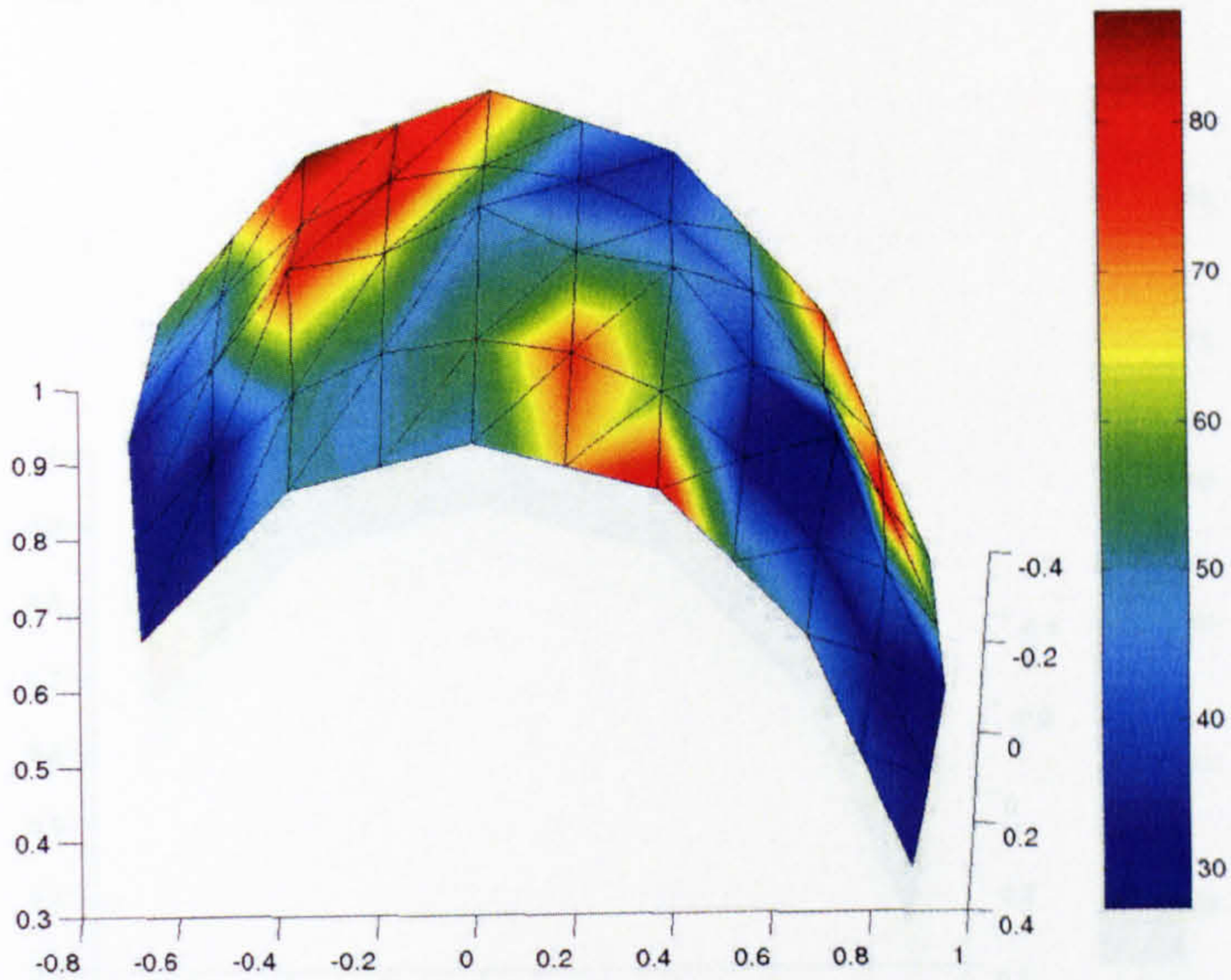
KNN



Subject 10
Euclidean Distance



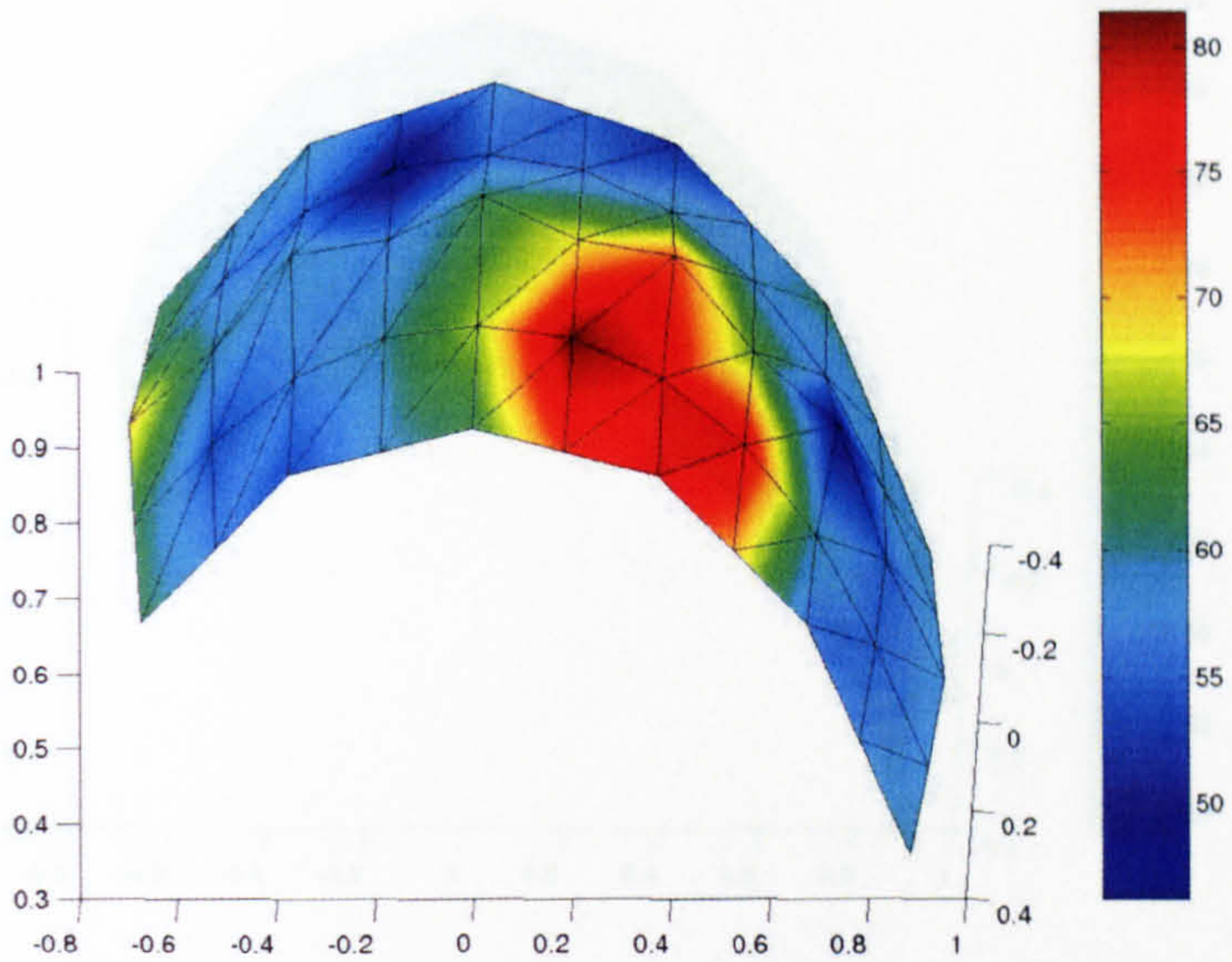
KNN



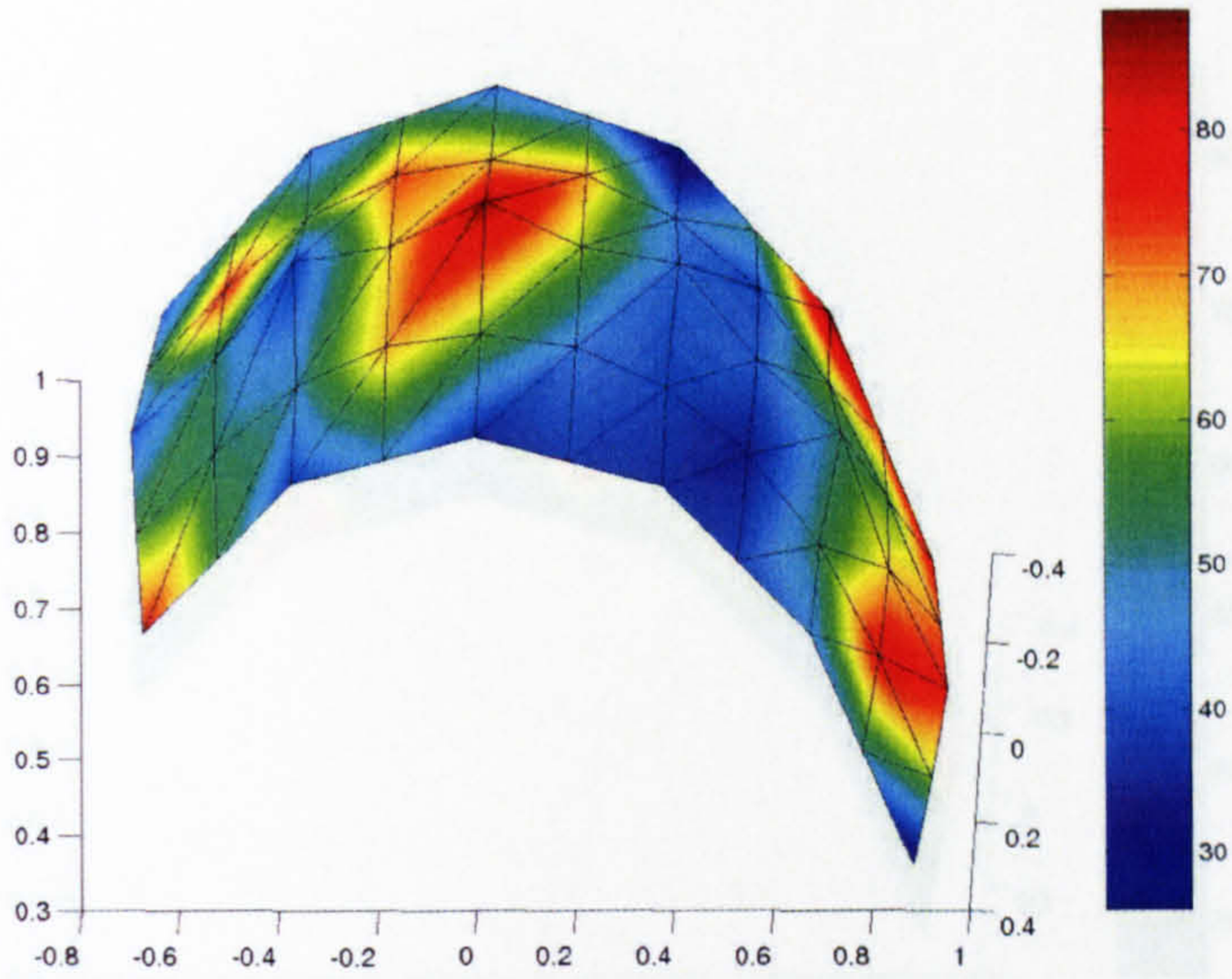
Self Determined

Subject 1

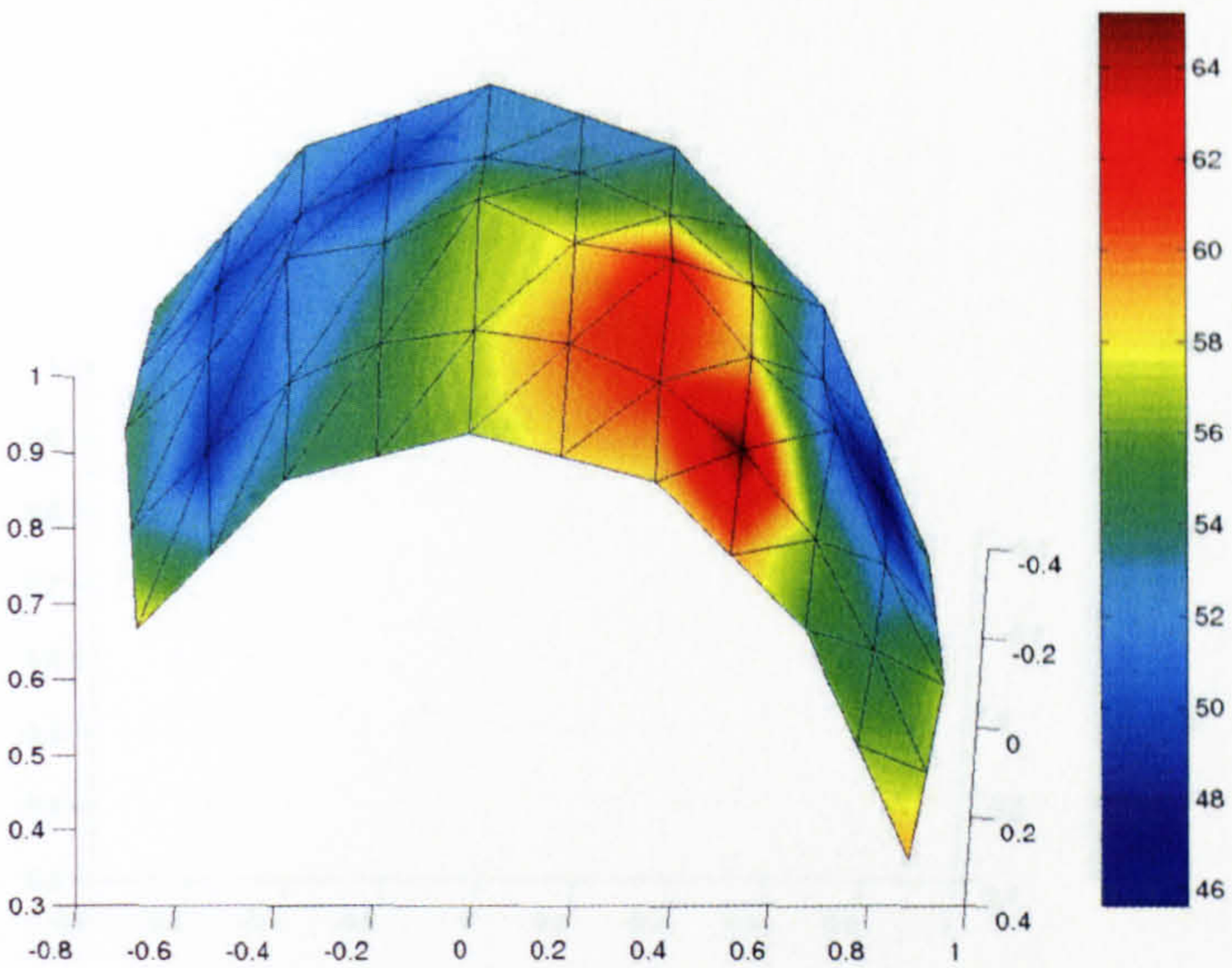
Euclidean Distance



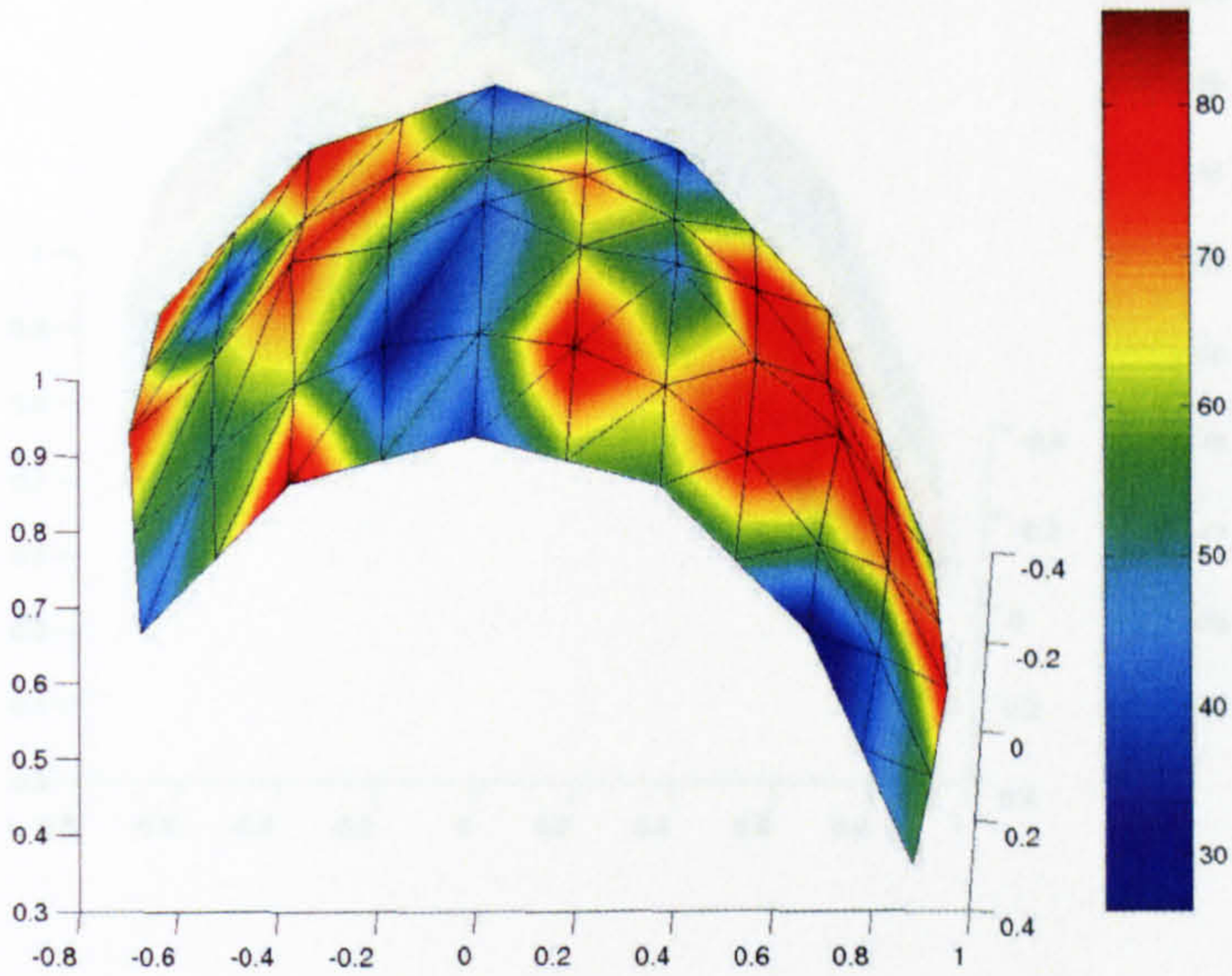
KNN



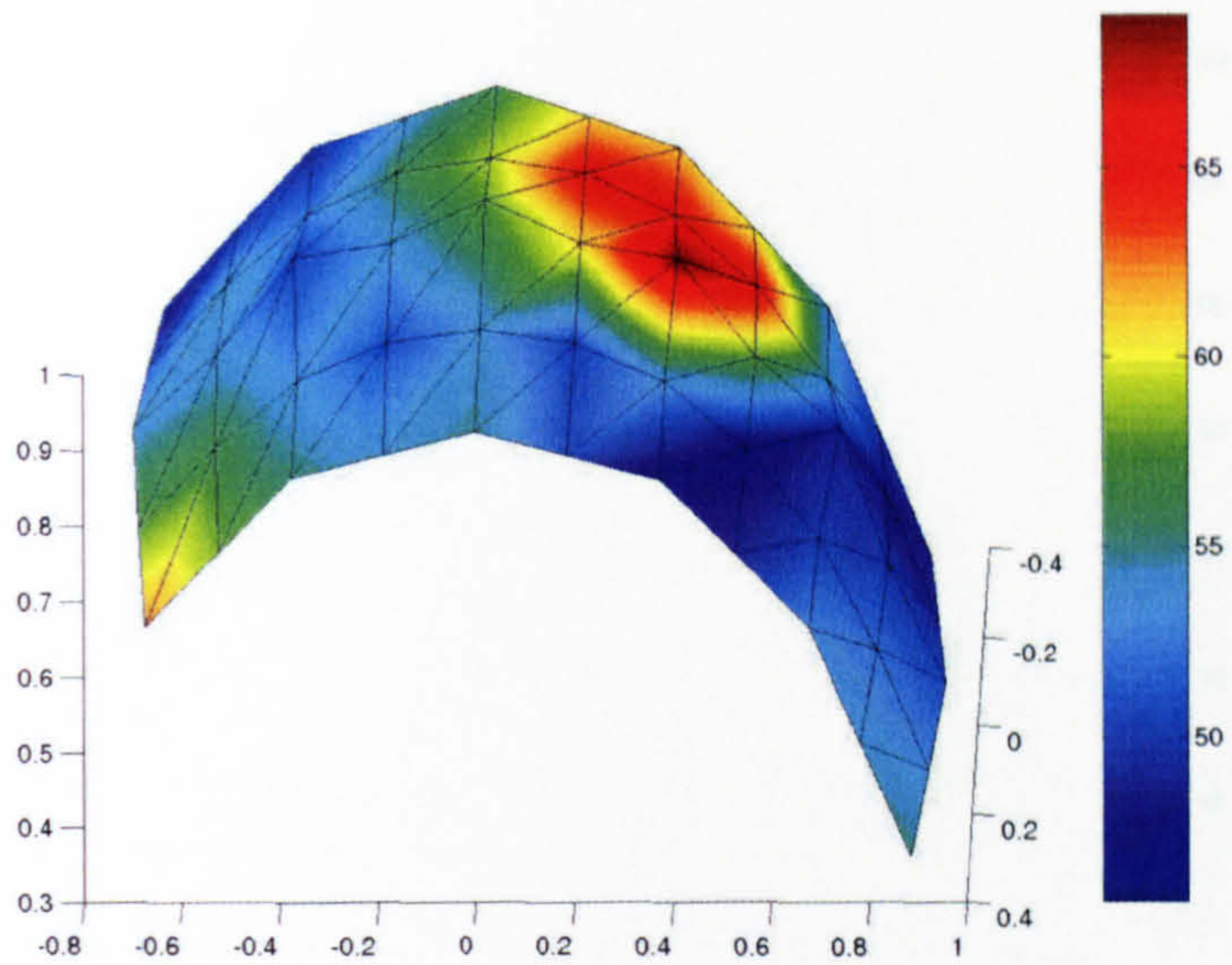
Subject 2
Euclidean Distance



