



UNIVERSITY COLLEGE DUBLIN  
Department of Electrical and Electronic Engineering

# Electroencephalograph based Brain Computer Interfaces

by

*Raymond Carl Smith*

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Research Supervisor: Dr. R. Reilly  
Head of Department: Prof. T. Brazil

## Publications arising from this thesis

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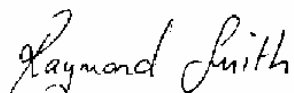
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## **Abstract**

Brain computer interfaces (BCIs) have the potential to offer humans a new and innovative non-muscular modality through which to communicate directly via their brain activity with their environment. These systems rely on the acquisition and interpretation of the commands encoded in neurophysiological signals without using the conventional muscular output pathways of the central nervous system (CNS). Brain imaging technologies such as EEG, fMRI and MEG are used to observe this neurophysiological activity. Electroencephalograph (EEG) is the only practical non-invasive, cheap and real-time capable imaging technology for use in a BCI system. BCIs propose to offer people who suffer from neuromuscular disorders, whom lack any voluntary motor movement, with the only possibility of communication and control.

This thesis firstly addresses the issues for using EEG as a BCI input modality by reviewing the methods for EEG acquisition and analysis. The components and methodologies for a BCI system framework and the current state of the art of this technology are then presented. Two studies that investigate different BCI system implementations and applications are presented and discussed.

The first study presents a left-right self paced typing exercise that was employed to highlight that the brain generates a movement-related potential (MRP) that can be used to distinguish upcoming left or right finger movement. The study proves that we can predict the laterality of upcoming left or right finger movements with an offline accuracy of approximately 60%. The second study involves an implementation of a real-time video game controlled by the user's selective attention of different visual stimuli. Steady-State Visual Evoked Potentials (SSVEPs) generated at the occipital cortex are used as the input signals. The game requires the user to maintain the balance of a tight-rope walker. The implemented online system achieved approximately 89% accuracy with 41 of the 48 games successfully completed.

This thesis has described and demonstrated by implementation the components and framework of a BCI system to facilitate the use of brain signals to control a computer system. It concludes by discussing the future potential of BCI technology and the work needed to improve information transfer rates and usability for the development of marketable applications not only for the disabled but a potential wider audience.

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# Chapter 1 Introduction

## 1.1. Background

Human-computer interaction has been a topical research concept since the birth of the computer era. Methods of computer interaction have progressed rapidly over the years from cards with punched holes to keyboards and mice. Today there exist a multitude of innovative technologies that allow humans to interface with computers for the purposes of data entry, control or communication. Most of the efforts over the years have been dedicated to the design of user-friendly and ergonomic systems to produce a more efficient and comfortable means of communication. Interfaces such as voice recognition, gesture recognition and other technologies based on physical movement have received enormous research attention over the years and successful examples of these technologies are being rolled out commercially as a consequence.

The past two decades have seen an explosion of scientific interest in a completely different and novel approach of interacting with a computer. Inspired by the social recognition of people who suffer from severe neuromuscular disabilities, an interdisciplinary field of research has been created to offer direct human computer interaction via signals generated by the brain itself. Brain-Computer Interface (BCI) technology, as it is known, is a revolutionary communication channel that enables users to control computer applications through thoughts alone. The development of the cognitive neuroscience field has been instigated by recent advances in brain imaging technologies such as Electroencephalography (EEG), Magnetoencephalography (MEG) and functional magnetic resonance imaging (fMRI). EEG is an imperfect and distorted indicator of brain activity, yet the fact that it can be acquired cheaply, is non-invasive and demonstrates direct functional correlations with high temporal resolution makes it the only practical direct brain-computer communication channel. It is a new and challenging medium for us to exploit in a similar manner to the other communication modalities such as voice or vision. The endless potential of tapping into human brain signals may see the fantasies of science fiction writers becoming reality in the future.

The growing field of BCI research is however in its infancy. First signs of BCI research can be dated back to the early 1970s. The work of Dr. J. Vidal and his military research group at UCLA is cited as the first successful BCI implementation endeavour [1]. The current goal of BCI research is to develop replacement communication and control means for severely disabled people.

For those who have lost all voluntary muscle control, referred to as locked-in syndrome<sup>1</sup>, BCI technology offers the only means of communication or environment control. Locked-in syndrome can be caused, for example, by amyotrophic lateral sclerosis (ALS)<sup>2</sup>, brainstem stroke, mitochondrial disease, spinal-cord injury, traumatic-brain injury<sup>3</sup> and even later-stage cerebral palsy. Despite these sufferers being completely physically paralyzed and unable to speak, they are however, cognitively intact and alert and thus have a need to communicate. It is estimated that in the order of one million people worldwide suffer from locked-in syndrome. It is this motivation that has inspired researchers to explore the possibility of harnessing the intact brain signals of these people as a means of communication.

BCI design represents a new frontier in science and technology that requires multidisciplinary skills from fields such as neuroscience, engineering, computer science, psychology and clinical rehabilitation to achieve the goal of developing an alternative communication medium. Despite the technological developments, there remain numerous obstacles to building efficient BCIs. The biggest challenges are related to accuracy, speed and usability. Due to these limitations, no BCI system has become commercially available as yet. If a disabled person can move their eyes or even one muscle in a controlled way, the interfaces based on eye-gaze or EMG switch technology are more efficient than any of the BCIs that exist today. The maximum transfer rate of current BCI systems is in the order of 25 bits per min. The standard dial-up modem can transfer information at a rate of 56 Kbits per second and even this is rapidly being replaced by Megabit and even Gigabit technology. The question that remains to be answered by the scientific community is: what is the future of BCI technology outside rehabilitative communication and control applications for the severely disabled? Can the wider population expect to play games, browse the internet and navigate other multimedia rich applications via thought alone? The research carried out in this thesis explores the field of BCI design and implementation in the hope of understanding the potential of this technology.

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<sup>1</sup> **Locked-in Syndrome** - Locked-in syndrome is a rare neurological disorder characterized by complete paralysis of voluntary muscles in all parts of the body except for those that control eye movement. It may result from traumatic brain injury, diseases of the circulatory system, diseases that destroy the myelin sheath surrounding nerve cells, or medication overdose. Individuals with locked-in syndrome are conscious and can think and reason, but are unable to speak or move. The disorder leaves individuals completely mute and paralyzed. There is no cure for locked-in syndrome, nor is there a standard course of treatment. (Courtesy of the American National Institute of Neurological Disorders and Stroke - [http://www.ninds.nih.gov/health\\_and\\_medical/disorders/lockedinsyndrome\\_doc.htm](http://www.ninds.nih.gov/health_and_medical/disorders/lockedinsyndrome_doc.htm))

<sup>2</sup> **Amyotrophic lateral sclerosis (ALS)** is a devastating neuromuscular disease that strikes adults in the prime of their life. ALS attacks motor neurons which control the movement to voluntary muscles, and progresses rapidly, leading to complete paralysis followed by death within a 3 to 5 year period. 5,000 cases are diagnosed annually in the United States (MDA).

<sup>3</sup> **Traumatic Brain Injury (TBI)** is an injury to the brain caused by trauma, i.e. a blow to the head. Annually 80,000 to 90,000 TBI suffers in the US experience the onset of long-term or lifelong disability associated with TBI. In Ireland it is estimated that over 13,000 people sustain TBI every year (Courtesy of Headway Ireland Information and Support Department).

## **1.2. Aim and Objectives**

The aim of this research was to gain an insight into the rapidly developing field of BCI research. Focusing on the EEG as the BCI input modality, the goal was to develop a deep understanding of the neurophysiological processes that could be exploited to implement a BCI system. After performing a state-of-the-art review of BCI systems, it was envisaged to design and implement a system. A sound knowledge of the data acquisition process, EEG waveform characteristics, signal processing methodologies for feature extraction and classification is a prerequisite before attempting to design and implement a BCI system. The projects objectives can be summarised as follows:

- To develop a neurophysiological understanding of the human brain.
- To investigate electroencephalography as a means of identifying mental activity.
- To provide a comprehensive review of EEG based BCI systems implemented to-date.
- To develop experimental BCI systems.
- To discuss the future of BCI technology

## **1.3. Thesis Outline**

This thesis presents the fundamental knowledge behind developing an Electroencephalogram based BCI, presents a state-of-the-art review of BCI research and then describes two systems implemented by the author. The thesis concludes by looking to the future of BCI technology. The author highlights the challenging areas that must be addressed to facilitate further progression of this line of research.

Chapter 2 performs a thorough review of Electroencephalography (EEG), a brain imaging technology based on the electrophysiological activity within the brain. The chapter describes in detail the origin, functional behaviour, acquisition, characterization and applications of EEG recorded signals. The purpose of this chapter is to familiarise the reader with terminology and EEG characteristics that will be exploited and referred to in later chapters.

Chapter 3 begins by introducing the idea and purpose of a BCI. The essential components of a BCI framework are described and some of the signal-processing methodologies behind them are reviewed in detail. A large portion of this chapter is devoted to performing a state-of-the-art review of BCI technology and describing the approaches of various different BCI research groups around the globe. The chapter concludes by reviewing necessary standardised performance metrics and discusses the challenges for future progression of this technology.

Chapter 4 describes an offline BCI system based on activity in the brain related to limb movement. It introduces the fundamental brain patterns and signal processing methodologies exploited in this study to predict upcoming limb movement. A discussion analyses the results to conclude the performance and potential of such a system.

Chapter 5 presents a real-time BCI controlled video game with immersive audio-visual feedback. The chapter describes the brain activity associated with visual stimulation and the methodologies that are exploited in this study to offer control. The real-time deployment of this system and the associated performance results are reviewed. Finally, a discussion reviews the success and future work of this type of BCI implementation.

Chapter 6 provides a conclusion on the issues addressed by this research and on the future of BCI technology.

## **Chapter 2      Electroencephalography (EEG)**

This chapter serves as an introduction to the electro-biological brain imaging technique known as Electroencephalography (EEG). It begins with a brief introduction to the origins of EEG and its comparison to other brain imaging techniques. The neurophysiological and anatomical structure of the human brain is then presented to introduce some terminology and to serve as background information on its structure and function. This will particularly focus on the creation of the electrochemical currents that are picked up by scalp electrodes and that form the EEG. The subsequent section highlights the methods, potential complications and equipment necessary in relation to EEG acquisition. Section 2.4 explains from a digital signal processing (DSP) point of view, the characteristic signal properties of EEG activity. This will form an important basis for later discussion when we hope to elicit pertinent features from continuous EEG that identifies with a particular event or function for the purposes of developing a Brain Computer Interface. Finally, the chapter catalogues the many clinical applications of EEG and concludes with an introduction to EEG as a new alternative and augmentative communication medium.

### **2.1.    Introduction**

The great Greek philosophers such as Aristotle and Plato spawned an inquisitive era for hypothesizing the anatomical and biological make-up of the human body. Herophilus (335-280 B.C.), often referred to as the ‘Father of Anatomy’, was the first man to begin meticulously cataloguing his anatomical findings. Through mankind’s insatiable curiosity, this quest developed into modern day medicine. Today every aspect of the human body from our very genetic make-up to the historical progression of the human genome is explored.

Throughout these periods, the human brain was the great medical and philosophical fascination of the human body. It began with human autopsies to explore the anatomical structure and then developed to live in-situ brain experiments to explore its behaviour and functionality. These were first performed on animals and then later on humans with severe cranial fractures or terminal illnesses. Slowly, on a trial-by-trial basis, an understanding of the physiology of the human brain was developed. It generated much interest for philosophers, psychologists and surgeons alike. Mankind was no longer content to simply know the anatomical make-up of the brain but we now wanted to know how this frail organ performed so many complex functions. This multi-disciplinary collation gave birth to the field of Neuroscience. Its goal was to explore and



understand the physiological and psychological behaviour of the brain, spinal cord and peripheral nerves that make up this complex integrated information processing and control system.

### 2.1.1. History

The existence of electrical currents in the brain was discovered in 1875 by a Liverpool surgeon named Richard Caton (1842-1926). He studied action potentials from the exposed brains of rabbits and monkeys. Hans Berger (1873-1941), a German neuropsychiatrist working on cerebral localization and intracranial blood circulation, followed on from Caton's work. In 1924, he used his ordinary radio equipment to amplify the brain's electrical activity measured on the human scalp. This was the first Electroencephalogram (EEG) recording of humans. He showed that weak electric currents generated in the brain can be recorded without opening the skull, and depicted graphically on a strip of paper [2].

*“We see in the electroencephalogram a concomitant phenomenon of the continuous nerve processes which take place in the brain” ...Berger (1929).*

The activity that he observed changed according to the functional status of the brain, such as during sleep, anaesthesia, lack of oxygen and in certain neural diseases such as in epilepsy. He was correct in his assertion that brain activity changes in a consistent and recognizable way when the general status of the subject changes, as from relaxation to alertness [3]. Berger was the first to use the word “electroencephalogram” to describe the brain electric potentials in humans. He laid the foundations for many of the present applications for EEG (as covered later in section 2.5) and as a result earned himself the title as the ‘father of EEG’. An interesting review of the historical progression of EEG to its modern day applications is presented by Collura [4].

The modern day Electroencephalogram (EEG) is defined as the electrical activity of an alternating type generated by brain structures and recorded from the scalp surface by metal electrodes and conductive media [5]. Many variations of the scalp recorded EEG exist. EEG measured directly from the cortical surface using subdural electrodes is called the electrocorticogram (ECoG) while when using a depth probe is called electrogram. In this thesis, we will refer only to EEG recorded from the surface of the scalp. In the following subsection, Electroencephalography is compared with other brain imaging technologies, highlighting its advantages for the purposes of BCI design.

### 2.1.2. Brain imaging

Modern medicine applies a variety of imaging techniques to analyse the functioning of the human body. The group of electro-biological measurements consist of electrocardiography (ECG, heart), electromyography (EMG, muscle contraction), electrogastrography (EGG, stomach),

electrooculography (EOG, eye dipole field) and electroencephalography (EEG, brain). EEG involves the recording of scalp electrical activity generated by brain structures. It is just one of the many brain imaging technologies that have been developed in the pursuit of the ability to visualise brain condition and understand brain function. Based on various physical properties, other brain imaging technologies include x-ray Computed (Axial) Tomography (CT), Positron Emission Tomography (PET) [6], Single-Photon Emission Computed Tomography (SPECT) [6], rapid-rate Transcranial Magnetic Stimulation (rTMS), Event-Related Optical Signal (EROS), Magnetoencephalography (MEG) [7] and (functional) Magnetic Resonance Imaging (fMRI) [8]. Table 2-1 provides a summary of each brain imaging technique, its physical measurement property, highlights its applications and presents its relative advantages and disadvantages. See [5] for a review of Electroencephalography as a brain imaging modality.

Brain scans are subject to a phenomenon analogous to physics' Heisenberg uncertainty principle: they could detect either the localization or the timing of neural activation, but not both. Figure 2-1 depicts the relative spatio-temporal resolutions for some brain imaging technologies and the progression towards a method with both good temporal and spatial resolution (bottom left of Figure 2-1). Perhaps in the future, the multimodal fusion of multiple technologies such as EEG and fMRI may facilitate further improvements.

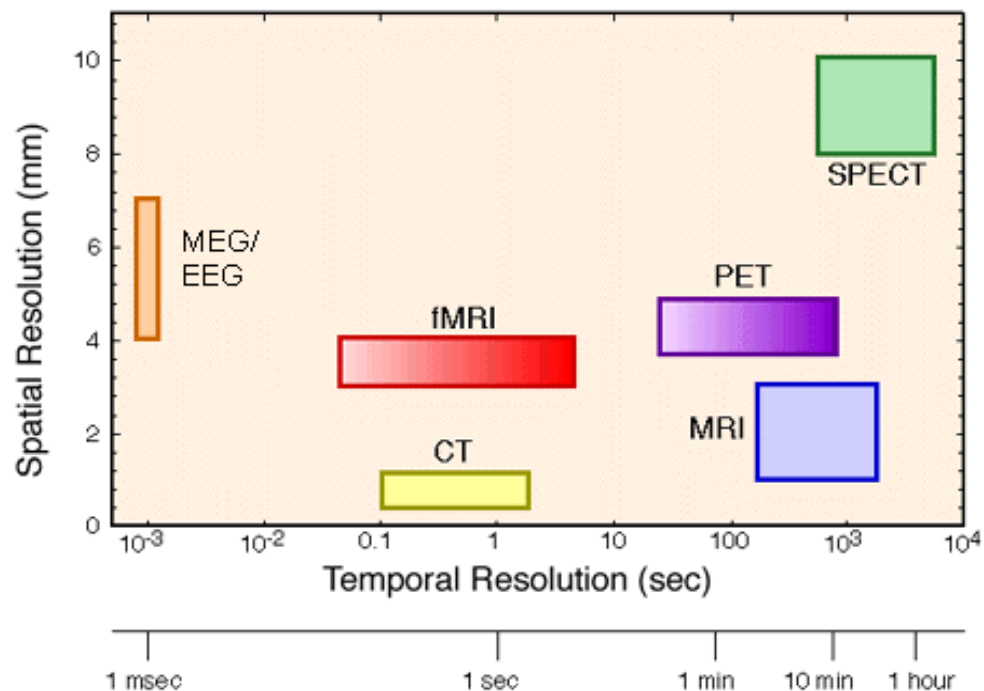


Figure 2-1: Scale of spatio-temporal resolution for various brain imaging technologies

Table 2-1: Comparison of brain imaging technologies

| Brain Imaging Tech. | Physical Measurement Property   | Advantages  | Disadvantages   |
|---------------------|---|---|---|
| <b>EEG</b>          | Macroscopic brain electrophysiology.  | Inexpense & ease of acquisition<br>High temporal resolution<br>Non-invasive   | Poor spatial resolution<br>Trial-to-trial variability of ERPs<br>Volumetric smearing effects of skull   |
| <b>ECoG</b>         | Electrophysiology of extra-cellular currents.   | High temporal resolution<br>Good spatial resolution<br>Equipment inexpensive  | Highly invasive<br>Requires surgery, craniotomy required<br>Procedurally expensive  |
| <b>MEG</b>          | Cortical magnetic fields associated with the electrical activity.   | Completely non-invasive<br>Spatial resolution up to 3mm<br>Good temporal resolution   | Extremely expensive equipment<br>Difficult to acquire, requires magnetic isolation room<br>Not practical for real-time analysis   |
| <b>CT</b>           | X-Ray brightness intensity maps in relation to brain tissue density. Superseded by MRI technology   | Excellent spatial resolution  | Only anatomical information, none on cognitive function<br>Extremely expensive<br>X-Ray radiation hazard  |
| <b>SPECT</b>        | Tracking of radioactive tracers in blood stream. The measurement of blood flow, oxygen and glucose reflects the amount of brain activity.   | Do not require on-site cyclotron to produce SPECT tracers, unlike PET<br>Less technical and medical staff required than PET   | Measures blood flow instead of electrophysiology<br>Poor time and spatial resolution<br>Ionizing radiation hazard<br>Procedurally expensive<br>More limited than PET tracers  |
| <b>PET</b>          | Tracking of gamma radiation from decaying radioactive tracers in blood stream. Measures the regional cerebral metabolism and blood flow that reflect the amount of brain activity.                      | More versatile than SPECT<br>More spatial resolution than SPECT, particularly for deeper brain structures.<br>Able to identify which brain receptors are being activated by neurotransmitters, abused drugs and potential treatment compounds | Measures metabolism of oxygen and sugar rather than electrophysiology<br>Ionizing radiation hazard<br>Poor time resolution (~2 mins)<br>Measurements cannot be repeated, annual maximum dosage is one examination<br>Equipment extremely expensive. (cyclotron required)<br>Highly qualified staff required |
| <b>MRI</b>          | Radio waves pass through a large magnetic field (~1.5T). A computer monitors the variations in the radio waves due to the electro-magnetic activity in the brain to generate a picture.                 | High anatomical detail (spatial resolution)<br>Non-invasive   | Only anatomical information, none on cognitive functionality<br>Poor temporal resolution<br>Expensive equipment and procedure   |
| <b>fMRI</b>         | Magnetic fields and radio waves exploit the magnetic properties of blood to track its flow. It involves monitoring the Blood Oxygenation Level Dependence (BOLD) in response to a function or stimulus. | Good spatial resolution<br>Non-invasive   | Depends on haemodynamic response of blood which introduces an inherent lag<br>Trades off some spatial resolution from MRI to improve temporal resolution.<br>Expensive equipment and procedure<br>Temporal resolution (~1s) not as good as EEG  |
| <b>(r)TMS</b>       | Induced electrical activity of neuronal regions by pulsed magnetic fields to stimulate a brain region   | Diagnostic aid to check that the nerve pathways are intact<br>Able to influence many brain functions, including movement, visual perception, memory, reaction time, speech and mood   | Stimulator of brain function rather than an imaging technique<br>Unknown health risks   |
| <b>EROS</b>         | Changes occur in optical parameters (scattering and absorption) of cortical tissue when active  | Good temporal resolution<br>Non-invasive<br>Good spatial resolution<br>Non-ionizing radiation<br>Relatively low cost  | Penetration only several centimetres<br>Studying the cortical activity rather than the sub-cortical<br>Infancy of its development   |

Despite the EEG's poor spatial resolution, it has excellent temporal resolution of less than a millisecond. It is also relatively inexpensive and simple to acquire making it the only practical non-invasive brain imaging modality for repeated real-time brain behavioural analysis. For this reason, the remainder of this thesis will focus on EEG as the input brain imaging modality for BCI design.

In the advent of the miraculous invention of the MRI machine, neuroscience has become a hugely popular research area spanning disciplines such as neurophysiology, psychology, engineering, mathematics and clinical rehabilitation. It has inspired many researchers to explore every aspect of clinical and cognitive brain imaging. fMRI, has enabled researchers to locate with high precision the regions within the brain associated with a function, e.g. the response to a stimulus. Similarly, it has inspired the use of EEG in parallel to observe with high precision the dynamics of such brain activity. The section that follows highlights the physical make-up of the brain, focusing on its electro-biological behaviour which explains how EEG allows an insight into brain activity.

## **2.2. The human brains' neurophysiology**

This section explains the anatomical and physiological structure of the brain. It focuses on how, why and where the brain generates electrical activity that can be recorded on the scalp. In order to understand the creation of local current flows within the brain, one must first look at the fundamental brain cell, the neuron. For a greater insight into the physiology that leads to an understanding of the human brain, the avid reader is referred to the book by Carlson [9].

### **2.2.1. The neuron**

Any biometric potentials observed on the skin are due to the flow of ion-based electrical currents within the body. In the case of EEG, the potentials are due to the summation of the electrical potentials of many brain nerve cells, called neurons. The human brain at birth consists of approximately 100-billion ( $10^{11}$ ) neurons at an average density of  $10^4$  neurons per cubic mm [10]. The number of neurons decreases with age. Neurons share the same characteristics and have the same parts as other cells, but the electrochemical aspect lets them transmit electrical signals and pass messages to each other over long distances. Neurons have three basic parts (Figure 2-2):

- **Cell body** - This main part has all of the necessary components of the cell, such as the nucleus (contains DNA), endoplasmic reticulum and ribosomes (for building proteins) and mitochondria (for supplying energy). If the cell body dies, the neuron dies.

- **Axon** - This long, cable-like projection of the cell carries the electrochemical message (action potential - AP) along the length of the cell.
- **Dendrites** - These small, branch-like projections of the cell make connections to other cells and allow communication with other neurons. Dendrites can be located on one or both ends of the cell.

There exist different types of neurons that can have varying structures depending on their functionality. Sensory, motor and cortical pyramidal cell neurons are examples of such different types. The pyramidal neuron cell is the most prevalent neuron cell in the cerebral cortex, particularly in the cortical peaks and valleys (gyri and sulci respectively) that are parallel to the scalp. It is the key neuron structure responsible for most electrical activity recordable by EEG. It has a long straight dendrite that extends up perpendicularly towards the surface of the brain. Hence most neurons in the cerebral cortex have parallel dendrites, which cause a summation of potentials in one direction. Furthermore many neighbouring neurons will have the same presynaptic sources causing a synchrony of potentials that can be readily picked up on the scalp.

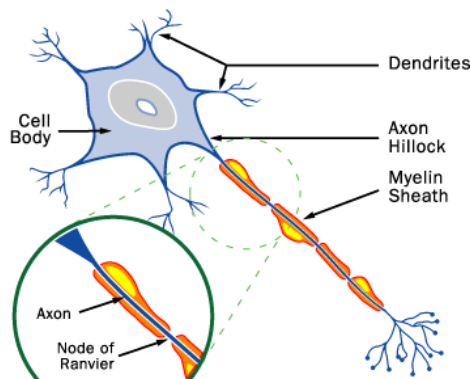


Figure 2-2: The structure of the Neuron

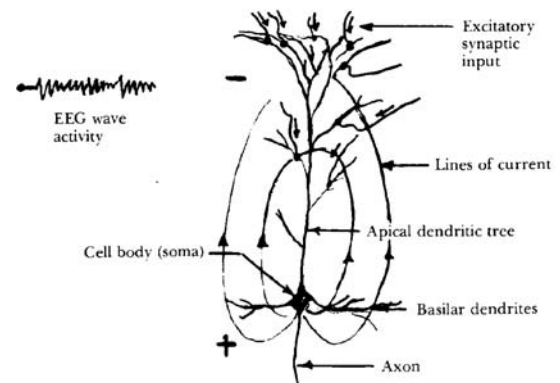


Figure 2-3: A single cortical pyramidal cell showing the current flow that contributes to the surface EEG during a net excitatory input.

The inter-neuron communication system as shown in Figure 2-4 and resulting brain electrical activity consists mostly of  $\text{Na}^+$ ,  $\text{K}^+$ ,  $\text{Ca}^{++}$  and  $\text{Cl}^-$  ions that are pumped through channels in neuron membranes in the direction governed by the membrane potential [11]. When neurons are activated by means of an electrochemical concentration gradient, local current flows are produced. The electrical activity of neurons can be divided into two subsets: action potentials (AP) and postsynaptic potentials (PSP). If the PSP reaches the threshold conduction level for the postsynaptic neuron, the neuron fires and an AP is initiated.

The electrical potentials recordable on the scalp surface are generated by low frequency summed inhibitory and excitatory PSPs from pyramidal neuron cells that create electrical dipoles between the soma and apical dendrites (see Figure 2-3). These PSPs summate in the cortex and

extend to the scalp surface where they are recorded as the EEG. Nerve cell APs have a much smaller potential field distribution and are much shorter in duration than PSPs. APs therefore do not contribute significantly to either scalp or clinical intracranial EEG recordings. Only large populations of active neurons can generate electrical activity recordable on the scalp.

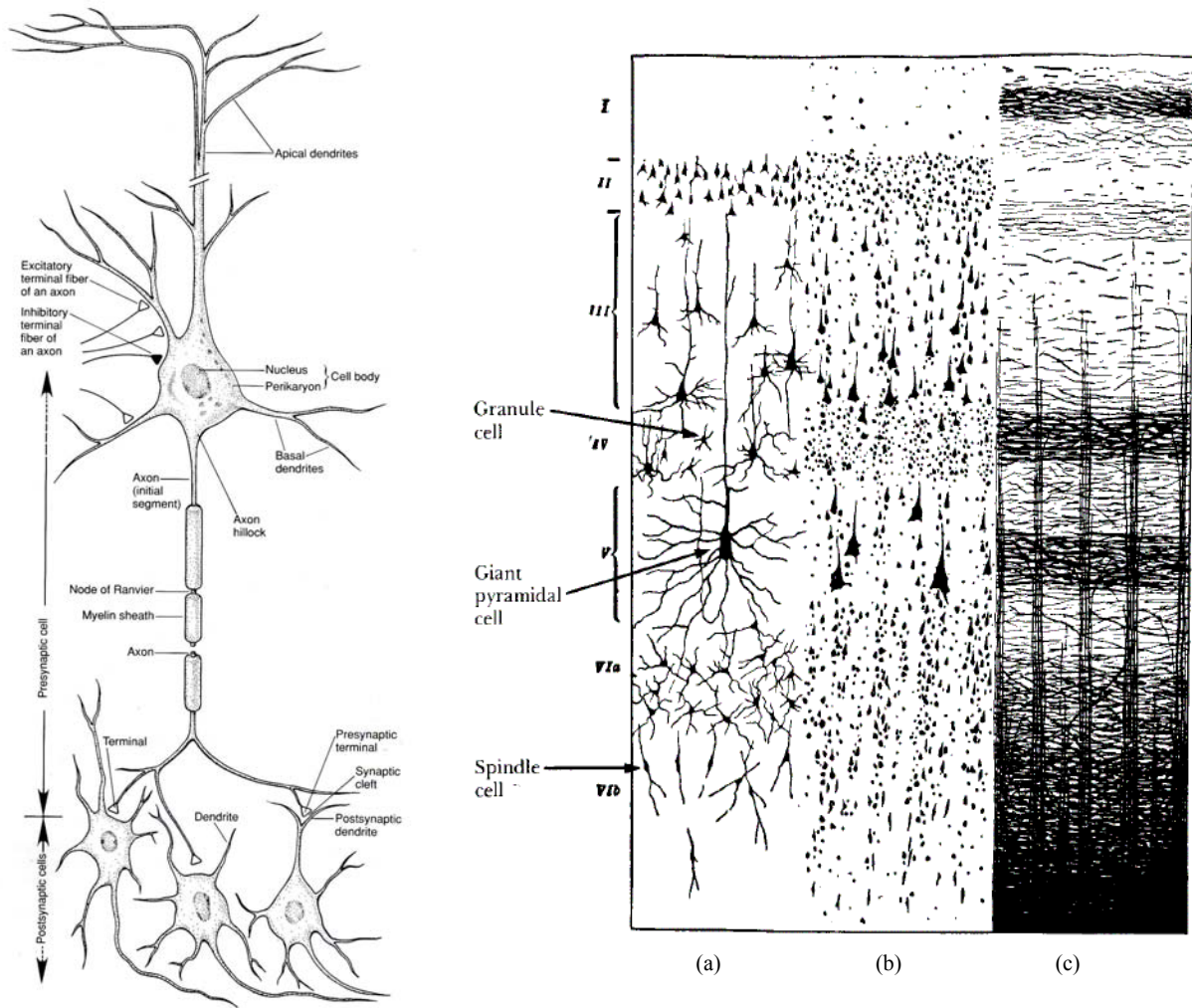


Figure 2-4: The pyramidal cell neuron demonstrating its structure and interconnectivity with a neural community

Figure 2-5: Structure of the cerebral cortex, which consists of six layers, shown using three different stains under the microscope: (a) Golgi stain showing cell bodies and dendrites, (b) Nissl cellular stain and (c) myelin sheath stain showing axons. The six layers on the vertical axis are: I molecular layer, II external granular layer, III external pyramidal layer, IV internal granular layer, V large or giant pyramidal layer (ganglionic layer), VI fusiform layer

Allison [12] lists four prerequisites, which must be met for the activity of any network of neurons to be visible in an EEG recording:

- a) The neurons must generate most of their electrical signals along a specific axis oriented perpendicular to the scalp

- b) The neuronal dendrites must be aligned in parallel so that their field potentials summate to create a signal which is detectable at a distance
- c) The neurons should fire in near synchrony
- d) The electrical activity produced by each neuron needs to have the same electrical sign

Thus a majority of neuronal communication remains invisible to EEG.

### 2.2.2. The brain and its functions

The average adult human brain weighs around 1.4 kg. The terminology for its orientation with respect to the body is shown in Figure 2-6. The brain is surrounded by cerebrospinal fluid that suspends it within the skull and protects it by acting as a motion dampener. In relation to the stages of brain development, Carlson [13] categorises its components into three groups; the Forebrain, Midbrain and Hindbrain. Anatomically the brain can be divided into the three largest structures: brain stem (hindbrain), cerebrum and cerebellum (forebrain). This is illustrated in Figure 2-7. The functions of these structures are summarised as follows:

- The **brainstem** controls the reflexes and autonomic nerve functions (respiration, heart rate, blood pressure).
- The **cerebrum** consists of the cortex, large fiber tracts (corpus callosum) and some deeper structures (basal ganglia, amygdala, hippocampus). It integrates information from all of the sense organs, initiates motor functions, controls emotions and holds memory and higher thought processes.
- The **cerebellum** integrates information from the vestibular system that indicates position and movement and uses this information to coordinate limb movements and maintain balance.
- The **hypothalamus** and pituitary gland control visceral functions, body temperature and behavioural responses such as feeding, drinking, sexual response, aggression and pleasure.
- The **thalamus** or specifically the thalamic sensory nuclei input is crucial to the generation and modulation of rhythmic cortical activity.

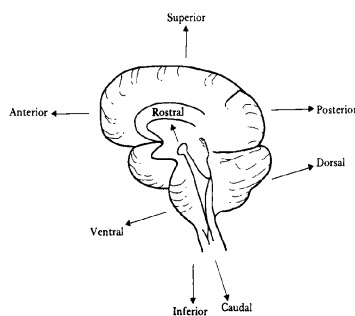


Figure 2-6 : Orientation of brain with respect to the rest of body

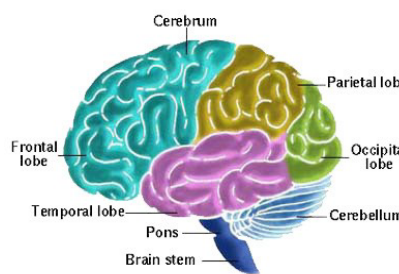


Figure 2-7: Anatomical areas of the brain

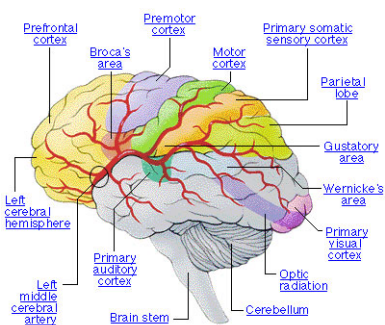


Figure 2-8: Functional areas of the brain

The cerebrum can be spatially sub-divided. Firstly into two hemispheres, left and right, connected to each other via the corpus callosum. The right one senses information from the left side of the body and controls movement on the left side. Similarly the left hemisphere is connected to the right side of the body. Each hemisphere can be divided into four lobes. They are the frontal, parietal, occipital and temporal lobes. The cerebral cortex is the most relevant structure in relation to EEG measurement. It is responsible for higher order cognitive tasks such as problem solving, language comprehension and processing of complex visual information. Due to its surface position, the electrical activity of the cerebral cortex has the greatest influence on EEG recordings. The functional activity of the brain is highly localized. This facilitates the cerebral cortex to be divided into several areas responsible for different brain functions. The areas are depicted in Figure 2-8 and the related functions are described in Table 2-2.