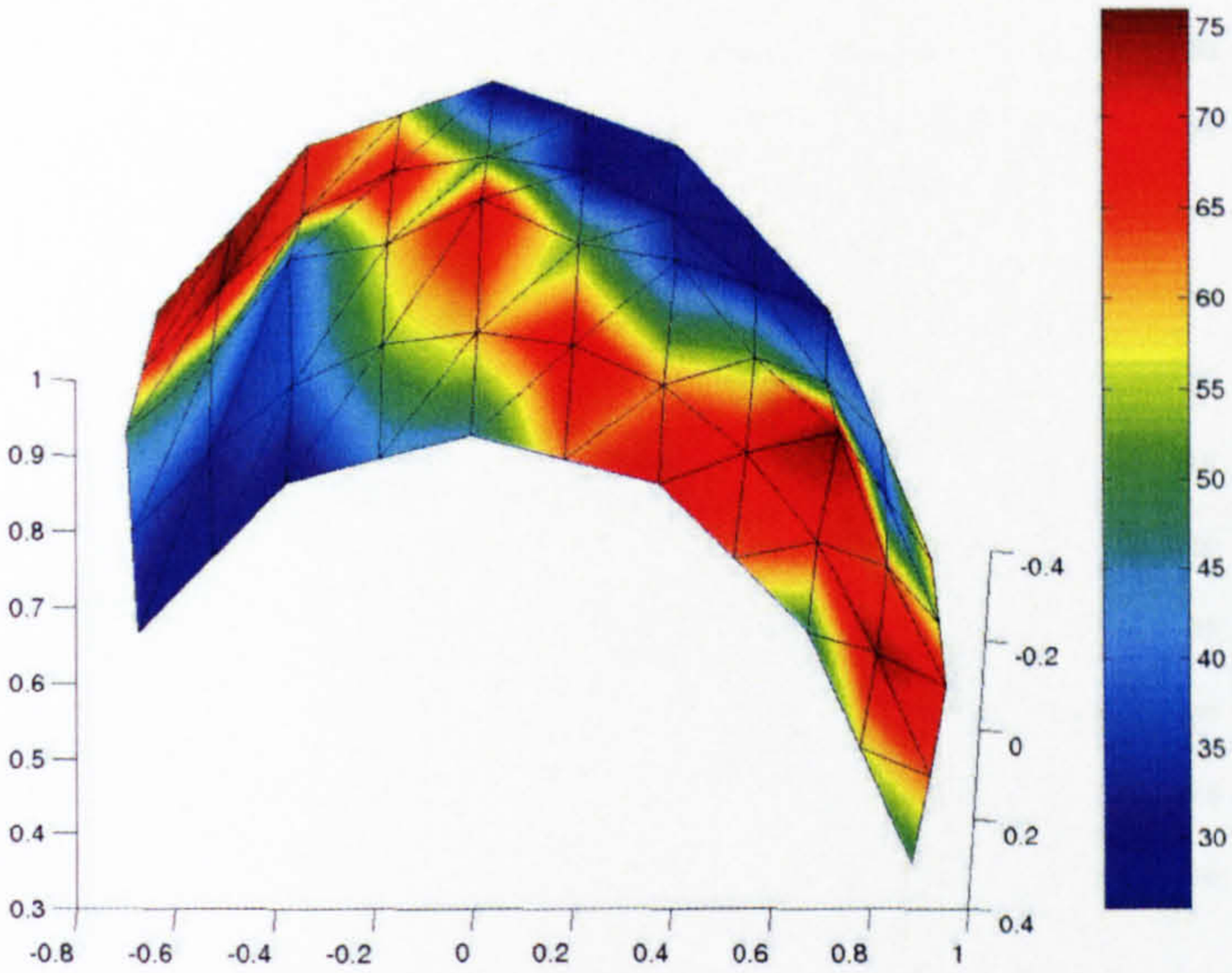
KNN



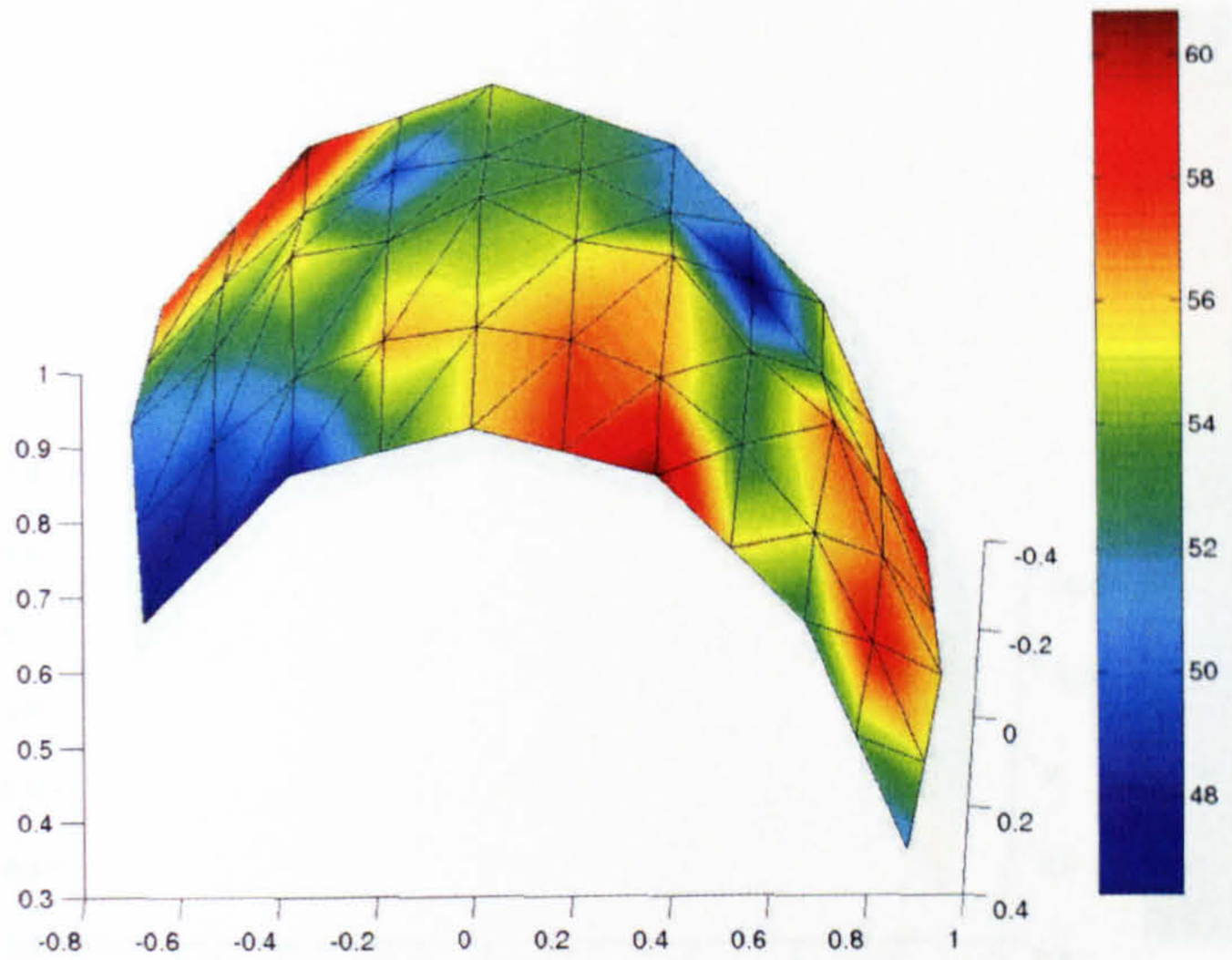
Subject 3
Euclidean Distance



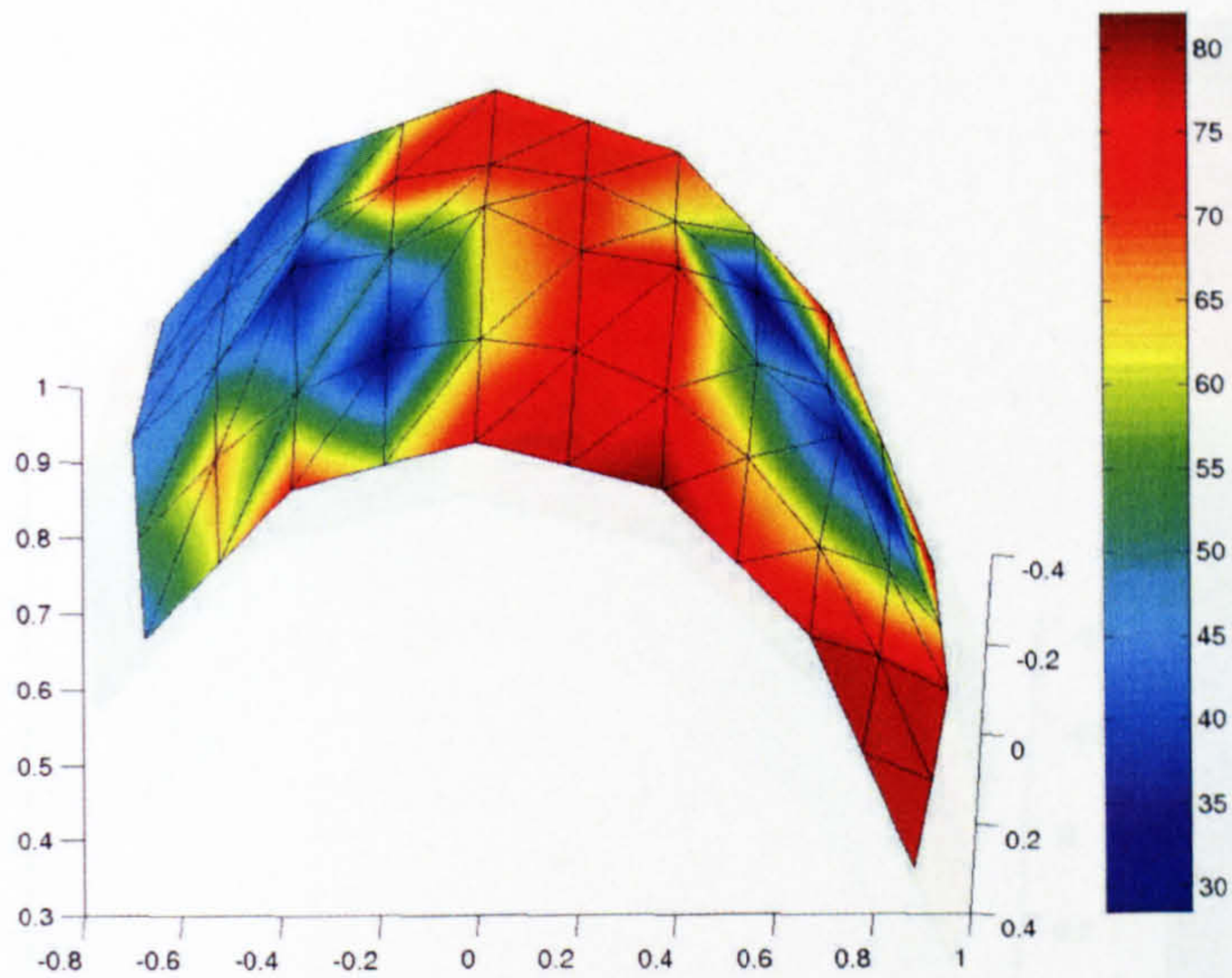
KNN



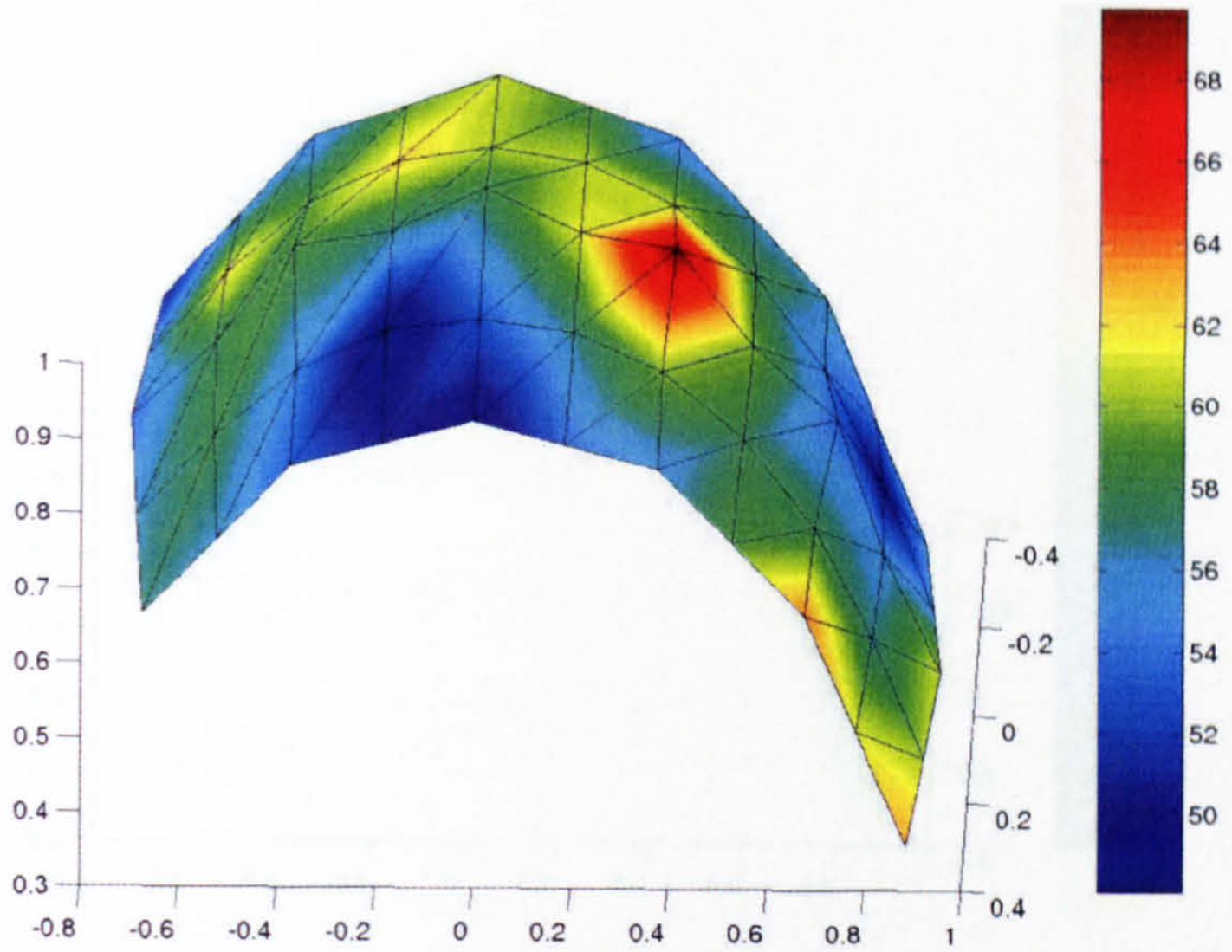
Subject 8
Euclidean Distance



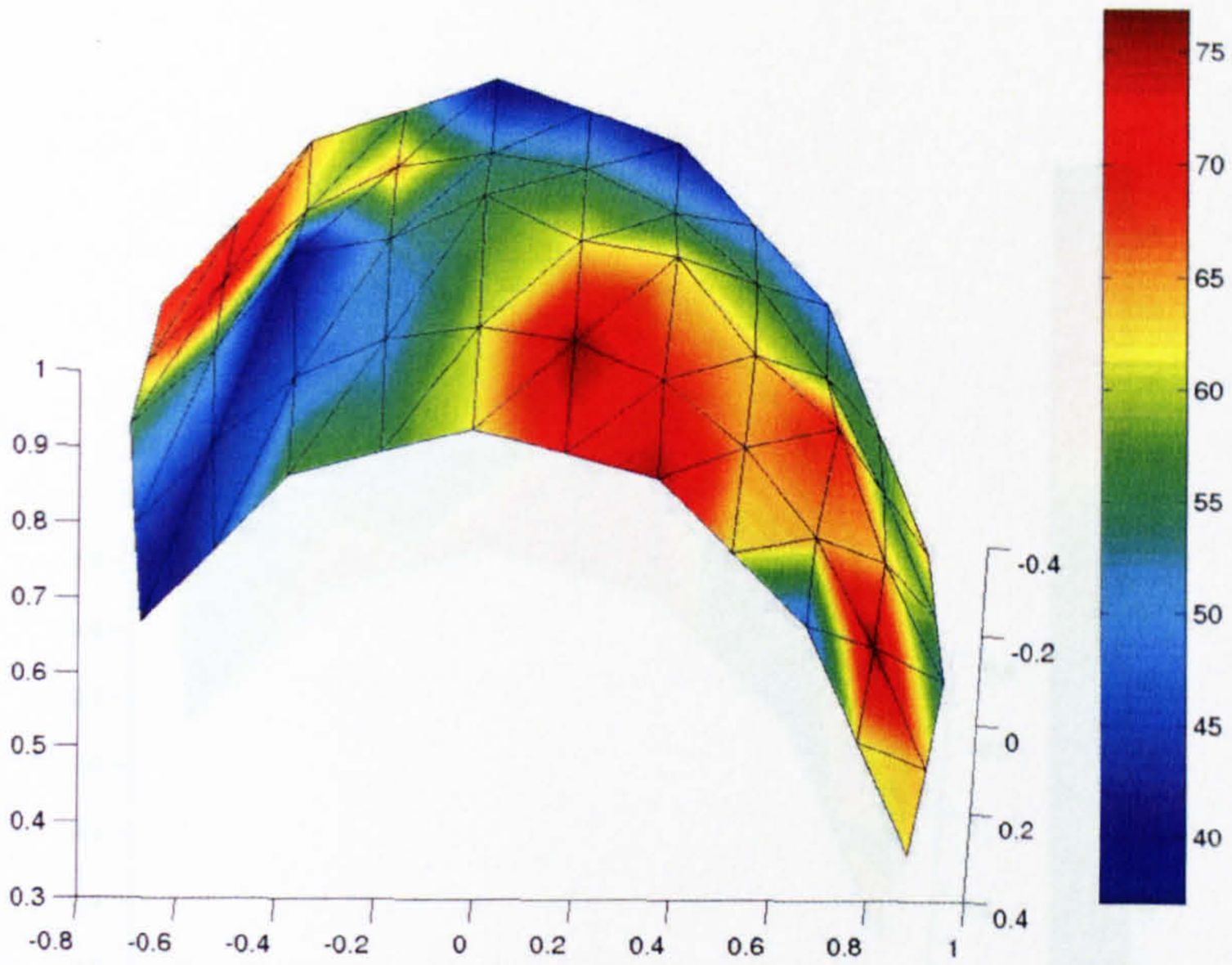
KNN



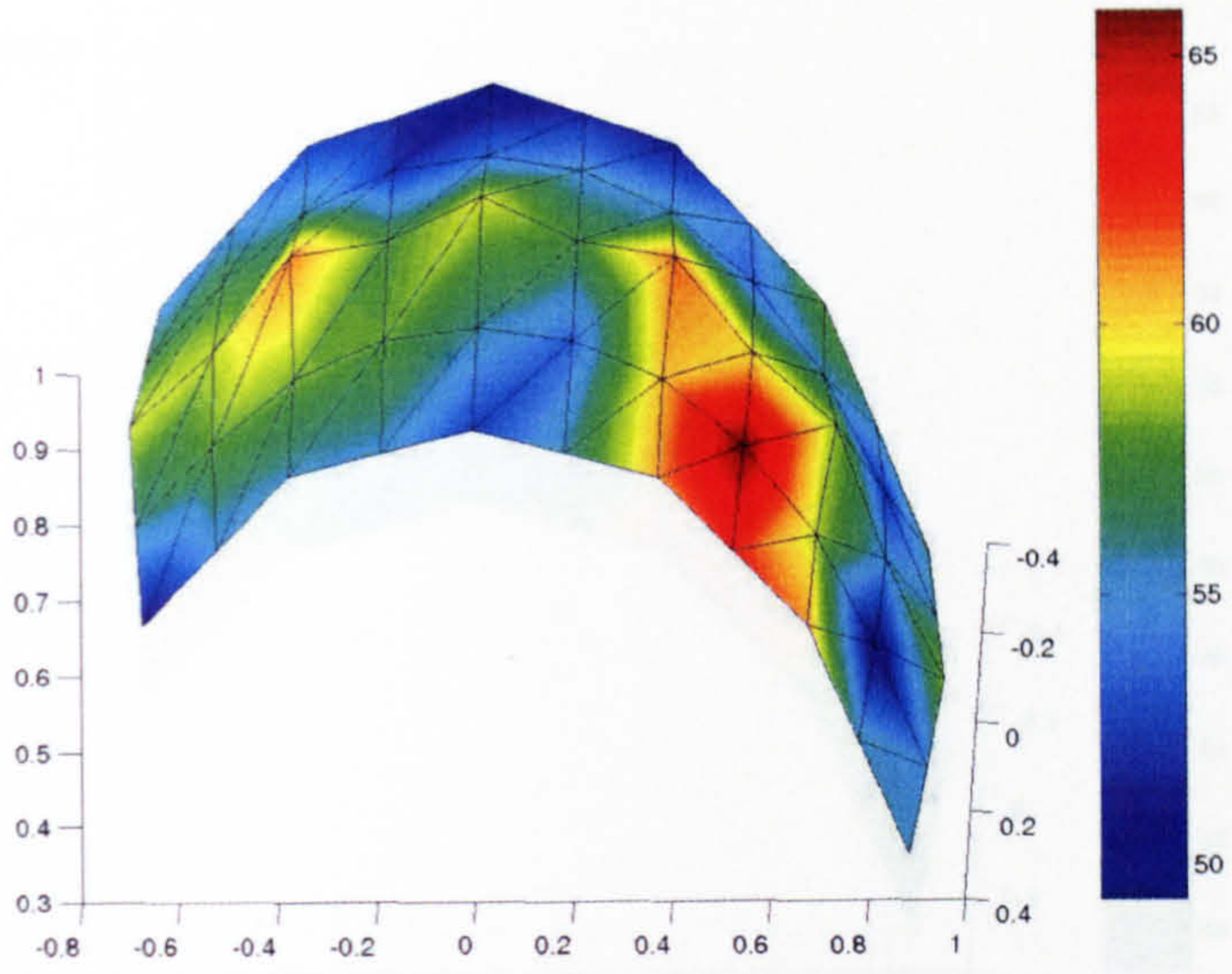
Subject 9
Euclidean Distance



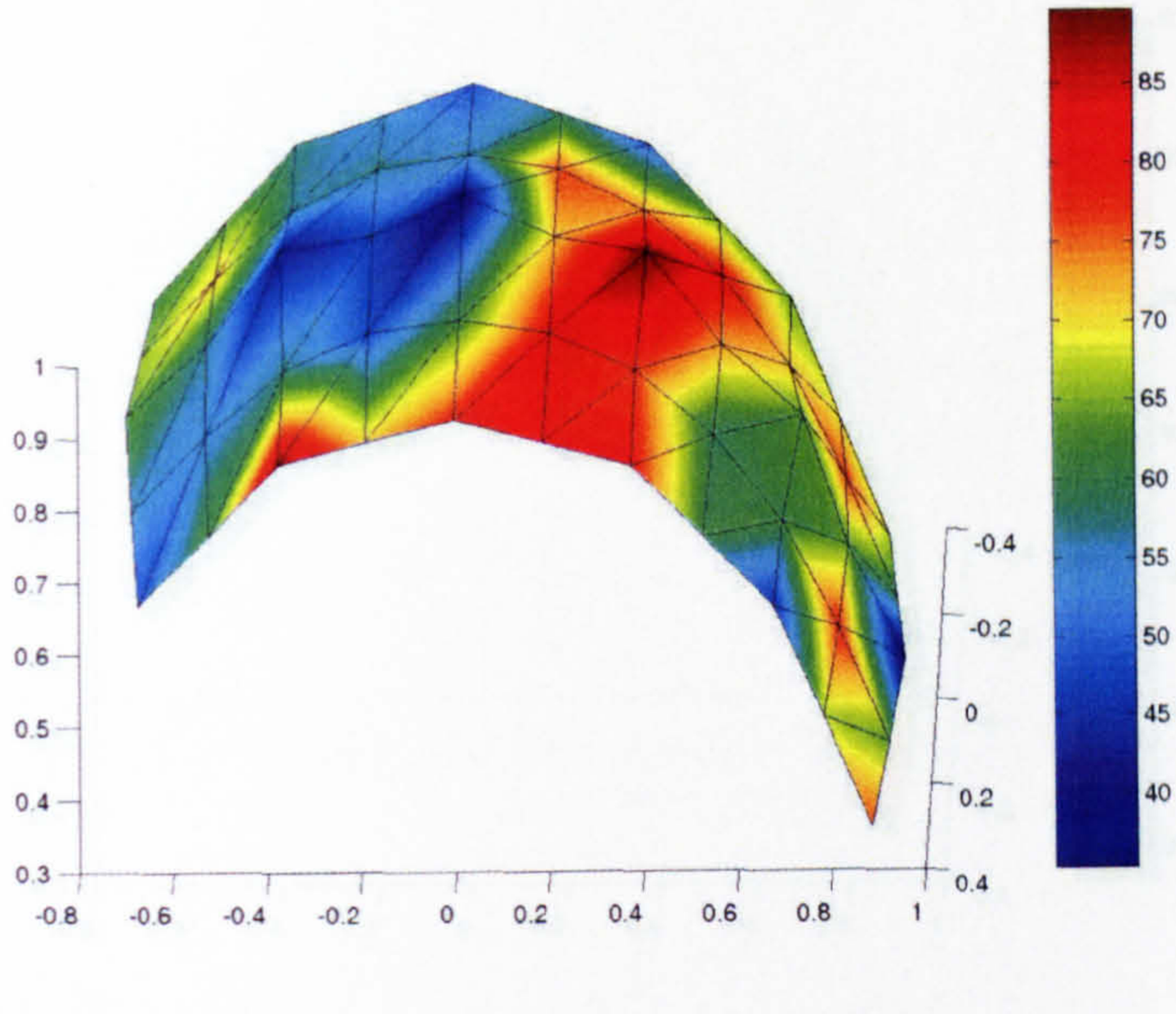
KNN



Subject 10
Euclidean Distance



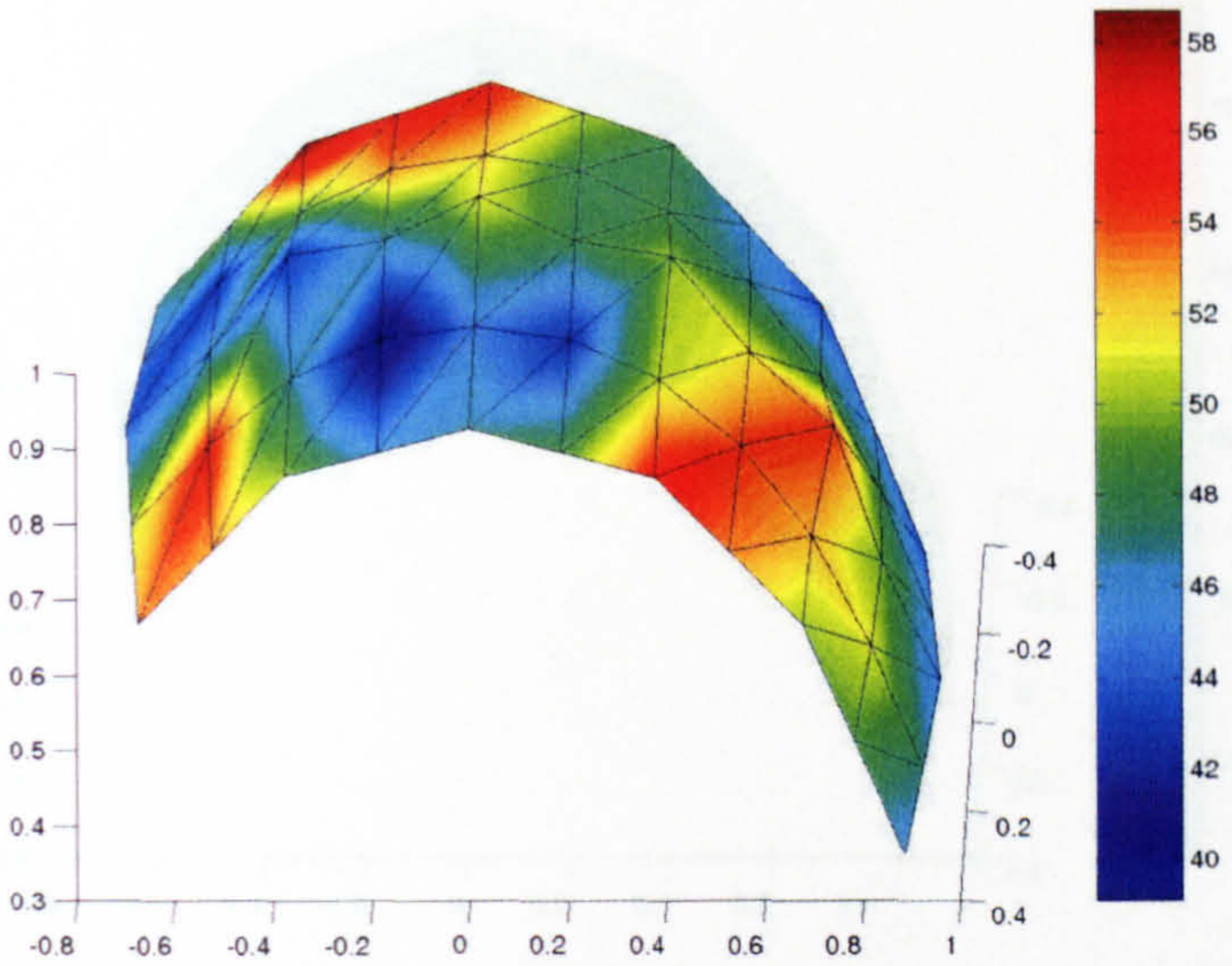
KNN



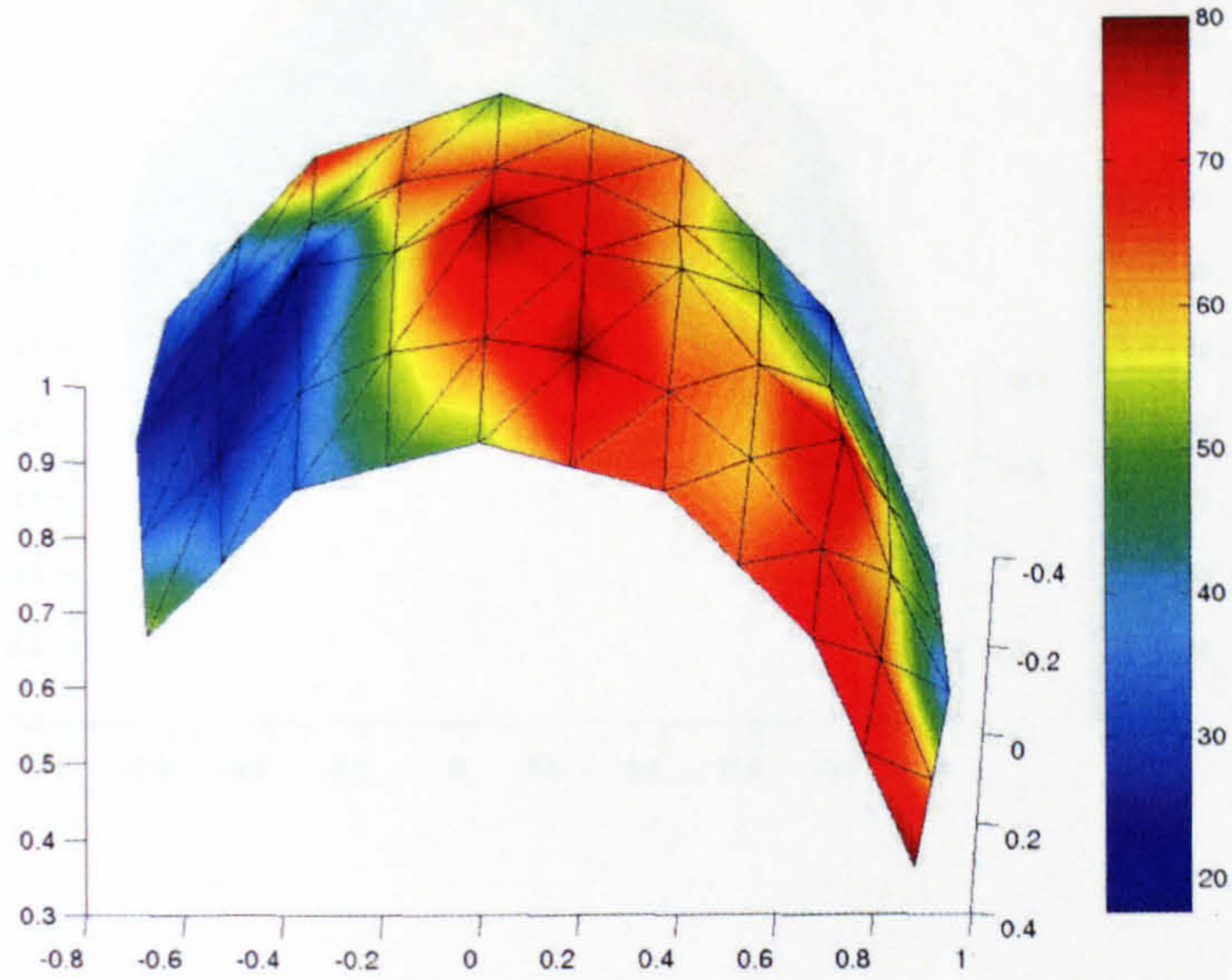
Imagination

Subject 1

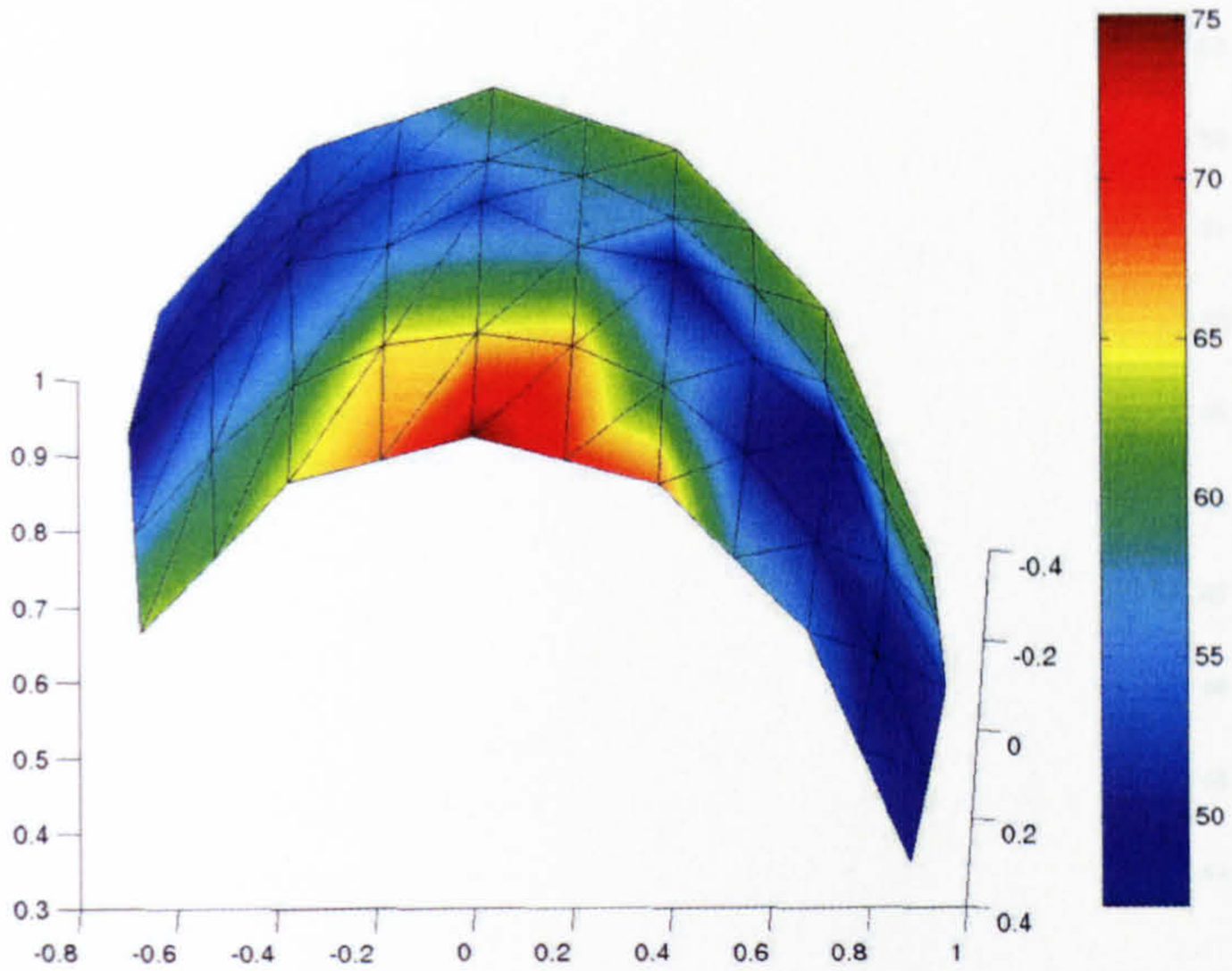
Euclidean Distance



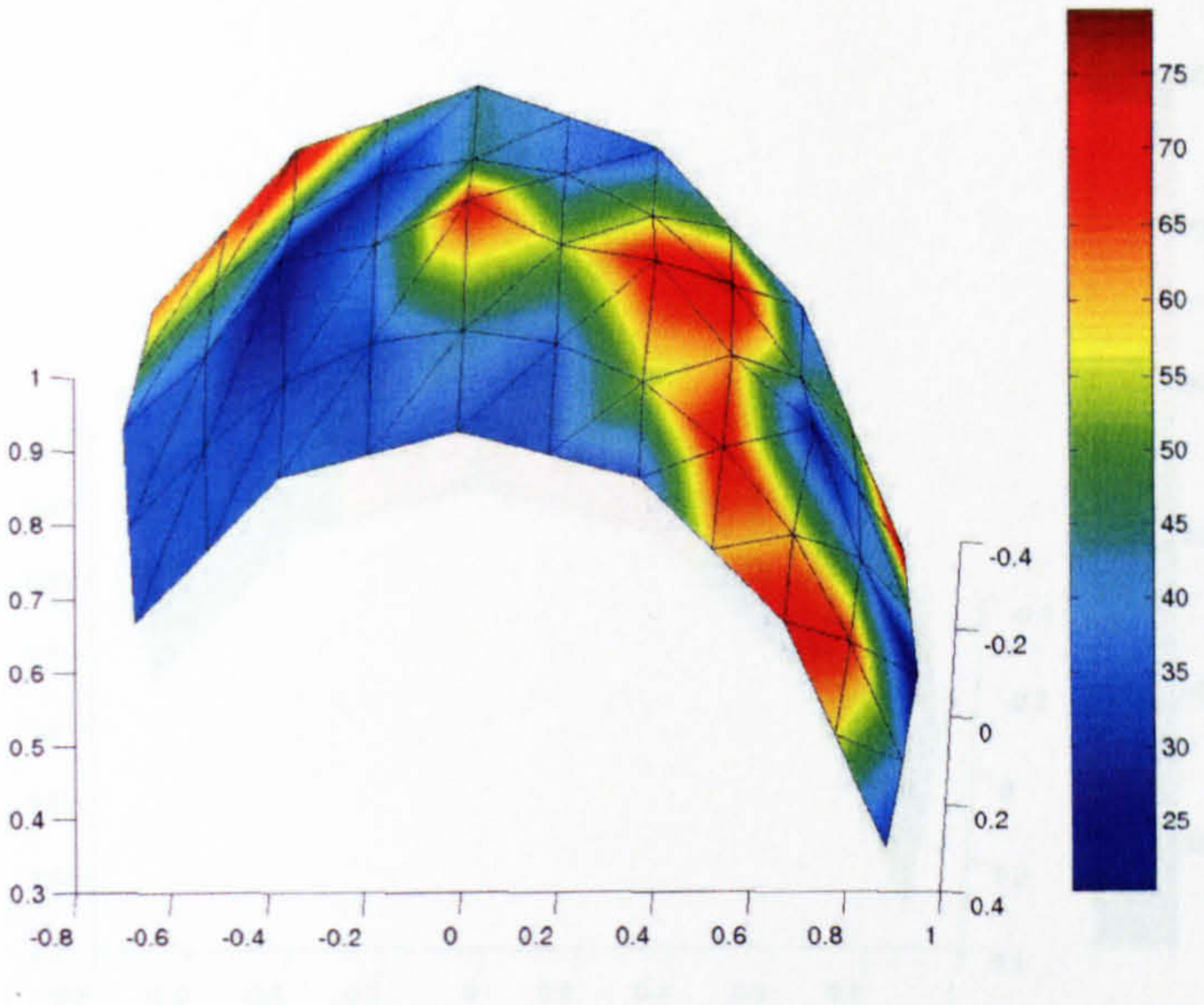
KNN



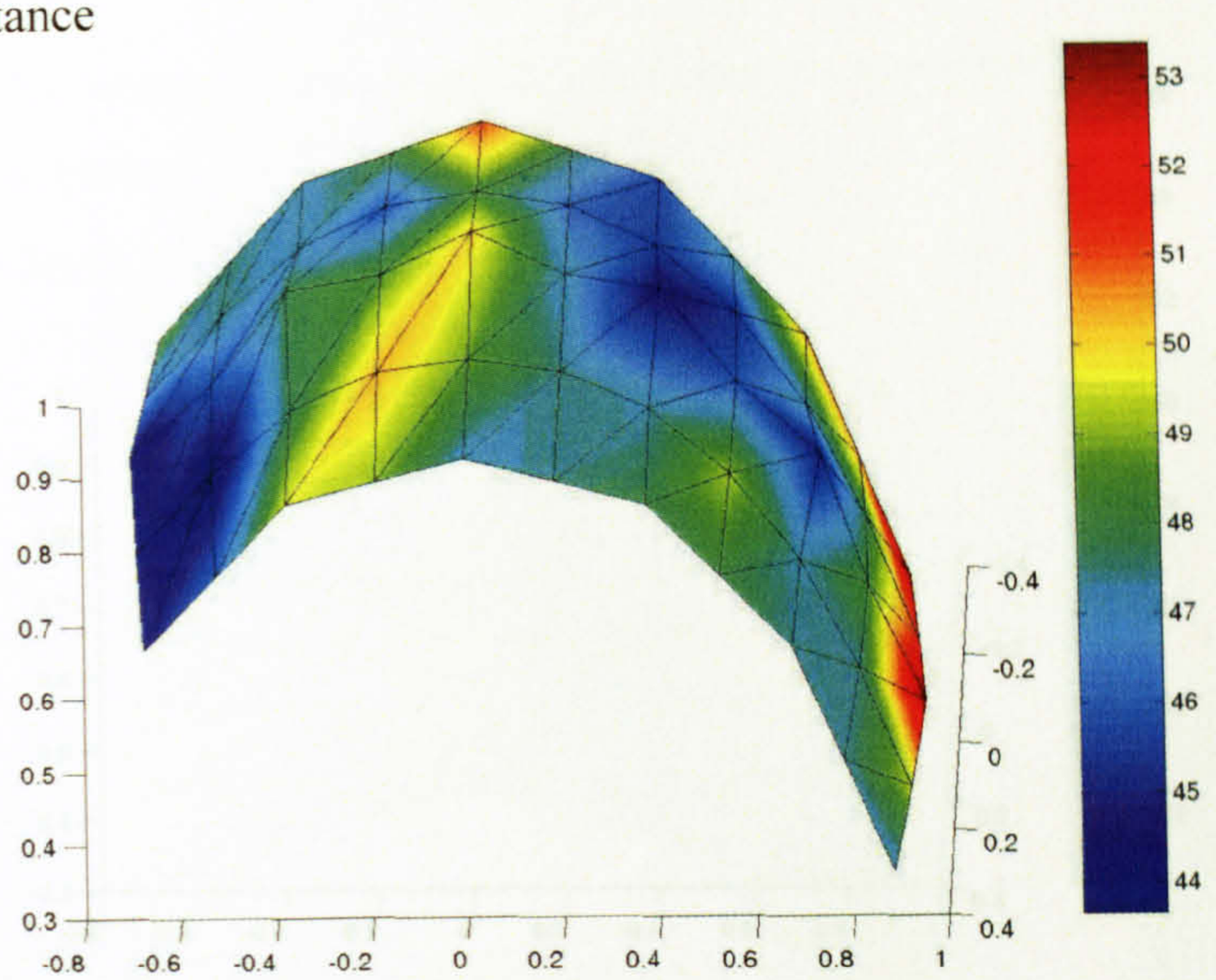
Subject 2
Euclidean Distance



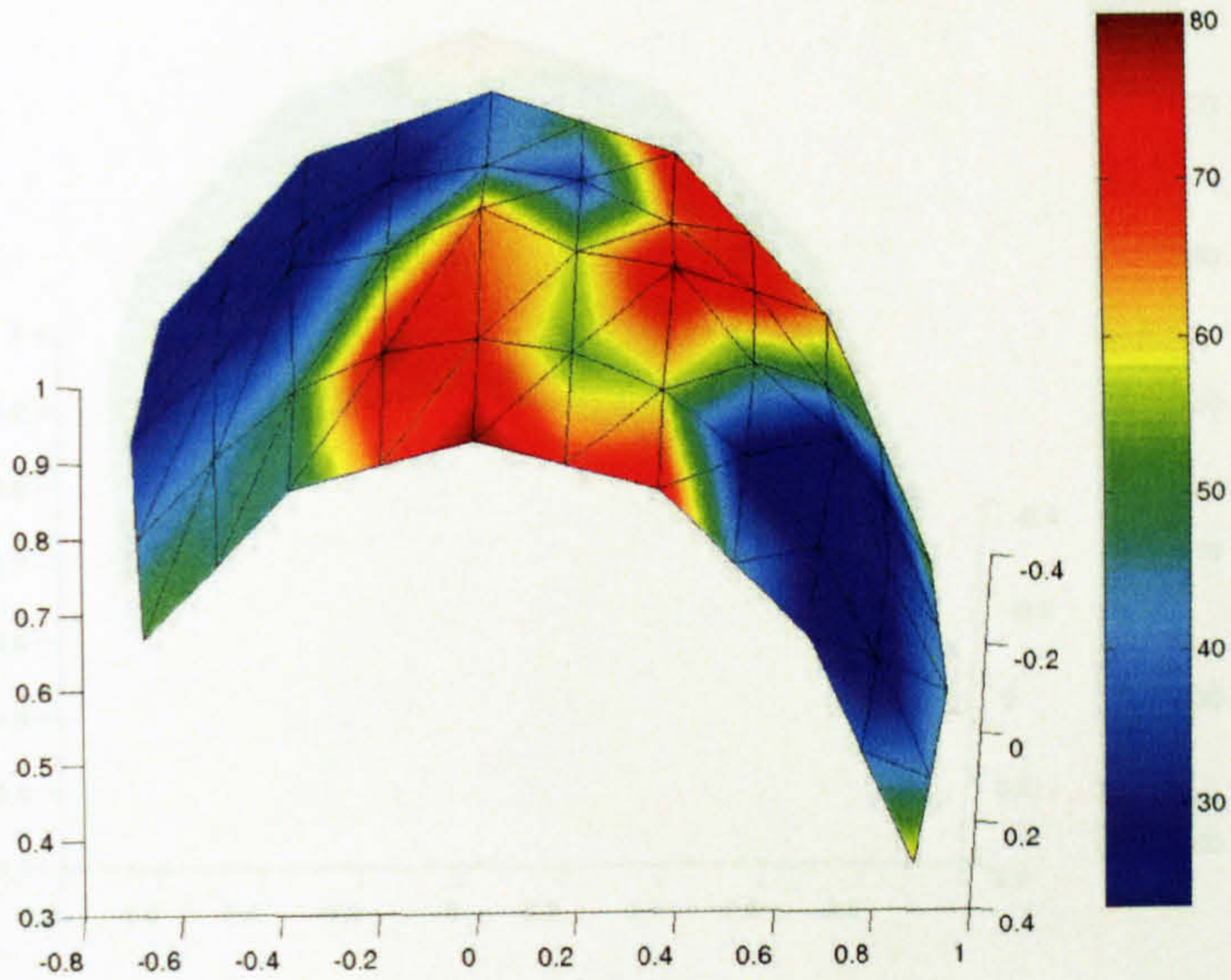
KNN