Table 2-2: Cortical areas of the brain and their function

| Cortical Area                | Function                                    |
|------------------------------|---|
| Auditory association area    | Complex processing of auditory information  |
| Auditory cortex              | Detection of sound quality (loudness, tone) |
| Broca's area (speech centre) | Speech production and articulation          |
| Prefrontal cortex            | Problem solving, emotion, complex thought   |
| Premotor cortex              | Coordination of complex movement            |
| Primary Motor cortex         | Initiation of voluntary movement            |
| Primary somatosensory cortex | Receives tactile information from the body  |
| Sensory association area     | Processing of multisensory information      |
| Gustatory area               | Processing of taste information             |
| Wernicke's area              | Language comprehension                      |
| Primary Visual Cortex        | Complex processing of visual information    |

Since the architecture of the brain is non-uniform and the cortex is functionally organised, the EEG can vary depending on the location of the recording electrodes. With this brief introduction into the physiological creation of EEG, we can now move on to look at how to acquire, process and interpret the EEG signals recorded from the various locations on the scalp.

### 2.3. Acquisition Methods

In the scalp recorded EEG the neuronal electrical activity is recorded non-invasively, typically using small metal plate electrodes. Recordings can be made using either reference electrode(s) or bipolar linkages. While the number of the electrodes used varies from study to study, they are typically placed at specific scalp locations. The voltages, of the order of microvolts ( $\mu\text{V}$ ), must be carefully recorded to avoid interference and digitized so that it can be stored and viewed on a computer.



The amplitude of the recorded potentials depends on the intensity of the electrical source, on its distance from the recording electrodes, its spacial orientation, and on the electrical properties of the structures between the source and the recording electrode. The greatest contributions to the scalp recorded signals result from potential changes which (a) occur near the recording electrodes, (b) are generated by cortical dipole layers that are orientated towards the recording electrode at a 90 angle to the scalp surface, (c) are generated in a large area of tissue, and (d) rise and fall at rapid speed [14].

This section will briefly highlight the equipment, methods and standards involved in acquiring a scalp recorded EEG. It serves as a review of the key issues related to acquisition however for a more detailed review of the principles of digital and analog EEG processing see [3,5,14].

### 2.3.1. Equipment

The basic EEG recording system consists of electrodes with conductive media, amplifiers with filters, an analog-to-digital (A/D) converter and finally a recording device to store the data. Electrodes, in conjunction with the electrode gel, sense the signal from the scalp surface; amplifiers bring the microvolt and often nanovolt signals into a range where they can be digitized accurately; and the A/D converter changes signals from analog to digital form that can be finally stored or viewed on a computer. Table 2-3 provides a summary of the necessary EEG acquisition equipment and the typical specifications or products. The equipment used in the DSP laboratory in UCD is shown in Figure 2-9.

Table 2-3: Necessary EEG acquisition equipment specifications.

| EEG acquisition component    | Typical Specifications or Products   |
|------------------------------|--|
| Electrodes                   | Electrode cap with conductive jelly<br>Ag-AgCl or Au disc electrodes with conductive paste   |
| Amplifiers (with filters)    | Amp Gain between 100-100K<br>Input Impedance >100M $\Omega$<br>Common-mode rejection ratio >100dB<br>High pass filter with cut-off in range 0.1 -0.7Hz<br>Low pass filter with cut-off below half the sampling rate<br>Notch filter at mains frequency. (50 / 60 Hz) |
| Analog-to-Digital Converter  | At least a 12 bit A/D converter with accuracy lower than overall noise (0.3-2 $\mu$ V pp.) and sampling frequency typically between 128-1024 Hz per channel.   |
| Storage / Visualization unit | Sufficiently fast PC for presentation, processing and storage  |

### 2.3.2. Electrodes & electrode placement

An electrode is a small conductive plate that picks up the electrical activity of the medium that it is in contact with. In the case of EEG, electrodes provide the interface between the skin and the recording apparatus by transforming the ionic current on the skin to the electrical current in the electrode. Conductive electrolyte media ensures a good electrical contact by lowering the contact impedance at the electrode-skin interface.

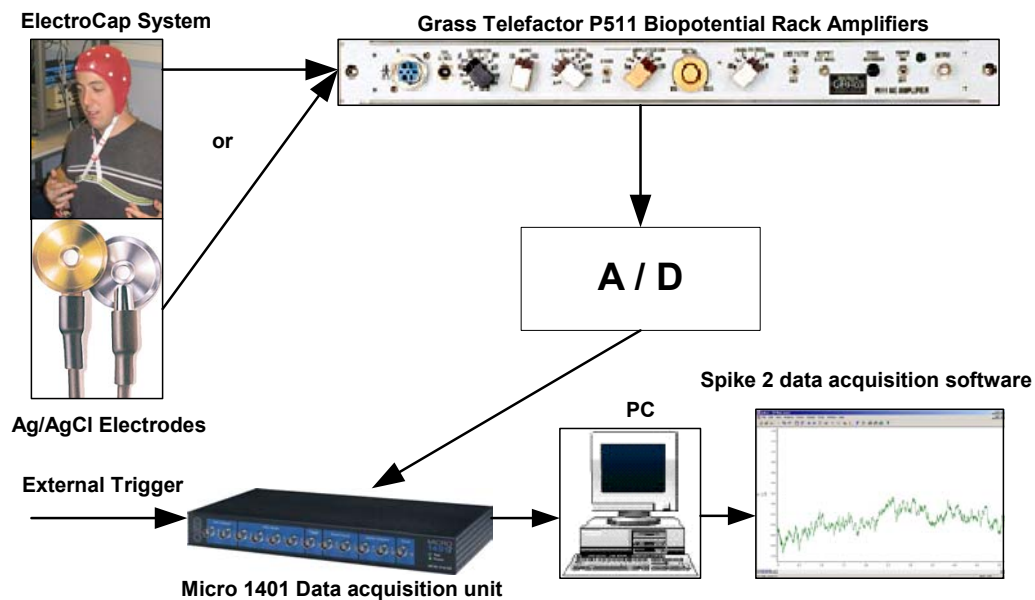


Figure 2-9: EEG acquisition system at the DSP laboratory in UCD. Equipment suppliers include Electrocap International Inc<sup>4</sup>, Grass Telefactor Inc<sup>5</sup> and Cambridge Electronic Design (CED)<sup>6</sup>

The following types of electrodes are available:

- Disposable (gel-free, and pre-gelled types)
- Reusable cup electrodes (gold, silver, stainless steel or tin)
- Electrode caps
- Needle electrodes
- Nasopharyngeal and Sphenoidal electrodes

<sup>4</sup> ElectroCap Inc.: <http://www.electro-cap.com>

<sup>5</sup> Grass Telefactor Inc.: <http://www.grass-telefactor>

<sup>6</sup> Cambridge Electronic Design (CED): <http://www.ced.co.uk/indexu.shtml>

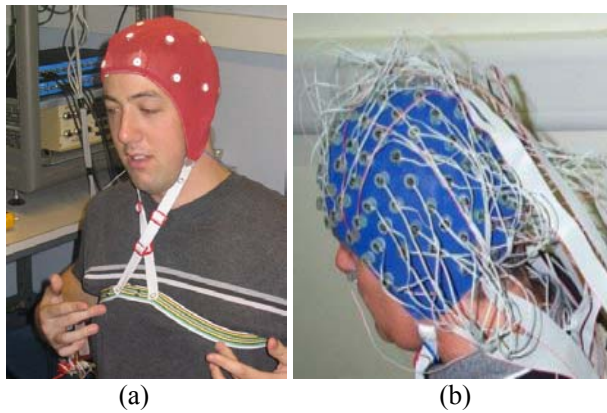


Figure 2-10: (a) ElectroCap System I® consisting of 21 electrodes according to 10-20 system, (b) 128 channel electrode cap based on a modified 10-20 system (right).

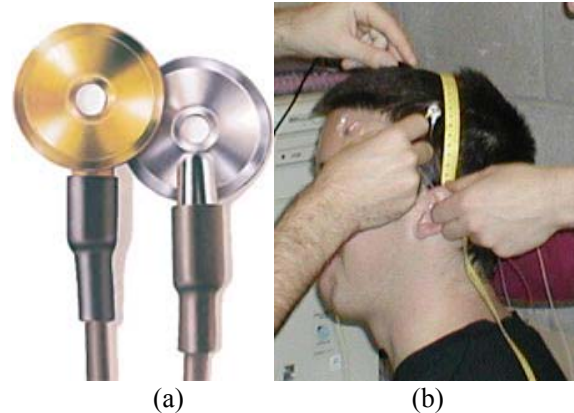


Figure 2-11: (a) Gold (Au) and Silver-Silver Chloride (Ag-AgCl) disc electrodes, (b) Electrode placement over C3 and C4. The inter-electrode and skin-electrode impedance is checked.

For large multi-channel montages comprising of up to 256 or 512 active electrodes, electrode caps such as those shown in Figure 2-10 are preferred to facilitate quicker set-up of high-density recordings. Commonly, Ag-AgCl cup or disc electrodes of approximately 1cm diameter are used for low density or variable placement recordings as shown in Figure 2-11. For optimum performance, the space between the electrode disc and the skin is filled with conductive paste which also helps them to bond to the scalp.

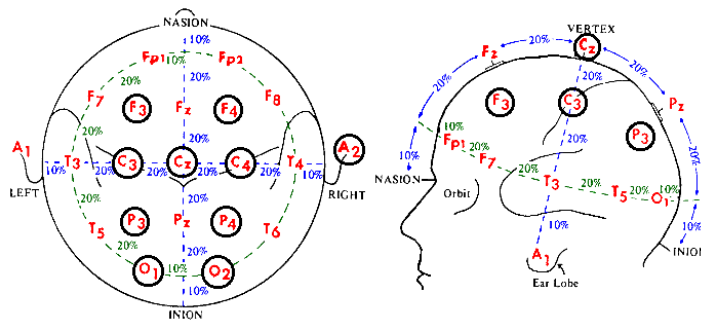


Figure 2-12: The International 10-20 electrode system: side and top views [15]

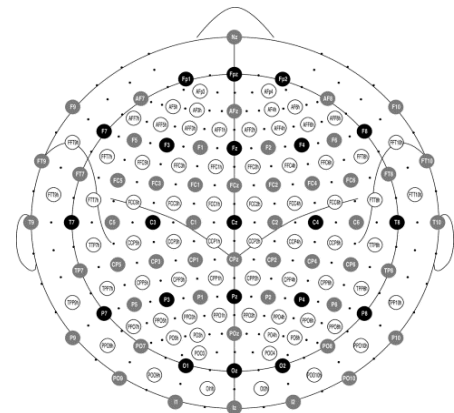


Figure 2-13: Electrode positions and labels for various systems. Black circles indicate positions of the original 10-20 system, grey circles indicate additional positions in the 10-10 extension and small dots indicate additional positions in the 10-5 extension [16] (from [16]).

To improve the stability of the signal, the outer layer of the skin (stratum corneum) should be removed under the electrodes by light abrasion. In the case of the electrode caps, the blunt syringe for conductive gel insertion is also used for skin scraping. The cleaning of the skin surface

from sweat, oil, hair products and dried skin is also highly recommended. Sterile alcoholic medical wipes are useful here to prepare the skin and maintain hygiene.

In order to standardize the methodology of applying the electrodes on the skull, in 1949 the International Federation of Societies for Electroencephalography and Clinical Neurophysiology (IFSECN) adopted a system proposed by Jasper [15] which has now been adopted worldwide and is referred to as the 10-20 electrode placement International standard. This system, consisting of 21 electrodes, standardized physical placement and nomenclature of electrodes on the scalp. This allowed researchers to compare their findings in a more consistent manner. In the system, the head is divided into proportional distances from prominent skull landmarks (nasion, inion, mastoid and preauricular points see Figure 2-12). The '10-20' label in the system title designates the proportional distances in percents between the nasion and inion in the anterior-posterior plane and between the mastoids in the dorsal-ventral plane (see Figure 2-12). Electrode placements are labelled according to adjacent brain regions: F (frontal), C (central), P (parietal), T (temporal), O (occipital). The letters are accompanied by odd numbers for electrodes on the ventral (left) side and even numbers for those on the dorsal (right) side. The letter 'z' instead of a number denotes the midline electrodes. Left and right side is considered by convention from the point of view of the subject. Based on the principles of the 10–20 system, a 10–10 system and a 10-5 system have been introduced as extensions to further promote standardization in high-resolution EEG studies (see Figure 2-13 and Figure 2-14).

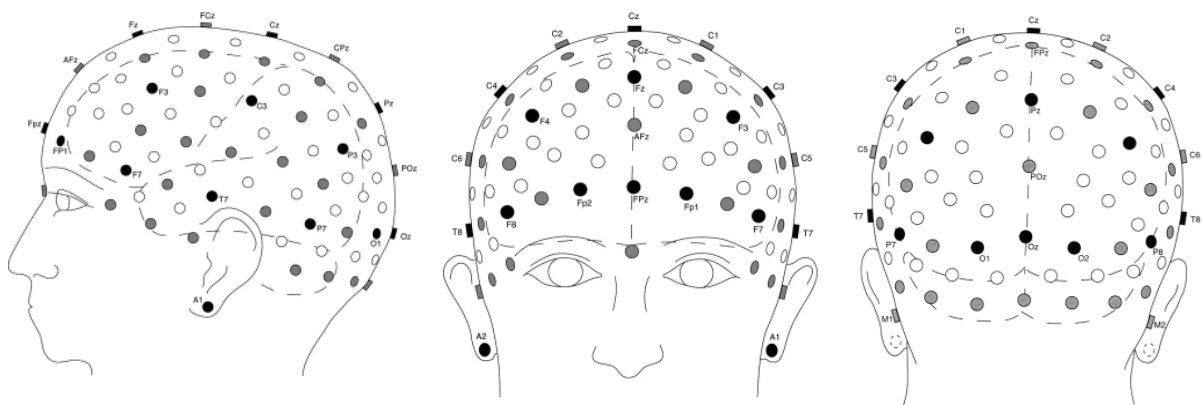


Figure 2-14: Selection of 10–10 electrode positions in a realistic display. Lateral, frontal and posterior views. The head and brain contours based on typical models. Black circles indicate positions of the original 10–20 system, grey circles indicate additional positions in the 10–10 extension (from [16]).

The high density EEG electrode placement can help pinpoint more accurately the brain region contributing to the recording at a given electrode. This is known as source localization. There exist signal-processing methods to generate inverse solution models to estimate the origins

of the main components of the EEG recordings. However the scalp electrodes may not reflect the activity of particular areas of the cortex, as the exact location of the active sources is still unknown due to the limitations caused by the non-homogenous properties of the skull, different orientation of the cortex sources and coherences between the sources etc. [10].

### 2.3.3. Referencing and bipolar recordings

Scalp recordings of neuronal activity in the brain, identified as the EEG, allow measurement of potential changes over time in a basic electric circuit conducting between signal (active) electrode and reference electrode [17]. For getting a differential voltage, an extra third electrode called the ground electrode, is needed by the amplifiers to subtract the active and reference channels from it. The placement of the ground electrode plays no significant role in the measurement. Typically the forehead (FPz), ear lobe, wrist or leg is the preferred ground location.

The EEG recordings can be divided into two major categories: reference recordings and scalp-to-scalp bipolar linkages. In the reference recording each electrode is referred to either a distant reference electrode, one common electrode on each side of the head or to the combined activity of two or more electrodes. The reference electrode(s) must be placed on the parts of the body where the electrical potential remains fairly constant. Several different recording reference electrode placements are mentioned in the literature [3,5,14,18-20]. These include references such as the vertex (Cz), linked-ears, linked-mastoids (bones behind the ear), ipsi-lateral-ear, contra-lateral-ear, FPz, AFz and the tip of the nose. In addition to one single reference electrode, two reference electrodes shorted together can be used. The choice of reference may produce topographic distortion if relatively electrically inactive locations such as the ear and mastoid are not chosen. Linking reference electrodes from both earlobes or mastoids reduces the likelihood of artificially biasing activity in one hemisphere [20].

The most preferred reference is linked ears due to the relative electrical inactivity, ease of use and symmetry which prevents a hemispheric bias being introduced. The vertex (Cz) is also predominant due to its central location. Reference-free methods are represented by common average reference, weighted average reference, and source derivation. These methods use the average or weighted average of the activity at all electrodes as the reference. This can be carried out by means of a resistor network or digitally as part of post-processing method. These do not suffer the same artifact problems associated with an actual physical reference.

Bipolar recordings are differential measurements that are made between successive pairs of electrodes. In the literature, C3-C3', refers to a bipolar link from one channel at C3 and the other in close proximity (typically around 2-3 cm from electrode in direction away from Cz). Closely linked bipolar recordings are affected less by some artifacts, particularly ECG, due to the

differential cancelling out of signals similarly picked up at the pair of electrodes. Bipolar referencing is not commonly used due to placement issues and a lack of spatial resolution.

#### 2.3.4. Artifacts

Artifacts are undesirable potentials of non-cerebral origin that contaminate the EEG signals. As they can potentially masquerade and be misinterpreted as originating from the brain, there is a need to avoid, minimise or ideally remove them from the EEG recording to facilitate accurate interpretation.

Table 2-4 : Groups of physiological artifacts and their origins during EEG recordings

| Physiological artifact type   | Possible sources  |
|-------------------------------|---|
| Movements:                    | Movements of the head, body or scalp  |
| Bioelectrical potentials:     | Moving electrical potentials within the body such as those produced by eye, tongue and pharyngeal muscle movement. Also those generated by the scalp muscles, heart (ECG) or sweat glands |
| Skin resistance fluctuations: | Sweat gland activity, perspiration and vasomotor activity   |

Typical EEG artifacts originate from two sources, technical and physiological. Technical artifacts are mainly due to line interference, equipment malfunction or result from poor electrode contact. Incorrect gain, offset or filter settings for the amplifier will cause clipping, saturation or distortion of the recorded signals. Technical artifacts can be avoided through proper apparatus set-up, meticulous inspection of equipment and consistent monitoring. Physiological artifacts arise from a variety of body activities that are either due to movements, other bioelectrical potentials or skin resistance fluctuations as summarised in Table 2-4.

The predominant physiological artifacts include electrooculargraphic activity (EOG, eye), scalp recorded electromyographic activity (EMG, muscle), electrocardiographic activity (ECG, heart), ballistocardiographic activity (heart-related pulsatile motion) and respiration. These artifacts are always present to some extent and are typically much more prominent on the scalp than the macroscopic cerebral potentials. This results in an undesirable negative signal-to-noise ratio in the EEG. Physiological artifacts are often involuntary and hence cannot be controlled or ‘turned off’ during acquisition. They pose a much greater challenge than technical artifacts to avoid or remove them. Traditionally non-cerebral recordings such as EOG, ECG or EMG are also performed to aid in the discrimination and potentially the removal of the relevant artifacts from the EEG signals, as will be discussed more fully later. Table 2-5 presents a summary of the most common technical and physiological artifacts, their probable causes and potential steps to avoid / remove them.

Vertical eye movements such as eye closure or blinking, which are recorded as vertical electrooculographic (vEOG) spikes, spread to a certain degree to all scalp locations, particularly

the frontal sites. Although subjects are typically asked not to move or blink during acquisition, blinking is for most an involuntary response to dry eyes or prolonged visual focus.

Table 2-5 : Common technical and physiological artifacts, their possible causes and solutions

| Origin               | Artifact examples                          | Potential sources  | Possible solutions  |
|----------------------|--|--|---|
| <b>Technical</b>     | Line Interference (50/60 Hz)               | Power Supply Interference – The surrounding electrical equipment may induce a 50Hz (Europe) or 60Hz (USA) component in the signal especially in the case of high electrode impedance at contact. | Use shorter electrode wires.<br>Reduce electrode impedance.<br>Scalp-electrode impedance < 5K $\Omega$ .<br>Electrode-electrode impedance ~ 1M $\Omega$ .<br>Perform recordings within a shielded room.<br>Use an analog or digital notch filter. |
|                      | Electrode impedance fluctuations           | Loose or damaged wire contacts.<br>Inconsistencies in electrode gel application (contaminants or dried pieces).<br>Cable movements.  | Check impedances with digital multi-meter and ensure good electrode contact.  |
| <b>Physiological</b> | Electrooculographic (EOG), eye activity    | Eye movements.<br>Blinking.<br>Saccadic activity related to focus variation.   | Instruct subject to minimise eye movement.<br>Do not stare, as this will force eye-blinking.<br>Allow brief intervals between stimuli for subject to blink.   |
|                      | Electromyographic (EMG), muscle activity   | Muscle movement or tension particularly masticatory (jaw & tongue), neck & forehead causes EMG artifacts.  | Ensure no movement particularly the neck, mouth, tongue or face.  |
|                      | Electrocardiographic (ECG), heart activity | Heart beating.<br>Ballistocardiographic (pulsatile motion of heart).<br>Respiration.<br>Pacer.   | Close bipolar referencing.<br>Reference electrode having similar ECG activity.  |
|                      | Skin conduction variation                  | Sweating offers an epidermal layer of lower impedance for current conduction. It produces a slow baseline drift in EEG recording.  | Cool environment.   |

Eye movement artifacts in EEG can be identified by their frontal distribution, their symmetry and their characteristic shape. The amplitude of vertical eye movement decreases in successive channels from anterior to posterior. In addition, typical eye blinks are 100ms in duration. Therefore repetitive eye movements may mimic cerebral rhythms at around 10Hz (alpha band) which is an important rhythm in most EEG studies as will be discussed in section 2.4.1. In the hope that we can eliminate or at least minimise other artifacts, EOG activity is typically the most dominant and corruptive artifact that must be eliminated by other means, namely signal processing techniques.

There are three main approaches to combat the problem of artifacts in EEG recordings:

- Artifact minimisation or avoidance
- Artifact rejection
- Artifact removal

Although these approaches may appear similar, they have very different methodologies and resulting EEG data.

Artifact minimisation is a prerequisite to most EEG recordings, whether or not artifact rejection or artifact removal is performed in conjunction. It uses a thorough understanding of the

artifacts' origins to first identify them and then reduce or eliminate its impact on the EEG by some appropriate steps. This is predominantly effective for technical artifacts but can also be applied to physiological artifacts. For example, potential changes generated by the heart are picked up mainly in EEG recordings with wide inter-electrode distances, especially in inter-hemispheric linkages across the head or referencing to the left ear and particularly in subjects who are overweight [14]. This understanding can then be used to avoid or at least limit the impact the ECG artifact may have on the EEG signals by employing linked-ear referencing or a grounding collar. Similarly for other artifacts, an understanding of their origins can be exploited to minimise their influence.

Artifact rejection, involves the identification and exclusion of the artifact segments from the EEG trace. In the past it was conventionally performed by trained experts who visually score the EEG data or the artifact activity itself (such as EOG, EMG, ECG etc.), rejecting any periods of EEG with unacceptable levels of artifact activity. This is an extremely laborious and inconsistent approach but is typically done in clinical studies. More popular today are automated signal processing approaches (e.g. threshold-based rejection methods) that make it much less labour intensive to implement but at the cost of under- or over-rejection of EEG data. The goal in artifact rejection is to produce EEG data that is as clean as possible, ignoring the cost of discarding valuable periods of EEG recordings. This is a huge drawback and would be unacceptable for the purposes of processing EEG signals in real-time or on a single trial basis where every segment of EEG data is required. This requires the artifact to be *removed* from the continuous EEG and can only be performed with the aid of digital signal processing algorithms.

Artifact removal methods utilise such algorithms to isolate and remove, as best as possible, certain artifacts from the recorded EEG activity while most importantly unlike the other approaches retaining the period of EEG. These methods are a very topical research area and may be divided into two different approaches:

- Filtering and,
- Higher-Order statistical separation

Filtering, involves the development of a filter model to emulate the artifact activity and use it to remove the artifact from the EEG recorded signals. The filter coefficients can either be established from definitive artifact properties such as line interference at 50Hz or from empirical processing of the non-cerebral bioelectrical artifact recordings such as ECG, EMG and EOG. This may result in a conventional low-pass, high-pass, band-pass and notch filter or a more complex filter model. Typically continuous adaptive regressive filtering is used in this approach. Regressive filtering methods in the time [21,22] or frequency domain [23,24] can, despite their computational



efficiency, overcompensate for the artifact contribution resulting in the loss of EEG information or the introduction of new artifacts.

The ultimate goal is a method of removing any artifacts on a single trial basis from EEG recordings without corrupting or smearing the underlying EEG data, thus removing the need to reject corrupted periods or trials of EEG data. However, due to the uncertainty and variability in the desired EEG signals, the large number of potential artifact sources and the significant background neuronal (EEG) noise, this becomes a very difficult goal to achieve. Due to the large number of unknown sources of neuronal and non-neuronal origins contributing to the recorded signal, it becomes a blind source separation (BSS) challenge to identify and remove artifacts on a single trial basis. The BSS method exploits the higher-order statistical differences between the contributory signals to discriminate possible artifact and cerebral components. This is a very difficult problem if one is uncertain of the properties of the artifacts one wishes to separate from the EEG. Artifacts such as EOG, ECG and EMG activity can be monitored and used as inputs in such algorithms to identify the isolated components and subsequently filter out their contributions to the EEG recordings without smearing the underlying EEG activity. Makeig, Jung et al. successfully employ Independent Component Analysis (ICA), a BSS method, to remove blink (EOG), EMG and line interference artifacts [25-27] and highlight its superiority over PCA and regressive methods [28]. This approach is however very computationally intensive.

The ICA and regressive filter approaches have their own relative advantages and disadvantages in terms of effectiveness, computational complexity and implementation practicality. Despite this research topic receiving much attention, a de-facto standard has not yet been set for EEG artifact removal due to the underlying uncertainty of the contributory neuronal and non-neuronal signals. Some of the methods mentioned above will be discussed later in greater detail in section 3.23 with relation to EEG signal preparation prior to its use as a BCI input.

## **2.4. EEG signal properties**

This section performs an introduction to the analysis and characteristics of scalp recorded EEG signals from both a clinical and signal processing point of view. It is the most important section in this chapter for the purposes of following succeeding chapters but more importantly for understanding how EEG can be used as a BCI input modality. A review is performed in this section on the numerous ways to characterise EEG activity but more importantly features that can be associated with a brain response to a function or stimulus that could act as a BCI input and an ultimate control or communication means.

An individual's brain wave patterns are unique. In some cases, it is possible to distinguish a person according to their characteristic brain activity, e.g. location of alpha peak [29]. Subjects

who regard themselves as rational types or as holistic/intuitive types may demonstrate certain higher activity in their frontal left and frontal right regions respectively. An EEG signal consists of many components with different characteristics. A large amount of data received from even one single EEG channel presents a difficulty for interpretation.

The EEG recorded brain waves originate from a multitude of different neural communities from various regions of the brain. These neural communities produce electrical contributions or components that can differ by a number of characteristics such as topographic location, firing rate (frequency), amplitude, latency etc. A big assumption in BSS methods, which will be addressed later, is that these components are independent of one another thereby inferring that certain neural populations are acting in isolation of one another, even if it is in response to the same stimulus. Due to the complex interconnectivity of neuronal cells from one brain region to another, it would be difficult to justify such an assumption physiologically. The volumetric effect of the cerebrospinal fluid, skull and scalp result in a smearing of these many electrical components that result in the scalp recorded EEG macropotential. Similar coherent electrical activity can be picked up in nearby electrodes. Through the use of high density EEG recordings one can hope to perform an inverse solution to undo as best as possible the volumetric smearing effects of the medium through which the neuro-electric signals permeate. These BSS methods attempt to isolate dominant (independent) components and localize them to particular brain regions to aid in the understanding of the cognitive processes that resulted in their creation or to identify abnormalities. The results are often used to create 2D or 3D colour topographic brain maps to enhance visualization. Whether it is the macropotential EEG signal or its contributory components, there is a need to characterise the EEG waveforms using standard terminology to help characterise the functional behaviour of the brain.

This section highlights the many descriptors that are used with EEG recorded signals or its decomposed components to help in the categorization and description of complex brain activity. A brief summary of these are listed in Table 2-6 along with examples, for a more detailed insight in both pictorial and descriptive form the reader is referred to [14,19] for a review. Clinical electroencephalography uses a large number of these descriptors, particularly in the study of epilepsy, to facilitate accurate analysis. In relation to cognitive research the most important aspects of EEG activity are distribution, frequency, amplitude, morphology, periodicity but more importantly the behavioural and functional correlates. In summary, EEG requires a considerable level of experience to accurately identify and characterise the signals.

Table 2-6: Common descriptors of EEG activity: explanation, examples and comments

| Descriptor of EEG signals | Explanation  | Characterisation examples  | Comments  |
|---------------------------|--|--|---|
| Morphology                | Shape of the wave  | Rhythmical (regular)<br>Arrhythmical (irregular)<br>Sinusoidal<br>Spindles<br>Complexes<br>Spikes<br>Polyspikes<br>Sharp waves                         | Morphology is the primary EEG descriptor in epileptic studies<br>Brain patterns form wave shapes that are commonly sinusoidal<br>A complex can be made up of a combination of sharp and slow waves and tend to last longer than 0.25s therefore do not repeat over rates of 4Hz.          |
| Repetition                | Defines the type of waveform occurrence  | Rhythmic<br>Semi rhythmic<br>Irregular   | Spindles are groups of rhythmical repetitive waves that gradually increase and then decrease in amplitude.  |
| Frequency                 | How often a repetitive wave recurs   | Frequency Bands<br>Delta<br>Theta<br>Alpha<br>Beta   | An symmetry seen in one bipolar montage should be verified using another montage orientated at 90° to the first or reference montage.<br>Differences of amplitude are sometimes caused by factors outside the brain, especially by unequal spacing and impedance at recording electrodes. |
| Amplitude                 | Measured in microvolts ( $\mu\text{V}$ ) peak-to-peak or from the calibrated zero reference                            | Clinical reference:<br>Low ( $< 20\mu\text{V}$ )<br>Medium ( $20\text{--}50\mu\text{V}$ )<br>High ( $> 50\mu\text{V}$ )<br>Amplitude Asymmetry         | Typically between 10 and 100 $\mu\text{V}$ (in adults more commonly between 10 and 50 $\mu\text{V}$ ) [30]<br>Longer inter-electrode distances produce increasing amplitudes up to an inter-electrode distance of about 8cm   |
| Distribution              | The occurrence of electrical activity recorded by electrodes positioned over different parts of the head               | Widespread, diffuse (generalised)<br>Lateralised<br>Localised (Focal)  | Lateralised activity is suggestive of a cerebral abnormality<br>In describing the location of local patterns electrode names should be used, not head regions or brain areas.   |
| Phase Relation            | The relative timing and polarity of components of waves in one or more channels e.g. Do the troughs and peaks line up? | In-phase<br>Out of phase<br>Phase Angle  | In a single channel, phase refers to the time relationship between different components of a rhythm.  |
| Timing                    | Relative occurrence of activity in time at different parts of the brain recorded by different channels                 | Simultaneous (Synchronous)<br>Independent (Asynchronous)<br>Bilaterally synchronous  | The resolution of time relations deteriorates if more distant channels are compared<br>Gives an idea of possible triggering mechanism   |
| Persistence               | How often a wave or pattern occurs during a recording session  | Index Percentage (Proportion of time for which these waves appear in the recording)<br>Poorly / Well sustained<br>High, moderate & low persistence     | Very common in Polysomnography (Sleep staging studies)<br>The persistence and amplitude are often described together in terms of Quantity, Amount & Prominence  |
| Reactivity                | Refers to changes that can be produced in some normal and abnormal patterns by various manoeuvres or functions         | EEG alteration in response to:<br>Closing the eyes<br>Hyperventilation<br>Visual or sensory stimulation<br>Changes in levels of alertness<br>Movements | Useful in abnormal or drug addiction studies<br>Useful to prepare or evaluate the subjects condition prior to recording   |

For the purposes of BCI system design, there exist various EEG signal properties that discriminate brain function and hence can be used as an input mechanism to offer control or communication. EEG signal properties for BCI systems can be categorised into one of the following groups:

1. Rhythmic brain activity
2. Event-related potentials (ERPs)
3. Event-related desynchronization (ERD) and event-related synchronization (ERS).

### 2.4.1. Rhythmic brain activity

Frequency is one of the most important criteria for assessing abnormality in clinical EEG and for understanding functional behaviour in cognitive research. With billions of oscillating communities of neurons as its source, the human EEG potentials are manifested as aperiodic unpredictable oscillations with intermittent bursts of oscillations having spectral peaks in certain observed bands: 0.1-3.5 Hz (delta,  $\delta$ ), 4-7.5 Hz (theta,  $\theta$ ), 8-13 Hz (alpha,  $\alpha$ ), 14-30 Hz (beta,  $\beta$ ) and  $>30$ Hz (gamma,  $\gamma$ ) [5]. Figure 2-15 illustrates examples of these EEG rhythms and the reactivity of the important alpha band to eye closure. The band range limits associated with the brain rhythms, particularly beta and gamma, can be subject to contradiction and are often further sub-divided into sub-bands that can further distinguish brain processes [29,31]. Table 2-7 summarises some common brain rhythms and their resulting EEG characteristics such as typical amplitude, frequency, location and reactivity.

Activity that is either less than 0.5 Hz or greater than 20 Hz is often assumed to be of limited clinical utility. Some recent papers have published the existence of cognitive brain process in the beta and gamma bands. The literature does not clarify whether the higher frequency activity ( $>30$  Hz) is of cerebral origin.

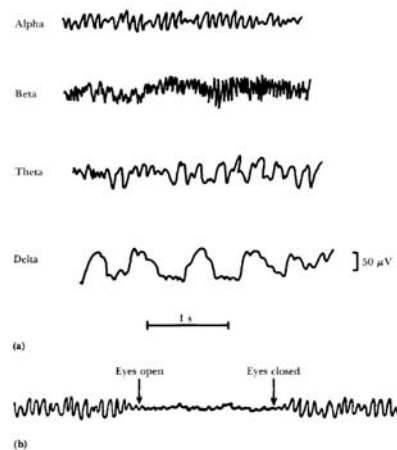


Figure 2-15: (a) Examples of alpha, beta, delta and theta EEG rhythms, (b) Change from alpha waves to asynchronous pattern when subject opens eyes

Human EEG rhythms are affected by different actions, thoughts and stimuli. For example the planning of a movement can block or attenuate the mu rhythm (as described in Table 2-7). The fact that mere thoughts affect the rhythmical activity of the brain can be used as the basis for a BCI system. In the next chapter, some BCIs based on rhythmical property variation are used as a discriminatory control feature.

Table 2-7: Normal EEG rhythms characteristics

| Brain Rhythm | Typical Frequency range (Hz) | Normal Amp. ( $\mu$ V) | Where it can be found  | Reactivity  | Comments   |
|--------------|------------------------------|------------------------|--|---|--|
| <b>Delta</b> | 0.1 - 4                      | <100                   | Dominant in infants, during deep stages of adult sleep and serious organic brain disease. Central cerebrum and parietal lobes                              | Focal in pathologies. Occur after transactions of the upper brain stem separating the reticular activating system from the cerebral cortex  | Polymorphic delta: severe, acute, or ongoing injury to cortical neurons. Rhythmic discharge: psychophysiologic dysfunction.  |
| <b>Theta</b> | 4 – 8                        | <100                   | In drowsy normal adult, in frontal, parietal and temporal regions. In children when awake  | Rare in EEG of awake adults. During emotional stress in some adults. Sudden removal of something causing pleasure will cause about 20s of theta waves   | Niedermeyer lists some studies in which the theta activity of 6-7 Hz over frontal midline region had been correlated with mental activity. Focal or lateralized theta indicates focal pathology, Diffuse theta more generalized neurologic syndrome.   |
| <b>Alpha</b> | 8 - 13                       | 20-60                  | The most prominent rhythm in the normal alert adult brain. Most prominent at occipital and parietal regions. About 25% stronger over the right hemisphere. | Fully present when a subject is mentally inactive, alert, with eyes closed. Blocked or attenuated by deep sleep, attention, especially visual, and mental effort. When a person is alert and their attention is directed to a specific activity, the alpha waves are replaced by asynchronous waves of higher frequency and lower amplitude. Eye opening/closure offers the most effective manipulation | Location of central alpha peak declines with age and in dementia. Alpha waves are usually attributed to summated dendrite potentials. Slowing is considered a non-specific abnormality in metabolic, toxic, and infectious conditions. Asymmetries - unilateral lesions. Loss of reactivity - a lesion in the temporal lobe. Loss of alpha - brainstem lesion. |
| <b>Mu</b>    | 10 - 12                      | <50                    | Central electrodes, over motor and somatosensory cortex  | Does not react to opening of eyes like alpha rhythm. Blocking before movement of the contra lateral hand. Blocking for light tactile stimuli. Blocking for readiness or imagination to move limbs   | Physiologically and topographically different to alpha rhythm. Not clinically useful. Useful as a BCI input in relation to actual and imagined limb movement. Typically appears as part of a background rhythm.  |
| <b>Beta</b>  | 14 – 30                      | <20                    | Three basic types<br>Frontal beta<br>Widespread<br>Posterior   | Frontal beta blocked by movement. Widespread beta often unreactive. Posterior beta shows reactivity to eye opening  | Beta I waves, lower frequencies, which disappear during mental activity. Beta II waves, higher frequencies, appear during tension and intense mental activity. Under intense mental activity beta can extend up as far as 50Hz   |
| <b>Gamma</b> | > 30                         | <2                     | Widespread   | Found when the subject is paying attention or is having some other sensory stimulation  | Due to its really low amplitude it is very difficult to isolate without band-pass filtering  |

### 2.4.2. Event-related potentials (ERPs)

Event-related potential (ERP) is a common title for potential changes in the EEG that occur in response to a particular “event” or a stimulus. ERPs provide a suitable methodology for studying the aspects of cognitive processes of both normal and abnormal nature, such as neurological or psychiatric disorders. Mental operations such as those involved in perception, selective attention, language processing and memory, proceed over time ranges in the order of tens of milliseconds. Whereas PET and MRI can localize regions of activation during a given mental task, ERPs can help in defining the time course of these activations.

Amplitudes of ERP components are often much smaller than spontaneous EEG components, typically a factor of  $\sim 10$ . They are subsequently unrecognisable from the raw EEG trace. They can be elicited by ensemble averaging EEG epochs time-locked to repeated sensory, cognitive or motor events [32]. The assumption is that the event-related activity, or signal of interest, has a more or less fixed time delay to the stimulus, while the spontaneous background EEG fluctuations is random relative to the time when the stimulus occurred. Averaging across the time-locked epochs highlights the underlying ERP by averaging out the random background EEG activity (similar to additive white noise), thus improving the signal-to-noise ratio. These electrical signals reflect only the activity which is consistently associated with the stimulus processing in a time-locked manner. The ERP thus reflects, with high temporal resolution, the patterns of neuronal activity evoked by a stimulus. This approximation to the real ERP however, offers no phasic information. ERPs can be divided into exogenous and endogenous [33]. Exogenous ERPs occur up to about 100ms after the stimulus onset. They depend on the properties of the physical stimulus. The potentials pre-stimulus and 100ms after the stimulus are termed endogenous. DC-shifts or Slow-Cortical Potentials are endogenous ERPs and are used by Birbaumer [33] in their “*Thought Translation Device (TTD)*” BCI system.

Evoked-potentials (EPs) are a subset of the ERPs that occur in response to or during attention to certain physical stimuli (auditory, visual, somatosensory etc.). They can be considered to result from a reorganization of the phases of the ongoing EEG signals [34]. The EPs can have distinguishable properties related to different stimuli properties, for example, the EEG or *Visual Evoked Potential (VEP)* over the visual cortex varies at the same frequency as the stimulating light [5]. There are many successful EP based BCI systems that utilise VEPs [35], steady-state VEPs [36] or P300s [37] as inputs which will be reviewed later.

Readiness Potential (RP) or Movement-Related Potentials (MRP) is an ERP of the order of  $1\mu\text{V}$  generated in response to a cognitive desire to perform or imagination of limb movement and is prevalent at highly localised areas of the brain related to that function (primary motor cortex). The ERP pattern recognition approach to BCI design produces a more natural brain response directly related to the function. Most relevant for the BCI use is the fact that these patterns do not require actual movements and are similarly generated by imagined movements [38]. Most present-day BCIs based on imagined movements use a synchronous cued approach to time-lock the event [38-46]. This restricts the user to fixed time periods but dramatically simplifies the classification process. The system knows the exact timing of when a brain pattern can occur and consequently only has to classify the event rather than both the occurrence of an event and then the event itself. In contrast, an asynchronous paradigm has the difficult task of detecting an event from continuous EEG amidst the widely varying baseline or background EEG activity.

A common goal in many BCI research groups is to detect these small ERPs of approximately  $1\mu\text{V}$  from the background EEG (10-50  $\mu\text{V}$ ), extract distinguishable features and classify them for subsequent use as inputs to a computer interface. The largest portions of BCI systems to date are based on using event-related or evoked potentials. A review of some of these systems is presented in chapter 3.

### 2.4.3. Event-related (de)synchronization (ERD/ERS)

Pfurtscheller and Aranibar first quantified event-related desynchronization (ERD) in 1977 [47]. Pfurtscheller developed a BCI known as the Graz BCI in the 1990s that was based on detecting ERD and ERS of the different mu and beta rhythms bands during the imagination of left and right hand movements [47-52]. ERD is amplitude attenuation and ERS is amplitude enhancement of a certain EEG rhythm. In order to measure ERD or an ERS, the power of a chosen frequency band is calculated before and after the event over a number of trials. The average power across a number of trials is then measured in percentage relative to the power of the reference interval. The reference interval can be an arbitrary period prior to the event representing a period of inactivity or rest. The ERS is the power increase (in percent) and the ERD is the power decrease relative to the reference interval that is defined as 100%. ERD/ERS measurements selected over specific frequency ranges are typically used to produce a spatio-temporal map to visualise the functional behaviour of the brain. The reader is referred to [49] for a more detailed quantification of ERD/ERS in time and space.

## 2.5. Applications

This section highlights the many clinical and cognitive research applications that have been established over the years for EEG. Hans Berger in his original papers (grouped together and translated in [2]) laid the foundations for most of today's clinical uses for EEG. The greatest advantage of EEG over other brain imaging technologies is speed and cost. Complex patterns of neural activity can be recorded with millisecond resolution. As mentioned above, EEG however provides poor spatial resolution ( $\sim 1\text{cm}$ ) compared to MRI or PET ( $< 1\text{mm}$ ). Thus for better insight into the origins of neural activity EEG inverse solution images are often compared with MRI scans for a similarly but separately run trial.

According to Bickford [18] research and clinical applications of the EEG in humans and animals are to:

- Monitor alertness, coma and brain death
- Locate areas of damage following head injury, stroke, tumour etc.
- Test afferent pathways (by evoked potentials)
- Monitor cognitive engagement (alpha rhythm)
- Produce biofeedback situations, alpha, etc.
- Control anaesthesia depth ('servo anaesthesia')

Investigate epilepsy and locate seizure origin  
 Test epilepsy drug effects  
 Assist in experimental cortical excision of epileptic focus  
 Monitor human and animal brain development  
 Test drugs for convulsive effects  
 Investigate sleep disorder and physiology

Symmetry of alpha activity within hemispheres can be monitored. In cases of restricted lesions such as tumour, haemorrhage, and thrombosis, it is usual for the cortex to generate lower frequencies. EEG signal distortion can be manifested by reduction in amplitude; decrease of dominant frequencies beyond the normal limit; production of spikes or special patterns. Epileptic conditions produce stimulation of the cortex and the appearance of high-voltage waves (up to 1000 $\mu$ V) referred to as “spikes” or “spike and wave” [18]. EEG patterns have been shown to be modified by a wide range of variables, including biochemical, metabolic, circulatory, hormonal, neuroelectric, and behavioural factors [3]. By tracking changes of electrical activity during such drug abuse-related phenomena as euphoria and craving, brain areas and patterns of activity that mark these phenomena can be determined. As the EEG procedure is non-invasive and painless, it is widely being used to study the brain organization of cognitive process such as perception, memory, attention, language comprehension and emotion in normal adults and children. For this purpose, the most useful application of EEG recording is the ERP analysis method.

Taking the functional and cognitive insight that EEG offers a step further, would allow humans to modulate their brainwave activity in order to communicate. This gives rise to the rapidly developing area of neuroscience and engineering that is brain computer interface design. Its development is in its infancy with respect to other communication technology such as mobile phones, television etc. but despite it presently offering limited communication rates, it could possibly replace other communication modes particularly within the area of rehabilitation in the future.

### **2.5.1. Biofeedback**

Biofeedback is the process in which a subject receives information about his physiological state [53]. It creates an external loop by which a subject can monitor one or more of his physiological states to aid in training or performance of a task. The most popular biofeedback methods include; galvanic skin response (GSR), body temperature, EEG, ECG, heart-rate variability (HRV), EMG and respiration. These various methods are used for different clinical purposes to report on the physiological state of the human body. EEG biofeedback or neurofeedback can be dated back to the early 1970's when the self-regulation of the alpha rhythm was used to aid in relaxation and meditation [54]. Today it proposes to offer a greater insight into the physiological and mental state of a subject compared to other biofeedback modalities.



While many researchers are sceptical about neurofeedback, some assume that subjects can improve their mental performance, normalize behaviour and stabilize mood through its use. There are a wide range of applications which market the use of EEG biofeedback. Predominantly it is used in monitoring and rehabilitation for conditions such as attention deficit hyperactivity disorder (ADHD), depression, anxiety, epilepsy, sleep disorders and alcoholism. Biofeedback is a powerful therapeutic tool which teaches people to take responsibility to learn self-regulation of their bodily systems and behaviour [53].

The EEG signals at the neurofeedback input are typically fed into a computer to decipher the physiological or mental state of the subject. This allows the feedback to be presented to the subject in a more stimulating and meaningful manner using a combination of sensory feedback methods such as visual, auditory and tactile. It is necessary to provide interesting feedback, particularly in studies with children, to maintain the subjects' attention during the typically long and tedious EEG biofeedback treatment sessions.

Neurofeedback in a training situation may help a subject to modify his or her brainwave activity. Through the use of extensive training, it can allow a subject to alter the EEG so that it can then be used as a BCI input to offer control or communication. This BCI application of EEG biofeedback is fundamentally different to its use in clinical treatment. In biofeedback treatment the goal is to reach a certain condition and maintain it, whereas in BCI design the goal is that the user learns to alter his or her EEG activity between two or more conditions (functional classes) [55,56]. The positive effects of EEG biofeedback will be readdressed in greater detail in section XX in relation to BCI system design and then again in chapter 5 in a BCI gaming system implementation.

## **2.6. Summary**

EEG is limited by the vast number of electrically active neuronal elements, the complex electrical and spatial geometry of the brain and head, and the disconcerting trial-to-trial variability of brain function [57]. The layers of cerebrospinal fluid, skull and scalp between the electrodes and the brain itself, act as an electrical shield severely attenuating and volume smearing the electrical contributions of neuron communities to EEG recordings. This presents a difficult challenge to localize and decipher the contributions of neuron communities to the EEG recorded macropotentials. Despite EEG's poor spatial resolution, its excellent temporal resolution of less than one millisecond and ease of acquisition makes it the only practical brain imaging modality for real-time BCI systems. Despite the Herculean challenges for utilising EEG as the input modality to a BCI, recent advances in signal processing techniques make it more feasible than ever before.

The next chapter will review the key components to an EEG based BCI system, paying considerable attention to signal processing methods involved. Then a literature review is provided

on all aspects of BCI design, implementation and performance. The fundamentals of EEG as covered in this chapter coupled with a review of the components and methodologies of an EEG based BCI system as covered in the next chapter will prepare the reader for the subsequent three chapters which report on different BCI designs and implementations that were carried out.

## **Chapter 3      Brain Computer Interfaces (BCIs)**

This chapter serves as an introduction and state of the art review of EEG-based BCI technology. It begins by introducing the idea of a direct human computer interaction via the electrical signals generated within the brain. It explains the social and scientific need of such a system that inspires this line of research. Having clarified the concept and purpose of a BCI, the chapter moves on to discuss the various approaches and methodologies that are employed to realise a fully functional BCI system. Section 3.1 highlights the two fundamentally different approaches to designing a BCI system based on the nature of brain signal generated as the control mechanism. The next section identifies and briefly explains the necessary components to a typical BCI system. Section 3.5 goes further to describe some of the signal processing methodologies involved with these BCI components. The chapter performs a review of BCI technology to date by cataloguing in tabular form a large selection of implemented systems and describing the varying approaches taken. The work of the principal BCI research groups from around the world is reviewed. To facilitate comparison, the chapter concludes by introducing performance metrics that can be used to evaluate BCI systems. The key issues that need to be addressed to facilitate a more rapid development of BCI research and the future prospects of this technology will be discussed in the conclusion after the presentation of two BCI system implementations in the next two chapters.

### **3.1.    Introduction**

This introduction serves to provide the reader with a clear understanding of what is involved with the novel idea of a direct human-computer interaction via signals generated within the brain. This BCI technology will first be briefly introduced and then discussed in more detail by answering some of the commonly posed questions on BCI systems.

For many years the scientific community has identified direct correlations between brain activity and cognitive functional and mental tasks. This sparked huge interest over the years in the multidisciplinary field of cognitive neuroscience that culminated with much speculation as to the enormous potential of harnessing this correlation to offer a new non-muscular channel for sending messages and commands to the external world. Over the past two decades, productive BCI research groups have arisen to explore this new potential communication modality. Facilitated and encouraged by new understanding of brain function, by the advent of powerful low-cost computer equipment, and by growing recognition of the social needs of people with disabilities, these groups focused their attention on developing a new alternative communication and control technology to

exploit this medium. Today, BCI systems propose to offer humans a new non-muscular modality through which to communicate directly with their environment. They rely on the acquisition and interpretation of the user-controlled commands encoded in the neurophysiological signals.

### **What is a Brain Computer Interface?**

BCI technology provides a direct interface between a brain and a computer. In the first international BCI workshop held in June 1999 in Rensselaerville, New York involving 22 research groups, a formal definition of the term BCI was set forward [58]:

*“A brain-computer interface is a communication system that does not depend on the brain’s normal output pathways of peripheral nerves and muscles”*

In basic terms, a BCI involves monitoring brain activity (via a brain imaging technology) and detecting characteristic brain pattern alterations that the user controls in order to communicate (via digital signal processing algorithms) with the outside world. In a BCI, messages and commands are expressed not by muscle contractions as with conventional communication means, but rather by electrophysiological signals generated within the brain.

### **What is the Research motivation?**

The original motivation that inspired this line of research was to develop an alternative and replacement communication technology for severely disabled people. For people who are ‘locked-in’ as a result of a severe neuromuscular disability such as ALS<sup>7</sup>, TBI<sup>8</sup>, CP<sup>9</sup>, mitochondrial disease and SCI<sup>10</sup>, this may offer the only means of communication and environment control. Several rehabilitative communication systems have been developed over the years to compensate for this communication impairment, but most of these require some sort of limited movement ability in order to function. In the worst cases of the aforementioned disabilities when the sufferers lose all voluntary muscle control but remain cognitively intact, harnessing brain activity is the only viable method of communication.

Despite the principal motivation being to offer a means of communication for individuals with neuromuscular impairments, more and more media attention has been attributed to exploring the full potential of this communication medium for the wider audience in areas such as multimedia applications and video games.

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<sup>7</sup> ALS - Amyotrophic Lateral Sclerosis

<sup>8</sup> TBI - Traumatic Brain Injury

<sup>9</sup> CP - Cerebral Palsy

<sup>10</sup> SCI – Spinal Cord Injury

### **Why EEG as the BCI input modality?**

There exist a number of technologies that can monitor brain activity. These include, for example, functional Magnetic Resonance Imaging (fMRI), Magnetoencephalography (MEG), Positron Emission Tomography (PET), Single Photon Emission Computer Tomography (SPECT) and Electroencephalography (EEG). As summarised in section 2.1.2, EEG is the only practical non-invasive brain imaging technology for the following reasons:

- Inexpensive
- Ease of acquisition
- High temporal resolution (i.e. almost instantaneous representations of brain activity, within 1ms)
- Real-time implementation possible
- Direct correlation of functional brain activity with EEG recordings

Almost all of BCIs reported to date have been based on EEG for these reasons. Research reported in this thesis focuses for these reasons on EEG-based BCI system design and implementation.

### **How can users modify their EEG signals to select a specific control attempt?**

Communication or control based on BCI technology requires patterns of brain activity that can be consciously generated or controlled by a subject and ultimately clearly distinguishable by a computer system. EEG based BCI systems decipher patterns in the scalp recorded electrical signals.

These *patterns* can be created by one of two possible BCI approaches which will be discussed in greater detail in section 3.12. One approach requires the BCI user to concentrate on a mental task in order to produce a characteristic brain pattern that identifies with the desired control, for example, the imagination of hand movement. The performances of different mental tasks generate different EEG responses and hence can be translated into a control codebook for the user, assuming the BCI system can be trained to decipher the associated EEG activity. The other approach requires users to perform extensive training to develop the ability to self-regulate their EEG activity, for example, the mu rhythm.

### **How can a BCI system detect the control attempts from the EEG signals alone?**

Once the user can generate ‘distinguishable’ brain activity associated with different control commands, the goal of the BCI system is to identify this EEG activity by extracting features or signal characteristics that identifies with this specific control and maximally distinguishes it from activity associated with other control commands. The fundamental requirement of a BCI is to identify a control or communication attempt from EEG signals by attributing values associated to characteristic activity. As summarised in section 2.4, there are many ways to categorise EEG

signals for this task. Broadly speaking, most EEG-based BCIs approaches can be characterised into three groups of EEG patterns: Rhythmic brain activity, Event-related potentials (ERPs) and Event-related (de)synchronization (ERD/ERS) that can identify with various control attempts. Successful BCI operation requires that the user have control over the activity that generate these signal features and that the BCI correctly derive the user's intentions from them.

#### **What is the relationship between the user and the system?**

BCI operation depends on the interaction of two adaptive controllers, the user, who must maintain close correlation between his or her intentions and these signal features, and the BCI, which must translate them into device commands that accomplish the user's intentions. The user and the BCI system need to adapt to each other both initially and continually so as to ensure stable performance.

#### **What is the current research attention?**

The last 25 years since the first successful BCI implementation by Prof. J. Vidal at UCLA [1] has witnessed an explosion of scientific interest in the area of BCI research. Due to the realisation of the enormous potential for exploiting this innovative direct communication medium, there are now more than 40 research groups around the globe investigating BCI systems and its potential applications. Consequently more and more research grants are being allocated to this rapidly developing multidisciplinary field. However, Donchin expressed in [59] that the potentially huge human impact of such a technology is not reflected by the funding or commercial interest. An excellent review of all the efforts to make BCI technology a mature field of research can be found in [57].

#### **What is the goal of BCI Technology?**

Present-day BCIs provide maximum information transfer rates up to 25 bits/min. With this relatively limited capacity, they can provide basic communication and control functions (e.g., environmental controls, simple word processing) to those with the severe neuromuscular disabilities. It also supports basic limb control such as a hand grasp to those with mid-level cervical spinal cord injuries through its incorporation with FES. This area of neuroprosthesis is becoming an important aspiration of this technology. More complex BCI applications targeted at a wider population of users depend on the achievement of higher information transfer rates. Thus accuracy and speed of this technology hinder the goals of this technology.

### **3.2. Two fundamental approaches to BCI design**

The ideal BCI system would be capable of simply detecting a user's commands or communication attempt directly from the electrophysiological signals generate. There would be no need to perform

a wilful alteration of one's thoughts in order to change the brain activity in a characteristic manner to result in a control decision. It would simply involve an effortless 'wish'. This could be considered similar to the way humans perform limb movements. A BCI system that could interpret human desire directly in this manner would have enormous potential for the widespread population.

Unfortunately, this is not possible with today's technology and neurophysiological understanding. As the best alternative, BCI researchers have utilised their knowledge of the brain's electrophysiology to exploit brain activity that can be characteristically altered by the user in order to offer distinguishable commands. It requires a much more conscious effort on behalf of the user compared to the ideal case described above. In some cases extensive training is also required. It is a very difficult signal processing challenge to extract the control signals from the electrical soup that make up the EEG recordings even when the user is fully devoted to the task. It is questionable that in the near future, one would be capable of deciphering the subtleties of desire from any brain imaging modality.

There exist two basic approaches widely referred to in the literature to modify ones brain activity to form as the BCI input. The first is the *pattern recognition approach* based on identification of characteristic brain activity in response to performing a cognitive mental task. The second is the *operant conditioning approach* based on the self-regulation of the EEG response.

### **3.2.1. Pattern Recognition (PR) approach**

Earlier in section 2.2.2 it was discussed that the human brain is functionally organised. The activity associated with certain mental tasks is highly localised to specific and known regions of the brain. BCI researchers utilize this knowledge and cognitive psychology to devise suitable experimental paradigms to guide the user to generate distinguishable brain patterns in response to different cognitive mental tasks. The principle of choosing the different mental tasks is that they produce detectable and different EEG patterns. The Pattern Recognition (PR) approach employs signal processing algorithms for feature extraction and classification that identify and distinguish the brain activity in response to these mental tasks, thus offering a means of control or communication.

The mental tasks used in BCIs to date have included motor imagery, visual, arithmetic and baseline tasks. Activation in response to the chosen task should occur close to the cortex so that it can be detected with scalp electrodes. The simplest approach to generating different EEG patterns is to ensure that the mental tasks activate different parts of the brain. This topographic PR approach looks for activity level variations in specific brain regions that identify with the mental task and hence offer a means of control. For example, the imagination of right hand movements

should activate the left motor cortex and the imagination of left hand movements the right motor cortex. Similarly, visual and arithmetic tasks should activate the visual association area and the prefrontal cortex respectively. A more challenging PR approach is to decipher distinguishable patterns from brain activity in the same brain region related to different mental tasks (localized PR approach).

Decoding brain patterns is a challenge however due to the inter-trial variability of brain activity, the low signal-to-noise ratio (SNR) of the brain response to the mental task with comparison to the background activity, the subtlety between the responses to different tasks and the real-time requirement of the decoding process. It should also be noted that some mental tasks suit some people better than others. For example, a subject with poor spatial relation visualization may find the cube rotation mental task by Keirn and Aunon in [60] too difficult. Penny describes in [61] the PR approach taken by his Oxford BCI research group and discusses the additional signal-processing challenges compared with the operant approach. It will be shown later in the state-of-the-art review that the majority of implemented BCI systems take the PR approach.

### 3.2.2. Operant Conditioning (OC) approach

The Operant Conditioning (OC) approach to BCI design requires the user to perform lengthy training sessions in a biofeedback environment to master the skill of being able to *self-regulate* one's brain activity. It was first defined by Niels Birbaumer [62-64] and the Tübingen BCI research group<sup>11</sup> in their BCI called the Thought Translation Device (TTD). The system was based on the self-regulation of slow-cortical potentials (SCP), a low-frequency modifiable potential shift.

As discussed earlier in section 2.4 there exist many descriptors of EEG activity. Rhythmic brain activity, event-related potentials and event-related (de)synchronization (ERD/ERS) are the most common method of categorizing EEG patterns for use in a BCI system. The brain activity that one hopes to regulate in the OC approach is often empirically discovered by studies that investigate the effects of biofeedback. The most prominent BCI research groups have based their BCIs on the self-regulation of specific brain rhythms and potentials. Birbaumer et al. [62-65] and their TTD device exploits controllable variations in SCPs. Wolpaw et al. [57,58,66-69] at the Wadsworth Center<sup>12</sup> have based their BCI on the self-regulation of  $\mu$  or  $\beta$  rhythms.

The nature by which a given EEG signal property is self-regulated by the user with the OC approach is an ambiguous area. Wolpaw et al. [68] report that the users of their BCI are advised before any experiments that various kinds of motor imagery are helpful to affect control. Wolpaw

<sup>11</sup> Institute of Medical Psychology and Behavioral Neurobiology, University of Tübingen, Germany- <http://www.uni-tuebingen.de/medizinischepsychologie/projekte/als.htm>

<sup>12</sup> Neuroscience Program, Wadsworth Center, NYS Dept. of Health, NY <http://www.wadsworth.org/resnres/neurosci.htm>



et al. describes how the users later develop self-regulation without the need to use mental imagery. In the case of the TTD, the users were simply instructed to be attentive to the feedback and to develop whatever mental strategy to offer maximum control. Patients that utilized the TTD device were reported in [63,70] to have used very different mental strategies of affect control. These varied from the subject visualizing ‘carrying a heavy object up a hill’ to ‘electrifying the brain’. The varied nature of the mental strategies points to the importance of the feedback in the learning procedure, irrespective of the strategy employed. According to Kübler et al. [70] there are three necessary elements required to facilitate the learning procedure in the self-regulation of EEG activity:

- 1) Real-time feedback of the specific EEG activity
- 2) Positive reinforcement of correct behaviour
- 3) Individual shaping schedule in which progressively more demanding tasks are rewarded

The OC approach hinges on the effective use of biofeedback in the training scenario for a subject to develop the ability to self-regulate an EEG signal property. The performances of BCIs based on the OC approach are reasonably successful but the lengthy and arduous training requirement makes it difficult for rapid deployment. Also the number of possible different self-regulation states limits the possible information transfer rates. Some subjects in [63] and [68] displayed the inability to develop the skill of brain activity self-regulation. The OC approach places the biggest requirement on the subject’s ability to adapt compared to the PR approach whereby it is up to complex signal processing to ensure success. The PR approach is more challenging to ensure high classification accuracy. It however requires limited classifier training, does not explicitly require feedback, has the potential to offer many control states and can offer a more natural control method.

### **3.3. BCI control: synchronous Vs asynchronous**

A BCI can be either cue-based (synchronous) i.e. when mental activities are triggered by external stimuli or un-cued (asynchronous) i.e. when the user decides by wilful control that a mental task should occur and the resultant control signal be generated. The former case is computer-driven and the EEG has to be analyzed only in predefined time windows. The latter is user-driven and the EEG signals have to be analyzed and classified continuously.

The cue-based BCIs are dramatically less demanding in the feature extraction and classification stages compared with the un-cued systems. Only a small segment of EEG data, time-locked to the cue, needs to be analyzed in comparison to the un-cued approach. The synchronous approach does not need to estimate from the continuous EEG when a control attempt occurred

seeing as it is relative to the cue. It only has to distinguish what control occurred within the small window of EEG data. The synchronous BCIs offers a less natural method of control because one must wait for the appropriate cue in order to make a decision. This limits the speed of command generation for such an approach. However, synchronous BCIs tend to have higher accuracies due to their simplicity and the removal of the need to identify a large range of features from the widely varying continuous EEG signals.

Asynchronous BCIs are user driven i.e. the control is not system-initiated but user-initiated. This offers complete control to the user. They tend however to have lower accuracy compared to synchronous systems because of the need to identify what and when a control occurred from the continuous EEG activity. Mason and Birch present an interesting hybrid approach in [71] to combine the benefits of both the time-locked synchronous and user-guided asynchronous approach. They introduced an additional EEG feature set that is controlled by the subject to initiate a new synchronous trial.

### 3.4. BCI framework

This section highlights and explains the functional components involved in an EEG-based BCI system. The basic components required for implementation are depicted in Figure 3-1 and summarised as follows:

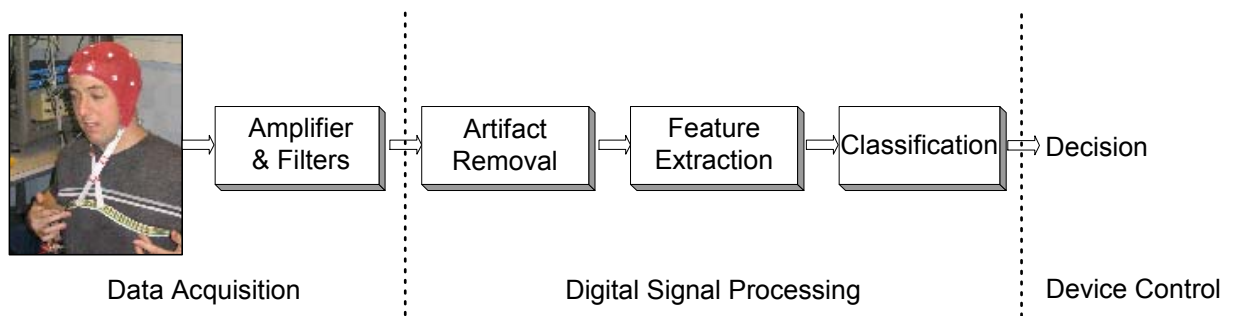


Figure 3-1: Processing Stages necessary for BCI implementation

- 1) The data acquisition stage involves the recording of the raw EEG data from electrodes at specific locations on the scalp that form the input to the BCI system. Choices such as the number, position and density of electrodes determine the input channels. The pre-processing stage of the acquisition process involves amplification, analog filtering and A/D conversion. See section 2.3 for a review on the methods and potential problems associated with EEG data acquisition.

- 2) The next stage is an optional information optimisation stage that involves improving the signal-to-noise ratio (SNR) by removing artifacts and reducing information redundancy from the EEG channels. See section 2.3.4 for a review on artifacts and methods to counteract their adverse effect on EEG recordings.
- 3) Feature extraction is the most important stage to any BCI. It involves the development of command-dependent discriminatory features from the pre-processed EEG signals by employing DSP algorithms to identify with command-related activity. It is this stage that often characterises the BCI design approach. If robust features that are resilient to artifacts and the volumetric smearing effect of the neuronal signals can be extracted, the need for the previous information optimisation stage is reduced. It also reduces the challenge on the classifier to discriminate between the features of different controls. It is important to note that the experimental paradigm is as crucial as the feature extraction methods for the consistent elicitation of physiological brain patterns.
- 4) The classification or feature translation stage involves the identification of the feature patterns to facilitate the categorisation of the user's commands. It can be anything from a simple threshold or linear model to a complex nonlinear neural network based classifier that can be trained to categorise the features according to the control selection. Most classifiers are based on a probabilistic approach whereby the class of highest probability is chosen. A 'nothing' class can be included to offer a no selection instead of a control.
- 5) The output of the classification stage is the controlling input of the device. The device control transforms the classification into a device action. The output of the classification stage may instruct the device that no appropriate control was classified and hence to perform no action.

Mason & Birch proposed in [72] a general framework for brain-computer design in the hope of standardising terminology and functional models to facilitate the benchmarking of BCI systems. They proposed the generic functional model for a BCI system in Figure 3-2. They stressed the importance of having such a model to compare the performance of BCI communication technologies within the research community.

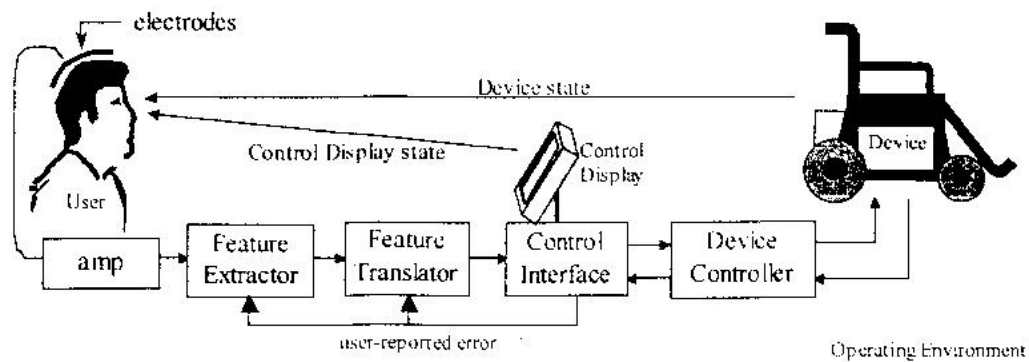


Figure 3-2: A functional model of a BCI system proposed by Mason & Birch [72]

With the explanation of the various components to a BCI system listed above, the question still remains about how the BCI design process begins and how all these components interlink. The preliminary stage to any BCI requires an investigation into the paradigm and the brain activity which one hopes to generate to offer distinguishable controls. This requires recording numerous sessions or trials of data to later examine for distinguishable features. Ensemble averaging of trials in the time or frequency domain is initially carried out in the hope of observing a general characteristic pattern. The greatest challenge is to see if this characteristic activity can be elicited on a single-trial basis or over a small segment of continuous EEG data. If this can be satisfactorily achieved, feature extraction methods must be employed to represent these characteristics by a number of values that can distinguish the different brain activity and resulting controls on a single-trial or online basis. Thus a BCI system can be designed to exploit this human-controlled EEG activity alteration to offer control.

### 3.5. BCI system methodologies

This section discusses the methodologies and digital signal processing involved with implementing a BCI system. Particular attention is given to the methods that will be discussed in context of the author's BCI implementations covered in later chapters.

#### 3.5.1. Experimental paradigm design

The experimental paradigm decides the environmental conditions in order to prompt or allow the user to generate the controlling EEG activity. This is extremely important during the investigation stages of BCI design whereby a command-related EEG activity (neuromechanism) has to be established through extensive testing. A deep understanding of the human psychology and neurological behaviour associated with the experimental environment is paramount to the feature extraction and classification tasks for the purpose of eliciting distinguishable electrophysiological

brain patterns to offer communication. It is clear in the literature that, subtle variations in the environment during experiments, e.g. lighting, visual angle etc. for a visual task, can dramatically alter the brain response and thus hinder extraction of the controlling feature for a BCI system. It will be shown later in Study 2 (Chapter 5) that the exploited Visual Evoked Potential (VEP) was sensitive to a wide-range of visual stimuli characteristics. Similarly for movement-related activity, whereby the somatosensory cortex is closely located to the primary motor area, contamination of the desired control signals could be caused by unnecessary sensory stimulation.