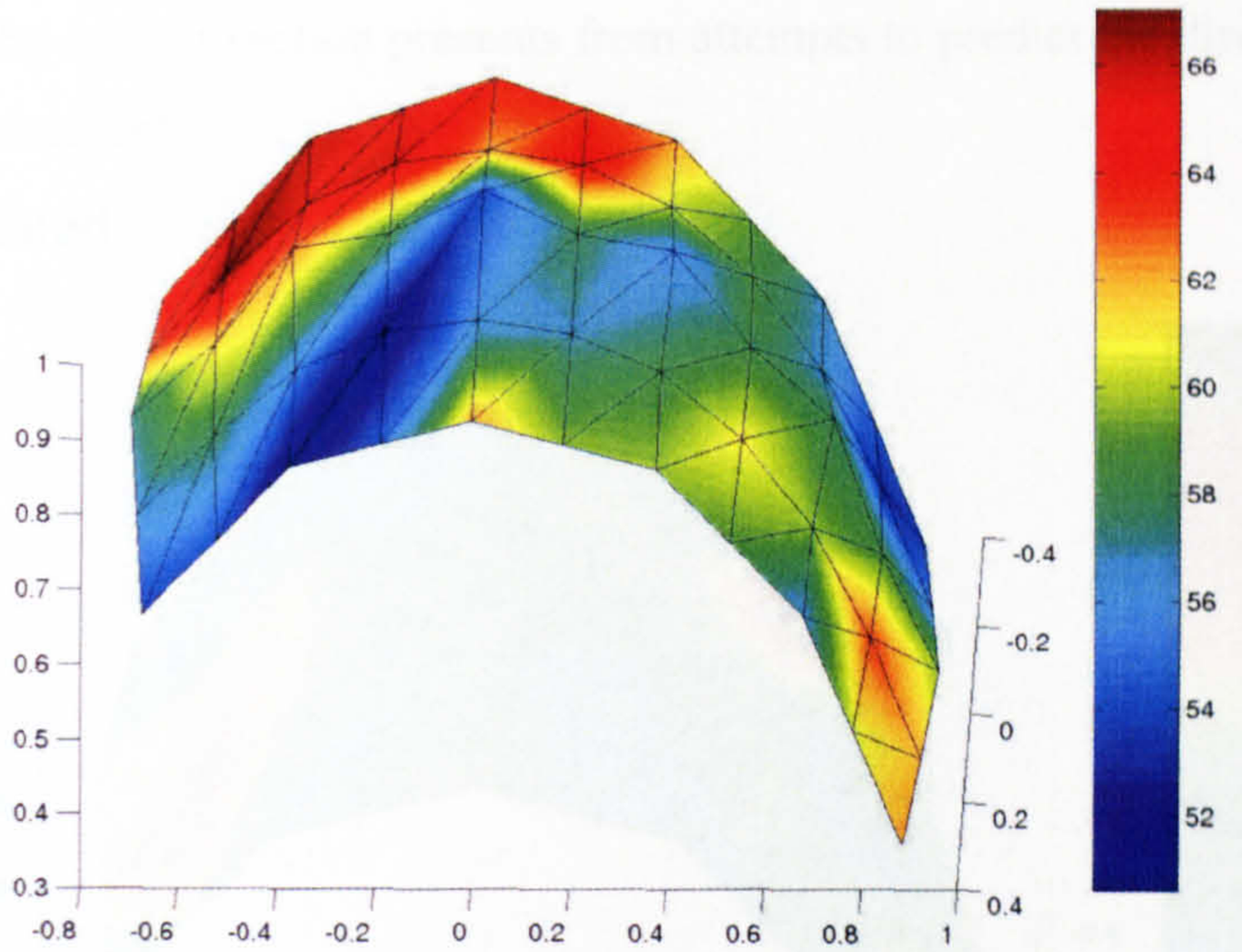
Subject 3
Euclidean Distance



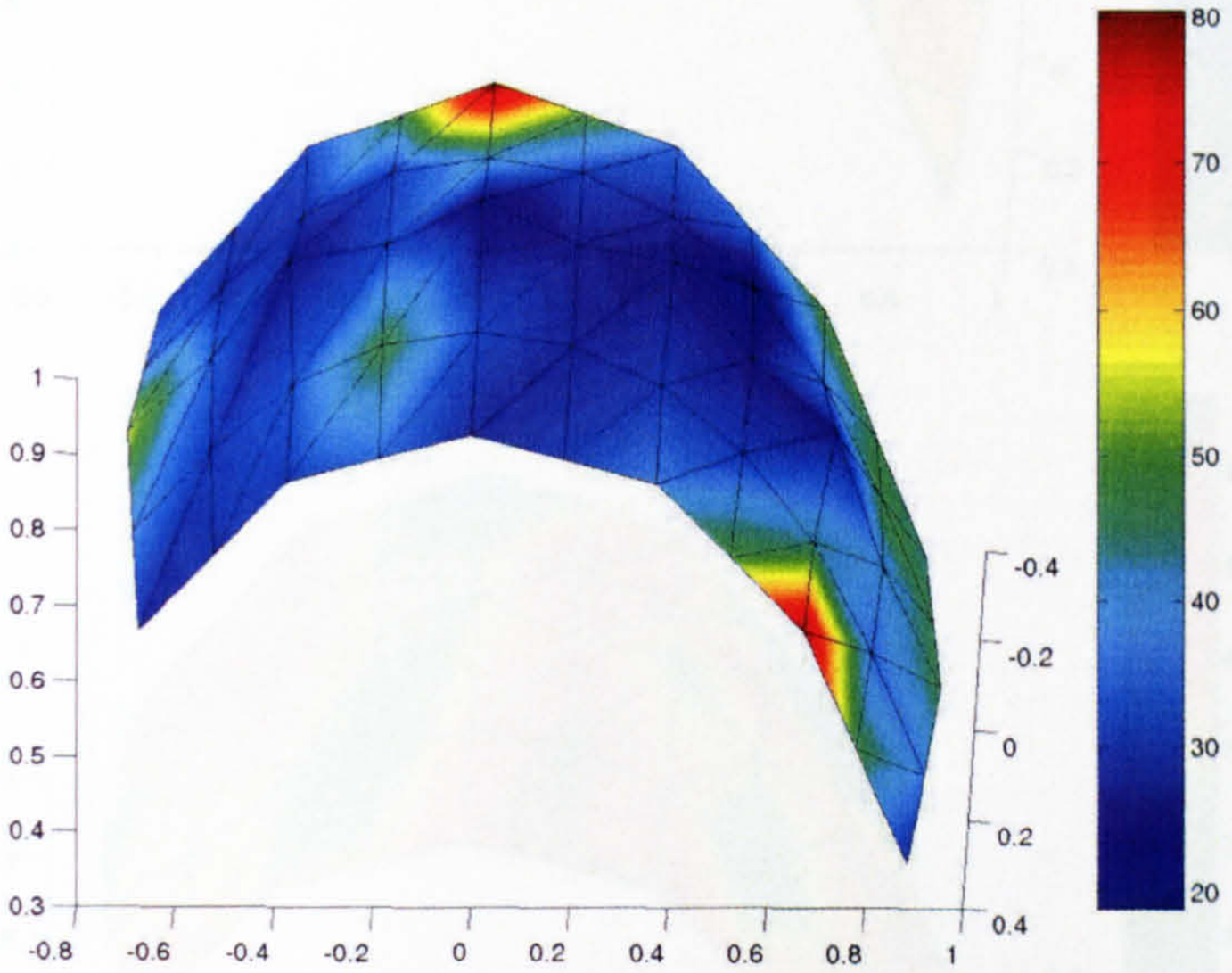
KNN



Subject 5
Euclidean Distance



KNN

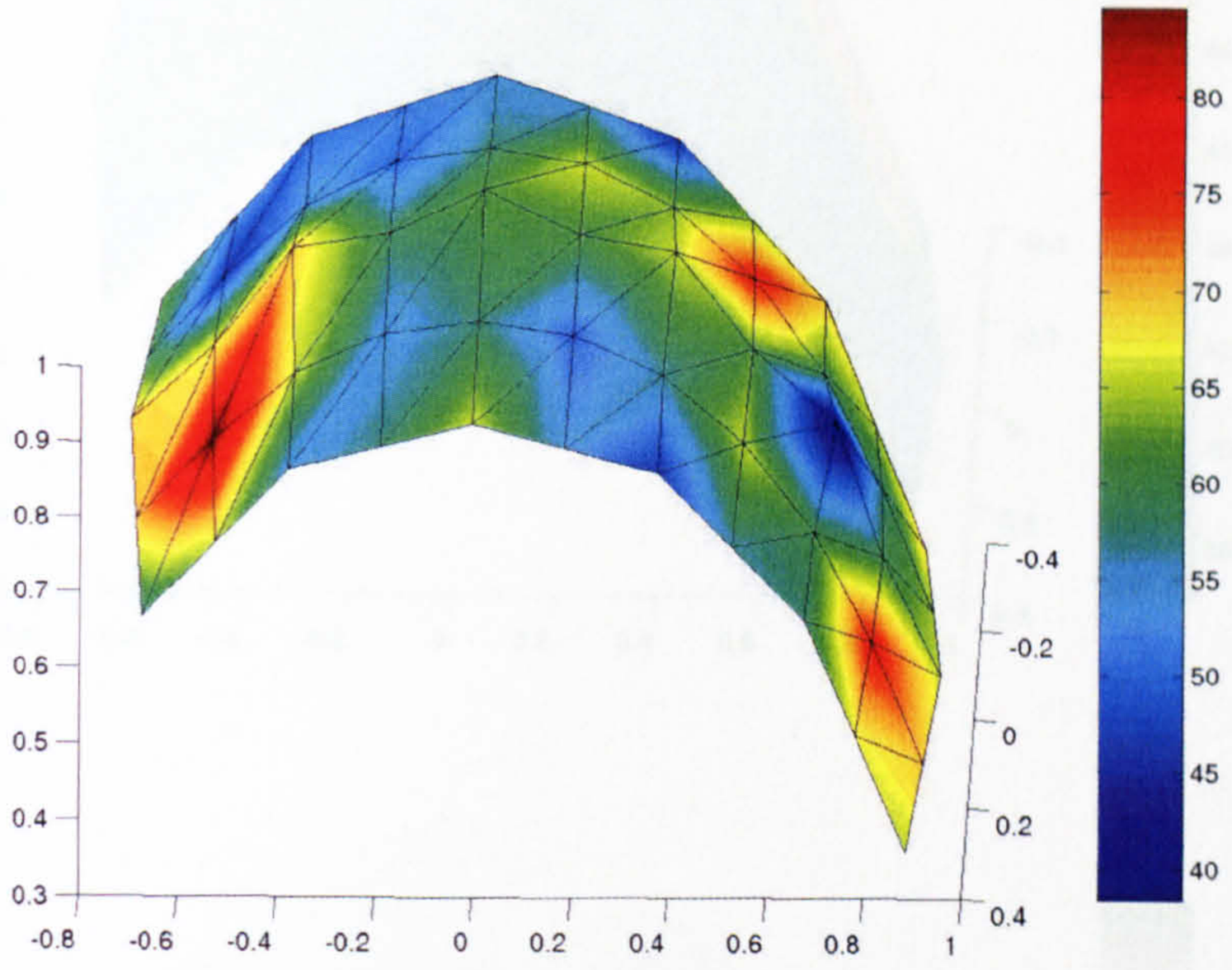


Classification Results: Prediction of Direction

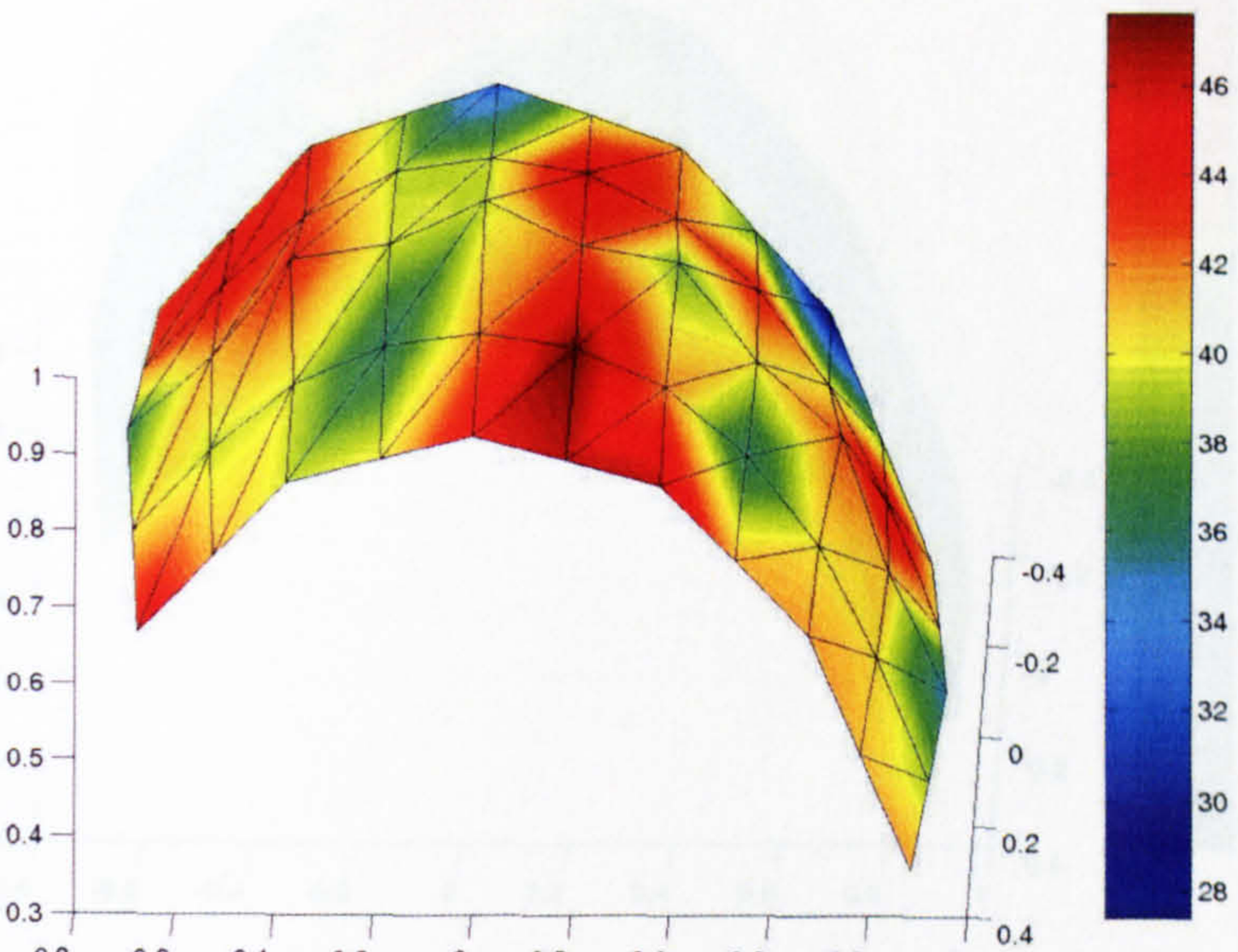
The results in the current section presents from attempts to predict the direction of actual or imagined movement.

Externally Cued

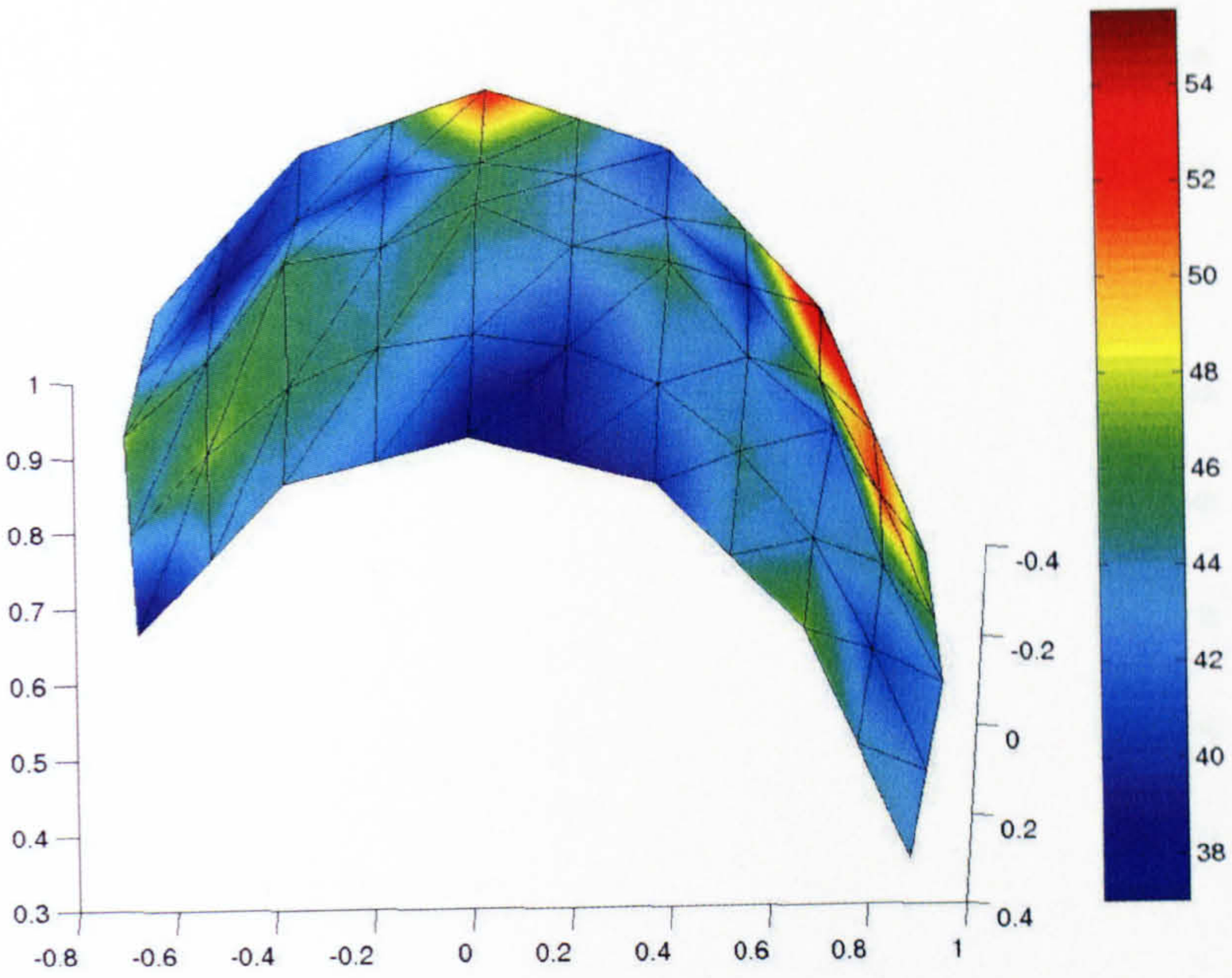
Subject 1



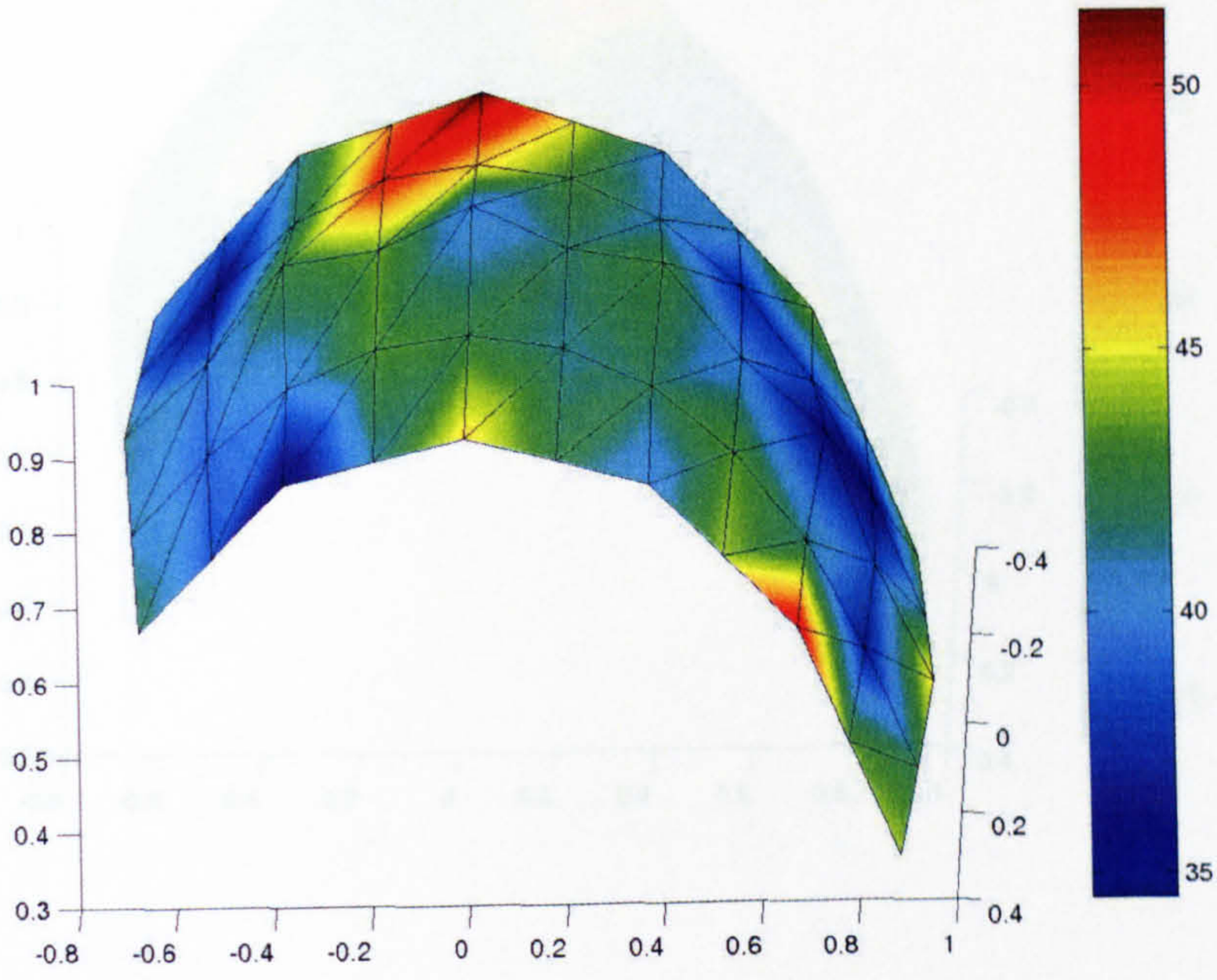
Subject 2



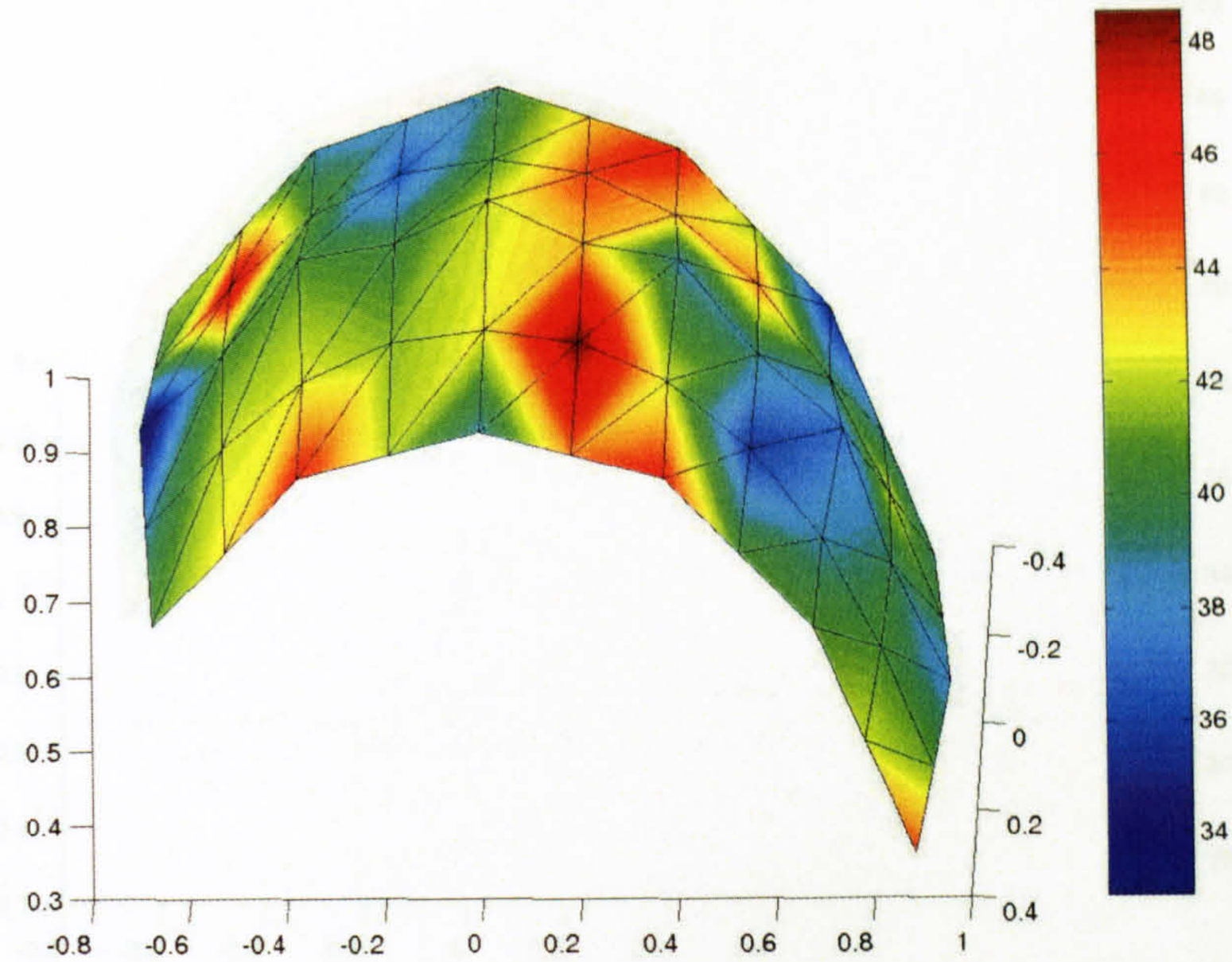
Subject 3



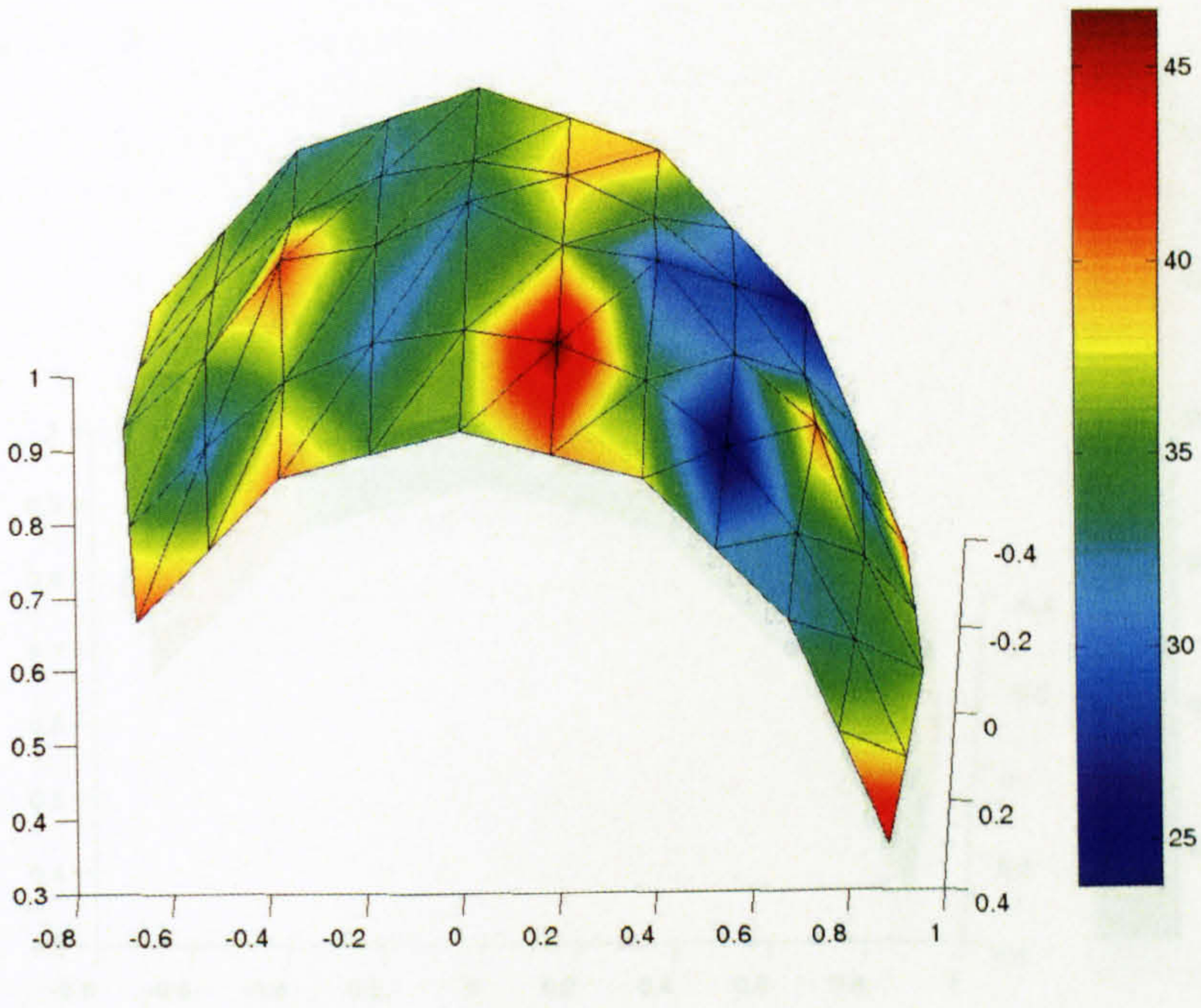
Subject 4



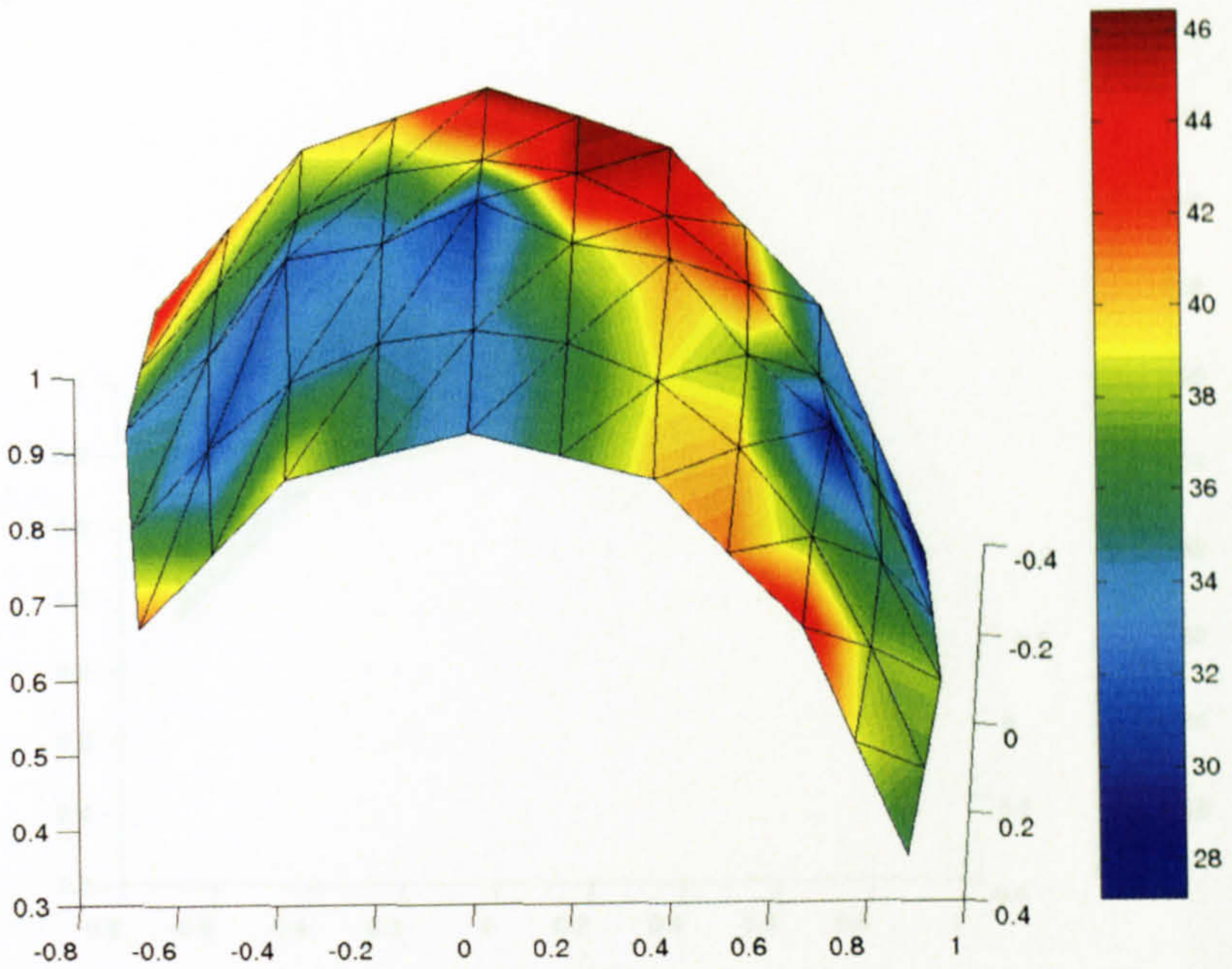
Subject 5



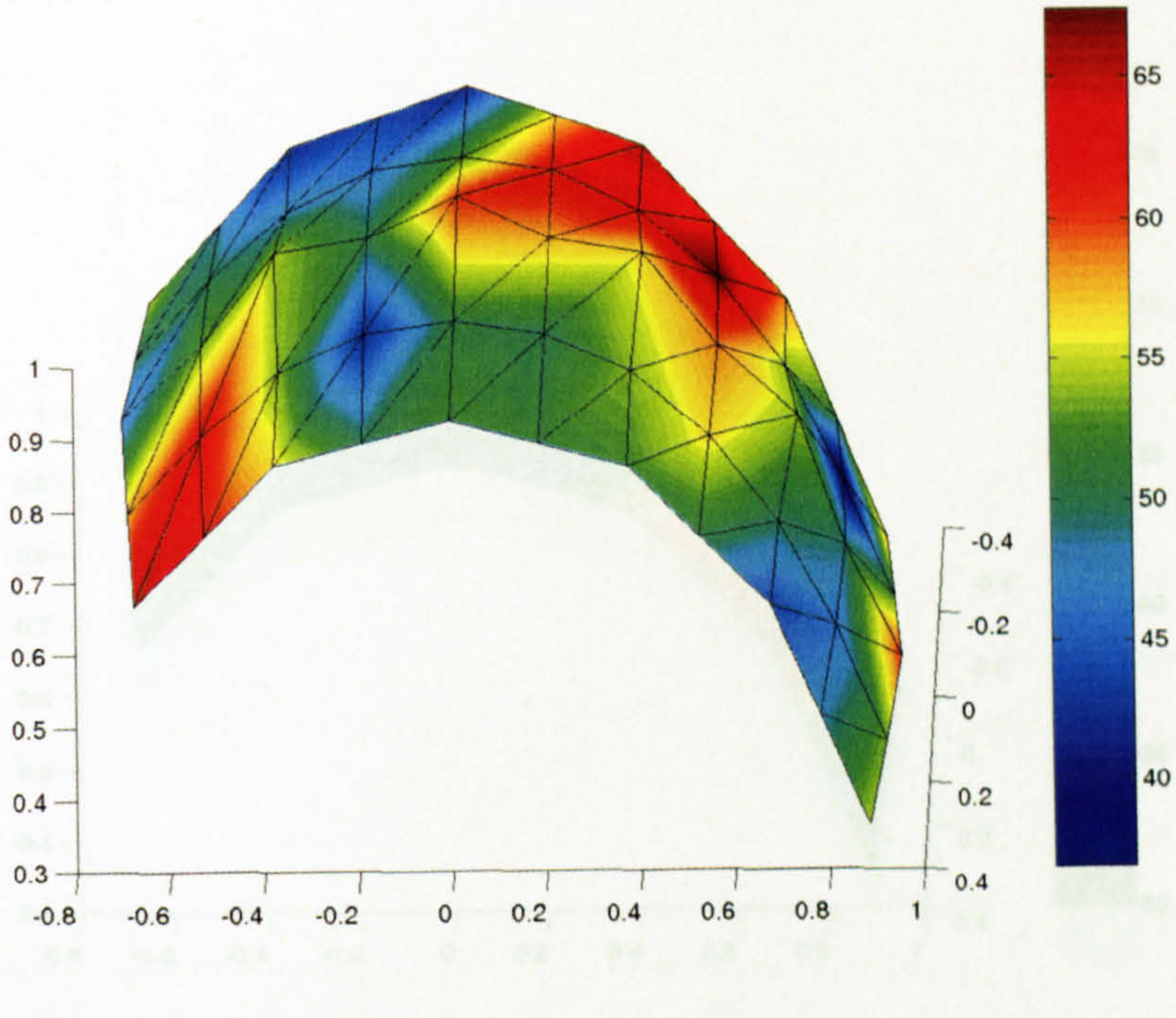
Subject 6