It is clear that our experimental environment should be as idyllic as possible, whereby the only brain activity should be associated with the mental or functional task of communicating via the BCI system. The brain however, is continuously performing many voluntary and involuntary tasks that cannot be controlled during the experiments. We are also attempting to replicate real life in a contrived experimental set-up whereby the user is repeatedly required to perform a task. In real-life, a BCI system would be expected to function in a ‘noisy’ environment at any instant. This is the ultimate goal of any experimental paradigm design, to imitate as best as possible a real-life scenario. Unfortunately this would not be practical for the early investigatory stages of BCI design whereby we need to work with clean and artifact-free data in order to identify the desirable controlling brain activity pattern. When a satisfactory working BCI prototype from the ideal testing environment is achieved, the goal is then to make the system robust enough to function in a real-life scenario. There is however an inherent psychological difference between subjects performing an event on a sporadic basis as in day-to-day life compared with repeated monotonous trials in a contrived experimental environment.

The author’s collaboration with Trinity College Institute for Neuroscience (TCIN)<sup>13</sup> and Nathan Kline Institute for Psychiatric Research (NKI)<sup>14</sup> offered the physiological and psychological background knowledge for designing the experimental protocol for acquiring data during various BCI related studies.

### **3.5.2. Pre-processing**

Pre-processing involves the preparation of the EEG recordings prior to any form of digital signal processing. In addition to sample rate conversion, it is an important stage that decides the filtering, segmentation and detrending methods employed to prepare the EEG data for further BCI processing stages. Filtering and segmentation (or epoching as it is referred) are used to identify and maximise the information over a certain time or frequency range that is associated with the characteristic brain activity to be elicited. It is widely assumed that no cognitive EEG activity

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<sup>13</sup> Trinity College Institute for Neuroscience (TCIN), Dublin – <http://www.tcd.ie/Neuroscience/index.html>

<sup>14</sup> Nathan Kline Institute for Psychiatric Research (NKI), NY – <http://www.rfmh.org/nki>

exists above around 40 Hz and thus filtering thereafter reduces the noise. A notch filter at the mains frequency is typically performed in addition. Breaking the EEG data into epochs time-locked to a stimulus (synchronous BCIs) identifies the time-window for which the desired activity occurs, thus reducing the task to identifying what control activity occurred instead of what and when in the case of continuous EEG data (asynchronous BCIs). It dramatically simplifies the feature extraction and classification process. Detrending removes any baseline drift associated with the EEG recordings. This is important to ensure the quasi-stationarity of small EEG segments. The sample rate can be converted to represent the data in as few samples as possible to reduce the computational demands of processing a large number of samples. The sampling rate must be chosen to be at least twice that of the maximum frequency contained in the data (Nyquist rate) in order to prevent aliasing. A sampling rate of 128 Hz is typically chosen in the literature as it is capable of representing frequencies up to 64 Hz, thus the entire accepted range of EEG activity.

### 3.5.3. Artifact removal

Artifacts are undesirable potentials of non-neural origin that contaminate the underlying EEG activity that one hopes to elucidate to offer control in a BCI system. The simplest approach to dealing with artifacts is to discard EEG trials with an unacceptable level of artifact corruption. This is commonly carried out for the collection of training data or for an offline investigation [44,73-75]. For an online BCI implementation however, these artifacts must be dealt with without eliminating any single trials or control attempts. Artifact removal as described in section 2.3.4, involves the use of adaptive signal processing methods to identify, isolate and remove artifacts from the EEG recorded activity on a single-trial basis. This all must be carried out without corrupting the underlying EEG activity such as an event-related potential. As reviewed in section 2.3.4 there exist two main approaches to artifact removal:

- Filtering
- Higher-order statistical separation and elimination

The filtering method typically requires the recording of the artifact activity itself. It is typically applied to EOG [25,76,77], EMG [78] and ECG [23] activity related artifacts. Regressive filtering methods in the time [21,22] or frequency domain [23,24] can smear the EEG data or add additional artifacts.

Higher-order statistical separation methods are often referred to as global techniques due to the fact that they simultaneously use information from all available electrodes (typically >32 channels). This approach offers the most promising approach of removing artifacts from the EEG recordings without corrupting valuable EEG data. The problem is analogous to the source

localisation task common in digital signal processing. If we can determine the origins of the *components* that make up the EEG recording (such as EOG originating from the eye) we can remove ones that correspond to artifacts. This is a form of spatial filtering. It is often referred to as the Blind Source Separation (BSS) challenge to identify and remove artifacts on a single-trial basis, see [79] for a review of the statistical principles. Principal component analysis (PCA), a BSS method, is used to decompose a multi-electrode EEG trial into linearly uncorrelated components, and then reconstruction is performed by omitting unwanted artifact components such as EOG. The unwanted components are either visually scored or automatically detected by correlation with simultaneous artifact recordings. An example of PCA artifact removal on a single-trial is demonstrated in Figure 3-3 and Figure 3-4. See [80] for a review of PCA for EEG artifact removal.

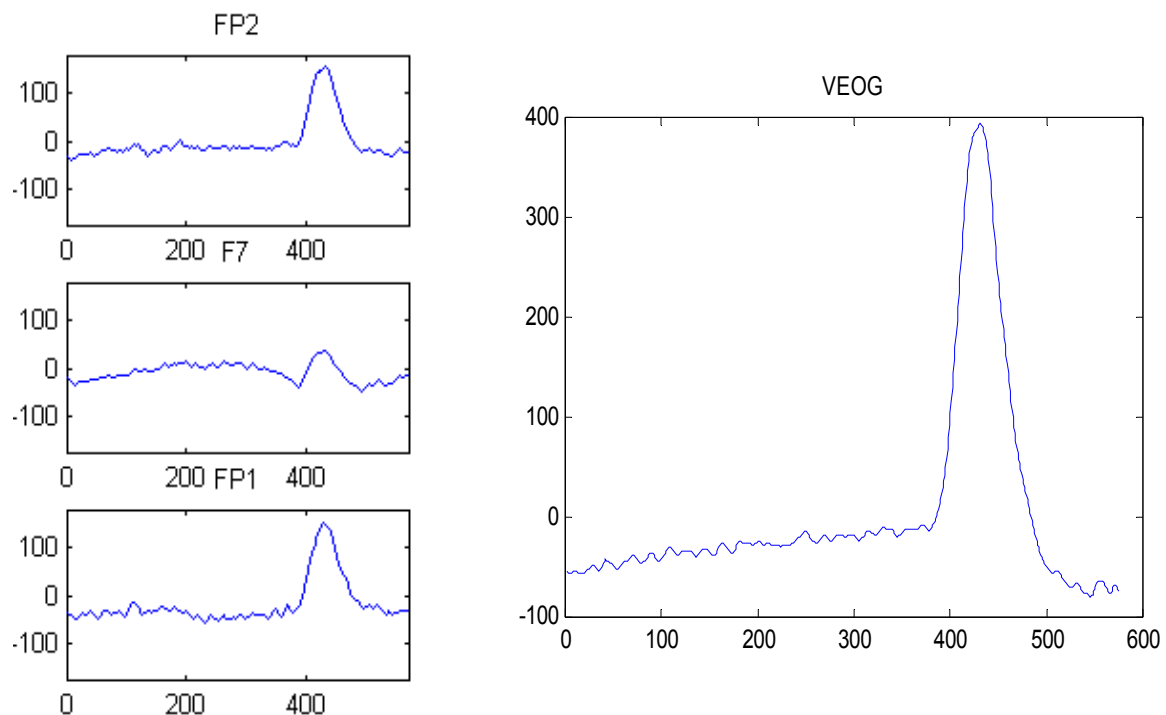


Figure 3-3: EEG single-trial recording from frontal electrode sites FP1, FP2 and F7 (left) and the simultaneous vertical EOG recording from the left eye (right). The y-axis in the plots represents magnitude in microvolts ( $\mu\text{V}$ ) and the x-axis represents sample number ( $f_s=512.82$  Hz). It is clearly noticeable that the VEOG activity due to an eye blink has significantly corrupted the EEG recordings.

An extension of PCA is Independent Component Analysis (ICA) [81,82]. ICA decomposes simultaneous recordings into linearly independent components (statistically more distinctive components than simply uncorrelated). A justification of the ICA assumptions (linear independence of sources hypothesis) for the application to EEG recorded signals is presented in

[83]. Makeig, Jung et al. have successfully applied ICA to the removal of EOG, EMG and line interference artifacts [25,28]. A quantitative comparison in [84] and [76] confirms the superiority of ICA over PCA and regressive filtering methods. ICA is however impractical for online implementation due to the computational demands of the iterative algorithm. For a review of ICA and its possible applications to EEG the interested reader is referred to [85-88]. ICA is also capable of extracting event related potentials (ERPs) or components from the background EEG [26,89,90].

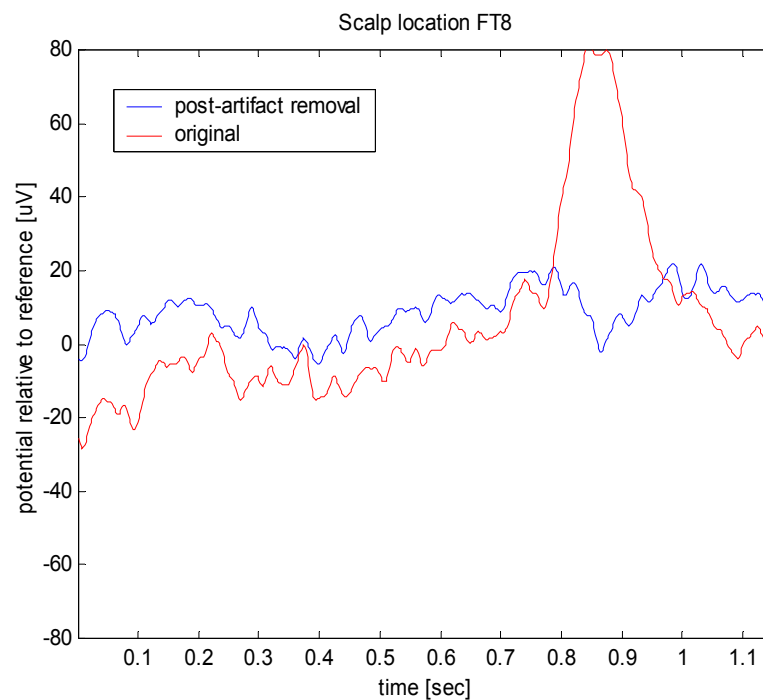


Figure 3-4: An example of the PCA artifact removal algorithm. The original single-trial from the FT8 electrode position and the post-artifact removal single-trial are depicted. The large peak due to an eye-blink can be seen to be effectively removed without corrupting the underlying EEG.

Artifact removal is a very computationally demanding processing stage. It forces most BCI researchers to design experimental paradigms and extract features that will be resilient to most artifacts. A large number of BCI groups do not implement an artifact removal stage in their systems. It is critical that future BCI systems address this issue to facilitate real-life application development. As can be seen in Figure 3-4, a simple eye blink, can dramatically corrupt the EEG.



### 3.5.4. Channel selection and dimension reduction

In any successful BCI application, the optimal recording sites associated with the command-related EEG activity needs to be determined (e.g. P300 is dominant over the central vertex and VEPs are dominant over the occipital lobe). Once the ideal locations have been determined and it has been established that the command-related activity actually comes from brain generated signals and not artifacts, the number of recording sites can be reduced to the minimum number needed to extract the activity associated with the control attempt. A reduced number of channels typically results in smaller feature vector dimensionality and hence reduced processing requirements.

Traditionally EEG channel dimension reduction has been physiologically motivated, selecting electrodes positioned near the interested region of cortical activity. Now other signal processing techniques, such as principal component analysis (PCA), independent component analysis (ICA), spatial pattern analysis and mutual information estimation, not only support the physiological motivation but also go further to optimise the information contained within the reduced channels by removing redundancy and noise. Spatial pattern analysis is able to estimate the impact of the expected information from different electrodes and to weight this information appropriately. This facilitates an optimal electrode set-up to be determined specific for each subject and has been proven to yield optimal results compared with PCA [91]. The danger in applying higher order statistical channel reduction techniques such as PCA/ICA to EEG is the uncertainty of the accuracy and order of the components these algorithms may return.

### 3.5.5. Feature extraction

The goal in feature extraction is to characterise an object by a set of measurements whose values are very similar for objects in the same category but very different for objects in different categories [92]. For a BCI system one hopes to attribute features or values to EEG recordings that are representative of a recently occurred control event. These features identify with some characteristic that describes the EEG activity and maximally discriminates between the control classes. A summary is performed in section 2.4 of the many EEG signal descriptors that can characterise the type of EEG activity.

EEG events may be characterised in the time-domain such as is typical with the case of Slow-Cortical Potentials (SCPs)<sup>15</sup>, P300 evoked potentials<sup>16</sup>, Movement-Related Potentials

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<sup>15</sup> **Slow Cortical Potential (SCP)** - is a slow voltage variation that occurs on time scales of 0.5 to 10 seconds (i.e. over low frequency range 0.1 - 2 Hz) and is associated with movement and cortical activation. It can be self-regulated by a user in order to offer control (operant conditioning BCI approach). It has been used by the Tübingen group in their so-called TTD [62-64,70]. An excellent review of the origins and applications of SCPs is performed in [93].

(MRPs)<sup>17</sup>, Visual Evoked Potentials (VEPs)<sup>18</sup>. Time domain feature extraction involves the analysis of the morphology of the EEG waveform using descriptive parameters such as amplitude etc. However due to the dominating presence of background EEG activity and the low SNR of the desired command-related EEG pattern, time domain feature extraction has moved more towards parametric modelling methods. This involves fitting a time-series to the EEG activity or its components and the parameters that describe this curve can discriminate each command-related activity.

Frequency domain features are more commonly used by BCI systems. Frequency domain events such as mu and beta rhythm power variations are commonly exploited in BCI design. These rhythms are related to cortical activity in the sensorimotor area. This can be stimulated or controlled through the actual or imagination of limb movement. Most systems use the mental task of left versus right hand motor imagery as the mental task to offer binary control in a BCI [39,41,94,95,101,102].

Phase relationships or estimations of the synchronisation levels for a community of neurons or a series of EEG channels propose an alternative source of information for EEG activity. Event-related synchronization and event-related desynchronization (ERD/ERS) is an estimation of the amplitude attenuation or enhancement of a certain EEG rhythm. It was first quantified by Pfurtscheller and Aranibar for detecting command-related patterns in the mu and beta rhythms. The ERD/ERS features are used in [49,103-106] to identify with EEG command-related activity for the purposes of BCI design. Methods of calculating ERD/ERS is summarised in section 2.4.3 but for a more detailed insight the reader is referred to [48]. The information contained within phase relationships of different EEG locations has not yet been explored to its full potential.

Features associated with the topographical variations of EEG activity offer significant information regarding the origins of the dominant neural community that contributes mostly to the recordings. Spatial filtering or spatial pattern analysis methods can be employed to improve the

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<sup>16</sup> **P300 Evoked Potential** – is a significant mid-central positive peak that occurs 300ms after an infrequent or significant stimulus imbedded amidst a series of routine stimuli. It generates a different response to a desired randomly occurring stimulus compared with non-target routine stimuli. It can thus be exploited to offer control. Donchin has successfully implemented a BCI system in [59] based on the P300.

<sup>17</sup> **Movement-related Potential (MRP)** – is an increasingly negative potential that occurs on the contra-lateral side of the motor cortex area to the side of limb movement. The imagination of limb movement generates similar responses to actual movements and thus the imagination of left versus right hand movement has been exploited by many BCI systems [38,40-44,46,94-96].

<sup>18</sup> **Visual Evoked Potential (VEP)** – is a potential generated in the occipital region in response to a changing visual stimulus. The evoked activity displays properties that are characteristic of the type of visual stimulus. By directing one's attention to stimuli of different properties, one can use the VEP response to select a control in a BCI system. It was one of the first neuromechanisms exploited in a BCI system [1,35,97]. Today, steady-state VEPs (SSVEPs) are heavily exploited in BCI systems using frequency based features [98-100].

time or frequency features to generate scalp maps. The Surface Laplacian (SL)<sup>19</sup>, Common Spatial Patterns (CSPs) and Signal Space Projection (SSP) are common spatial filter methods that are implemented to improve on the raw EEG to facilitate the extraction of better features [39-44,75,80,107]. Through the use of these high-resolution algorithms the spatial resolution may be reduced to around 2-3 cm compared with around 6-10cm for the raw EEG.

### 3.5.6. Feature selection

The feature selection process is an optional stage that prevents the accumulation of irrelevant features to describe the EEG command-related activity. Too many overlapping features will cause the classifier to have poor generalization, increase the computational complexity and require many training samples to reach a given accuracy [108]. All features generated at the feature extraction stage were used in the classification stages of research reported in this thesis. Through the use of feature selection methods that choose an optimal subset of features, it is possible to dramatically improve performance. Information theoretic approaches involving mutual information estimation methods have proven to optimise the features selected as inputs to the classification stage but is hindered by the computational overheads [109].

Genetic algorithms (GA) offer an alternative approach. A GA can be described as a stochastic search and optimization technique based on evolutionary computation. They can be divided into three main groups [108]: Embedded algorithms, where the selection is embedded within the induction algorithm; Filter algorithms, where features are selected before passing them to the classification stage; and wrapper algorithms, which performs feature selection in unison with the classification algorithm. See [110] for a review of the above feature selection algorithms in relation to the classification of Movement Related Potentials (MRPs). The use of a wrapper method in conjunction with a non-linear support vector machine (SVM) classifier has been successfully employed by the Tübingen group in a BCI system [111].

### 3.5.7. Classification

The role of the classification stage is to recognise patterns in training data to facilitate the online translation of EEG features to controls. While important to system performance, the choice of the classification method for the feature translation task is less crucial than the features themselves for developing a robust BCI. The classification stage has three main criteria; accuracy, computational efficiency and complexity. Ultimately the aim for a BCI classification stage is to ensure a high accuracy, robust adaptability and transferability, and real-time implementation. A decision tree is

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<sup>19</sup> **Surface Laplacian (SL)** – is a second order spatial derivative of the scalp potential at each electrode that provides an estimation of the local radial surface current flow through the skull [10]. It can be viewed as a spatial high pass filter as it removes the blurring effect due to the volume conduction effects of the skull and cerebrospinal fluid.

used in [73], a local neural network in [61], a Bayesian network in [1,60,112], a K-Nearest Neighbour algorithm in [71,94,113,114], Linear Discriminant Analysis in [66] and threshold-based methods in [35,36,67,97,100,103,105,115-117].

The two fundamental classifier choices include a systems analysis approach or a machine learning approach. The traditional systems approach seeks to model the underlying biophysical system whereas the machine-learning methods need not create a mechanistic model. Machine-learning methods to classification may actually work well for an application without offering much insight into the underlying system. Although an understanding of the underlying processes is desirable, it is more important for the systems to function correctly. A review is performed in [118] that compares linear and non-linear methods for a BCI classification stage. It states that when control can be achieved with a linear classifier, then a non-linear classifier should not be used.

Linear Discriminant Analysis (LDA) is employed, unless stated otherwise, for the feature-to-control translation or pattern recognition task in this thesis. LDA requires less training and computation compared with neural network based classifiers but as a trade-off requires more discriminatory feature vectors to distinguish successfully between the classes [119]. The uniform application of a fixed classifier facilitated the comparison of feature extraction methods and an exploration of different feature combinations to yield the optimum classification accuracy. LDA consists of estimating  $k$  discriminant functions to construct  $k$ ,  $n$ -space, hyper-planes that optimally distinguish the  $k$  classes using  $n$  features.

In more explicit detail, consider a set of  $c$  classes  $C_k$ . Given an input vector  $x$  of features, we may formulate the classification problem in terms of a set of discriminant functions  $y_1(x)$ ,  $y_2(x)$ , ...,  $y_c(x)$  where an input vector  $x$  is assigned to class  $C_k$  if

$$y_k(x) > y_j(x) \quad \forall \quad j \neq k \quad (1)$$

Therefore the class for which has the largest corresponding discriminant function is chosen. The discriminant function may be derived in terms of Bayes' theorem given by

$$P(C_k | x) = \frac{p(x | C_k)P(C_k)}{p(x)} \quad (2)$$

Bayes' theorem relates the posterior probability to the product of the class conditional probability and prior probability. The  $p(x)$  term serves as a normalisation so that the posterior probabilities sum to unity. The usefulness of Bayes' theorem stems from the fact that it is easier to calculate the right hand side of equation 2 than the left hand side. The simplest discriminant function might be  $y_k(x) = P(C_k | x)$  and we may go further by omitting the normalising class independent

probability and taking logs of the right hand side to get  $y_k(x) = \ln(p(x | C_k) + \ln(P(C_k)))$ . Next, we assume a normal distribution for the class conditional densities, given in d dimensions as

$$p(x) = \frac{1}{(2\pi)^{d/2} |\Sigma|^{1/2}} \exp\left\{-\frac{1}{2}(x - \mu)^T \Sigma^{-1} (x - \mu)\right\} \quad (3)$$

where the mean vector and covariance matrix are given respectively by  $\mu = E(x)$  and  $\Sigma = E[(x - \mu)(x - \mu)^T]$ . By assuming that covariance matrices are identical for all classes  $\Sigma_k = \Sigma$ , and dropping constant terms, we form the linear discriminant function

$$y_k(x) = \mu_k^T \Sigma^{-1} x - \frac{1}{2} \mu_k^T \Sigma^{-1} \mu_k + \ln(P(C_k)) \quad (4)$$

The feature vectors determined by the feature extraction stage are used as the inputs to the classifier. An M-shuffle by N-fold cross-fold validation technique was employed to form an unbiased estimate of an offline system performance.

### 3.5.8. Feedback

The basic concept of human feedback enables mankind to take account of their actions or performance. How this feedback information is assimilated is entirely up to the person. Feedback in a training environment either encourages the trainee to strive to do better or else give up and quit. Through the use of feedback such as exam results, rankings and reports people have the potential to improve on their performance.

It is similarly an important concept in BCI system design to ensure rapid human adaptation and skill development with using the alternative communication medium. For BCIs based on the Operant Conditioning approach, feedback training is essential for the user to acquire the control of his or her EEG response and develop the skill of EEG self-regulation. BCIs based on the Pattern Recognition approach do not explicitly require feedback training but it can speed up the learning process and improve performance. Feedback is typically visual, although as will be shown later in Chapter 5 a combination of audio-visual feedback can be used to captivate the user's attention.

There are two methods of feedback that are utilized in most BCI systems, discrete and continuous feedback. The choice is application dependent. Discrete feedback involves presenting to the user the performance of a control attempt *after* the event has completed. For example, the Graz BCI system [52,120,121] indicates to the user at the end of the trial the classified result associated with the left versus right imagined hand movement. If the requested movement could be correctly classified, a '+' was shown. If the data of the current trial was identified to the other class

than was requested, a ‘-’ was shown. Ambiguous results were shown as ‘o’. Discrete feedback cannot directly affect the EEG activity as it does not occur during the acquisition windows.

Continuous feedback on the other hand is continuously presented to the user during the acquisition of the command-related EEG activity. Cursor control is the most common form of continuous feedback. It is used in a number of BCI systems mainly based on the Operant Conditioning approach [63,64,68-70,122,123]. In BCIs using the Operant Conditioning approach (see section 3.2.2), the feedback about the performance is essential to skill development, i.e. in acquiring control over the EEG response. In the TTD device users are instructed to control the cursor, up or down from the centre, by self-regulating their SCP. The trial ends when the user moves the cursor (‘ball’) all the way to the side they desire. Figure 3-5 shows an example of the feedback display used in the TTD device. The smiley face and ‘very good’ remark offers the user positive reinforcement for the achievement of correctly moving the cursor to the target side. This is an important aspect to feedback whereby if the user feels a sense of achievement or being rewarded for their attempt, the training progress can be improved. Continuous feedback can directly impact the EEG generation process. If the user is succeeding or failing at a task, the continuous feedback can encourage or discourage and thus modify the continually recorded brain activity. It is not possible with the current BCI systems to offer ‘true’ continuous feedback due to inherent classification delays. A finite sample of EEG data needs to be analyzed and classified before the feedback can be presented to the screen. For example, the Wadsworth BCI [68] boasts one of the shortest EEG sample windows of 200 ms. Therefore the cursor movement is not actually continuous but instead jumps.



Figure 3-5: The feedback display used in the TTD. The user is presented with a smiley face as positive reinforcement after successfully moving the cursor to the target side of the screen.

Graded feedback can also be incorporated in the discrete or continuous case whereby the user is presented with how well the classifier recognizes the control attempt. It is directly proportional to how distinguishable the command-related features are and thus an indication of how ‘well’ the mental task is being performed.

The effects of feedback cannot be directly monitored. It is clear that it is an important aspect to the Operant Conditioning approach of BCI design to facilitate learning self-regulation of EEG activity. Very little research has been reported on the long-term effects of biofeedback. McFarland et al. documented the possible beneficial and harmful effects of cursor feedback in relation to the Wadsworth BCI [124] as follows.

| Beneficial effects  | Harmful effects   |
|---|---|
| <ul style="list-style-type: none"> <li>▪ Improves performance by allowing rapid reaction to wrong classifications</li> <li>▪ Furnishes continual motivation</li> <li>▪ Ensures attention to the task by maintaining the subject's interest</li> </ul> | <ul style="list-style-type: none"> <li>▪ The feedback stimulus might prevent concentration on internal state</li> <li>▪ The visual feedback stimulus might affect the alpha rhythm</li> <li>▪ The correct classifications might lead to anticipation and thus affect the EEG response (for example, cause EEG synchronization)</li> <li>▪ The false classifications can elicit frustration and thus affect the EEG response (for example, cause EEG desynchronization)</li> </ul> |

The training of the human and BCI system interaction, jointly referred to as the man-machine learning dilemma, is a mutual process. Vaughan et al. define in [125] that BCI operation depends on effective interaction between two adaptive controllers, the user who encodes his or her commands in the neurophysiological input provided to the BCI, and the BCI that recognizes the commands contained in the input and expresses them as device control. Pfurtscheller and Neuper address this issue in [38] and stress that the human being is as important as the BCI system to the successful performance.

### 3.6. BCI systems: State of the art

To date there exist over 45 BCI research groups worldwide. United by the same goal of developing a new alternative communication and control technology for the motor-impaired, they have explored many different approaches with varying success rates. Apart from the review of different BCI methodologies discussed earlier in this chapter, it would be too lengthy and cumbersome to discuss in detail the many different approaches taken by different research groups around the world. The following table presents a review of some of the key systems implemented and the methodologies employed by the research group.

| Research Group             | Year | Neuro-Mechanism   | Input  | Feature Extraction Technique   | Feature Translation   |
|----------------------------|------|---|--|--|---|
| Vidal [1]                  | 1977 | Single-Trial VEP evoked by a strobed checkerboard determining the direction of eye-gaze                                   | EEG over occipital cortex  | Wiener filtering of the time locked input signal followed by a step-wise discriminant procedure to reduce feature vector dimensionality  | Bayesian Classifier with outlier rejection  |
| Sutter [35,97]             | 1984 | Steady-state VEPs (SSVEPs) evoked by alternating symbols on computer screen   | EEG over occipital cortex  | The feature vector (FV) was the single-trial, time-domain signal time locked to the VEP stimulus   | The time-domain signal was correlated with templates related to 6 possible responses. A state was selected when one of the time-averaged correlation values exceeded a threshold                            |
| Farwell & Donchin [59,117] | 1988 | P300, evoked by flashing symbols on computer screen   | EEG at Pz referenced to linked mastoids  | 36 feature vectors were produced, one for each cell of the 6x6 menu on the Control Display. When a row of the menu was flashed, a 600ms time-locked window of the input signal was added to all the feature vectors corresponding to cells in that row. Similarly for columns        | The feature vectors representing signal averages were continually ranked and either a correlation/threshold was used to select a cell, or the highest ranked cell was selected after a fixed length of time |
| Keirn & Aunon [60,112]     | 1990 | Differences in lateralized spectral power levels related to various cognitive mental tasks such as imagined cube rotation | EEG over parietal and occipital lobes  | Three feature vectors were generated using three methods: two spectral power estimation methods (FFT and AR spectral estimation) followed by band-pass filtering in four frequency bands; and a method that used AR coefficients of signals in four frequency bands                  | Bayesian quadratic classification of power or AR coefficient features   |
| Wolpaw et al. [66]         | 1991 | Active control of mu rhythm power   | EEG from a bipolar link anterior and posterior to C3                           | The feature vector (FV) was produced by calculating the EEG power spectrum (FFT) with 3Hz resolution. Power value centred at 9 Hz was used as amplitude of mu rhythm   | Linear discrimination of mu rhythm power with heuristic thresholds into 5 levels.   |
| Pfurtscheller [114]        | 1993 | Active control of mu event-related desynchronization (ERD)  | EEG recorded over sensorimotor cortex  | The FV was generated by filtering the input signal to 8-12Hz. Then the result was squared as an estimate of instantaneous power. Five consecutive power estimates of mu power related to ERD were bundled into a 5-D FV  | One-nearest neighbour (1-NN) classification, using reference vectors selected with a learning vector quantization (LVQ) method  |
| Wolpaw et al. [67]         | 1994 | Active control of distributed mu rhythm power   | EEG across sensorimotor cortex using bipolar electrodes at FC3-CP3 and FC4-CP4 | The FV was generated for each of the two EEG channels. The square root of signal power in a 5Hz (or 4Hz) band centred at 10 Hz (or 12 Hz) was calculated for both inputs. The mu rhythm signal power was estimated for both inputs using a FFT.                                      | The sum of the power level features was mapped (using an adaptive linear transform) to vertical movement and the difference of power level features was mapped to horizontal movement.                      |
| Pfurtscheller [113]        | 1994 | Active control of spectral power of several frequency bands related to finger, toe and tongue movement                    | EEG over sensorimotor cortex   | The FV was generated by calculating spectral power of several frequency bands. The instantaneous signal power was estimated from the input signals using four, narrow band-pass filters (between 8-40Hz). Eight consecutive power estimates (1/4 second) were bundled into an 8-D FV | One-nearest neighbour (1-NN) classification, using reference vectors selected with LVQ  |
| McMillan & Calhoun [115]   | 1995 | Magnitude of the steady-state VEP evoked by 13.25Hz strobe light  | EEG from bipolar electrode between O1 and O2                                   | The FV was generated by band pass filtering the bipolar EEG (centred on 13.25 Hz), followed by signal amplification and power level estimation   | Linear discrimination with two heuristic thresholds for dwell time period. Feature values were mapped to three states based on the thresholds   |



|                           |      |   |  |   |  |
|---------------------------|------|---|--|---|--|
| Pfurtscheller [94]        | 1997 | Active control of the alpha and beta rhythm power related to imagined hand movements    | EEG over sensorimotor cortex   | The FV was generated by estimating signal power from two user-specific signal inputs and two user specific frequency bands. These estimates were calculated four times over a period of 1 second. The 16 power features (within each second) were bundled into a 16-dimensional feature vector  | One-nearest neighbour (1-NN) classification, using reference vectors selected with LVQ   |
| Middendorf et al. [36]    | 2000 | Self-regulation of an SSVEP and also the response to multiple stimuli.                  | Differential EEG between O1 and O2 and grounded at the left mastoid  | Relative amplitude, phase and a combination of both at O1 and O2 create the FV for the self regulation task. The magnitude of the centre frequencies associated with the stimuli above a threshold were used in the multiple stimuli task   | Individual threshold and amplitude ratio criteria were determined for each operator by a calibration process.                                  |
| Penny et al. [61]         | 2000 | Single-trial, imagined movement related potentials (MRPs)                               | Two 11-electrode arrays over the left and right sensorimotor cortex. | AR features   | The AR features are classified using a logistic regression model trained using the Bayesian evidence framework                                 |
| Birbaumer et al. [62-64]  | 2000 | Slow cortical potentials (SCP)  | EEG over frontal cortex  | The FV represented the amplitude of SCP waveform averaged over sliding window   | Linear classification with heuristic threshold   |
| Kennedy et al. [126]      | 2000 | Active control of neural group firing rate  | Two electrodes implanted within hand area of primary motor cortex    | The FV represented the neural group firing rate extracted from both signal sources  | Increases in neuronal firing rate resulted in increases in output level. Decreases resulted in a zero output.                                  |
| Mason & Birch [71]        | 2000 | Single-trial, imagined movement related potentials (MRPs)                               | EEG over SMA and primary motor cortex                                | The FV was calculated from windowed 1-4Hz EEG (over 1/8 second periods) using a custom spatiotemporal transform   | One-nearest neighbour (1-NN) classification, using reference vectors selected with LVQ   |
| Cheng et al. [100,116]    | 2002 | Multiple stimuli attention selection SSVEP paradigm                                     | EEG from O1 and O2 electrodes  | The FV consisted of the spectral magnitude at the stimuli frequencies and their first harmonic.   | A threshold based classifier was employed. The threshold for detection was twice the mean value of the amplitude spectrum between 4 and 35 Hz. |
| Graimann et al. [103,105] | 2003 | Active control of single trial imagined movement related oscillatory activity (ERD/ERS) | EEG from 34 electrodes predominantly over the sensorimotor cortex    | ICA was performed on all channels to remove artifacts and increase SNR. ERD/ERS maps spanning 6-36Hz were calculated for all ICs. ICs with prominent ERD/ERS activity were selected for wave packet analysis for feature extraction. The selection and combination of the most important features for detecting oscillatory activity was done by a genetic algorithm (GA) | Threshold based detector of the 1-D GA transformed FV.   |

### 3.6.1. Categorisation

Previously in this chapter, BCIs were divided into those using the Pattern Recognition approach and those using the Operant Conditioning approach. However, BCIs can be categorized in a number of ways depending on various different BCI aspects or methodologies employed. This subsection aims to highlight a number of ways to describe or characterize a BCI system while at the same time identifying and explaining the various options.

- 1) ***Invasive or non-invasive:*** As highlighted in section 2.1.1, electrical currents produced by synchronized synaptic currents within the brain can be measured by (list by order of increasing invasiveness) scalp recorded EEG, using epidural electrodes, and using intracortical electrodes known as electrocorticography (ECoG). Scalp recorded EEG based BCIs are most common because they are non-invasive and cheap. Intracortical electrodes achieve higher spatial resolution at the expense of spatial coverage and significant increase in cost and risk. Single neuron cortical activity has been successfully applied in BCI systems [103,105,126-128]. Aside from the practical issues such as cost, invasiveness and comfort, the choice of invasive versus non-invasive recordings depends on the volume of cortical tissue producing useful information, the ability of the intracortical electrode to locate the appropriate tissue masses, and on the ability of the scalp EEG to produce stable, robust, intentional signals that can be controlled by the user.
- 2) ***Online or offline:*** The fundamental aspect to a BCI is that it can be implemented in real-time to facilitate actual direct user control. Offline systems are for theoretical simulations of an actual BCI system to facilitate exploratory investigations of the BCI components. This makes it possible to examine, for example, different electrode positions, pre-processing and feature extraction methods, classifiers etc. Offline systems quote a predicted or simulated accuracy by employing unbiased methods for separating training and test data, for example cross-fold validation. The performance can be comparable with a similarly implemented online BCI without feedback provided that all the recorded EEG data is used, i.e. no EEG data is rejected containing EOG or EMG artifacts. As most training data during an offline investigation has rejected artifact corrupted trials, the performance could be very different to an actual online real-life implementation where artifacts and EEG inter-trial variability could cause significant feature outliers that would result in poor control classifications. Online systems require the signal processing components of the BCI framework to be done in real-time. Real-time implemented systems make it possible to provide feedback to the user. As feedback is such an integral

part of a BCI framework, particularly for the operant conditioning approach, online systems are the only true indicator of a BCI performance.

- 3) ***Synchronous or asynchronous:*** As discussed above in section 3.3, a cued and an un-cued approach to BCI design exists.
- 4) ***Universal or individual:*** Universal BCIs assume that by gathering EEG data from multiple users it is possible to find features and a classification function that will be valid in general for every user. In individual BCI design, the system is tailored to the individual and the fact that no two individuals are the same both physiologically and psychologically. Adaptive systems such as the Adaptive Brain Interface project [129,130] boast the adaptability of the system to user, time and psychological variations. A universal BCI design that is too general will have poor performance.
- 5) ***Independent or dependent:*** Dependent BCIs rely on upon ocular activity to generate a specific EEG pattern, i.e. a visual evoked potential (VEP) associated with the direction of visual attention [35,97,98,100,131]. If a person has the use of their eye muscles, there exist a number of eye-tracking or eye-blinking based methods of communication that offer better performance than BCI systems. Independent BCIs do not require any muscular intervention of any kind to generate the command-related EEG activity. This approach is more closely linked to the definition of a BCI system set out in [58].
- 6) ***Paradigm:*** BCIs can be categorized according to what kind of imagery or mental tasks the users are required to perform in order to generate the command-related EEG activity. This choice is closely linked with the type of brain activity or neuromechanism that the BCI designer wishes to exploit. Motor imagery is one of the most common methods of EEG elicitation that has been used in many BCIs [38,45,46,94,96,101,132]. It is used to generate sensorimotor activity. Mental tasks such as arithmetic or spatial relations have also been used [61,122]. Visual related tasks have been heavily exploited in the area of P300 and VEP elucidation [98-100,133,134]. BCIs based on the Operant Conditioning approach may leave the choice of imagery or mental strategy up to the user [62-64,70,123].
- 7) ***EEG Neuromechanism Input:*** The most common method of categorizing a BCI is based on the mechanism exploited to generate the characteristic and distinguishable brain activity for the BCI input. These include: SCPs,  $\mu$  or  $\beta$  rhythms, P300, MRP, VEPs and the firing rate of a single cortical neuron. The systems listed in Table 3-1 are real-time implemented systems that are described in peer-reviewed articles. The subjects of these systems controlled a device and immediately witnessed the results of the control selection.

Table 3-1: A summary of implemented BCI systems by various researchers and grouped according to the neuromechanism or characteristic EEG activity that was employed.

| Neuromechanism Input            | BCI Researchers  | Year | Ref.      |
|---------------------------------|--|------|-----------|
| Visual Evoked Potentials        | ▪ Vidal JJ.  | 1977 | [1]       |
|                                 | ▪ Sutter EE.   | 1984 | [35,97]   |
|                                 | ▪ Middendorf M, McMillan G, Calhoun G, Jones KS.   | 2000 | [36,135]  |
|                                 | ▪ Cheng M, Gao X, Gao S, Xu D.   | 2002 | [100,116] |
| Slow Cortical Potentials        | ▪ Elbert T, Rockstroh B, Lutzenberger W, Birbaumer N.  | 1980 | [136,137] |
|                                 | ▪ Birbaumer N,   | 1999 | [62,64]   |
|                                 | ▪ Birbaumer N, Kübler A, Ghanayim N, Hinterberger T, Perelmouter J, Kaiser J, Iverson I, Kochoubey B, Neumann N, Flor H. | 2000 | [63]      |
| P300 Evoked Potentials          | ▪ Farwell LA, Donchin E.   | 1998 | [117]     |
|                                 | ▪ Donchin E, Spencer KM, Wijesinghe R.   | 2000 | [59]      |
| Sensorimotor related activity   | ▪ Wolpaw JR, McFarland DJ, Neat GW, Forneris CA.   | 1991 | [66]      |
|                                 | ▪ Pfurtscheller G, Flotzinger D, Kalcher J.  | 1993 | [114]     |
|                                 | ▪ McFarland DJ, Lefkowitz AT, Wolpaw JR.   | 1997 | [138]     |
|                                 | ▪ Guger C, Schlogl A, Walterspercher D, Pfurtscheller G.   | 1999 | [139]     |
|                                 | ▪ Wolpaw JR, McFarland DJ, Vaughan TM  | 2000 | [68]      |
|                                 | ▪ Pfurtscheller G, Neuper N, Guger C, Harkam W, Ramoser H, Schlogl A, Obermaier B, Pregenzer M.                          | 2000 | [121]     |
|                                 | ▪ Kostov A. and Polak M.   | 2000 | [123]     |
|                                 | ▪ Penny WD, Roberts SJ, Curran EA, Stokes MJ.  | 2000 | [61]      |
| Single cortical neuron activity | ▪ Kennedy PR. and Bakay RA.  | 1998 | [128]     |
|                                 | ▪ Kennedy PR, Bakay RA, Moore MM, Adams K, Goldwaithe J.   | 2000 | [126]     |

- 8) **Translation Algorithms:** The signal processing methodologies for feature extraction and classification that facilitate the translation of characteristic EEG activity into a control decision are important in BCI design. The many different signal processing algorithms allow further categorization of BCI systems and reflect the BCI designers approach.
- 9) **Biofeedback:** The employment of direct audio or visual biofeedback has a significant psychological effect on the user. The simultaneously (continuous feedback) or subsequently (discrete feedback) recorded EEG activity reflects this effect. The use or lack of biofeedback can distinguish the BCI system approach. As discussed earlier, feedback is an important aspect to the successful adaptation and development of the user's interaction with a BCI system.
- 10) **Intended application:** The type of application and the target users can further categorize the type of BCI system. Most applications are targeted at the severely disabled as an augmentative control and communication device. The applications can vary from spelling programs, limited phrase generators, simple environmental condition controllers etc.

### 3.6.2. Principal BCI research groups

In June 2002, the Second International Meeting of Brain-Computer Interfaces was held in Rensselaerville, NY. Organised by the Wadsworth Center of the New York State Department of Health, the meeting drew ninety-two researchers representing 38 different BCI research groups from the US, Canada, Europe and China. Appendix A lists some of the BCI research groups from around the globe, almost all of which attended this meeting. The most significant groups on the list are highlighted in bold and will be referred to repeatedly in this chapter. These are summarised in Table 3-2. In recent years, the Alberta group has scaled down their interest in BCI research since the death of their principal researcher, Alexandar Kostov. The Tübingen, Graz and Wadsworth groups are significantly better funded, staffed and experienced in the field of BCI research compared with any of the other institutions and generate many more peer-reviewed articles as a consequence.

Table 3-2: A summary of the principal BCI research groups and their approach

| Research laboratory | Group director and principal researchers                        | BCI name          | Ref          | OC / PR | Summary of main BCI approach   |
|---------------------|---|-------------------|--------------|---------|--|
| <b>Alberta</b>      | M. Polak  | -                 | [123,140]    | PR      | Scalp EEG (C3, C4, P3, P4), online, synchronous, independent, cursor movement paradigm with self-chosen mental strategy, sensorimotor EEG input, 4 <sup>th</sup> order AR features, adaptive logic network (ALN) classifier, continuous feedback (cursor), 2-D cursor control application, classifier output every 50 ms   |
| <b>FIRST</b>        | K-R Müller, B. Blankertz  | Berlin-BCI (BBCI) | [74,141,142] | PR      | Scalp EEG (over primary motor cortex), offline, synchronous, self-paced voluntary finger movements, predict the laterality of upcoming finger movement to offer control, spatio-temporal feature extraction based on hit / no-hit MRP feature, regularized Fisher Discriminant classification, no feedback, applications targeted at able bodied population, output every 1-2 seconds (equivalent to a momentary-on two-position switch). Classification accuracy of 85% with FP < 2%. 6-15 bits/min transfer rate.              |
| <b>Graz</b>         | G. Pfurtscheller, C. Neuper, A. Schlögl, B. Graimann, G. Müller | Graz-BCI          | [52,120,121] | PR      | Scalp EEG (29 channels), online, synchronous, independent, detection of ERD / ERS patterns of the mu and beta rhythms during motor imagery, imagination of left, right and foot movement initiated by auditory and visual stimulus, logarithm of the band power in 4s window for 5 bands (7-10, 10-13, 16-20, 20-24 Hz), one-nearest neighbour (1-NN) classification, discrete feedback after trial, environment control application, classifier output after 8 s trial. The channel capacities ranged from 0.42-0.81bits/trial. |

|                       |                                    |                 |               |    |  |
|-----------------------|------------------------------------|-----------------|---------------|----|--|
| <b>Oxford</b>         | S. Roberts, W. Penny               | -               | [61,122]      | PR | Bipolar scalp EEG (C3 and C4), online, synchronous, independent, motor imagery vs. math task for an up-down cursor movement, 8th order AR model of 1/3 second segments, Bayes logistic classifiers with latent-space smoothing and a classification reject option, continuous feedback, 1-D cursor control application, classifier output every 1/12 second (83 ms). Accuracy of 86 % (hard rejection) and 54% for no latent space smoothing or rejection classification.  |
| <b>Neil Squire F.</b> | G. Birch, S. Mason, Z. Bozorgzadeh | LF-ASD          | [102,143,144] | PR | Scalp EEG (6 bipolar linkages, F1-FC1, Fz-FCz, F2-FC2, FC1-C1, FCz-Cz, and FC2-C2), online, asynchronous, low-frequency asynchronous switch, self-paced imagined left-right hand movement, spatio-temporal features from the bipolar channels filtered below 4 Hz, LVQ3 implemented to select optimum features, one-nearest neighbour (1-NN) classification, discrete feedback showing switch state, environment control and game application, output every 1/16 <sup>th</sup> second (equivalent to a momentary-on two-position switch). Movement attempts every 4 s. Classification accuracy of >94 %  |
| <b>Tsinghua</b>       | G. Shangkai, G. Xiaorong, M. Cheng | -               | [43,100,116]  | PR | Scalp EEG (O1 & O2), online, asynchronous, dependent, virtual button selective attention paradigm, SSVEP based EEG input, frequency power feature, threshold-based classifier, discrete biofeedback, phone dialler application. Average transfer rate across 13 subjects was 27.15 bits/min. No training required.   |
| <b>Tübingen</b>       | N. Birbaumer, A. Kübler            | TTD             | [63,64]       | OC | Scalp EEG (Cz), online, asynchronous, independent, self-regulation of SCPs, magnitude of the SCP, user-chosen mental strategy to control up-down cursor movement, threshold based classifier, continuous feedback, language support (spelling) application, classifier output every 63 ms, trial length 4.5 s. Transfer rate of a letter every two mins. Extensive training required.  |
| <b>Wadsworth</b>      | J. Wolpaw, T. Vaughan              | Wadsworth - BCI | [68,69]       | OC | Scalp EEG (64 channels), online, asynchronous, independent, self-regulation of the $\mu$ (8 -12 Hz) and $\beta$ (13-28 Hz) rhythms, topographical, spectral and temporal features of $\mu$ and $\beta$ rhythm from a linear translation of 200ms segments from several (1-4) EEG channels (mainly an AR power spectral estimate in the bands), initially motor imagery (hand movements) is used as the mental task to control up-down movement, Threshold based classifier, continuous feedback, 1- and 2-D cursor control application, classifier output every 100 ms. Classification accuracy of >95 % and bit rates of 20-25 bits/min. Demanding training requirements. |

### 3.6.3. Performance metrics

The BCI state-of-the-art review above lacks a comparative analysis of performance. Unfortunately, comparisons are extremely difficult to make due to the many different approaches and applications of the implemented systems. The most important metrics for success in BCI system design reported in the literature are accuracy and speed. These are however unfortunately interdependent and result in inevitable trade-offs. For most applications targeted at the completely disabled, accuracy is often prioritised over speed and user-friendliness.

The methods of reporting accuracy in the literature has included correct classification rates<sup>20</sup>, confusion matrices<sup>21</sup>, hit rates<sup>22</sup> and rejection rates<sup>23</sup>. Even the presentation of these results can be misleading due to some systems rejection of trials due to artifacts or uncertain classifications. The system methodologies, such as artifact rejection or offline simulation, need to be explicitly stated alongside accuracy measures because they are closely linked. They can dramatically alter classification performance and produce misleading results. Information transfer rate or bit-rate is one of the most appropriate measures to compare the signal output of different BCIs in terms of speed and accuracy. This standard communication measure offers the amount of information communicated per unit time. However, other measures may be more suitable when comparing how efficiently an application takes advantage of the user's bandwidth. For example, a typing application with predictive word completion can be compared using the metric of words per minute.

Performance measures are predominantly focused on information transfer capabilities at this premature stage of BCI development. As BCI technology evolves and the bit rates are boosted, there will be a much wider range of general performance metrics for a BCI system. These may include for example the following;

- 1) Channel dimensionality
- 2) Bit rate of data transfer (channel capacity) – determined by accuracy and speed
- 3) Degree of bidirectional control (feedback)
- 4) Short- and long-term reliability
- 5) Cost effectiveness
- 6) User-friendliness (comfort, portability, ease-of-use)
- 7) Training requirements
- 8) Staff and service requirements (required assistance)

One of the most important yet subjective performance metrics involves a measure of the quality-of-life improvement for the user. The target population's lack of conventional

---

<sup>20</sup> **Correct classification rate** – is the percentage of correct classifications

<sup>21</sup> **Confusion matrices** – presents not only the correct classification rates of each class but also in which classes the false classifications were classified

<sup>22</sup> **Hit rate** – indicates how many times a user succeeds in hitting a target. Typically used in the operant conditioning approach where a certain number of steps are required to reach a target (e.g. move a cursor). It is a poor indicator of performance.

<sup>23</sup> **Rejection rate** – indicates the percentage of trials that result in uncertain classifications and are subsequently rejected. It is typically used in conjunction with a correct classification rate.

communication ability makes it initially difficult to quantify this metric but perhaps in the future, this will be the ultimate performance metric.

There is much talk in the literature for a standardised framework to facilitate the direct performance comparison of BCI systems and their individual components [72]. The development of benchmarks would be extremely valuable, enhancing the BCI research community's ability to objectively compare BCI technologies. It is important however not to hinder potential innovative approaches to BCI design by imposing a model framework or prototype on the research community.

### 3.7. Summary

This chapter began by introducing the concept and purpose of BCI technology. It highlighted the various different components, design methodologies and approaches behind a BCI implementation before performing a state of the art review of work in the field. Particular attention was focused on the principal BCI research groups and the work they are involved in. Sections 3.6.1 and 3.6.3 present methods of categorising and evaluating the performance of BCI systems

In summary, a current BCI system can provide for locked-in subjects the ability to communicate at transfer rates of up to 25 bits/min that facilitate the following applications;

- 1) Answer simple questions (yes or no answer every 2-3 s)
- 2) Control the environment (e.g. television remote, lights, heating, call for assistance)
- 3) Perform slow word processing (By incorporating predictive text, 25 bits/min can translate to 2 words/min on average)
- 4) Operate a neuroprosthesis (Hand grasp as demonstrated by [57,65,70])

This chapter has concluded without examining the future potential of EEG based BCIs and the issues that need to be addressed by the research community to move from demonstrations to actual marketable applications. The next two chapters present two very different BCI approaches and potential applications. Each chapter has a self-contained discussion of the BCI system and its potential. The final chapter of this thesis will predominantly focus the future prospects of EEG-based BCI technologies for the disabled and the wider population.



## Chapter 4      Study 1: MRP based BCI system

This study was inspired by the BCI competition 2003<sup>24</sup> [141,142,145,146] in which the author took part. The BCI competition was organised by a number of BCI researchers and their respective research groups such as Niels Birbaumer (Tübingen)<sup>25</sup>, Jonathan R. Wolpaw (Albany)<sup>26</sup>, Gert Pfurtscheller and Alois Schlögl (Graz)<sup>27</sup>, Klaus-Robert Müller and Benjamin Blankertz (Berlin)<sup>28</sup>, and Gabriel Curio (Berlin)<sup>29</sup>. Each group proposed their own datasets which focused on various BCI neuromechanisms such as the self-regulation of slow-cortical potentials (SCPs), self-regulation of mu- and/or central beta-rhythm, P300 speller paradigm, motor imagery and self-paced finger pressing, as reviewed in chapter three. Each data set consisted of a number of single-trials of spontaneous EEG activity, one part labelled (training data) and another part unlabeled (test data). The goal was to correctly label the test data by using a classifier developed by from training data that maximizes the performance measure for the true test labels. Applicants got to choose the dataset and subsequent experimental paradigm with which to work on and submit their results.

Due to the ease with which we could replicate the experimental paradigm and thus acquire additional data, the author chose to work on the self-paced typing paradigm data from the Fraunhofer-FIRST group. The dataset consisted of 316 training and 100 test trials recorded from 28 EEG channels according to the 10-20 placement standard. Each trial was a half second in duration that ended 130 ms prior to the key press. The training trials were labelled *0* for left and *1* for right. These labels had to be successfully inferred for the unknown 100 test trials by employing feature extraction and pattern classifications methods on any number of the electrode channels. Due to the offline nature of this competition, one had the opportunity to run lengthy simulations to recursively train a classifier to converge at the test labels. It was the hope of the author to implement a BCI system based in real-time and thus it was deemed futile to explore inefficient signal processing methods to label the test data.

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<sup>24</sup> BCI Competition 2003 - <http://ida.first.fraunhofer.de/~blanker/competition/>

<sup>25</sup> University of Tübingen, Institute of Medical Psychology and Behavioral Neurobiology - [http://www.medizin.uni-tuebingen.de/institute/med\\_psych\\_inst/index.html](http://www.medizin.uni-tuebingen.de/institute/med_psych_inst/index.html)

<sup>26</sup> Wadsworth Center, NYS Department of Health - <http://www.wadsworth.org/>

<sup>27</sup> Department of Medical Informatics, Institute for Biomedical Engineering, Graz University of Technology - <http://www-dpmi.tu-graz.ac.at/>

<sup>28</sup> Fraunhofer-FIRST, Intelligent Data Analysis Group - <http://ida.first.fhg.de/>

<sup>29</sup> Freie Universität Berlin, Department of Neurology, Neurophysics Group - <http://nroweb.ukbf.fu-berlin.de/Neuro>

This chapter will firstly present the aim of this study and then the origins and properties of movement related potentials (MRPs) that are exploited as the input mechanism. A brief overview is then presented of the BCI framework that could incorporate such a neuro-control mechanism. In section 4.4 the methodology behind decoding the neurological signals and translating them into a control signal is discussed. The next section provides a summary of the results associated with the channel selection, feature extraction and classification stages of this study. The chapter concludes with a discussion, which apart from reviewing the study discusses the future work possibilities to extend this BCI framework to the imagined limb movement paradigm that can facilitate its use for individuals with neuromuscular disabilities.

#### **4.1. Aim**

The aim of this study was to classify upcoming left/right self-paced voluntary finger movement from single trial EEG epochs time-locked to key-pressing events. The BCI competition was used as an initial milestone to achieve an insight into the practicalities of this aim. From the competition data, the goal was to predict the laterality of upcoming finger movements (left vs. right hand) solely from EEG trials a half second in duration that ends 130 ms before the key press and recorded from 28 electrodes.

The objective was to not only submit a satisfactory entry to the competition but also to replicate the experiments within the laboratory in UCD to investigate various aspects to EEG acquisition and signal processing for the purposes of BCI implementation. By recording our own data, we could experiment with various trial lengths and even attempt to asynchronously distinguish left/right finger movements from continuous EEG recordings as opposed to the time-locked trials. The project was fundamentally inspired by the desire to offer a basic means of communication and control for people who suffer from neuromuscular disorders.

#### **4.2. Introduction**

The earliest efforts to record and explore MRPs were performed by Bates [147] in the early 1950's using a cathode-ray tube (CRT) and photographic plates. He did not however find any potential variations prior to movement due to the short time constant of the superposition method he employed. It was not until the mid 1960's that Kornhuber and Deecke [148,149] extensively investigated MRPs and discovered the existence of pre-movement potential variations. This inspired further investigations into the origins of the neurological command signals that govern the desire and execution of limb movement. It gave rise to the big question: Can we predict movement before movement onset?

Deecke, Kornhuber et al. [150] characterised the MRP into a number of components, particularly for the pre-motor movement potential variations. The entire MRP is conventionally regarded to consist of three parts as shown in Figure 4-1; the Bereitschaftspotential (BP) [149], the motor potential (MP) (motor cortex potential (MCP) as defined by [151]) and the post-movement activity (PMA).

- 1) Deecke et al. defined the BP, or ‘readiness potential’ as a slowly ‘rising’<sup>30</sup> negative potential that occurs 1-2 seconds prior to volitional self-initiated movements. It is related to the preparatory process prior to limb movement.
- 2) The MP consists of an initial sharp negative deflection that follows the BP’s more gradual negativity. It is related to motor activity. At movement onset (at  $t=0$  as shown Figure 4-1), there exists a sharp positive inflection that peaks at around 200ms after the movement onset. Cerutti et al. [151] believed this *P200* to be a positive potential evoked by the visual stimulation that prompted movement. The paradigm employed here however was self-paced movement within a darkened room. Papakostopoulos et al. [152] considered it however as an index of somatosensory reafferent activity coming from the skin, joints and muscle receptors. While this is plausible it is yet unsubstantiated. This period is typically contaminated with EMG artifacts.
- 3) The PMA is the potential change ~200ms after the movement onset whereby the brain resynchronises and resumes ‘normal’ activity.

Figure 4-1 presents an averaged MRP template typical to such experiments [153-157] that illustrates these distinguishable periods in the MRP. A review of MRPs from a psychophysiological viewpoint is performed in [158] to offer an insight into the brain’s response to the desire and execution of limb movement.

For the purposes of this study, i.e. to establish the laterality of finger movements from time-locked EEG epochs prior to movement, the rest of this chapter focuses on the BP component of the MRP. As defined in [150], the BP consists of an early component (BP1) that lasts from the very beginning of the BP (starting 1-2s or more prior to movement onset depending on the complexity of the movement) to approximately 0.5s before movement onset and the late component (BP2) occurs for the last half second before onset (see Figure 4-1). BP2 has a steeper negative slope than BP1 as can be seen in Figure 4-1. For unilateral movement, BP1 is not lateralised about the motor cortex while BP2 is larger (more negative) over the contralateral

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<sup>30</sup> Clinical Electroencephalographers use a reversed axis polarity convention. This resulted from the fact that increased negative signals picked up on the surface of the scalp is as a result of increased cortical activation in that area (i.e. increased activity in that part of the brain ).

hemisphere. This is evident in Figure 4-1 for the last ~200 ms prior to finger press at time  $t=0$ . The electrode C4 is positioned on the right side of the head and for the left finger movement as shown exhibits a more negative potential on average than the contra-laterally placed C3 electrode. This supports the fundamental EEG theory that potential negativity can be related to activity of the cortical areas whereas positivity is related to inactivity [159]. Since the limbs of the human body are controlled by the contralateral side of the brain it stands to reason that there should be more activity and hence ‘negativity’ on the contralateral side.

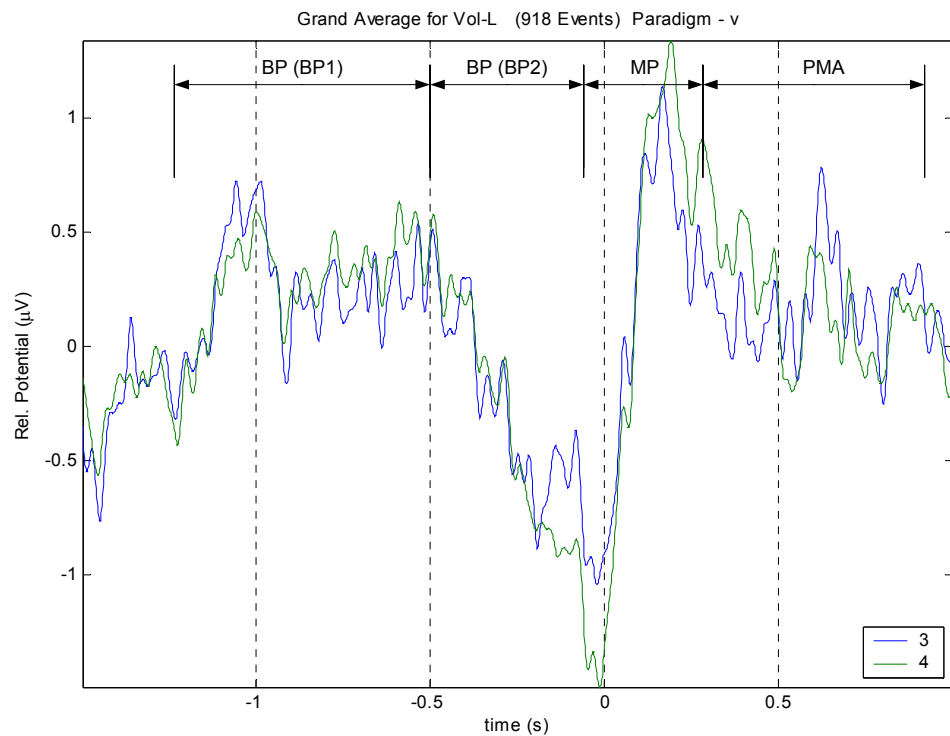


Figure 4-1: An example of an averaged MRP recorded for 918 left finger movement trials (onset at  $t=0$ ) at C3 (channel 3, blue) and C4 (channel 4, green). The main components of a MRP as highlighted by [151,153,160] are indicated. The difference between C3 and C4 in the BP2 will be addressed later in the chapter

The BP1 principal generator is the mesial prefrontal cortex including the supplementary motor area (SMA) and probably also the cingulate motor area (CMA), while the BP2 principal generator is the primary motor cortex (MI, precentral gyrus or ‘motor strip’) [160]. The reader is referred to [160-162] for a greater insight into the physiological dynamics within the motor region in response to the desire to perform movement and during the actual execution itself. In summary, the time-domain characteristics of the MRP prior to movement (more specifically the BP) as identified by Deecke et al. [163-165] are as follows:

- a pronounced contralateral negativity over the precentral and parietal areas starting about 500 to 200ms prior to movement
- a small positive deflection beginning around 90ms prior to movement
- a smaller negative potential starting about 50ms prior to movement over the primary motor cortex

It is the first brain pattern characteristic that will be exploited later in the attempt of classifying a left or right finger movement.

In terms of characteristic frequency domain activity, there also exist some notable features associated with the MRP. Oscillatory activity in the brain occurs when populations of neurons form complex networks involving feedback loops. Sensory stimulation, motor behaviour, and mental imagery can change the functional connectivity within the cortex that results in an amplitude suppression [Event Related Desynchronization (ERD)] or an amplitude enhancement [Event Related Synchronization (ERS)] of the *mu* (10-12Hz) and central beta rhythm (15-20Hz) [38,46,166]. Pfurtscheller et al. found that the *mu* band exhibits an ERD starting 2.5s before index finger movement onset at the contralateral central (C) area and whose magnitude increases steadily right up to movement initiation and then subsequently decreases. Also an ERS in the 36-40Hz section of the gamma band was seen at the same location. Like the BP, the ERD is more pronounced on the contralateral sensorimotor area. Given this phenomenon, other potential features for characterizing left versus right finger movement could include the power in these frequency bands (*mu* and beta) and how they change in time over the trial. To this end, short-time spectral density estimates will be reviewed later in section 4.4.5 as a feature extraction method.

#### 4.2.1. Elucidation of MRP on single-trial basis

The difficulty in the analysis of event-related potentials (ERPs) is that they are hidden amidst unrelated background EEG activity, regarded as neuronal noise. The magnitude of an ERP, specifically an MRP, is of the order of 1 $\mu$ V compared with 10-50 $\mu$ V for the background EEG activity. This results in a highly undesirable negative signal-to-noise ratio (SNR). Visual evoked potentials (VEPs) are characterized by a typical SNR of around 0dB. However, MRPs among other ERP types, may have a lower SNR ranging from -10dB to -30dB. There exist numerous methods in the literature that attempt to improve the SNR and elucidate the underlying ERP for detection [151,153,155,167-170]. Typically ensemble averaging of repetitively performed trials time-locked to the stimulus (movement onset in this case) is employed as an estimate of the ERP. This assumes that the background EEG activity behaves as additive white noise which averages out during synchronised averaging to expose the persistent ERP. This approximation to a true ERP offers no phasic information. It provides however a useful knowledge of the 'mean' properties of ERPs [171] based on the well known hypothesis of signal and noise additive superposition and

uncorrelation, provided that the signal is stationary and the noise has zero mean. A common challenge in ERP studies involves methods of improving the single-trial SNR to better highlight the characteristic EEG activity associated with the event-related brain function. The absence of a reference signal for the ERP increases the difficulty of evaluating performances of any kind of method designed to improve the single-trial SNR: the results could be comparable among themselves, or even with an ensemble averaged template, but not with the ‘true’ single-trial ERPs, that are, in fact, unknown [172]. Approaches based on averaging are unable to account for the variability among trials associated with ERPs. An interesting review of the methods for single-trial analysis is presented in [173]. Parametric modeling methods will be reviewed in section 4.4.5 where we attempt to extract the MRP from the recorded EEG activity on a single-trial basis in order to attribute features that will identify left or right hand finger movement.

### 4.3. Overview of the system

This section highlights the experimental environment and processing stages utilised in this study to investigate the possibility of predicting upcoming finger movements from EEG scalp-recorded signals. For investigation and exploratory purposes, this system was performed offline. Figure 4-2 presents an overview of the system developed in this study.

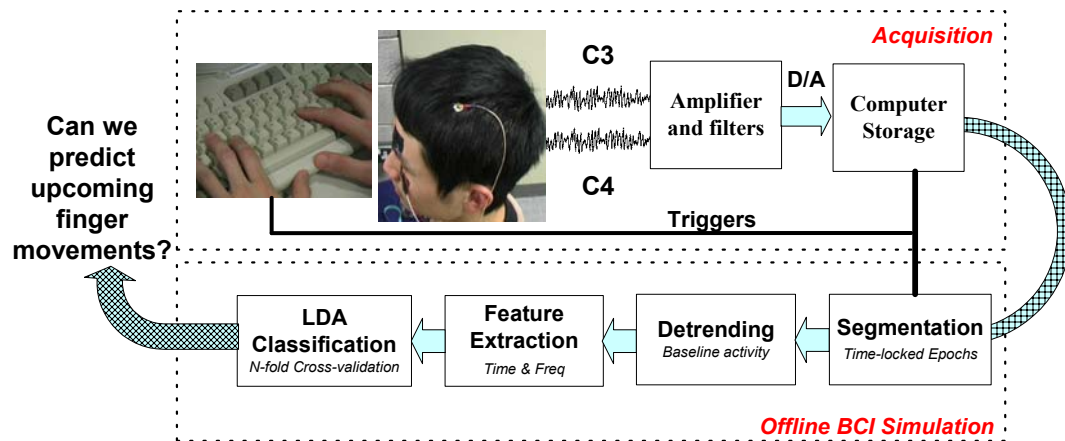


Figure 4-2: Overview of offline MRP based BCI system using self-paced voluntary finger movements

### 4.4. Methodology

This section describes the methods to facilitate the characterisation of voluntary finger movement laterality. The procedural steps, from acquiring the EEG data to processing the recorded signals, are presented.

#### 4.4.1. Experimental protocol

The self-paced left/right typing exercise paradigm was employed to attempt to classify voluntary finger movement from single-trial EEG epochs. Each subject was seated upright on a firm chair in a shielded room with their arms resting on a table and their fingers resting in the standard typing position over the home keys of a keyboard (see Figure 4-3). The subject was then



Figure 4-3: Sitting position of subject with arms comfortably resting on a table.



Figure 4-4: Hands resting over the home keys. Subjects were asked to press one of the home keys at a time on either side with their respective index fingers.



Figure 4-5: Measuring of the C3 and C4 electrode positions according to the 10-20 standard.

asked to press a left or right home key with their index finger (see Figure 4-4) in a self-chosen order, inter-trial duration ( $>2$  secs) and frequency. The subject was asked not to move or blink throughout the exercise in order to minimise motion, electromyographic (EMG) and electrooculographic (EOG) activity artifacts. No visual or auditory feedback was given to the subject.

Nine right-handed healthy subjects, all male, aged between 22 and 27 years with no reported history of neurological disorders or nervous system abnormalities, took part in the experiment in order to acquire data first-hand in addition to the competition and other data. Each session lasted about 10 minutes with all subjects performing a second session after a break of approximately five minutes. A total of 180 minutes of data was collected with key presses occurring on average every 3-4 seconds, resulting in a total of approximately 2500 left/right trials with equiprobable occurrence.

The EEG was acquired in a shielded room from two Ag-AgCl scalp electrodes placed at C3 and C4 (see Figure 4-5), according to the 10-20 International electrode-positioning standard [174], situated on the scalp above the left and right primary motor cortex respectively. Skin-electrode junction impedances were maintained below  $5k\Omega$ . The vertical EOG was recorded from the left eye to aid in blink artifact removal (see Figure 4-6). Each channel, referenced to the right

ear lobe on bipolar leads, was amplified (20K), 50Hz line filtered and band-pass filtered over the range 0.01-100Hz by Grass Telefactor P511 rack amplifiers. The key presses were recorded as two additional channels to allow the continuous EEG recordings to be segmented into left and right fixed length time-locked epochs. All signals were digitised at a sampling frequency of 512Hz

#### **4.4.2. Pre-processing**

The data was low-pass filtered up to 50Hz and then down-sampled to 128Hz to generate a lower resolution version of the original data. The continuous EEG recordings were broken up into left/right trial epochs of 1500ms length, ending 130ms before the keystroke, thus avoiding EMG contamination that could later masquerade as control signals. The BP inspired the selection of this fixed length time-window. Each trial was de-trended by removing the mean baseline activity, during a period of relative motor inactivity in the brain (assumed  $> 1.4$  sec preceding the onset of movement). The mean of a 0.5s window, 2s prior to the press was subtracted from each trial. For each subject, an ERP template was generated, specific to each channel and event, by ensemble averaging over all the subjects' relevant trials.