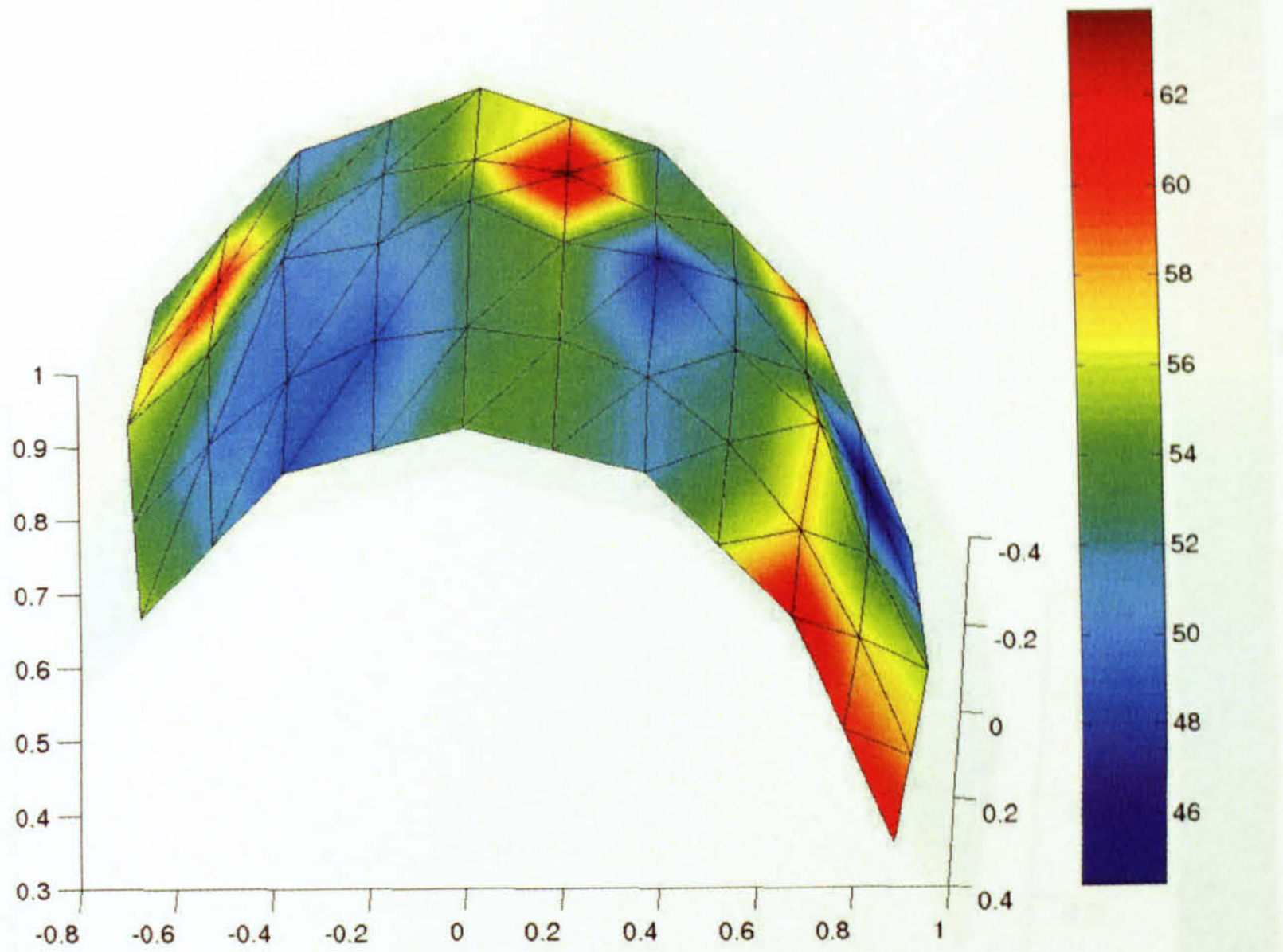
Subject 7



Subject 8

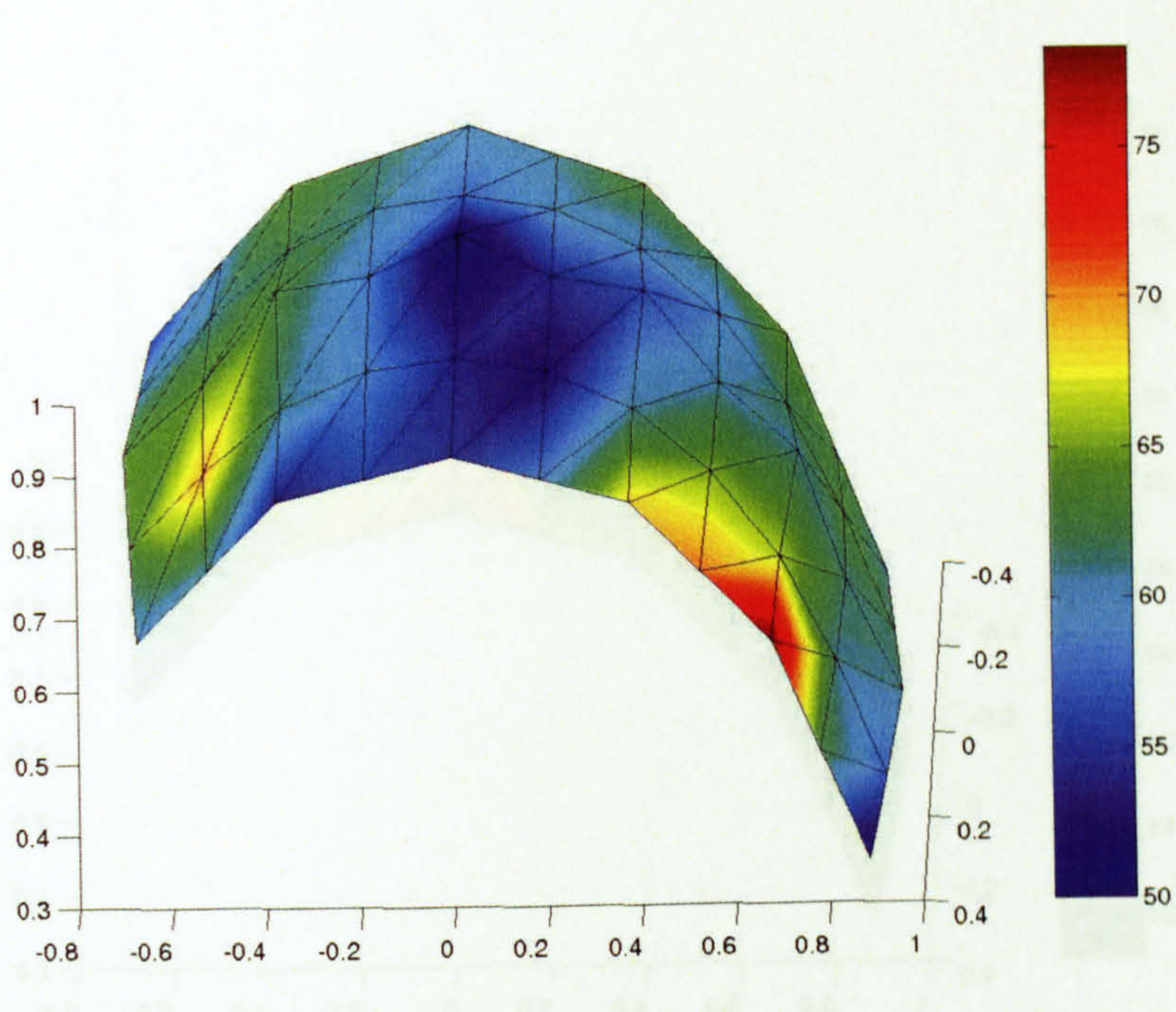


Subject 10

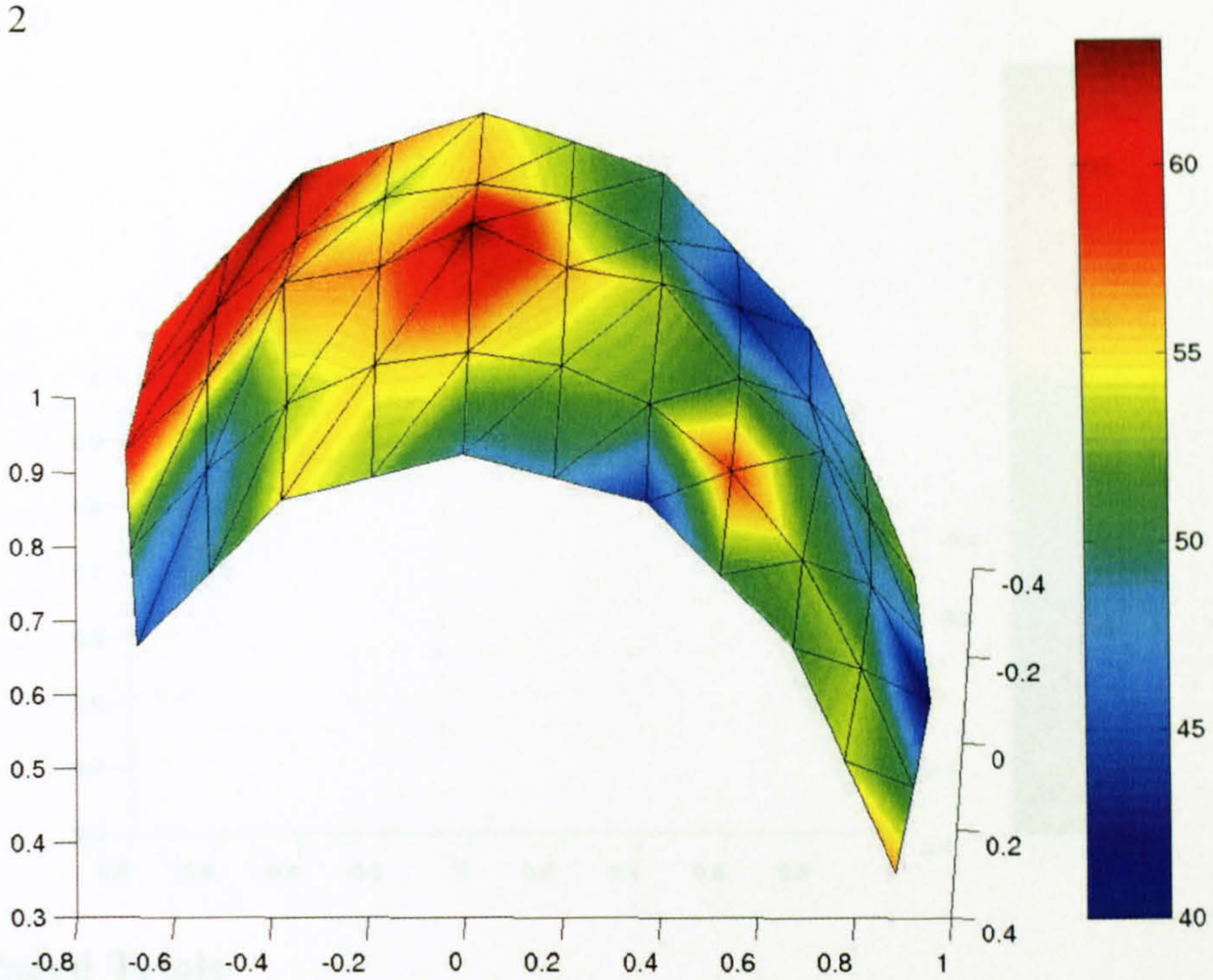


Forced Choice

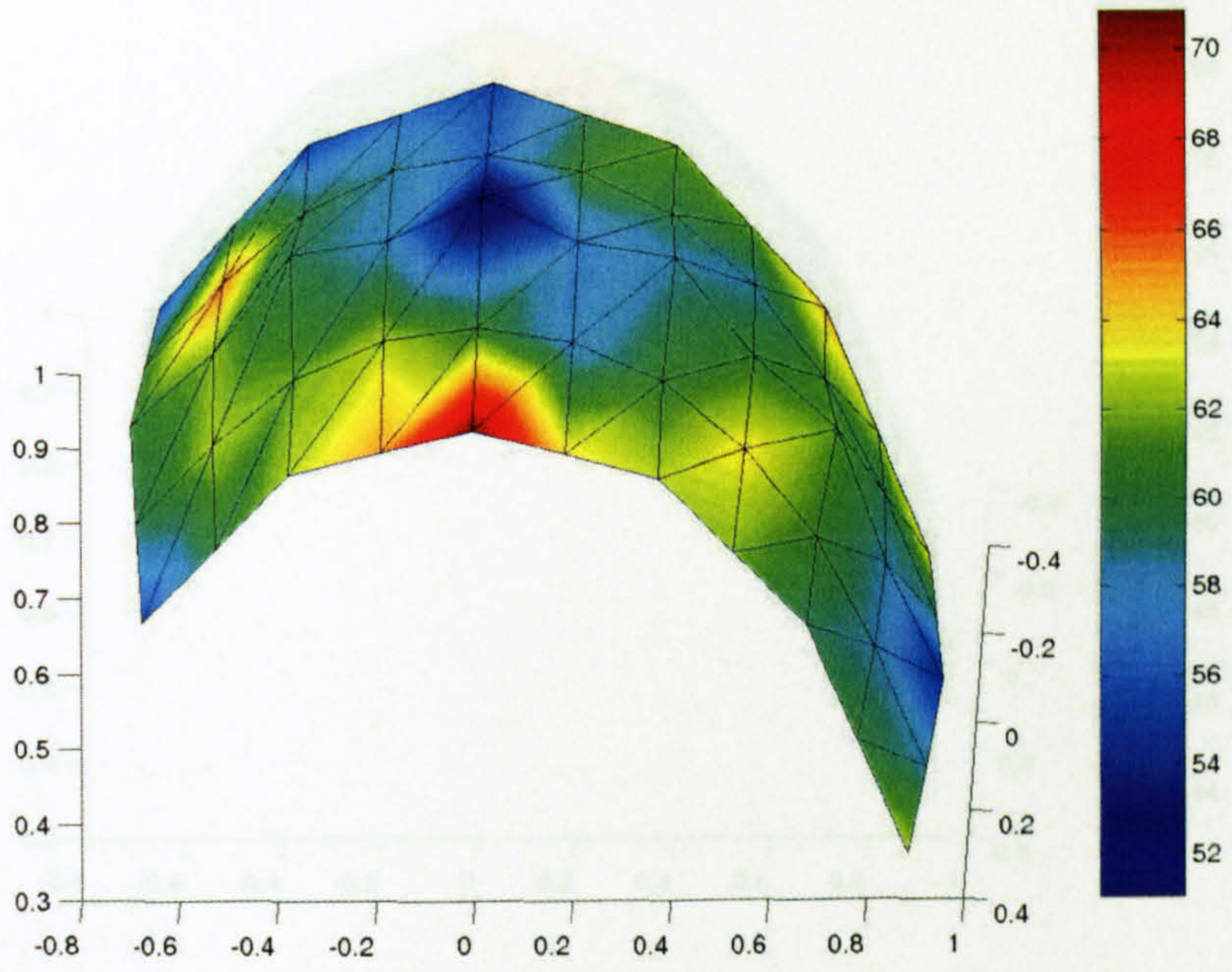
Subject 1



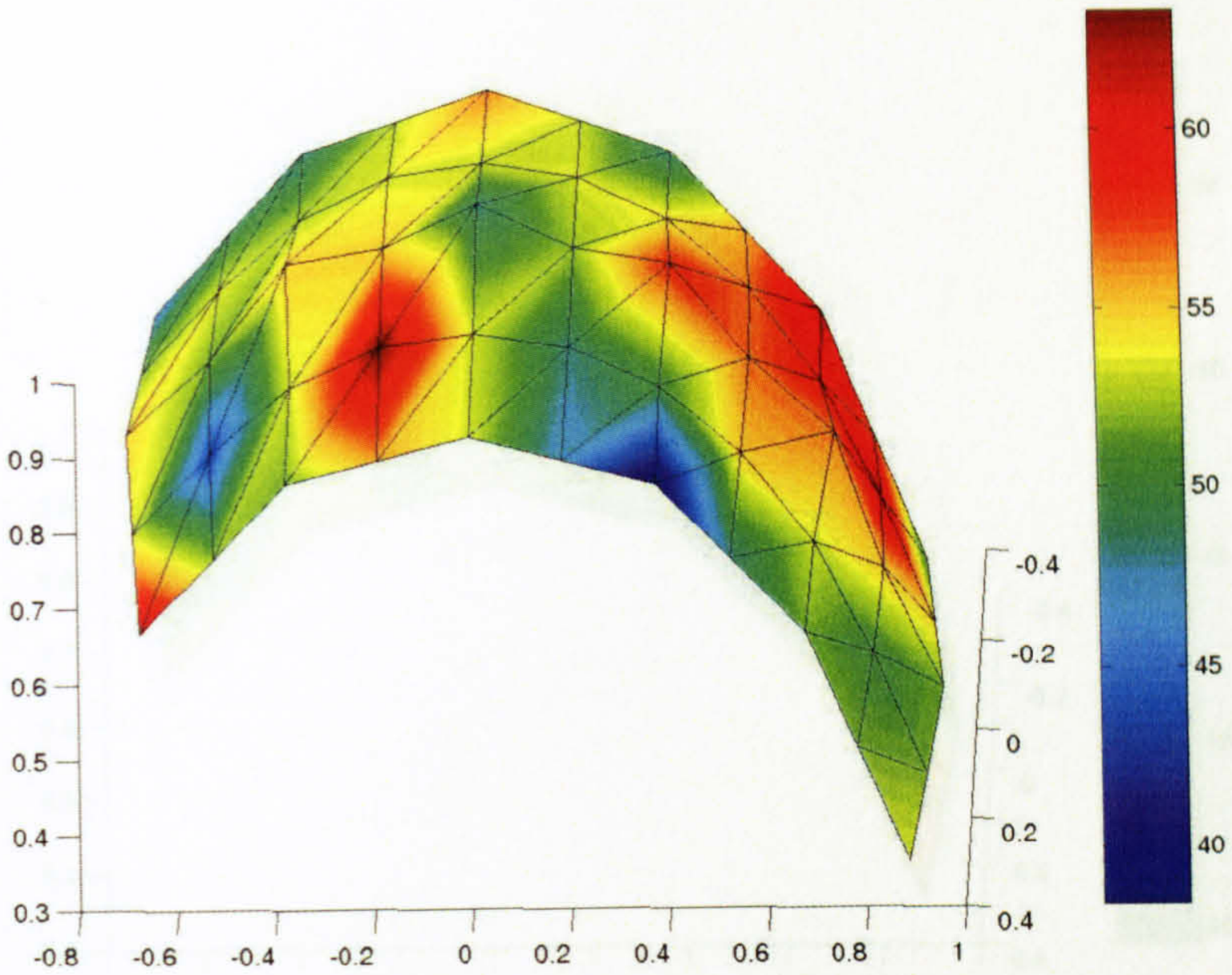
Subject 2



Subject 3

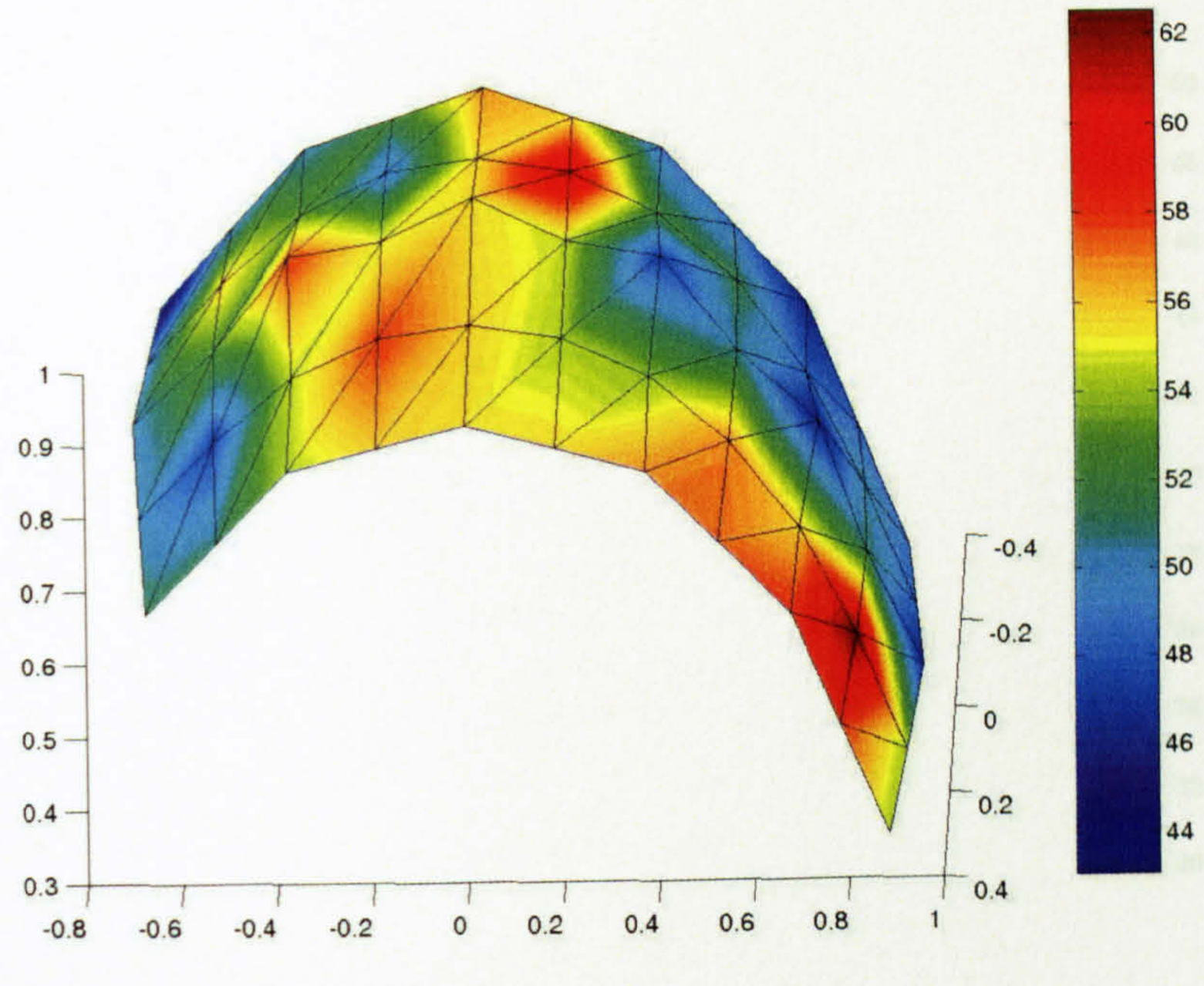