#### **4.4.3. Electrode selection**

This section applies to the Fraunhofer FIRST [141] data that consisted of 28 channels based on the 32 channel 10-20 electrode-positioning standard [174]. Electrode placement or selection is the most basic form of optimising the neurological information (spatial filtering). It is important to assess which electrodes carry significant information and which do not. To some extent each electrode, assuming good contact, carries information about the underlying brain activity. However, a trade-off exists between using an increased number of channels to improve the resolution of the underlying neuronal signal and introducing redundancy due to the volumetric smearing effect. Too many channels will result in increased feature vector dimensionality yielding the typical problem of classifying vectors in a high dimensional space. Increased computation and poor classification due to the additional noise and redundant information will result. Therefore it is preferable to determine which electrodes carry most information in a feature extraction strategy.

A cross-correlation method was employed as a simple technique to investigate how each channel varied from a left and right trial on average in the hope to yield channels with maximal difference between left and right finger press. The background EEG is assumed to be white noise whose autocorrelation is ideally zero. A cross-correlation between any two single-trials for any two electrodes would expect to yield a value close to zero due to the predominance of the neuronal noise in single-trial recordings. The contributions of background EEG activity are assumed to have an even effect on each channel across a large number of trials. It was envisaged that the average of the cross-correlation values across a large number of trials would elucidate the channels that differ



more on average above the common noise variations, thus highlighting the optimum channels to distinguish between Erg's resulting from left and right presses respectively.

The method consisted of cross-correlating each trial from a given channel with each trial from a contralateral press for the same channel and then averaging over all left (J) and right trials (K), see equations 5 and 6. The  $\Theta(x)$  value is an overall indication of how dissimilar an electrodes' ERP is for left and right movement and hence will be suggestive of the optimum electrode positions for feature extraction. The results in Table 4-1 clearly indicate the optimum channels for finger movement correspond to the electrode positions above the primary motor cortex thus confirming the widely accepted physiological fact as proven explicitly by Crone et al. [175] and his countless predecessors. Note that the contra-laterally placed electrodes have similar results and those sites such as the frontal and occipital lobes distinguish little between left/right motor movements as expected.

$$\Theta(x) = \frac{1}{JK} \sum_{l=0}^J \sum_{r=0}^K \frac{C_{LR}(l, r, x)}{\sigma_L(l, x) \sigma_R(r, x)} \quad (5)$$

$$C_{AB}(a, b, x) = \frac{1}{N} \sum_n^N \sum_k^N A_a^x[n] B_b^x[n - k] \quad (6)$$

|                   |  |
|-------------------|--|
| where $\Theta(x)$ | : is the average correlation coefficient for electrode channel x across all trials |
| $\sigma_L(l, x)$  | : standard deviation of single - trial / for a left movement (L) for electrode x   |
| x                 | : represents the electrode channel of the corresponding single - trial             |
| J, K              | : is the total number of left and right trials respectively                        |
| L, R              | : indicates that the trial is for left and right movement respectively             |
| l, r              | : indicates the index of the left and right trials respectively                    |
| N                 | : indicates the sample length of a single - trial                                  |

| Electrode | $\Theta(x)$ |
|-----------|-------------|
| C1        | 0.03197     |
| C2        | 0.03301     |
| FC6       | 0.03311     |
| C6        | 0.03327     |
| FC4       | 0.03358     |
| C3        | 0.03427     |
| CP5       | 0.03428     |
| C5        | 0.03443     |
| C4        | 0.03481     |

|    |         |
|----|---------|
| ⋮  | ⋮       |
| F1 | 0.05314 |
| F2 | 0.0734  |
| Fz | 0.09187 |

Table 4-1: Results of cross-correlative comparison for Left/Right press Vs electrode position. The closer the value is to the one the more similar the ERP is for a left and right for the electrode position.

#### 4.4.4. Artifact rejection

An automatic threshold-based rejection of trials was employed in this study for the purposes of simplicity and to ensure ideal training data. Vertical EOG (vEOG) was recorded from the left eye to aid in the artifact identification and rejection (see Figure 4-6). Initially, the threshold was empirically decided by visually scoring the rejected trials to ensure its effectiveness. On average, less than 8% of subjects' left/right trials were rejected resulting in around 200 out of the 2500 trials recorded being rejected.



Figure 4-6: Vertical EOG (vEOG) recording performed on the left eye to aid in artifact identification and rejection.

Every trial has to be accounted for and cannot be rejected for an online implementation of such a BCI system. The author anticipates further investigation into an efficient and effective artifact removal technique as summarised in section 3.5.3 in order to develop a robust real-time version of this BCI system.

#### 4.4.5. Feature extraction

The goal of this section is to extract features which represent the brain activity associated with upcoming left or right volitional movement and can maximally distinguish between the two brain states. This task is at the kernel to the development of a robust BCI. Feature extraction was the most time demanding stage in this study for this reason. It involved the exploration and investigation into many time and frequency representations of the single-trial EEG to facilitate the extraction of pertinent features without the influence of the neuronal noise or inter-trial variability. It was chosen to fix the classifier to facilitate comparison of the feature extraction methods. To this

end, an LDA classifier with 20 shuffles by 10-fold cross-validation was uniformly applied throughout this study as will be discussed in section 4.4.6.

The underlying time-course characteristic that we wish to elicit in this experiment is an event-related potential known as the Bereitschaftspotential (BP) [19] : a gradually rising negative potential occurring about 1000ms preceding the onset of movement largely localised around the sensorimotor area. Figure 4-7 illustrates the grand ensemble averages across all subjects for C3 and C4 recordings during left and right finger flexions. A very noticeable contralateral negativity occurring 500 ms before the onset of movement at time  $t = 0$  is noticeable across all subjects.

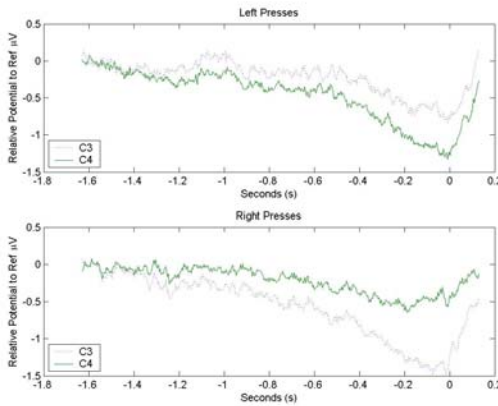


Figure 4-7: Ensemble averaged trials for Left and Right finger presses for electrode positions C3 and C4. The underlying ERP, the Bereitschaftspotential, is seen as expected with the more negative potential on the contralateral side. The BP1 and BP2 components of the BP are also noticeable.

The physiological occurrence of ERD/ERS is recognised in the frequency domain by power variations in the mu and beta bands preceding the onset of motor movement [48]. Figure 4-8 illustrates the average of PSD estimates of trials across all subjects for C3 and C4 recordings during left and right finger flexions. There is a distinguishable decrease in power (ERD) in the mu band on the contralateral side 300ms prior to finger press ( $t=0$ ).

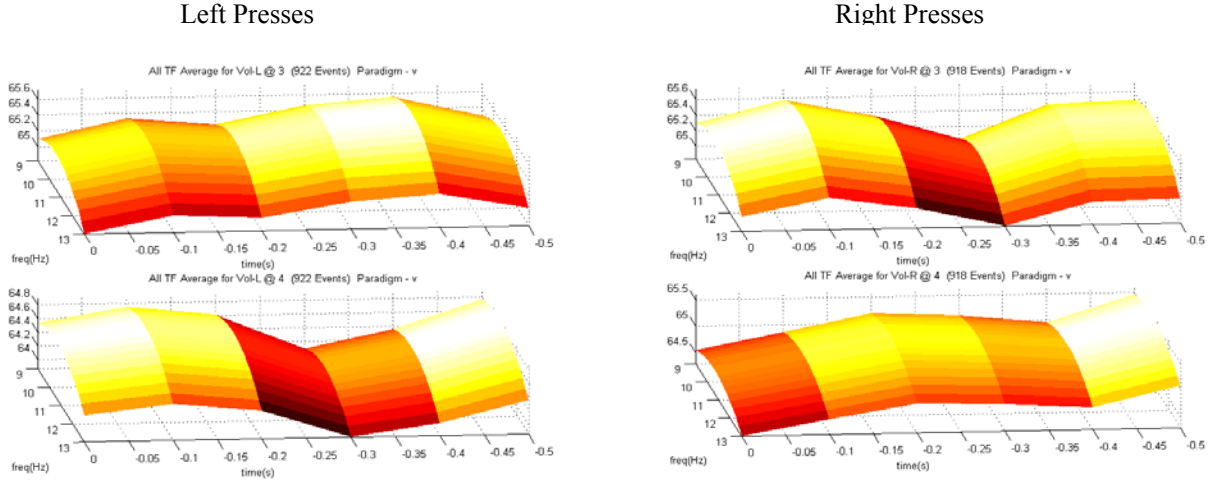


Figure 4-8: Grand ensemble average of STFT Time-Frequency PSD plots for electrodes C3 (top) and C4 (bottom) during left and right finger movement (left and right side respectively). The time window is 500ms prior to press (x-axis) over an extended mu frequency band (9-13Hz).

#### 4.4.5.1. Parametric modeling

Parametric modeling is a technique whereby a mathematical model is optimally fitted to a time series. It involves trading off parameter dimensionality and computational efficiency with the accuracy of the model (precision of the representation). EEG signals are non-stationary, i.e. its statistical characteristics such as frequency spectrum, vary with time. EEG recordings can however be assumed to be locally stationary over a short time period. This is a prerequisite for satisfactory modeling. Mc Ewen et al. [176] showed that 80-90% of EEG segments of duration 4-5 seconds can be modelled as being Gaussian, and wide-sense stationary. EEG segments of length 1-2 secs are presumed to be stationary in the literature. Autoregressive (AR) and AR with exogenous input (ARX) are two parametric modelling methods which will be presented in this section.

Autoregressive models attempt to fit a polynomial based on previous samples to optimally predict the next sample in the time-course as will be explained later. The coefficients of the polynomial that best fit the time-course can then be used as features to distinguish one time-series from another. AR models are a very common method for the evaluation of the spectra of short data segments due to the improved resolution. The fact that it is all-pole filter means it can represent sharp peaks in the frequency domain. It offers the advantage that the spectrum can be estimated based on Maximum entropy (MESE) [177].

For the model identification, the parametric modelling parameters have to be identified. There exist several methods in the literature for estimation of the parameters in various stationary and adaptive modeling approaches. These include the Yule-Walker, Burg [178] and the least-mean-squares (LMS) [179] method for AR models. Methods like the recursive-least-squares (RLS)

[177,180] are used for Adaptive AR (AAR) models. AAR models tend to offer better results compared with segmentation methods [169,181,182].

## AR

ERPs are usually concealed in the ongoing background EEG as explained above in section 4.2.1. The approach of using an Auto-Regressive (AR) model to emulate the background EEG activity for ERP elicitation is well known, see [167,183] for a review, and has been successfully applied in BCI systems [61,184]. This all-pole modelling technique lends itself well to producing the dominant frequencies occurring in the EEG [61]. The AR model can be intuitively rephrased in the frequency domain as a white noise source driving a spectral shaping network  $A^{-1}(z)$ .

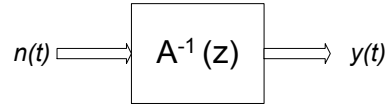


Figure 4-9: AR model

$$\hat{y}(t) = -a_1 y(t-1) - \dots - a_n y(t-n_a) + e(t) \quad (7)$$

where  $e(t)$  is the noise and  $a_i$  are the coefficients of the  $n_a$  order model. In the ideal case,  $n(t)$  is a purely random (white noise) process with zero mean and variance  $\sigma_n^2$ .  $n(t)$  is uncorrelated with the signal, and the cross-covariance  $E\{Y_t * N_{t-k}\}$  is zero for every  $k$ .

## ARX

ARX modeling has been used in event-related potential identification and SNR improvement by Lange et al. [153,155,185-187], Cerutti [151] and Liberati [188-190] amongst others. Less widely explored is the novel approach of using ARX model filter coefficients as features in a classification strategy. Unlike most of these other papers that are dedicated to the development of the methodologies of parametric single-trial information (or ERP) enhancement, parametric modeling is used here to extract features that can identify with the hidden ERP to distinguish a left and right trial.

ARX, an extension of AR modelling, involves the introduction of an exogenous input assumed to be a contributory signal to the overall signal being modelled. Its pole-zero filtered contribution and the AR noise estimate combine to form the forward prediction estimate of the overall recorded EEG signal. Using an AR Moving Average (ARMA) as the Exogenous input has proved to better model the underlying event-related potential amidst the background EEG offering improved classification rates [92,191]. It makes the distinction between the ERP and background

neuronal activity contributing to the single trial EEG recording. Cerrutti et al. have successfully applied ARX modelling for filtering the continuous EEG in order to extract the underlying ERP. However in this study the ARX filter coefficients are used as input features to characterise the single-trial EEG. The ARX method of modeling both the signal (underlying Bereitschaftspotential) and the noise (background EEG) is more physiologically reasonable than modelling the noise alone as ongoing EEG contributions from neighbouring neural populations contribute mostly to the background noise [19]. Ensemble averaging over a large number of trials exposes the underlying event-related potential (BP) that is hidden amidst background EEG by averaging out this random neuronal noise [19]. These ensemble average templates, specific to each channel and event, form the input to an ARMA model. Assuming a common denominator for the ARMA and AR filter results in the ARX model as illustrated in Figure 4-10.

The EEG activity in this experimental paradigm can be expressed by means of the following equation (assuming a linear relationship):

$$y(t) = s(t) + n(t) + a(t) \quad 0 \leq t \leq T \quad (8)$$

where:  $y(t)$  is the scalp recorded EEG response prior to the onset of movement,  $s(t)$  is the useful signal corresponding to the event-related Bereitschaftspotential attained by ensemble averaging across preceding trials [19],  $n(t)$  is the background EEG and  $a(t)$  is the component generated by a combination of all possible artifacts.  $T$  is the duration of each fixed length trial epoch ( $T=1500\text{ms}$ , 130ms prior to finger press). For our purposes with the subjects asked to remain still and employing our threshold based rejection of EOG corrupted trials it is assumed in our model that  $a(t) \rightarrow 0$ .

Alternatively, the ARX model can be extended for artifact filtering by introducing additional noise modelling stages to filter the acquired signal  $y(t)$ , resulting in increased exogenous inputs. This method was employed successfully by Filligoi et al. [22] to satisfactorily filter out blink and eye movement artifacts (BEMA) by feeding in an EOG channel as an input.

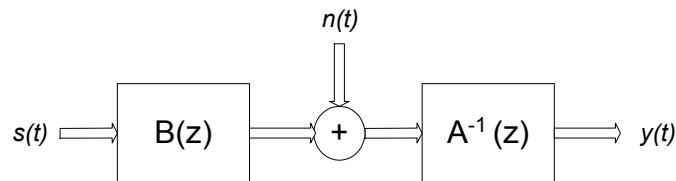


Figure 4-10: ARX model structure

The basic ARX model, in terms of the shift operator  $q$ , and assuming a sampling interval of one unit, is as follows

$$A(q)y(t) = B(q)s(t) + n(t) \quad (9)$$

The prediction is written as

$$\begin{aligned} \hat{y}(t) = & -a_1 y(t-1) - \dots - a_{n_a} y(t-n_a) \\ & + b_1 s(t-k) + \dots + b_{n_b} s(t-k-n_b) \\ & + e(t) \end{aligned} \quad (10)$$

where  $n_a$  and  $n_b$  are the model orders and  $k$  is the delay. Defining  $\theta$  as the vector of model parameters we can write the mean square prediction error as

$$E(\theta) = \frac{1}{N} \sum_{t=1}^N e^2(t, \theta) \quad (11)$$

where  $N$  is the number of samples and  $e(t, \theta) = y(t) - \hat{y}(t, \theta)$  is the forward prediction error. To fit the model to the data  $y(t)$  over a period  $t=1, \dots, N$  we choose  $\hat{\theta}$  such that it minimises  $E(\theta)$  in equation 11 resulting in a least squares error minimisation problem producing the Yule-Walker equations, which can be solved straightforwardly as reviewed in [167]. The single trial ERP estimate,  $\hat{s}(t)$ , can be interpreted as the BP template,  $s(t)$ , filtered by  $B(z)/A(z)$  [151]. Choice of the model orders is an optimisation task but Akaike's Final Prediction Error (FPE) criterion [192] can be used as a guide. The FPE penalizes higher order models and is given by

$$FPE(\theta) = \frac{N + n_a + n_b + 1}{N - n_a - n_b - 1} E(\theta) \quad (12)$$

where  $n_b=0$  for the case of a simple AR model. The filter coefficients that minimise the error then form the feature vector. The filtered template, the models' estimate of the single trial ERP contributing to the EEG recording, is compared to left and right templates for the corresponding channel to generate two cost functions per channel as additional parameters in the feature vector. The cost function is a simple mean square error comparison as follows:

$$MSE_x^y = \sqrt{\frac{1}{N} \sum_{n=1}^N [\hat{s}_x^y(n) - s_x^y(n)]^2} \quad (13)$$

where  $x$  represents the electrode channel (i.e. either C3 or C4) and  $y$  represents the event (i.e. either left or right {L, R}). Thus for a left movement we would expect the  $MSE_{C3}^L$  and  $MSE_{C4}^L$  to have a low value while the  $MSE_{C3}^R$  and  $MSE_{C4}^R$  to have a high value and vice versa.

Coefficients of the AR and ARX models are used as features in the classification. For the ARX case, we define four template signals: an ensemble average of ERPs for a left movement from C3 and C4 and similarly for a right movement. This generates four sets of ARX coefficients for classification per trial. This feature extraction technique is impractical for a large number of

electrodes due to the resultant large feature vector dimensionality and resulting computational demands.

#### 4.4.5.2. Time-frequency analysis

Preparation and planning of self-paced hand movement results in a short-lasting desynchronization (ERD) of rolandic mu (10-12 Hz) and central beta rhythms (14-20Hz) on the contralateral side to the movement beginning around 600ms prior to the press [38]. It is this frequency domain characteristic we hope to extract features from in order to distinguish between left and right movement at the classification stage.

Firstly the time-locked epochs are selected over the range 630ms to 130ms prior to the press and are Hanning windowed to preserve the frequency characteristics from smearing when taking short sample windows. The FFT was then taken over the epoch to provide an estimate of power over the frequency range. The power estimates in the mu and beta bands are then extracted and used as features.

Performing a Short-time Fourier Transform (STFT) or time-frequency analysis was an obvious extension of this approach that permits an insight into the ERD by analysing the power variation with respect to time. The difficulty with identifying time-frequency features is the inherent trade-off between the time and frequency resolution.

*“The more accurately we try to determine the spectrum as a function of time, the less accurately we determine it as a function of frequency, and vice-versa.”....[193]*

It is impossible to achieve a high degree of resolution in both the time and frequency domain of the short EEG segments and thus the domain of the feature that maximally identifies with the left or right trial must be prioritised. Due to the short epochs utilised in this system, the resolution in either domain was severely compromised. However, to ensure consistency from one trial to the next and to prevent over training the classifier we do not wish to have a high level of resolution in either domain. The STFT was estimated at 250ms windows in time with a 33% overlap. This limited the lowest detectable frequency to 4Hz. The frequency resolution was optimally chosen as 1Hz trading off classifier generality and overtraining. Using the *mu* and *beta* bands resulted in a feature vector with dimension 42 (7 frequency bins per band for 3 time windows). ERD/ERS can be recognised better using a large selection of electrodes localized above the sensorimotor cortex. Using simply C3 and C4 over short epochs would limit the derivation of distinguishable frequency domain features. This will be later seen in the results section.



#### 4.4.6. Classification

Linear Discriminant Analysis (LDA) is employed for the feature vector classification task in this study. LDA requires less training and computation compared with neural network based classifiers but as a trade-off requires more discriminatory feature vectors to distinguish successfully between the classes [119]. LDA consists of estimating  $k$  discriminant functions to construct  $k$ ,  $n$ -space, hyper-planes that optimally distinguish the  $k$  classes using  $n$  features. Optimisation of the model is achieved through direct calculation and is extremely fast relative to other neural network based models. It is very efficient thus making a real-time implementation possible.

When implementing a classifier it is important to be able to estimate the expected performance of the classifier on data not used in training. To this end, the available data is divided into independent training and testing sets. There exist a number of schemes for achieving this such as the Jack-Knife method [119] which involves the exclusion of a small subset of data for testing on the classifier trained with the rest of the data. The most suitable approach that optimises the use of all available data while at the same time maintaining an unbiased estimate is  $n$ -fold cross-validation [194]. This scheme randomly divides the available data into  $n$  approximately equal sized, mutually exclusive “folds”. For an  $n$ -fold cross validation run,  $n$  classifiers are trained with a different fold used each time as the testing set, while the other  $n-1$  folds are used for the training data. The choice of  $n$  influences the ratio of data used for training/testing with an optimal value of  $n$  in the range 5-20. Cross validation estimates are generally pessimistically biased, as training is performed using a sub-sample of the available data. The randomising process was “stratified” so that all the folds contained the same relative proportions of both classes (lefts and rights). Studies have shown that stratification of the folds decreases both the bias and the variance of the performance estimate. Cross validation is highly variable and depends on the division of the data into folds. A decrease in the variance of the performance estimate may be achieved by averaging results from multiple runs of cross validation where a different random split of the training data into folds is used for each run.

In the results section of this study, unless stated otherwise, the reported classification accuracy is the percentage of total cases correctly classified repeated and averaged across  $M$ -shuffles for an  $N$ -fold cross-validation and then finally averaged across all subjects.

## 4.5. Results

This section presents the experimental findings associated with this study. The results will be briefly introduced but will be discussed in greater detail in the ensuing discussion section.

In order to ensure an unbiased and reasonable estimate of classification accuracy based on training data, a  $N$ -fold cross-validation procedure was employed [119]. The data consisting of feature vectors compiled from the feature extraction stage is first randomly shuffled and subsequently stratified (evenly divided based on class) into  $N$  distinct segments.  $N-1$  segments are used to train an LDA classifier and the remaining segment is used as the test set. This process is repeated for each  $N$  possible sets and the mean test set accuracy is computed. Finally, the complete process is repeated  $M$  times with a new random shuffle to yield a mean accuracy. All the data was uniformly processed with  $N=10$  and  $M=20$ . In the following sub-sections the results for various feature extraction techniques are reviewed.

### 4.5.1. Parametric modeling

#### AR

Before blindly applying the well documented AR approach to single-trial EEG modelling, the author wished to get an intuitive feel for how the model performed and changed relative to any system changes, i.e. model order and input. The first step was to visually see how well the model performed by filtering white noise using the estimated model parameters. It was found that the frequency spectrum of the model output was consistently very similar to that of the single-trial being modelled whereas it differed slightly in the time domain. The initial few white noise samples would determine the initial shape of the time-domain waveform. To get a better time-domain representation, an Adaptive AR (AAR) approach would have to be taken but at the cost of the dimensionality dramatically increasing.

Figure 4-11 shows plots which demonstrate how the percentage of unexplained output variance changes with respect to the model order. This is an indication of how well the model is capable of representing the original signal which, in this case, is an EEG single-trial. Notably the plot on the right, representing the modelling of a particular trial with no filtering, is a better fit (lower percentage) as the model order is increased. The opposite is the case for the downsampled and filtered trial on the left. The best fit is represented in red which occurs at model order 5 for the filtered version and 40 for the original single-trial. Trading off computation and model accuracy, the optimum model order range to represent the single-trial is in the range 6-12.

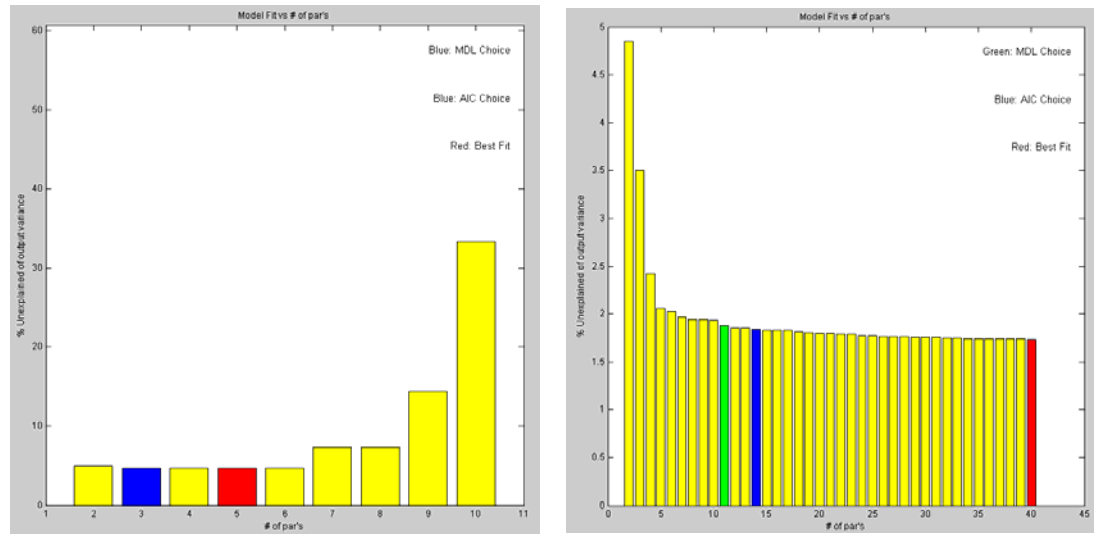


Figure 4-11: Plot of an AR model fit versus the number of parameter's for the downsampled and filtered version of the data (fs=100Hz, LPF fc=40Hz) (left) and the original high-resolution data (fs=1000Hz). Note the greater percentage of unexplained output variance for the filtered signal.

The next step was to investigate how well these estimated parameters could distinguish between two different single-trials, i.e. for left and right trials, based on the number of model parameters utilised. Table 4-2 shows the classification accuracy averaged across all subjects versus model order for various parameter estimation methods.

Table 4-2: AR feature extraction classification accuracy averaged across subject 1 versus model orders for various parameter estimation methods.

| Parameter Estimation Method | Least-Squares |           | Forward-Backward |           | Yule-Walker |           | Burg      |           |
|-----------------------------|---------------|-----------|------------------|-----------|-------------|-----------|-----------|-----------|
| Model Order                 | Session 1     | Session 2 | Session 1        | Session 2 | Session 1   | Session 2 | Session 1 | Session 2 |
| 6                           | 54.16         | 51.54     | 60.16            | 47.73     | 60.46       | 46.89     | 60.08     | 48.90     |
| 8                           | 54.31         | 48.24     | 60.54            | 49.84     | 60.92       | 52.27     | 60.84     | 49.91     |
| 10                          | 58.77         | 51.91     | 60.31            | 49.83     | 58.31       | 49.49     | 59.92     | 47.39     |
| 12                          | 56.62         | 50.84     | 58.08            | 50.42     | 56.92       | 49.33     | 57.10     | 50.58     |

The Yule-Walker offered the best classification accuracies of 61% and 53% for the first and second session respectively using a model order of 8. Notably, the second session has approximately a 10% less classification accuracy compared with the first session across the model order range of interest (6-12). Also, the methods consistently have their optimum accuracies for both sessions at the same model order. Table 4-3 shows the variation of accuracy versus model order for a wider range using the Yule-Walker method.

Table 4-3: AR feature extraction classification accuracy for subject 1 versus model orders for the Yule-Walker AR parameter estimation method. The parameters were used as the features and classified using 20 shuffle by 10-fold cross validation. Note: 50% represents an equiprobable occurrence.

| Model Order | Session 1 | Session 2 |
|-------------|-----------|-----------|
| 2           | 50.38     | 40.42     |
| 4           | 49.84     | 44.11     |
| 6           | 60.46     | 46.89     |
| 8           | 60.92     | 52.27     |
| 10          | 58.31     | 49.49     |
| 12          | 56.92     | 49.33     |
| 14          | 56.69     | 51.78     |
| 16          | 54.23     | 52.94     |
| 18          | 55.07     | 53.69     |
| 20          | 52.76     | 53.61     |
| 22          | 53        | 53.19     |
| 24          | 56.76     | 53.27     |
| 26          | 56.07     | 52.60     |
| 28          | 54.61     | 49.66     |
| 30          | 53        | 53.10     |

Table 4-4 presents the overall classification accuracy for the AR feature extraction strategy across all 10 subjects for both sessions. This is then depicted in Figure 4-12. Classification by chance is represented by a 50% accuracy. The performance accuracy for most subjects is close to this indicating that the AR method is poor at predicting upcoming left or right volitional movements. A pure guess would offer the same chances of accurate classification.

Table 4-4: Classification accuracy across 10 subjects using the AR feature extraction method with a chosen model order of  $n_a=7$

| Session | 1       | 2       |
|---------|---------|---------|
| Subject | %       | %       |
| 1       | 60.92   | 52.27   |
| 2       | 44      | 48.3    |
| 3       | 51.847  | 56.111  |
| 4       | 50.602  | 49.167  |
| 5       | 47.969  | 52.063  |
| 6       | 42.292  | 55.614  |
| 7       | 56.319  | 55.952  |
| 8       | 56.075  | 44.563  |
| 9       | 53.864  | 47.48   |
| 10      | 41.779  | 52.711  |
| Average | 51.3667 | 51.4231 |

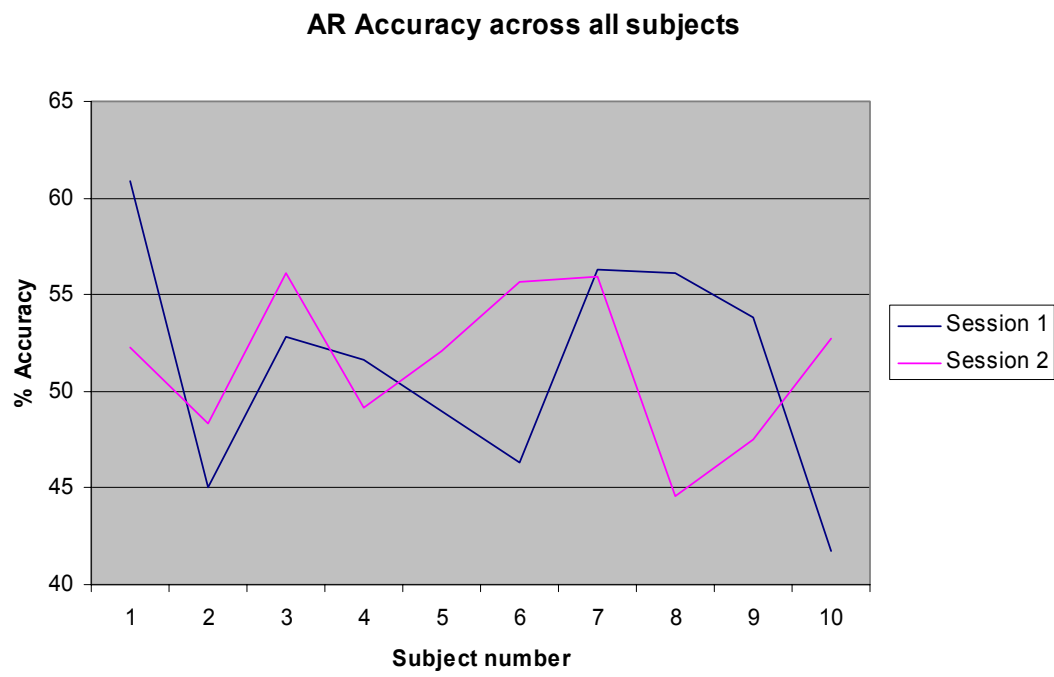


Figure 4-12: Plot of classification accuracy for each subject using the AR feature extraction method. Note that a random event is 50%

## ARX

Figure 4-13 presents an example of the input and output signals for the modelling of a random left trial (see Figure 4-10 for explanation). This demonstrates how the ARX model estimates the underlying ERP amidst the neuronal noise in any given single-trial. The estimated ERP or BP is produced by the filtered contribution of the ensemble averaged template. As can be seen, the estimate closely resembles the averaged template. In this case the averaged template and single-trial input happen to be for left finger movement. The BP estimate tends not to be similar to the template when using opposite movement related single-trials and templates.

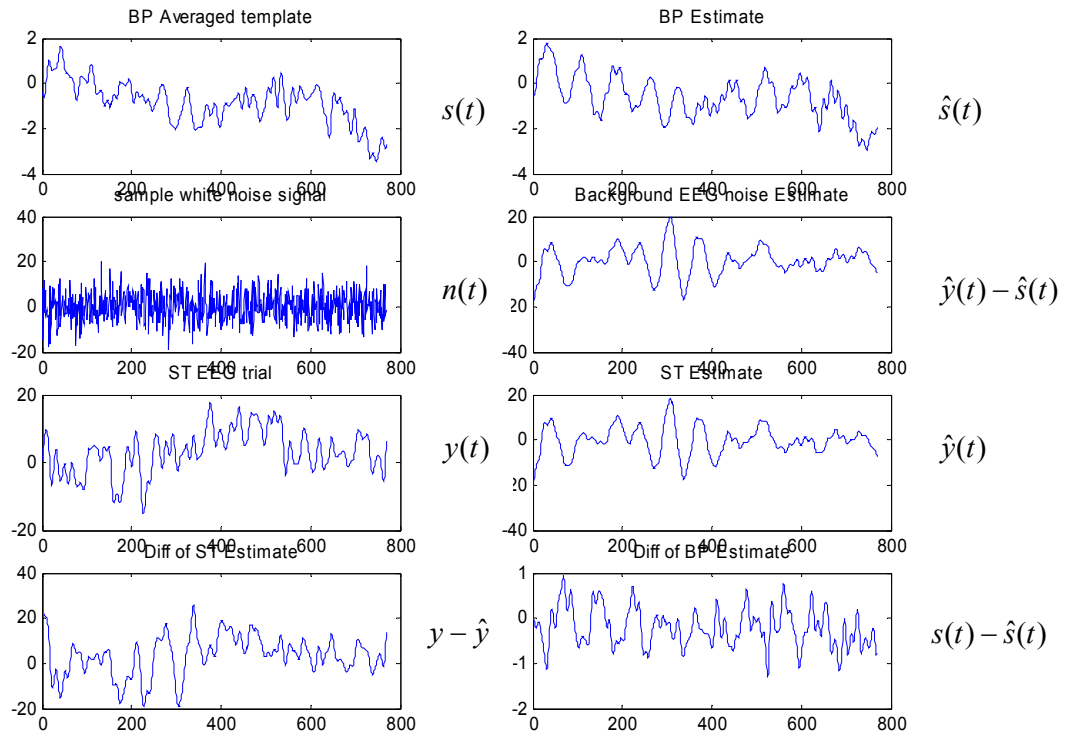


Figure 4-13: Representation of inputs and outputs of ARX modelling for a specific left trial

An important part of ARX modelling, similar to AR, is the estimation of the model parameters. Many simulations are required to analyse the variation of classification accuracy with respect to the many possible system criteria. These include model orders for the ARMA and AR filter stages, the exogenous input used in the model and the parameter estimation method. Table 4-5 presents the ARX model orders versus the classification for a single subject. The Yule-Walker method was employed to estimate the parameters and the exogenous input was an ensemble average of all that subjects appropriately suited trials (i.e. same electrode location and movement)

except for the current trial being modelled. The optimum accuracy is 66.8% which occurs for the model orders  $n_a=4$  and  $n_b = 4$ .

Table 4-6 presents the overall classification accuracy for the ARX feature extraction strategy across all 10 subjects for both sessions. In addition, all trials from both sessions were merged in order to see how the number of trials used to generate the input template would affect the accuracy. The performance is also depicted in Figure 4-14. The average classification accuracy across all subjects is approximately 60%. This indicates that the ARX method offers a bias for the accurate prediction of left versus right finger movement and thus is a superior method than the AR approach.

Table 4-5: ARX model orders versus the classification accuracy for subject 1. The optimum accuracy occurs for model orders  $n_a=4$  and  $n_b=4$  as highlighted.

| <b>na \ nb</b> | <b>2</b> | <b>3</b> | <b>4</b> | <b>5</b> | <b>6</b> | <b>7</b> | <b>8</b> |
|----------------|----------|----------|----------|----------|----------|----------|----------|
| <b>2</b>       | 52.895   | 55.752   | 53.722   | 59.737   | 60.391   | 55.827   | 54.398   |
| <b>3</b>       | 63.571   | 60.338   | 63.293   | 58.835   | 62.023   | 55.977   | 61.444   |
| <b>4</b>       | 56.429   | 62.594   | 66.805   | 58.985   | 61.248   | 58.083   | 58.158   |
| <b>5</b>       | 62.444   | 62.068   | 55.188   | 63.82    | 63.519   | 57.932   | 62.466   |
| <b>6</b>       | 55.15    | 59.286   | 52.88    | 57.857   | 56.504   | 58.383   | 56.429   |
| <b>7</b>       | 59.361   | 53.947   | 52.729   | 55.677   | 52.444   | 54.774   | 57.331   |
| <b>8</b>       | 57.932   | 57.03    | 51.09    | 57.481   | 53.496   | 54.248   | 54.098   |

Table 4-6: Classification accuracy across 10 subjects using the ARX feature extraction method with an optimally chosen model order of  $n_a=4$  and  $n_b=4$

| <b>Session</b> | <b>1</b> | <b>2</b> | <b>Merged</b> |
|----------------|----------|----------|---------------|
| <b>Subject</b> | <b>%</b> | <b>%</b> | <b>%</b>      |
| <b>1</b>       | 68.053   | 58.917   | 67.119        |
| <b>2</b>       | 62.556   | 54.921   | 63.082        |
| <b>3</b>       | 56.481   | 48.078   | 63.465        |
| <b>4</b>       | 59.118   | 54.917   | 57            |
| <b>5</b>       | 68.088   | 67.735   | 68.023        |
| <b>6</b>       | 53.162   | 54.193   | 52.61         |
| <b>7</b>       | 59.715   | 63.207   | 61.202        |
| <b>8</b>       | 58.296   | 62.421   | 58.256        |
| <b>9</b>       | 55.188   | 62.214   | 52.128        |
| <b>10</b>      | 59.785   | 59.611   | 58.429        |
| <b>Average</b> | 60.0442  | 58.6214  | 60.1314       |

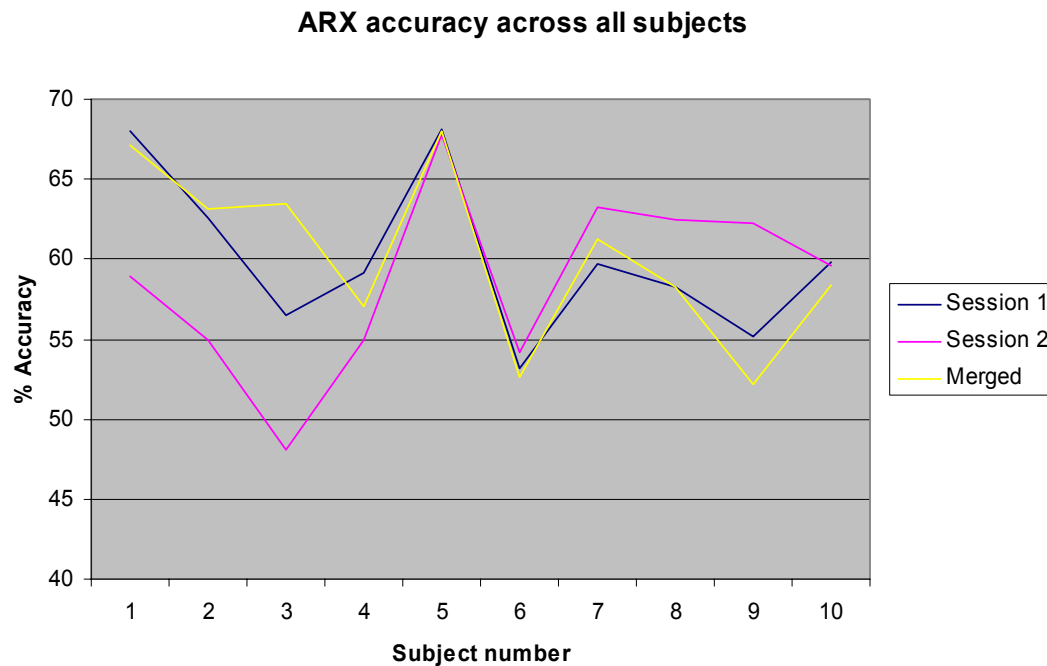


Figure 4-14: Plot of classification accuracy for each subject using the ARX feature extraction method. Note that a random event is 50%

#### 4.5.2. Time-frequency feature extraction

Figure 4-15 shows the grand averaged (for all subjects and trials) power spectrum estimate over the range 6-30 Hz for the 500 ms time window prior to finger press. As can be seen, there is no striking frequency characteristics to identify with either a left or right press. Figure 4-16 shows the grand ensemble averaged Bereitschaftspotential for left versus right finger movements for electrode positions C3 and C4 filtered over the frequency range of interest (2-25 Hz) for the 500ms preceding movement onset. There is a distinctive difference in the time-domain between the two possible states. Figure 4-17 shows the grand ensemble averaged short time power spectral density (STPSD) plots for left and right trials for C3 and C4 electrode positions over the range 0-25Hz for the 500ms preceding movement onset. The sliding time window for the STPSD was 125 ms with 25% overlap. For the finger movement paradigm it is expected to observe a decrease in power (ERD) within the *mu* rhythm of the contralateral sensorimotor area. This is evident in Figure 4-18.

Table 4-7 presents the classification accuracy for the STFT time-frequency feature extraction method that attempts to exploit the power differences between the contralateral and ipsilateral side of the sensorimotor area in the *mu* and central beta band during left/right finger movement.



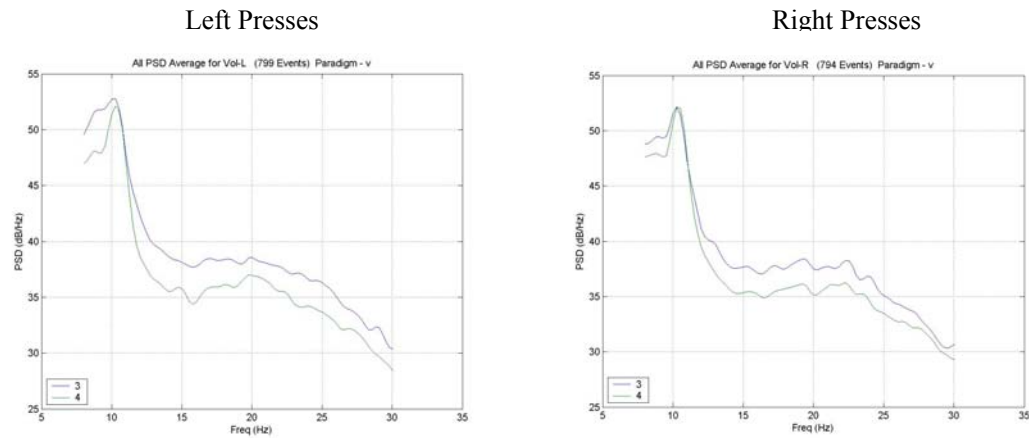


Figure 4-15: Grand ensemble averaged frequency spectrum power for left trials (*left*) and right trials (*right*) for C3 (*blue*) and C4 (*green*) electrode positions filtered over the range 6-30Hz for the 500ms preceding movement onset

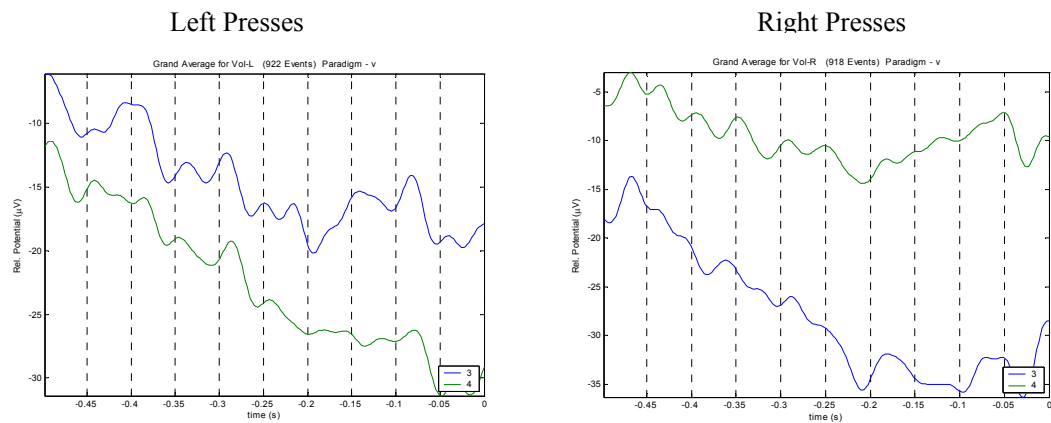


Figure 4-16: Grand ensemble averaged ERP for left trials (*left*) and right trials (*right*) for C3 (*blue*) and C4 (*green*) electrode positions filtered over the range 2-25Hz for the 500ms preceding movement onset

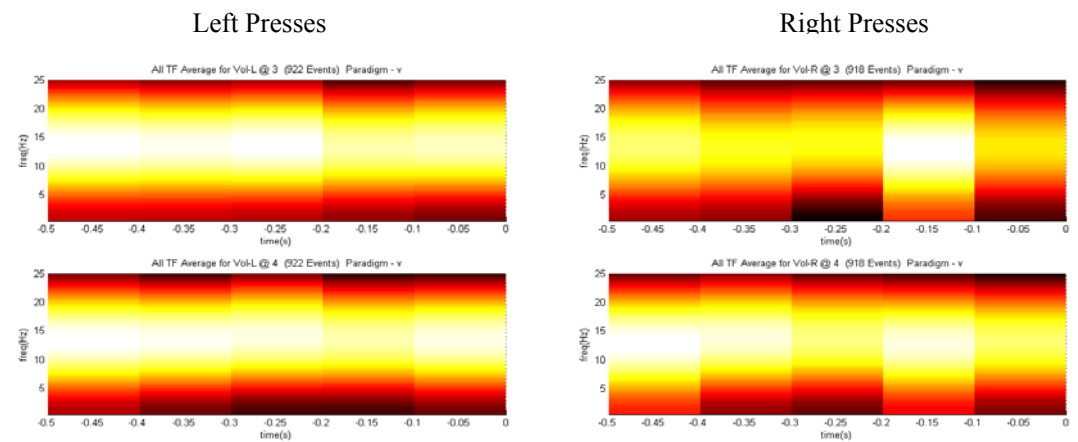


Figure 4-17: Grand ensemble averaged short time power spectral density (STPSD) plots for left and right trials (*respectively located*) for C3 (*top*) and C4 (*bottom*) electrode positions over the range 0-25Hz for the 500ms preceding movement onset. The time window for the STPSD was 125 ms with 25% overlap

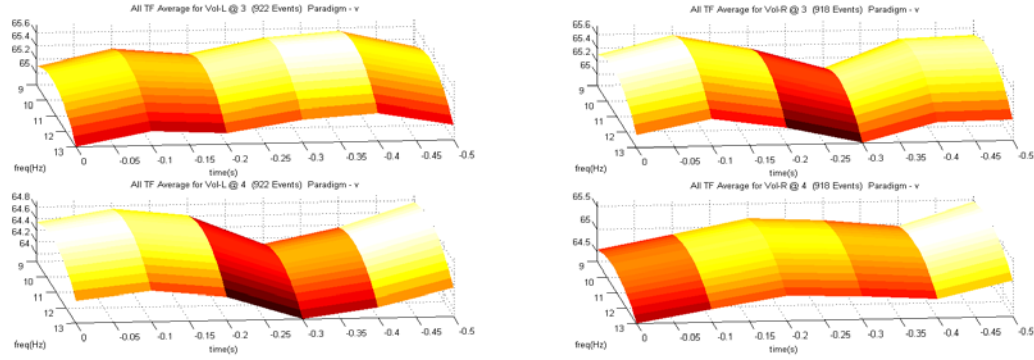


Figure 4-18: Grand ensemble average of STFT Time-Frequency PSD plots for electrodes C3 (top) and C4 (bottom) during left and right finger movement (left and right side respectively). The time window is 500ms prior to press (x-axis) over an extended mu frequency band (9-13Hz).

Table 4-7: Classification accuracy across 10 subjects using a time-frequency (STFT) feature extraction method. The feature consisted of an STFT in the bands 8-13Hz and 18-25Hz in 400 ms windows with 25 % overlap.

| Session | 1       | 2       |
|---------|---------|---------|
| Subject | %       | %       |
| 1       | 58.053  | 56.917  |
| 2       | 52.556  | 51.921  |
| 3       | 46.481  | 48.078  |
| 4       | 49.118  | 51.917  |
| 5       | 58.088  | 57.735  |
| 6       | 53.162  | 44.193  |
| 7       | 54.715  | 53.207  |
| 8       | 52.296  | 52.421  |
| 9       | 55.188  | 52.214  |
| 10      | 55.785  | 49.611  |
| Average | 53.5442 | 51.8214 |

#### 4.5.3. Competition Data

This section presents the results for the classification of the competition data (Berlin dataset) for the aforementioned BCI Competition 2003. The competition data used in this study was particularly constrained, both in the short time window leading up to the movement and by the truncation of the data 130ms before the onset of movement. This made it difficult to harness time-frequency features, for example, ERD [48,103], as additional features to aid in the classification stage.

Table 4-8 shows the training and test set accuracies for four different feature extraction methods. Cross-validation was performed on the training set to produce the training set accuracy results. When the actual competition labels were posted after the submission deadline, the performance of each method on the labelling of the test set was evaluated. It was found that the training set performance was comparable to the test set, thus validating the cross-validation

process of deriving an unbiased estimate of accuracy. It is slightly optimistically biased by approximately 2-5 % for each method. This can be seen in Figure 4-19.

Table 4-8: Training and test set accuracy for the competition data

| Feature Extraction Method     | Electrode Channels Used   | Orders / Frequency Band / Time Resolution                  | Training Set Accuracy % | Test Set (unlabelled) Accuracy % |
|-------------------------------|---|--|-------------------------|----------------------------------|
| AR                            | C1, C2  | na=8   | <b>52.1</b>             | <b>49</b>                        |
|                               | C3, C4  | na=8   | <b>50.9</b>             | <b>53</b>                        |
| ARX                           | C1, C2  | na=4, nb=4   | <b>64.2</b>             | <b>59</b>                        |
|                               | C3, C4  | na=4, nb=4   | <b>68.1</b>             | <b>63</b>                        |
| Power Frequency Band Analysis | 8,14,22,10,18,24,27,28<br>(localised around the motor cortex – as per competition ) | 8-16 and 17-25 Hz  | <b>73</b>               | <b>68</b>                        |
| Time-Frequency                | C3, C4  | 8-16 & 17-24 Hz<br>25 % overlapping<br>400 ms time windows | <b>67</b>               | <b>65</b>                        |

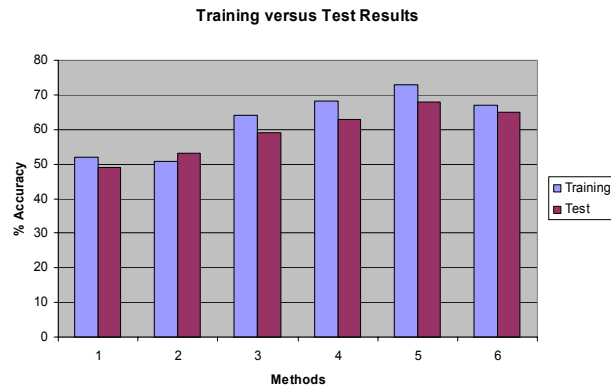


Figure 4-19: Plot of Performance Accuracy comparing the training and test results

The labels for the test data submitted as the author's competition entry were attained by weighting each of the labels classified using the ARX, power band and time-frequency feature extraction methods according to their respective training set accuracies and then taking the closest class as the resultant label. Due to the poor performance of AR for distinguishing between a left and right press it was omitted and had no effect on the submitted labels.

Table 4-9 shows the official competition results as posted by the organisers Blankertz et al. The winning entry for the Berlin left-right finger movement dataset used all 28 electrodes and a multilayered perceptron neural network. The features extracted involved a combination of

common subspace decomposition and Fisher discriminants. Considering the computational complexity of the winning approach, it was felt the author's submitted entry performed well. Especially in light of the fact that for the most part, only the filtered and downsampled trials from C3 and C4 were utilised and that the feature extraction and classification strategy employed was computationally efficient making real-time processing possible.

Table 4-9: Official BCI Competition results table for dataset 4 (Berlin dataset)  
<http://ida.first.fraunhofer.de/projects/bci/competition/results/index.html>

| #  | Contributor    | Error | Research lab                 | Co-contributors   |
|----|----------------|-------|------------------------------|---|
| 1. | Zhiguang Zhang | 16%   | Tsinghua University, Beijing | Yijun Wang, Yong Li, Xiaorong Gao, Shanghai Gao, Fusheng Yang |
| 2. | Radford Neal   | 19%   | University of Toronto        |   |
| 9. | Ray Smith      | 31%   | University College Dublin    | Richard Reilly  |

## 4.6. Discussion

This section is presented in two parts. The first part takes the form of a performance analysis for this BCI study. It discusses the performance of the different feature extraction methods discussed in this chapter by reviewing the results from the above section. It also goes further to highlight potential problems or shortcomings with the various feature extraction methods.

Secondly, in Section 4.6.2, an analysis is done on the areas of the BCI design in this study that requires additional work in order for it to be developed into a robust alternative communication device for individual's suffering from neuromuscular disorders.

### 4.6.1. Performance analysis

This section reviews the classification performance of the number of feature extraction methods employed in this study that were presented in the results section above. It also briefly highlights any important findings associated with using each method.

#### 4.6.1.1. AR

Autoregressive modelling has been proven to provide a suitably accurate model of the background EEG activity. As an AR model is intuitively a white noise source driving a spectral shaping network, the background neuronal activity that behaves as random noise can be closely modelled. The use of AR modelling to extract an ERP by subtracting the modelled background EEG signals from the actual recordings has been proven to be quite poor. Many papers have claimed to have

boosted the SNR of an ERP by this method but there exists no accurate means of quantifying it. It was shown in this study that despite a wide-range of AR model orders, the average accuracy for this method resulted in approximately chance (50%). Since a typical ERP has a really low SNR in the order of -30dB, attempts to identify and distinguish between two very similar ERPs would be near impossible using this method alone.

#### 4.6.1.2. ARX

The ARX model was found to be very sensitive to the exogenous input used. The ensemble averaged templates of single trial left/right epochs that represents the underlying ERP (BP) is used as the exogenous input in our ARX model of single trial EEG. In order to generate these templates a subject must perform a period of training whereby a series of labeled left/right trials are recorded. Templates, specific to a given electrode position and function (left or right), are then created by the average of the appropriate trials. The sensitivity arises due to the subject-specific templates and through the variability of the number of trials a template is averaged over. It was found that the system behaved optimally when approximately 100 trials were used to generate each subject-specific template. The author pondered creating the ensemble averaged exogenous input adaptively and questioned its ability to provide a more recent and accurate representation of the underlying ERP. Perhaps an exponential weighting system could be employed to weight the more recent trials in the template generation process.

It was shown in Table 4-5 that the classification accuracy performance varied widely over the range 2-8 for each filter stage. Beyond this range, performance dropped significantly due the additional noise and the greater classification dimensions. Simply taking the optimum model orders of  $n_a=4$  and  $n_b=4$  did not necessarily yield the optimum accuracy for each subject. Any adaptive assessment of the appropriate model orders for each subject would however be highly inefficient and not worth the slight improvement in accuracy.

It is shown in this study that the ARX method model goes further to model both the signal and the noise which is found to be more effective than modelling the noise alone. This is an intuitively satisfying result. This well published fact is reinforced by this study where approximately a 10% improvement in classification accuracy is achieved on the AR approach. Although an average classification accuracy of 60% is only achieved (65% for competition data), the classification bias reinforces the existence of a distinguishable difference between an MRP over the sensorimotor area for an upcoming left and right volitional finger movement.

ARX has proven its effectiveness and efficiency in the role of filtering and feature extraction of single trial EEG. Further investigation into the creation and effect of the exogenous input in conjunction with model order selection could further improve its potential. The author is

skeptical about the ability of the ARX method to discern the subtle differences of ERPs with a negative SNR. This casts a question mark over its ability to provide features to yield consistently high classification accuracy for the purposes of BCI implementation. The author had applied this method to VEPs which have an SNR  $>0$ dB and it yielded a much better identification performance. This not only due to the improved SNR but also to the fact that the VEP is better defined in terms of its morphology. The complex template used as the exogenous input is far more distinguishable from the neuronal noise and thus yields comparatively better results than the ERPs with their negative SNR and flat (low-frequency) morphology.

#### 4.6.1.3. Time-Frequency

The time frequency, STFT based, feature extraction method failed to establish features to elucidate the mu rhythm variations that occur on the contralateral side approximately 300 ms prior to a press (as can be seen in Figure 4-18). Varying the time and frequency resolution could not yield any improvement on the classification performance of this method as highlighted in Table 4-7.

The competition data yielded much better frequency domain features, particularly in the case where a greater number of electrodes were used. The power frequency band analysis using 8 electrodes located above or near the motor cortex yielded approximately 70% accuracy. The STFT time-frequency method for C3 and C4 yielded approximately 66% accuracy.

It is well publicised that time-frequency features distinguish best between the lateralisation of hand or finger movement. It is evident in the literature and also proven here that increasing the number of electrodes to an optimal number around the region of interest can help to maximise the brain activity information into the system. Without the restriction of segmentation (breaking the continuous EEG into short epochs), methods such as Pfurtscheller's [48] Event Related Desynchronization estimation method has been proven to yield good results.

#### 4.6.2. Future Work

This section highlights some of the key areas to this study that need to be further researched in order to develop this BCI approach into one that can be utilised by an individual with a severe neuromuscular disorder for communication purposes.

The author feels that this study requires the use of a greater number of electrodes as is typical in BCI research. By restricting ourselves to two electrodes as in this study the system relied far too much on the consistency and integrity of the information contained therein. By using a larger montage of electrodes about the motor cortex, it would improve the reliability of the event-related information. A large number of electrodes facilitates not only a wider range of features to be extracted but also the generation of spectral topographic plots to allow the BCI designer to

visualize the origins of activity. The author would have liked additional time to look into Laplacian based spatial filtering, ICA based source localisation and ERD/ERS features to develop better results in this study.

There is a need to extend this paradigm to facilitate the classification of imagined limb movement as opposed to actual movement. This would enable people with neuromuscular disorders to utilise a BCI system based on this approach. This is discussed in greater detail in the ensuing section.

#### 4.6.2.1. Imagined limb movement paradigm

Motor imagery can modify the neuronal activity in the primary sensorimotor areas in a very similar way as observable with a real executed movement [38]. Pineda et al. [96] studied the use of the mu rhythm in BCI systems and similarly concluded that

*“mu rhythm is not only modulated by the expression of self-generated movement but also by the observation and imagination of movement”*

It is broadly accepted that mental imagination of movements involves similar brain regions/functions that are involved in programming and preparing such movements. According to this view, the main difference between performance and imagery is that in the latter case, execution would be blocked at some cortico-spinal level [95]. The aim is to further explore this view by extending the above BCI system for imagined left/right hand movement. This section discusses the potential imagined movement experimental paradigm.

The ultimate goal for a BCI is information transfer for a human without the use of the ‘normal pathways of peripheral nerves and muscles’. This poses a serious challenge for the design and training of any BCI system. In order to elicit features from the continuous EEG recordings, event-related feedback is required to know at what moment in time did the subject perform a function and also what function i.e. imagine left or right movement. This sort of feedback is the very goal we desire for our BCI. With the actual finger movement paradigm, there was direct event-related feedback via the key presses due to motor movement. In the imagined paradigm we have no such method of simultaneously and endogenously recording the imagined movement with the EEG. The solution to this is to use a stimulus to trigger the desire for movement. This however contravenes the experimental paradigm by generating an evoked-potential in response to the stimulus which could mislead the classifier.

#### 4.7. Summary and Conclusion

This study successfully achieved the goal of submitting an entry into the BCI competition 2003. In the process, the author succeeded in developing invaluable hands-on experience for recording, processing and algorithmically manipulating EEG signals for the purposes of BCI.

A self-paced left/right typing BCI experimental paradigm was utilised in this study to generate distinguishable brain activity for the purposes of predicting upcoming left or right finger movements. The paradigm was devised to elucidate characteristic potential variations (MRP) in the EEG recordings over the sensorimotor cortex associated with a left and right press. The time-domain MRP characteristic that can distinguish between left and right finger movement is known as the Bereitschaftspotential (BP). The BP2 component of the BP is more negative over the contralateral side than the ipsilateral side during the 1000ms prior to the press. The frequency domain feature is a short lasting desynchronization (ERD) in the mu and beta rhythms on the contralateral side during the 600 ms prior to the press. Although these features can be easily exposed on grand averages, it is much more challenging to extract these distinguishable characteristics on a single-trial basis.

Three feature extraction methods were explored in this study to establish characteristic features on a single trial that identify with a left or right press. The AR method behaved poorly and it is the opinion of the author that the SNR of the underlying ERP is too low to establish distinguishable AR parameters to achieve any classification above chance. ARX performed better than AR by approximately 10% on average. It is however a very volatile method that is subject to wide ranging results depending on the exogenous input used (ensemble averaged template) and the model orders employed. Time-frequency features have been published in the literature to yield much better classification results than parametric modelling methods, particularly if a large number of channels are utilised. Frequency based features are less susceptible to artifacts and the trial to trial variability of the EEG. The data in this study was particularly constrained by the short time-windows prior to the finger press. This makes it difficult to harness, for example, Event Related Desynchronization (ERD) as an additional feature in the classification. With this considered, a poor classification accuracy of approximately 53% resulted using an STFT method.

The BCI considered in this study is a highly dependent one due to the requirement on the user to have the ability to move his arms. Despite this fundamental BCI conceptual flaw, it was an interesting study to investigate how a controllable mental 'event' could generate distinguishable brain activity which in itself could support communication or control. This study was also a convenient test bed for the goals of extending this paradigm to imagined limb movement due to the similarly generated pre-movement potential variations (as discussed in section 4.6.2.1). It is the author's opinion that there exist better neuromechanism and experimental paradigms for BCI



design that are capable of offering more robust communication with higher-transfer rates, such as an SSVEP based visual attention paradigm as will be covered in the next study.

## **Chapter 5      Study 2: SSVEP based real-time BCI gaming system**

This study was one of many as part of an ambitious collaboration between the DSP research group at University College Dublin and the Mindgames research group at MIT Media Lab Europe (MLE) to design and implement new biometrically controlled computer interfaces, specifically EEG based BCIs. The Mindgames research group has enjoyed some media attention for their development of biofeedback based applications such as Relax to Win<sup>31</sup>, Breathing Space and Still Life<sup>32</sup>. Their research centres on the use of intelligent biofeedback and sensory immersive environments to constructively affect a person's state of mind. This collaboration has brought together people from disciplines such as digital signal processing, hardware and graphic design in the hope of expediting the process of developing EEG based non-clinical applications.

This chapter will initially present the aim of the project and give an introduction to the origins and properties of visual evoked potentials that are exploited in this BCI study. This will follow with an explanation of the experimental set-up and methodology behind the BCI framework employed. The implementation of this BCI system into a real-time gaming environment using the C# programming language is then discussed. The results associated with the development and final stages of this study are presented in the ensuing section. The chapter concludes with a discussion that reviews the success of this study, highlights some interesting findings and finally outlines some future possibilities for such a BCI framework.

### **5.1.    Aim**

The objective of this study was to develop a system that utilizes brain activity to offer direct control within a real time video gaming environment. The project was initially inspired by the desire to develop a brain computer interface for people with limited motor movement capabilities. The hope was then to implement a BCI system coupled with a simple video game to pose the question;

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<sup>31</sup> Relax to Win<sup>©</sup>: UCD final year project that resulted in collaboration with MIT Media Lab Europe. It is a competitive racing biofeedback game which is controlled by the players' level of relaxation, as measured by their galvanic skin response.

<sup>32</sup> Breathing Space<sup>©</sup> & Still-Life<sup>©</sup>: Mind Games Research Group, Media Lab Europe Dublin - <http://mindgames.mle.ie/projects.html>

‘Can an immersive bio-feedback game improve the speed and accuracy of a Brain Computer Interface?’

Balance maintenance was the theme of the game envisaged. To this end, the Mind Balance<sup>®</sup> game involves a tightrope-walking Scottish behemoth named Mawg (see Figure 5-2), who the participant must assist by helping him maintain his balance, as he makes his way across an interstellar tightrope. A participant at the helm of the Mind Balance<sup>®</sup> game has no muscular input or video surveillance- only an electrode cap that non-invasively measures electrical signals from the head.



Figure 5-1: Mind Balance<sup>®</sup> game logo



Figure 5-2: Mawg<sup>®</sup>, the Scottish tightrope walking behemoth

Of the many BCI system approaches that exist in the literature, as reviewed in chapter three, it was hoped to employ a simple yet effective method to realise this goal. The experimental paradigm and the resulting characteristic brain wave pattern elucidation were crucial to the deciding BCI control approach for the game. The steady-state visual evoked potentials (SSVEPs) in the multiple visual stimuli selective attention paradigm was chosen due to its well publicized success, computational efficiency and limited subject training requirements [35,36,98,100,115,116,135,195]. In order to control the character's balance, the participant would be required to focus his attention to one of two stimuli flashing at different rates and positioned on both sides of the character. For example, if the Mawg character begins to fall to the left the participant should direct their visual attention to the right stimulus in order for the character to regain balance. In order to captivate the participant's game playing interest, it was imagined that there would be a number of degrees of imbalance prior to the character falling.

Having decided upon the distinguishable brain activity to offer the control in our BCI approach, the next section will introduce and explain the VEP based neuromechanism as a potential BCI control input.

## 5.2. Introduction

Visual evoked potentials (VEPs) are reflective of the electrophysiological mechanisms underlying the processing of visual information in the brain. They originate from the many potential changes within the occipital lobe in response to a visual stimulus change. The macroscopic potential variations can then be picked up on the scalp surface at the back of the head. The signals evoked by changes in the visual input have been shown to reflect certain properties of the stimulus [35]. A static stimulus in the visual field does not result in any significant alteration in the EEG activity. A transient (step-change) stimulus produces a VEP with a very characteristic waveform. It consists of a trough-peak-trough complex with the very noticeable peak (referred to as P1) occurring at around 100 ms after stimulus presentation. Figure 5-3 presents the time-locked ensemble averaged response, from the electrode position Oz, to a checkerboard pattern alternating at a rate of 2 Hz.

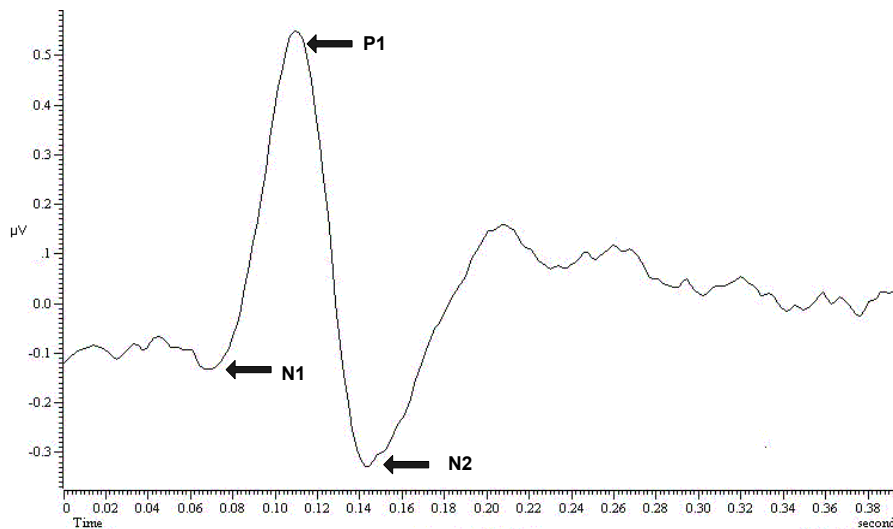


Figure 5-3: Ensemble averaged VEP response, from the electrode position Oz, to a checkerboard pattern alternating at a rate of 2 Hz. The N1, P1 and N2 trough-peak-trough occurs at 75, 110 and 140 ms respectively

A distinction is made in the literature between a transient VEP and a steady state VEP (SSVEP) based on the visual stimulation frequency. The former arises when the stimulation frequency is less than 2Hz. If the stimulus repetition rate is greater than 6 Hz, a periodic response called the SSVEP will result. The resultant SSVEP is a complex symbiosis of a series of components whose frequencies are integer multiples of the stimulus repetition frequency [100]. The amplitude and phase of the SSVEP are highly sensitive to stimulus parameters such as

repetition rate, contrast or modulation depth, and spatial frequency [196]. The SSVEP was also found to be strongly dependent on spatial attention, being substantially enlarged in response to a flickering stimulus at an attended versus and unattended location [197]. The increased SSVEP amplitudes reflect an enhancement of neural responses to a stimulus that falls within the range of spatial attention. It is this fundamental idea that justifies the use of SSVEP as a method to identify the visually attended target among a group of stimuli with sufficiently different flashing rates. For a more detailed review of SSVEPs see [198,199].