Subject 10

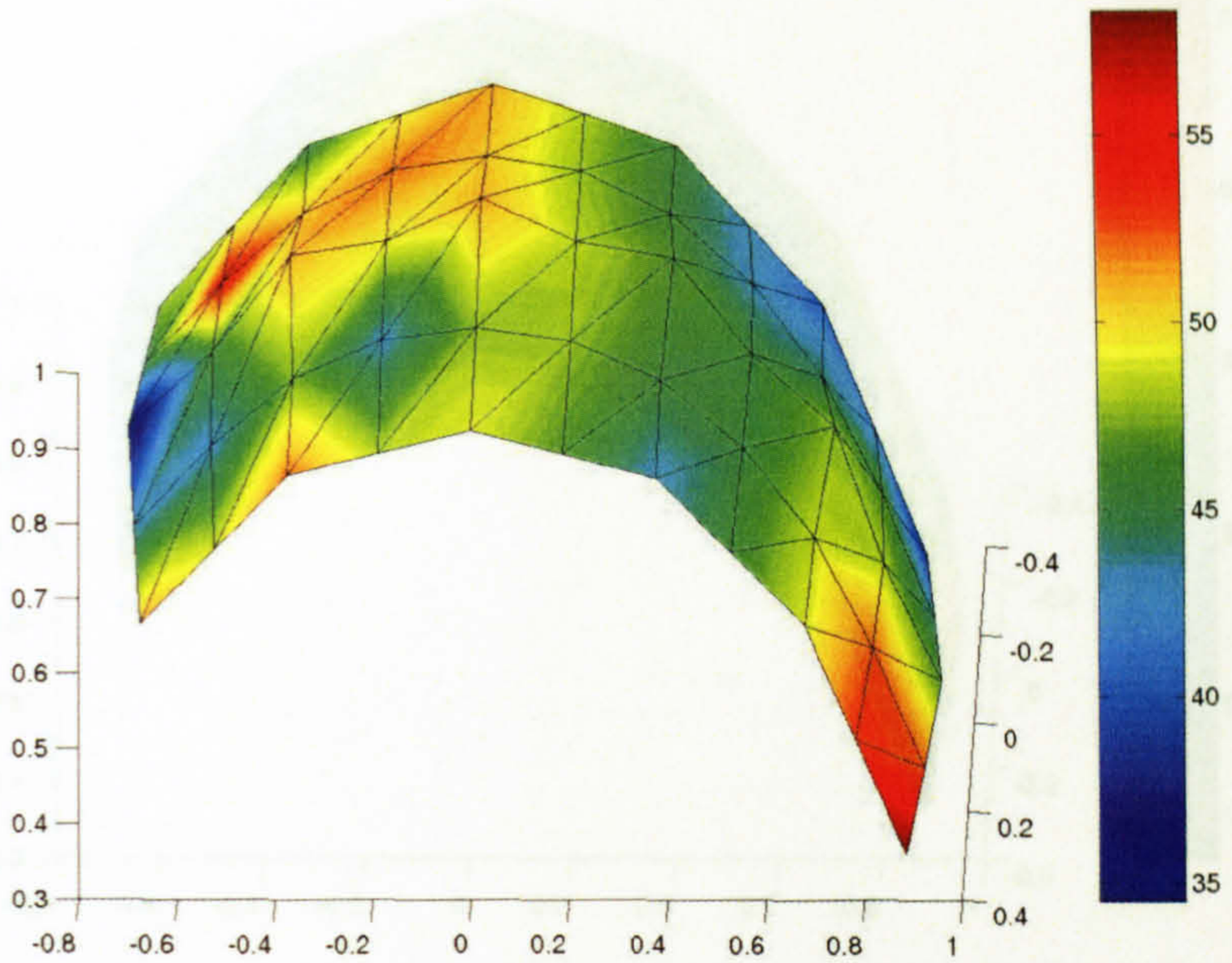


Self-Paced Trials

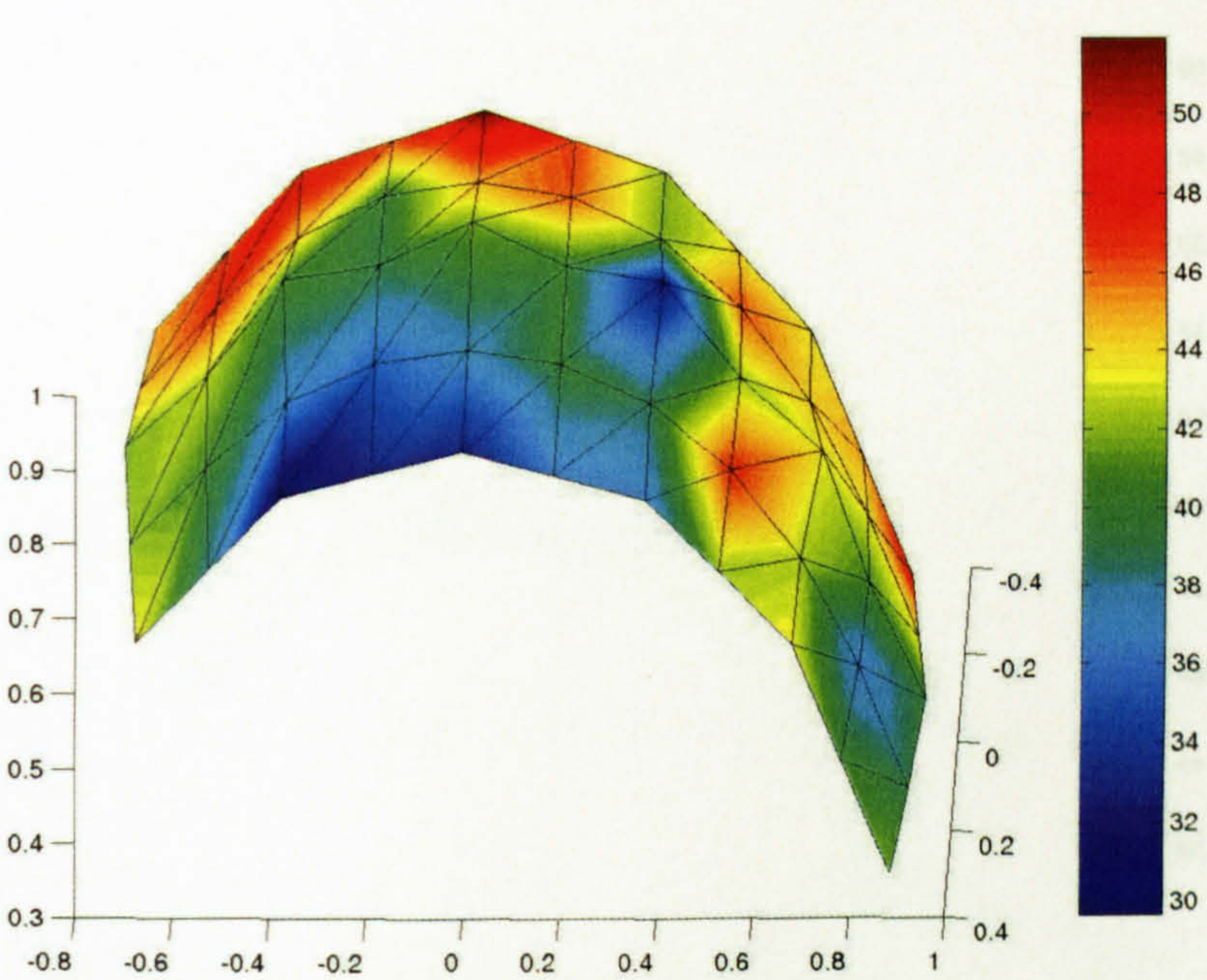
Subject 1



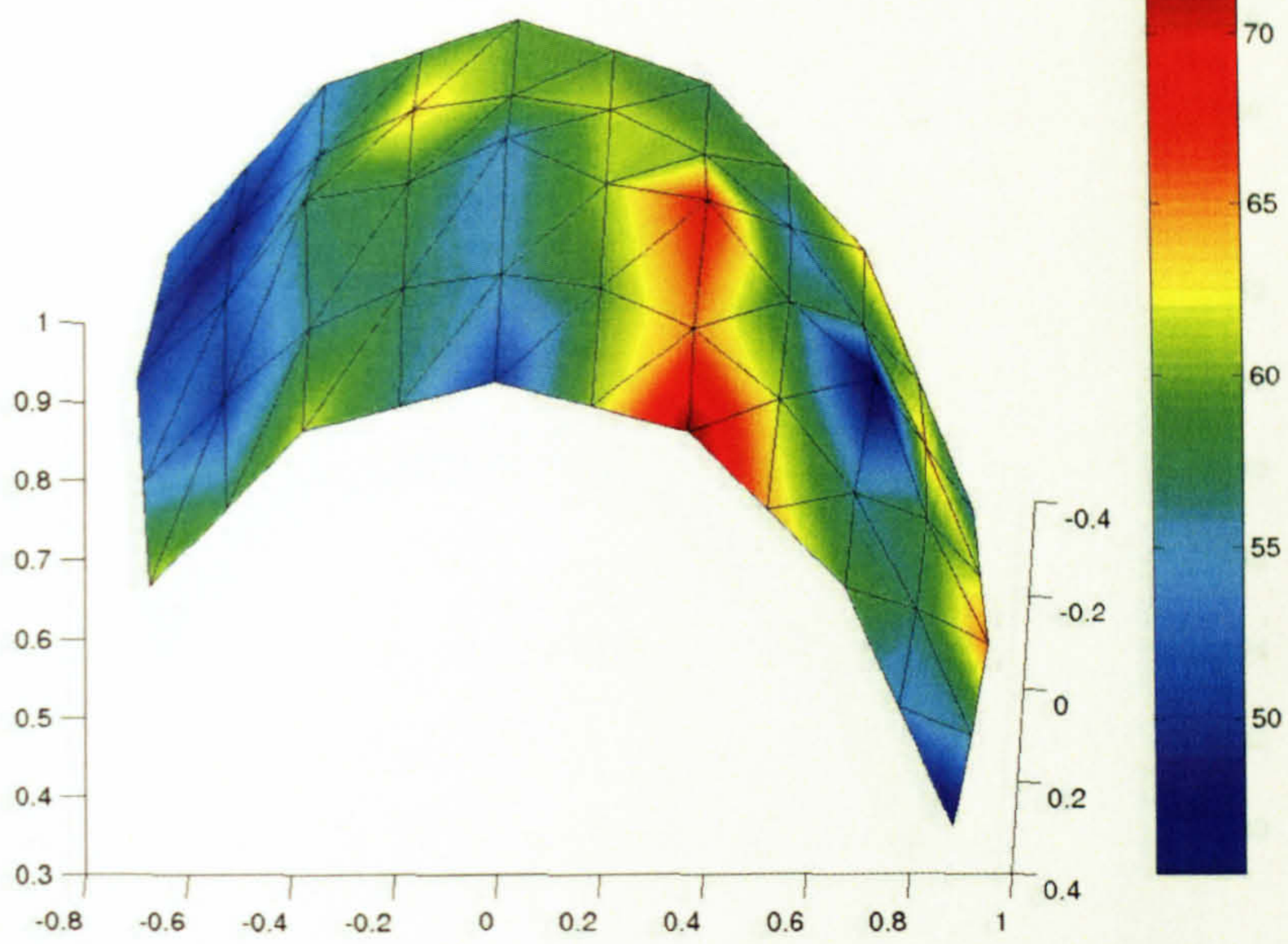
Subject 2



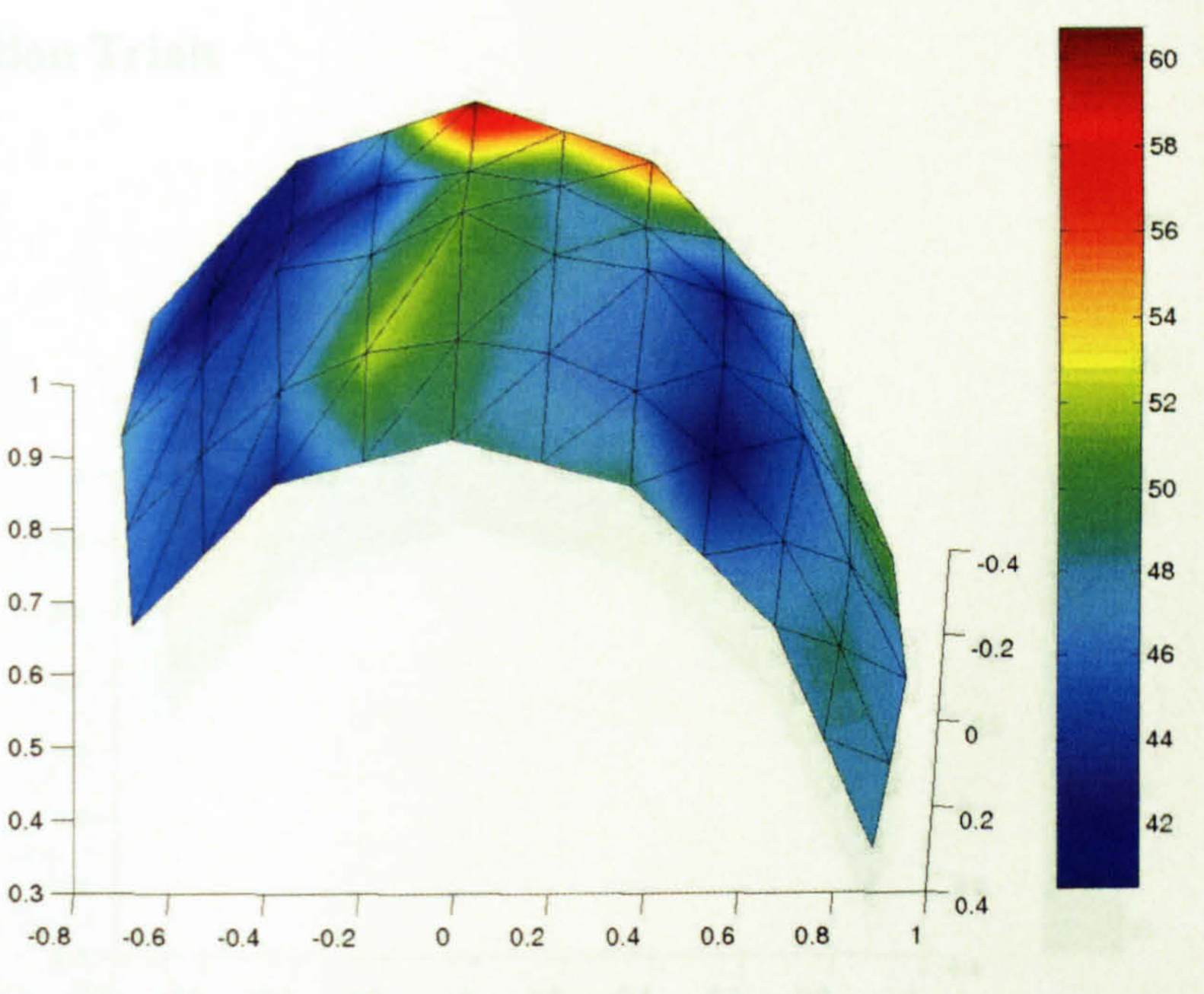
Subject 3



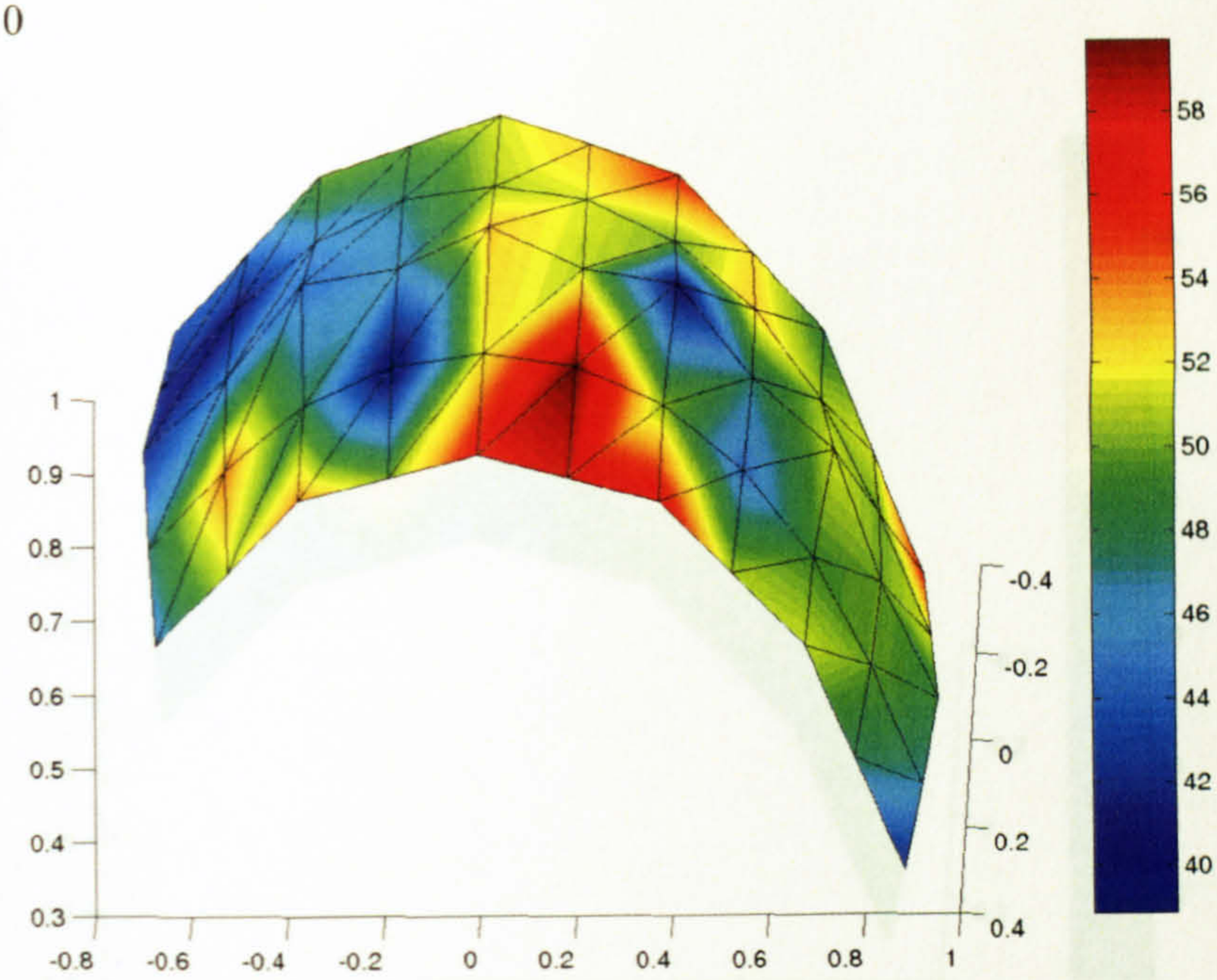
Subject 8



Subject 9

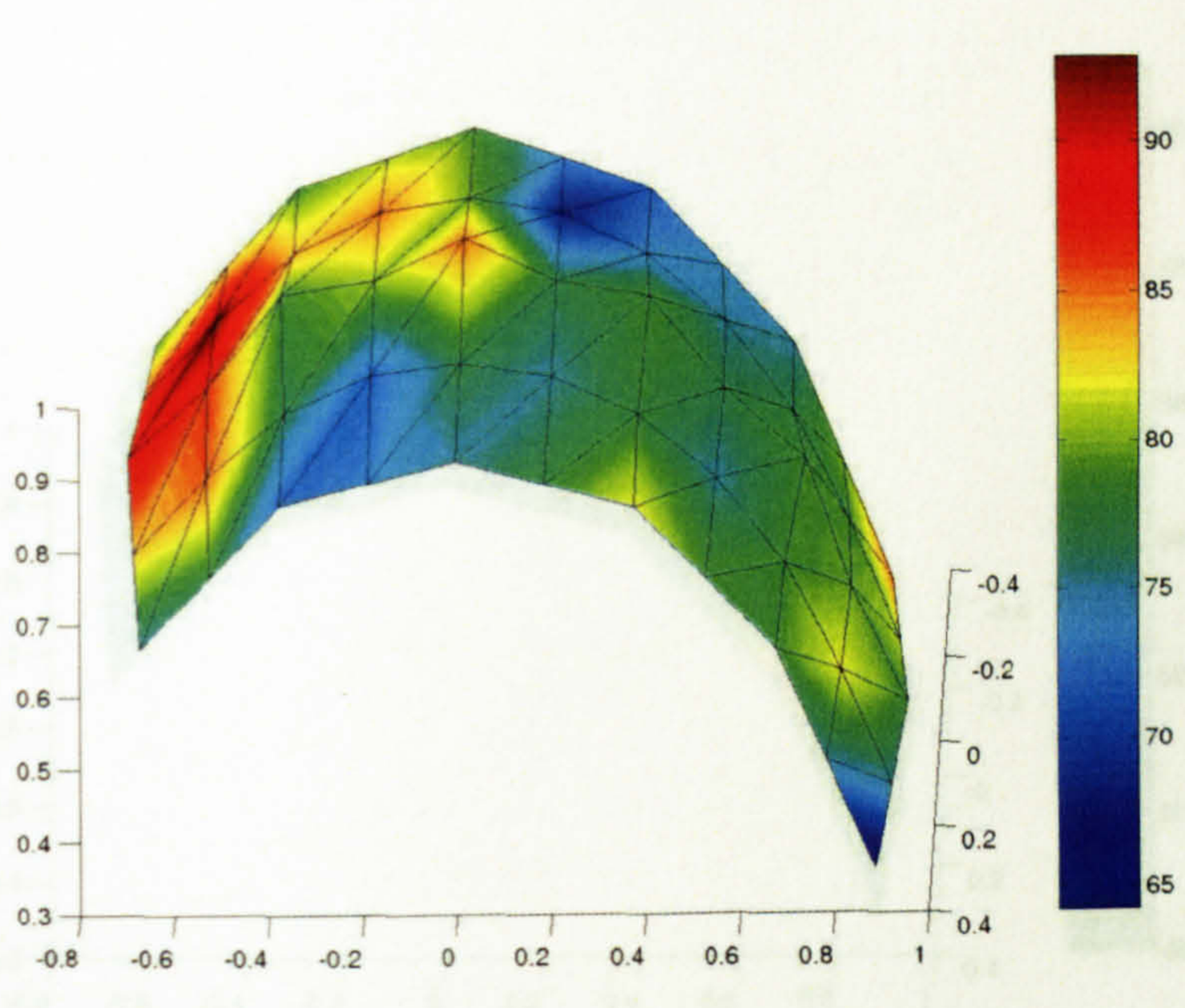


Subject 10



Imagination Trials

Subject 1



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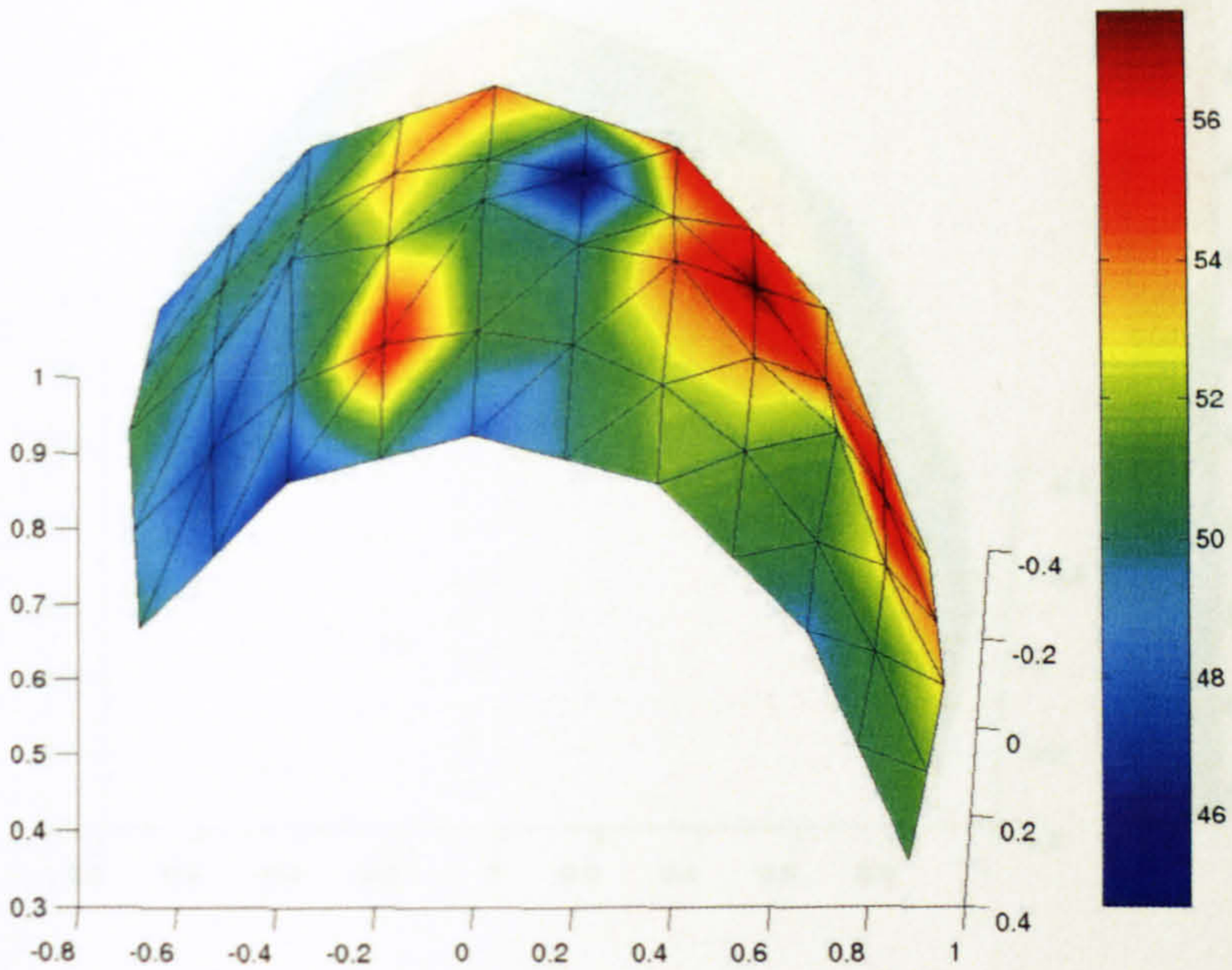

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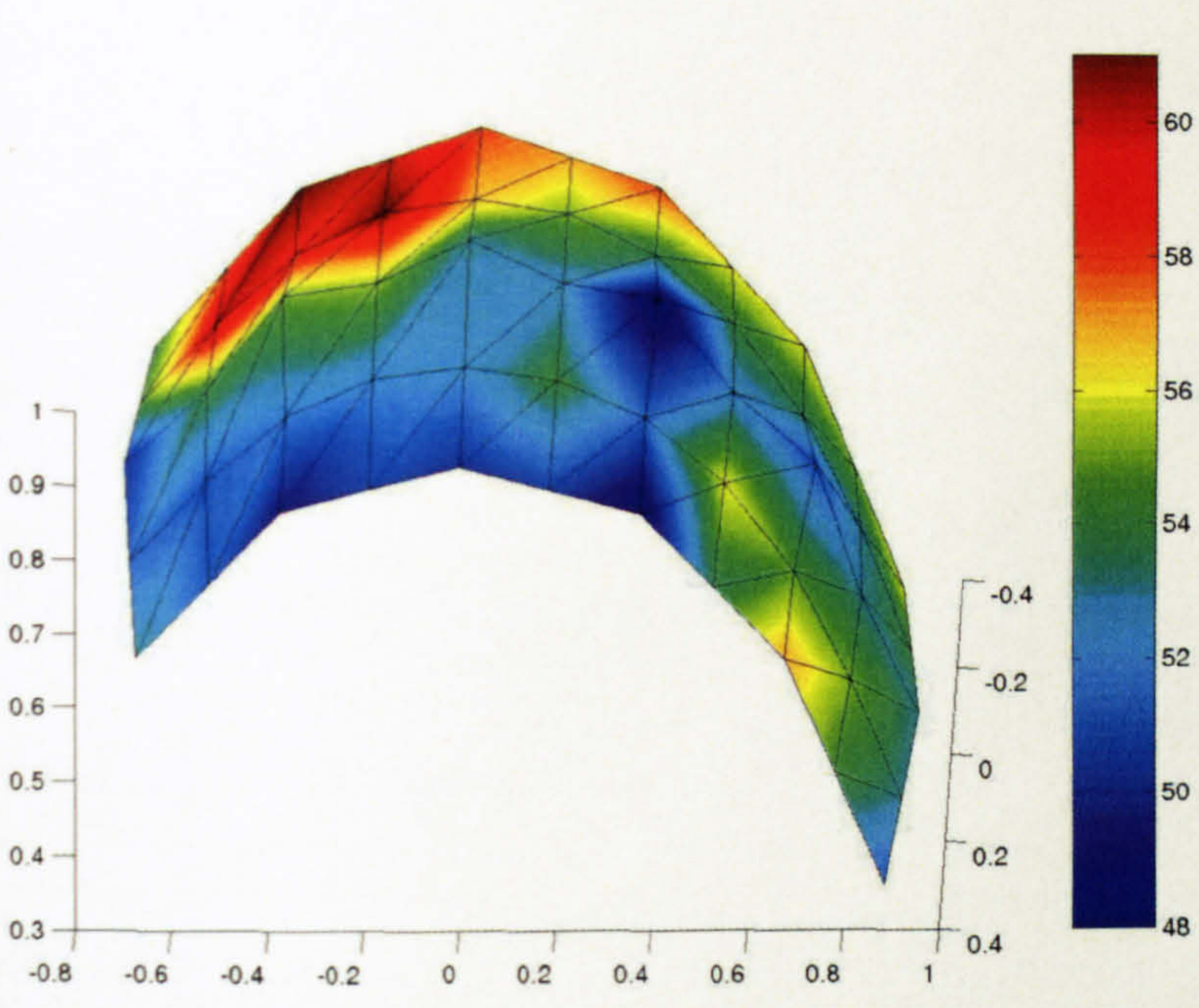
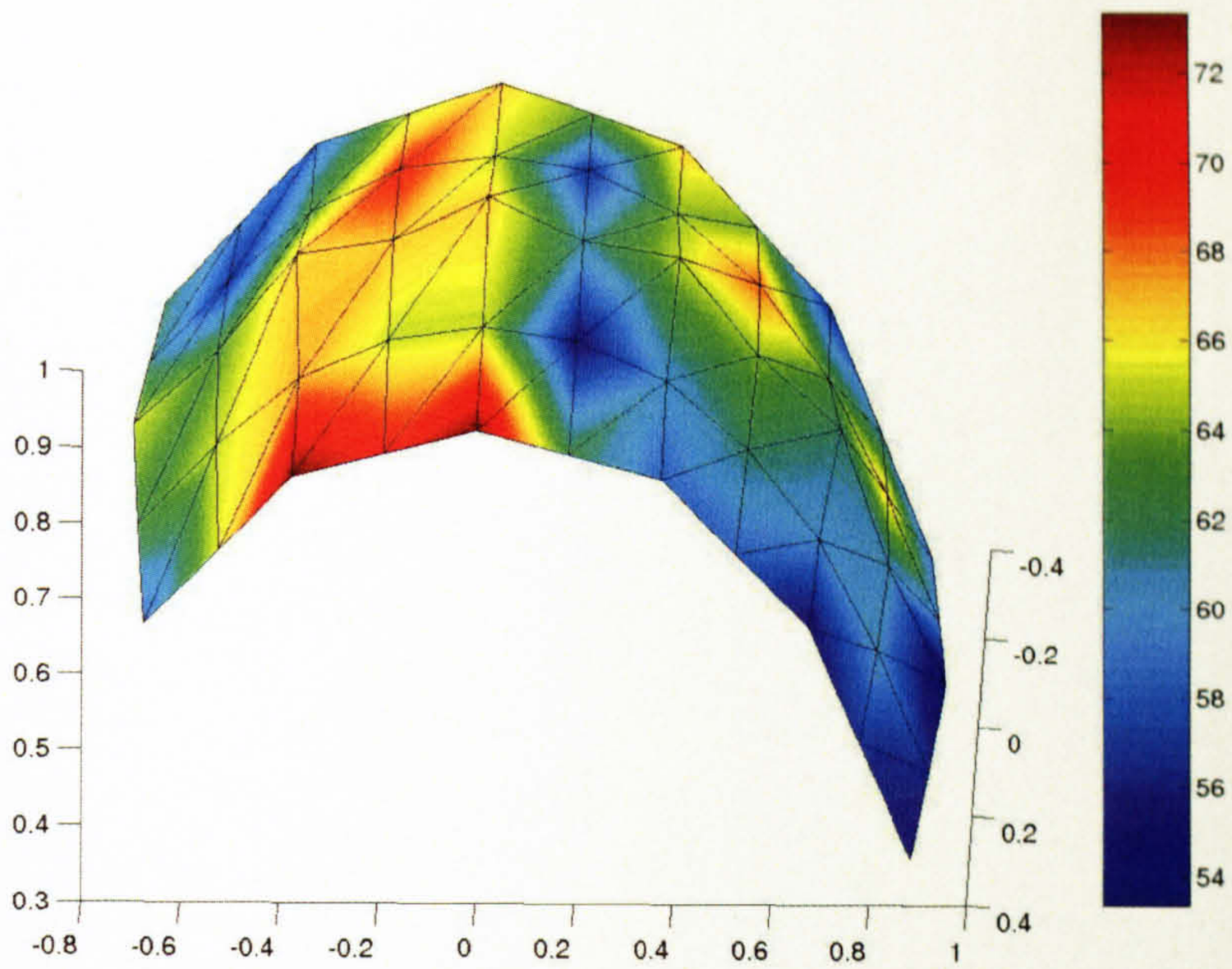


Subject 5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54