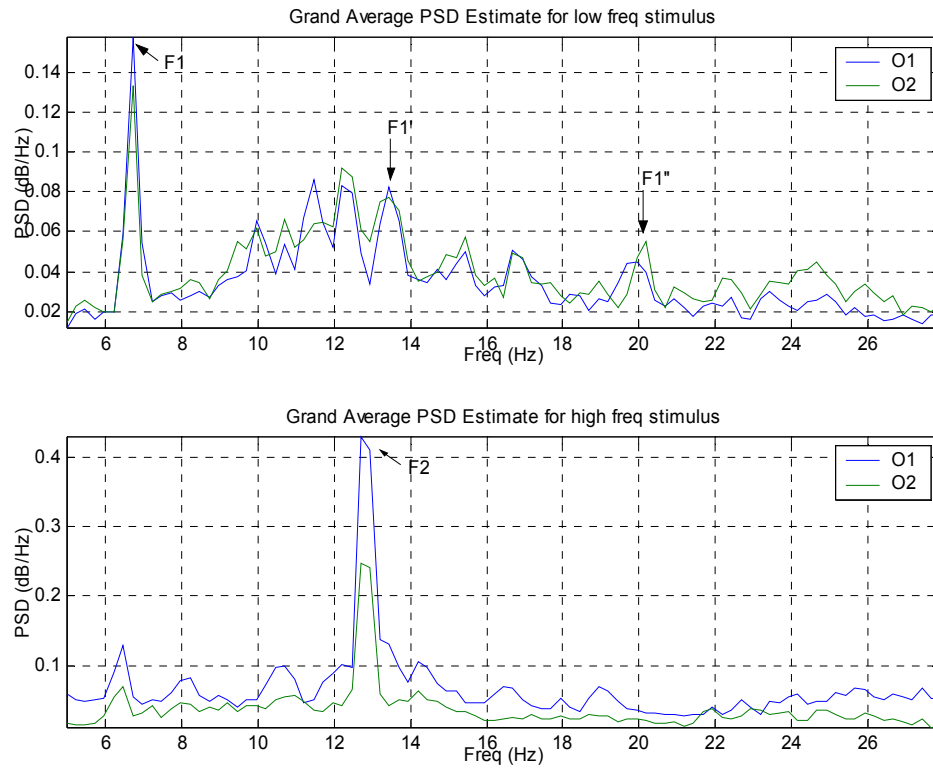


Figure 5-4: Grand average PSD response for all subjects under the same conditions during visual focus to low freq stimulus  $F1=7$  Hz (top) and high frequency stimulus  $F2=13$  Hz (bottom)

Most of the early BCI designs, such as that of Vidal [1], used single-trial VEPs evoked by a strobed checkerboard phase-reversal pattern and recorded over the occipital cortex to determine direction of eye-gaze. Sutter [35], used SSVEPs evoked by six different flashing symbols on a computer screen. The single-trial evoked potentials generated were correlated with ensemble averaged time-locked templates for each symbol and a simple correlation threshold then translated the feature to a classification. This time-domain template matching approach is reasonably successful but is subject to significant trial-to-trial variability. A series of papers were

subsequently published that investigated numerous methods of detecting the VEPs and their stimulus correlates from the continuous EEG signals compared to the previously time-locked approaches [99,134,200-202]. Calhoun et al. [115] used self regulation of the SSVEP amplitude to offer binary control. The most popular method involved the detection of the EEG signals spectral correlation to the repetition rate using Fourier analysis. Skidmore et al. discussed the possibility of establishing an evoked potential vision-tracking system utilising this feature [195]. They found that dual stimulating objects could generate separable responses.

More recent SSVEP based BCI systems involve multiple virtual buttons or targets modulated at appropriately selected characteristic frequencies to induce multiple SSVEPs [36,100,116,131,135]. The most dominant SSVEP will occur at the frequency corresponding to the flicker rate of the stimulus to which one's directing their attention. Figure 5-4 shows the power spectrum for the grand average of all the continuous investigation data from the O1 and O2 occipital electrodes and the resulting 7 Hz and 13 Hz induced SSVEPs. The peaks can be clearly seen at the frequencies corresponding to the attended visual stimulus flashing rate. Using SSVEPs as a BCI input has the advantage of focusing on EEG activity that occurs at the specific frequencies governed by the stimulus presentation. This simplifies the feature extraction methods dramatically and users require little or no training. The relative ease of the elicitation and extraction of the SSVEP frequency features from continuous EEG makes it algorithmically simplistic and thus practical for real-time system implementation. SSVEP-based BCIs belong to the family of dependent BCIs whereby an intact visual system is necessary which must also be completely devoted to the EEG-based communication task.

### **5.3. Methodology**

This section highlights the methods used in developing the real-time BCI game framework from the investigation stages through to application development and implementation.

#### **5.3.1. Preliminary investigation**

Based on the aforementioned paradigm, two different experimental procedures were employed in this study. The first was part of the preliminary investigation stage performed within a shielded room in the DSP Research Laboratory at UCD. The latter during the real-time gaming application development stage performed in Media Lab Europe (MLE).

Having decided upon the BCI approach to take, the first stage of this study involved an investigation into the factors that govern the creation of a SSVEP in the occipital cortex. By exploring different aspects of the visual stimuli presentation such as flicker rate, size, type, contrast modulation depth and relative position, we can empirically determine the best

experimental protocol to optimise the evocation of the SSVEPs to better discriminate between the attention to one of two different visual stimuli and the subsequent control classes in our game. The position of the subject relative to the monitor was also critically important in investigating the effects of visual angle and the perceived stimulus size. Five subjects performed numerous EEG recording sessions for this investigation. Each session was recorded from the O1 and O2 electrode positions. The ideal visual stimulation properties and experimental set-up for each session was progressively determined during this stage.

The use of the checker board phase reversal pattern is prevalent in the literature as the preferred method of SSVEP generation [133,198]. The striking black and white reversing checkerboard pattern is claimed to generate a SSVEP of the greatest magnitude. Some studies have outlined the relationships of the SSVEPs to the size of the checkerboard pattern and the subjects distance to the screen, or more specifically the percentage of the subjects' field of view dominated by the screen [199]. It was found that a single alternating checkerboard pattern (6 x 6 rectangles) covering the entire screen did in fact generate a significant SSVEP at the corresponding frequency. This was extended to two phase reversing checkerboard patterns of variable size, frequency and separation. Our findings showed that when the subject was attending to one of the two different stimuli that the SSVEP at the attended stimulation frequency was not as dominant as in the previous case and that there was also some parasitic effects caused by the unattended stimulus producing an SSVEP of lesser magnitude at the corresponding frequency. The attended stimulus produced a much more significant spectral peak at the corresponding frequency compared with the unattended thus proving the feasibility in distinguishing the attended from to the unattended stimuli from the SSVEP alone.

Inspired by the desire to have the tightrope walking character holding a balance bar, it was envisaged using spherical weights at either end of the balance bar to act as the differently flashing stimuli. To this effect, simple visual demonstration was developed that contained two simple yellow discs on the horizontal midline axis and evenly spaced about the vertical midline axis. The diameter of the spheres, the horizontal distance from each other and the frequencies with which they alternate from yellow to black were all variable parameters in this demonstration. This was to facilitate an investigation into the optimum settings for the intended BCI gaming system. Early findings proved that the discs performed similarly well as the checkerboard patterns for identifying the attended stimulus. It was empirically found that the generated SSVEP was relatively insensitive to the size of the discs in comparison to the effect of visual angle determined by the horizontal separation and subjects distance from the screen. The greater the horizontal visual angle between both stimuli (perceived horizontal separation) the greater the relative magnitude of the SSVEP of the attended to the unattended stimulus. Similarly as the discs were made smaller, the

visual impact of the unattended stimulus in the subjects' field of vision and the subsequent parasitic effects were reduced. As the optimum settings, it was empirically decided upon flashing yellow-black discs of diameter one-fifth the screen size and horizontal separation of seven-tenths the screen size from their respective centres. Based upon the screen size and subject location from the screen, these can be converted in terms of visual angle as can be shown in Figure 5-5.

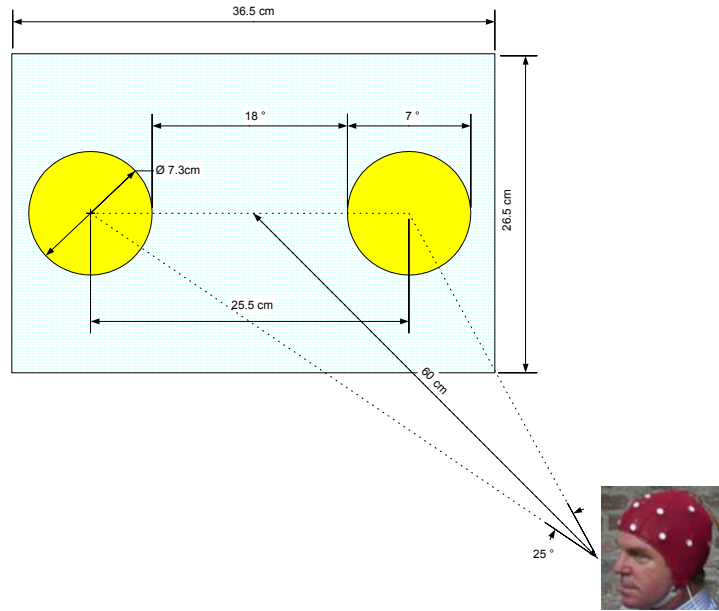


Figure 5-5: Dimensions and visual angle of subject relative to CRT monitor during investigation stage

In both of the above investigatory experiments, the magnitude of the SSVEP was most sensitive to the visual stimulation frequencies. There are a number of factors that must be considered in the selection of stimulation rates for concurrently presented visual stimuli. The frequencies must be chosen above 6 Hz, as defined by Ming et al. [100], to successfully generate a SSVEP. The upper limits are affected by the fact that higher frequencies are more attenuated than lower ones by the medium from the cerebral cortex to scalp [19]. This can readily be seen by the almost asymptotic exponential decay of EEG signal power with frequency in an awake adult. In the author's opinion, it is even questionable if an SSVEP can be generated above 20 Hz as a result of the general physical limitation of the visual processing system. In addition, the visual presentation frequency is limited by the monitor refresh rate and the capability of the computer graphics card. If a CRT monitor with a refresh rate of 80 Hz and a stimulus with a 50-50 duty-cycle lasting 2 frames each (as is typical in the literature to alleviate demands on the presentation computer), this would result in a theoretical limit of 20 Hz for the visual stimulation rate. Similarly 15 and 17.5 Hz are the upper limits for a 60 and 70 Hz monitor refresh rate respectively. Considering the above, an approximate range of 6 – 16 Hz is available to us for the selection of the



visual stimuli flicker rates. Within this range, the spontaneous EEG alpha rhythm can be most corruptive to the SSVEP elucidation. As it is similarly located at the back of the head and is typically in the range of 9-11 Hz, the alpha rhythm can particularly mask the presence of an SSVEP on a small segment of continuous EEG. A dominant alpha peak caused by a consistent alpha spindle, could masquerade as a potential SSVEP which could result in a misclassification in our brain-computer control interface. Another crucially important factor that must be considered when deciding the stimulation frequencies is the effect or presence of the SSVEP harmonics at integer multiples of the stimulus flicker rate. For example, choosing one stimulus at 8 Hz will generate SSVEP harmonics of progressively lesser magnitude at 16, 24 Hz etc. Therefore, choosing another visual stimulus at either of these frequencies will result in spectral activity that would masquerade as having originated from attention to an unattended stimulus and thus lead to a misclassified control input. Only two visual stimuli were required for our basic two class BCI control system. By taking all of the above into consideration in conjunction with some experimentation, 7 and 13 Hz were decided upon to represent F1 and F2 for the left and right flashing discs respectively due to their relative large difference in response to attended and unattended stimuli. Section 5.5 highlights some of the results from this preliminary investigation stage that helped decide upon the experimental protocol for our intended game application. The next sub-section explains in explicit detail the finalised paradigm used in the online gaming system.

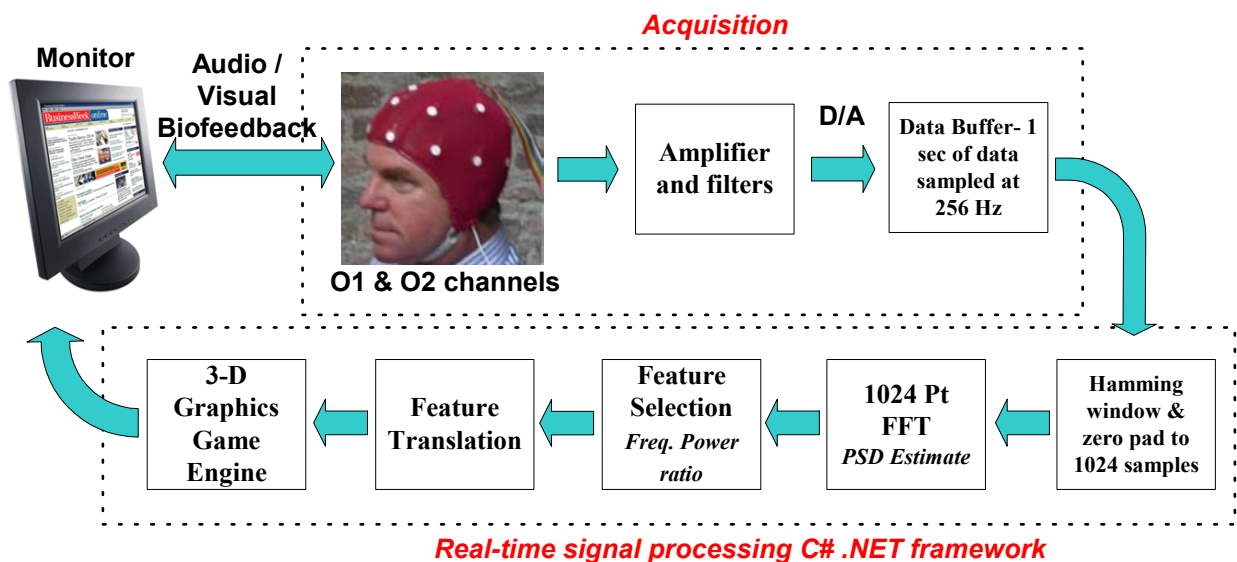


Figure 5-6: Block diagram of SSVEP-based BCI system for Mind Balance© game control. Nicholas Negroponte, founder of the Massachusetts Institute of Technology's famed Media Lab successfully plays the game at the open-day.

### 5.3.2. Game experimental protocol

Figure 5-6 shows a block diagram of the SSVEP-based BCI system used in this experiment. Each participant was seated comfortably in an upright position in front of a large vertically mounted projector screen with a refresh rate of 60 Hz (see Figure 5-7). Approximately fifty subjects of varied demographics tested the game during the October 2003 Media Lab Europe open-day.



Figure 5-7: Open day test environment illustrating projection screen and a user wearing an electrode cap

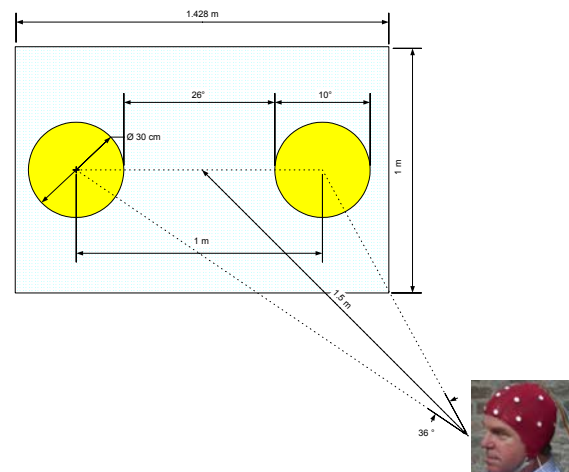


Figure 5-8: Dimensions and visual angle of subject relative to projector screen for finished gaming application

The game involves the tightrope walking character, Mawg, walking towards the participant and randomly stumbling every 2-4 seconds to either side. The participant must intervene to shift the creature's balance so that it stays on the tightrope. To do this, users were instructed to attend their visual focus to the disc on the opposite side of the screen to which Mawg is losing balance and is beginning to fall (see Figure 5-10). The direction and frequency to which the character loses his balance is random. There are two degrees of imbalance on both sides, after which Mawg will fall without successful user aid. There is a delay of about 2 seconds between each balance alteration stage to allow for the users visual focus and the resulting SSVEP to settle.

If the user does not accurately attend to the correct disc to control the character after he initially loses balance (1<sup>st</sup> degree), the character will move to a worse (2<sup>nd</sup>) degree of imbalance and similarly then to a 3<sup>rd</sup> degree where he falls. For correct user control Mawg will move up a degree of balance until he is perfectly upright allowing him to proceed forward again. The game is successfully completed by helping Mawg safely cross the interstellar tightrope. Audio-visual feedback is given to the user to inform him of stability progress. The visual feedback is the degree

of inclination in relation to the tight rope. The audio feedback is the character himself comically reporting in his Scottish accent that he is about to fall or has successfully escaped plunging to his death.

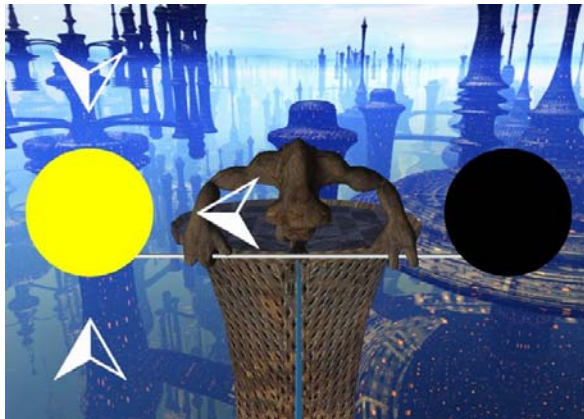


Figure 5-9: Training process: The user must attend to the flashing disc highlighted by the arrows in order to train the BCI to establish a classification threshold. The Mawg character remains inactive throughout.

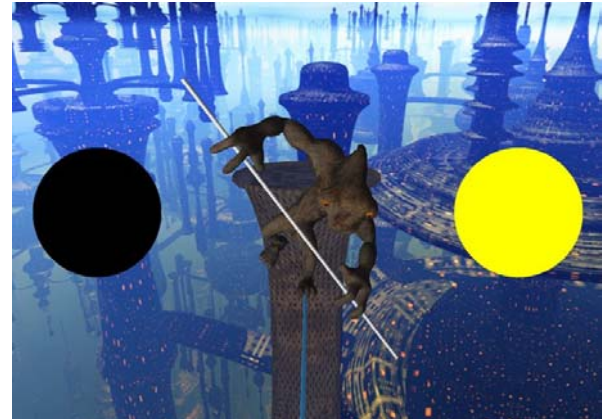


Figure 5-10: Mawg character losing his balance to the right requiring the user to attend to the left flashing disc for him to restore his balance

An electrode cap, Electro-Cap International System I<sup>33</sup>, was used to acquire EEG signals from the O1 and O2 electrode positions according to the 10-20 system. Each channel, referenced to the contra-lateral ear lobes, right and left for O1 and O2 respectively, was amplified (20K), 50 Hz line filtered and band-pass filtered over the range 0.01 – 100 Hz by Biopac<sup>34</sup> biopotential amplifiers. The signals were then digitized at a rate of 256 Hz using a National Instruments DAQ<sup>35</sup> (Data Acquisition Hardware) to facilitate digital processing.

### 5.3.3. Feature extraction

The fundamental EEG waveform characteristic feature is based on the fact that the most dominant SSVEP will occur at the frequency corresponding to the stimulus flicker rate to which one's attention is directed. It was hoped to extract frequency domain features to elucidate this fact. To this end, a power spectral density estimate of the continuous EEG signals was required. Only a pseudo-continuous spectral estimate can actually be achieved by basing it on estimates of short segments from the continuous EEG recordings. There is a trade-off that exists between frequency resolution and time resolution depending on the length of these segments. As we need the game

<sup>33</sup> ElectroCap Inc., Electro-Cap International System I : <http://www.electro-cap.com>

<sup>34</sup> Biopac Inc., Biopotential Amplifiers: <http://www.biopac.com>

<sup>35</sup> National Instruments Inc., Data Acquisition Hardware: <http://www.ni.com/dataacquisition>

input to be responsive, there is a need to keep the EEG segments short without jeopardising the association of the frequency feature with its controlling class.

Every 200 ms (~51 samples), the last 1 second (256 samples) of continuous EEG from O1 and O2 is buffered. This produces a considerable overlap of 80% (800ms) from one data segment to the next. It will be shown later that a number of EEG segments will be required to change from one classification state to another during a change in the attended stimulus. To prevent the edge windowing effects of short time segments in the frequency domain, a Hamming window of the one second EEG segments is used. These are zero-padded to 1024 samples. Zero-padding in the time-domain corresponds to interpolation in the frequency domain offering a higher estimated frequency resolution than was previously available. In this case, the resolution improved from 1 Hz (256/256) up to 0.25 Hz (256/1024). A 1024 point Fast Fourier Transform (FFT) of the zero-padded and windowed O1 and O2 EEG segments is then performed. A power spectral density estimate of these one second windows is achieved by taking the square of the absolute value of the FFT returned signal. Figure 5-11 shows the PSD estimate for two one second segments of continuous EEG from O1 and O2 during the separate attention to the stimulus F1 and F2. The peaks can be seen at 6.725 and 12.85 Hz corresponding to separate visual focus to the F1 and F2 stimuli. These peaks were expected to occur at 7 and 13 Hz but it was later found that during the investigation stage the stimuli did in fact flicker at these rates. Noticeably from the graphs, the peaks are not as pronounced as the grand ensemble averaged spectral estimate as shown in Figure 5-4.

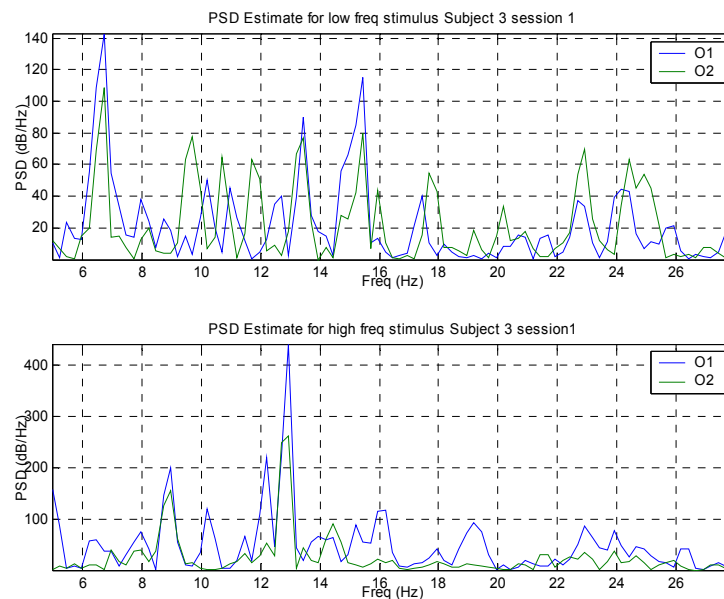


Figure 5-11: Random single trial (1 second duration) for subject NF during visual focus to low freq stimulus F1=7 Hz (top) and high frequency stimulus F2=13Hz (bottom)

Figure 5-12 summarises in a block diagram the signal processing employed to achieve the power spectral estimate of the EEG segments from O1 and O2. These were then averaged to produce a combined PSD estimate,  $X$ , to reduce feature vector dimensionality and any potential bias based on visual location of the stimuli as will be explained later in the discussion.

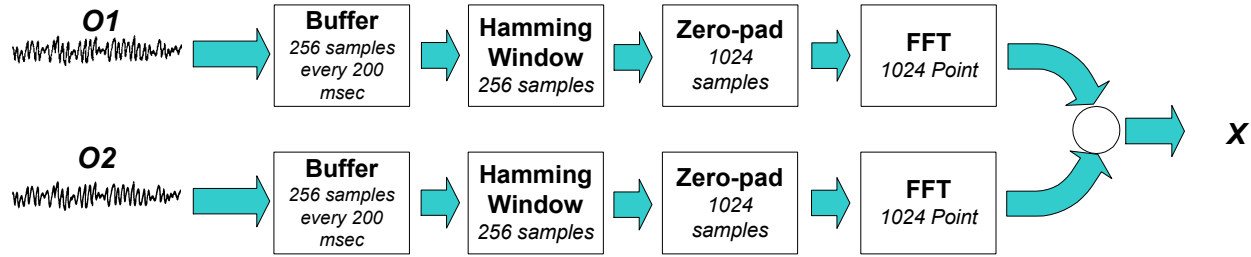


Figure 5-12: DSP signal processing performed on the continuous O1 and O2 EEG recordings to produce a combined power spectral estimate

The intensity of the response for each stimulation frequency, defined as the sum of the amplitudes of its' fundamental frequency and the second harmonic, was used by Cheng et al. [100] as the feature in their SSVEP based BCI. The threshold for detection was twice the empirically determined mean value of the amplitude spectrum between 4 Hz and 35 Hz. Inspired by this feature and the fact that the proposed BCI contained only two stimulation frequencies (F1 and F2) and the associated two functional classes, it was decided to take the ratio of the PSD at the frequencies F1 and F2 as a feature (F1/F2). It is necessary to logarithmically transform this ratio to convert it to a linear scale and to ensure a more Gaussian distribution. This feature would then only require a simple empirically determined threshold to classify the data. Unlike with Cheng et al. [100], this feature offers relative power information for the frequencies, making it more robust. Admittedly the extension of this relative power feature to an experiment with six functional classes and the corresponding six more tightly selected frequencies as in Cheng et al. [100] is more challenging. It would result in a feature vector of length 15 ( ${}^6C_2$ ) or  $\binom{6}{2}$  to allow the relative power ratios between the combinations at all six frequencies. This multidimensional feature vector would then need to be classified using more complex means than threshold based methods.

In addition to this feature, a number of other simple PSD features were explored in an attempt to find the most discriminatory feature or combinations thereof, to yield the optimum classification performance between the two classes. The features investigated are listed as follows:

$$MAXMIN : \log \left( \frac{\max(X(f1\_range)) - \min(X(f1\_range))}{\max(X(f2\_range)) - \min(X(f2\_range))} \right) \quad (14)$$

$$MEAN : \log \left( \frac{\text{mean}(X(f1\_range))}{\text{mean}(X(f2\_range))} \right) \quad (15)$$

$$STD : \log \left( \frac{\text{std}(X(f1\_range))}{\text{std}(X(f2\_range))} \right) \quad (16)$$

$$MAX : \log \left( \frac{\max(X(f1\_range))}{\max(X(f2\_range))} \right) \quad (17)$$

$$Pt\_Ratio : \log \left( \frac{X(f1)}{X(f2)} \right) \quad (18)$$

$$Pt\_Diff : X(f1) - X(f2) \quad (19)$$

where  $X$  : is the average spectral power estimate for O1 and O2  
 $fx\_range$  : is an FFT frequency range index of bandwidth BW around  $fx$   
 $fx$  : is the FFT frequency index corresponding to  $fx$

#### 5.3.4. Classification

During the early investigatory stages of this study, linear discriminant analysis (LDA) using an approximation to Bayes' theorem was employed as the pattern classifier. This approach identifies the features or combinations thereof that better discriminate between the SSVEPs of the attended from the unattended stimuli and the corresponding control selection. See section 3.5.7 for a review of this feature translation method.

For the purposes of simplicity it had been envisaged to use a threshold based approach to prevent the need to perform a computationally intensive covariance matrix inversion as required in LDA. Through investigation it was found that the  $Pt\_Ratio$  feature, i.e. the log of the ratio of the PSD estimate at the frequencies F1 and F2, was a very robust feature on its own and that the addition of others offered little improvement. Therefore a simple one-dimensional threshold based classifier was employed on this sole feature to perform the pattern recognition. The brain wave activity at O1 and O2 is effectively translated into a one-dimensional analog control axis that can be used to decipher the participant's control input and in this application to aid Mawg regain his balance.

The investigation stage showed that the  $Pt\_Ratio$  feature value overlapped for less than 8% of the continuous EEG data segments during the attention to the two different stimuli. This

causes a class ambiguity for the classifier and could lead to a potential misclassification. This small percentage could be attributed to when the subject had recently changed his attended stimulus and the SSVEP had not enough time to settle. It could also be due to the subject temporarily adjusting his focus while attending to the same stimulus allowing the parasitic effects of the unattended stimulus to dominate. To combat this problem, it was decided to average (low pass filter) the feature value of the last one second of continuous data and that of the two previous EEG segments, occurring 200 msec and 400 msec respectively prior to the current segment. It was this feature value that is ultimately compared to the threshold to generate the deciding classification. The averaging produced a smoother transition of the resultant feature value from one side of the threshold to the other in response to an attended stimulus change. Although this introduced an additional latency for the system to respond to the change (up to 400 msec ideally), it made the classifier more robust to single erroneous EEG segment feature values. The overall effective classification throughput of 400-600 msec places a similar time restriction on the characters responsiveness within the game. This is however overshadowed by the fact that the EEG segments used for these classification results are of the last one second of continuous data. There is therefore a need to wait for the majority of the last one second of EEG data to contain the SSVEP with the dominant frequency associated to the visually attended stimulus. To allow users enough time to readjust their focus and their resulting SSVEPs to settle, the BCI gaming system evaluates the classifier output or control command every 1.5 seconds.

The performance improved dramatically, with the above alterations to the classifier. The combined probability of misclassification was less than 1% for most subjects. This will be discussed later in the results section.

### 5.3.5. Training

This section explains the benefits of the brief training session prior to a participant taking part in the game. It was found during the investigation stage of this study that the *Pt\_Ratio* feature as mentioned above (log of spectral power ratio for F1 and F2) had Gaussian like distributions in response to both the low and high frequency stimulus (see Figure 5-16 in section 5.5). The modes (max of distribution) for the different sessions are clearly separable confirming the plausibility of its use as a class separating feature. However, the tail ends of the normal distribution for each session overlap to cause a region (~8%) of values that will cause ambiguity for the classification stage. The median value of the overlapping sections is typically chosen as the optimum threshold to distinguish one distribution from another. This point represents an equiprobable misclassification error for both classes. This optimum threshold was not located at zero as would have been expected. It was also found to differ from subject to subject. Klimesch [29] also published that the alpha rhythm reduces with age which could interfere with the SSVEP.



There was therefore a need to establish this subject specific threshold for the classification stage in order to decrease the overall probability of misclassification.

The training or calibration stage of the application required the subject to attend to each stimulus for a period typically no longer than 30 seconds. This provided the system with sustained periods of attention to each visual stimulus to facilitate the calibration of the optimum threshold for the feature. Figure 5-13 depicts the signal acquisition and processing graphic user interface (GUI) for an administrator to control during training. The analog linear slider bar that is visible on the bottom shows the feature value for the most recent EEG data (averaged value for three 1 s segments). This can be viewed by the administrator to visualize how the EEG and resulting feature are responding to a user's control attempt.

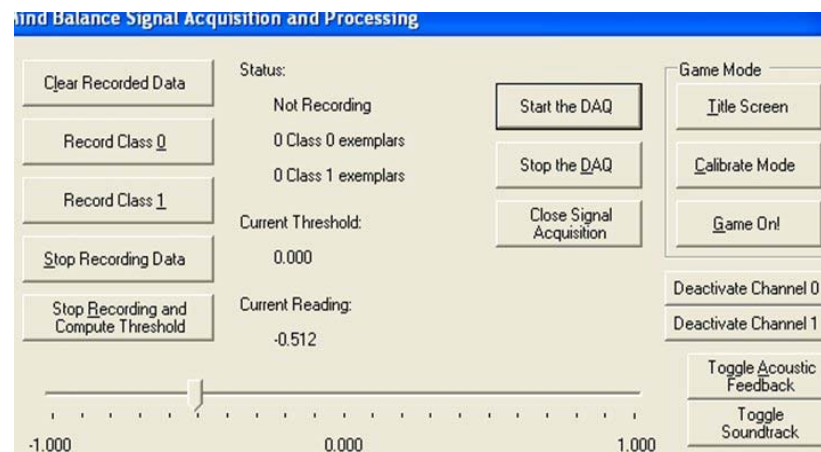


Figure 5-13: Signal Acquisition and Processing GUI that controls calibration and gaming modes

Due to the variability of the classification threshold from subject to subject, it was found that the game performance similarly varied without the inclusion of the threshold calibration stage. Classification was dramatically improved for some subjects through its use.

#### 5.4. Real-time game development

This section highlights the programming and graphic interface framework behind the real-time implementation of the BCI controlled video game application. The video game as described in section 5.3.2 requires a sophisticated graphical and signal processing footwork for real-time implementation. There are two important criteria to the real-time implementation. The first is that the flickering visual stimuli must be reliably presented at the set frequencies in order to correctly detect the SSVEP and the resulting control command associated with that frequency. To this end, the flickering stimuli must be rendered at least a consistent 60 frames-per-second. Secondly, the



signal processing of the continuous EEG signals as shown in Figure 5-6 and Figure 5-12 must be efficiently performed to offer real-time control within the gaming environment. The C# programming language as part of the .NET framework facilitates rapid and efficient implementation of these needs.

In order to further expedite application development and decouple the signal acquisition and processing steps from the actual game play, we used the Sponge signal processing framework to offload signal processing to another PC. On the signal acquisition PC, the electrical signals are acquired from the electrodes and the visual attention frequency feature is extracted. Then, the simple 1-D feature is sent over the network to the computer controlling the animated Mawg character and rendering the Mind Balance gaming environment.

#### **5.4.1. C# and the .NET framework**

The .NET platform is a development framework that provides a new way to create Windows applications. It goes beyond traditional Windows programming to facilitate creating web applications quickly and easily. The framework specifies how .NET programming constructs such as intrinsic types, classes, and interfaces are implemented. The goal of C# is to provide a simple, object-oriented, Internet-centric, high-performance language for .NET development [203]. It includes all the support for structured, component-based, object-oriented programming that one expects of a modern language built on the shoulders of C++ and Java. The C# language can be used to develop three types of applications; Console applications, which display no graphics; Windows applications, which use the standard Windows interface and Web applications, which can be accessed with a browser. For a more detailed insight and tutorial into programming with C#, the interested reader is advised to consult the book by Liberty [203].

In relation to this study, a programming engine and platform capable of rendering detailed 3-D graphics while at the same time processing continuous EEG data to control a sprite within the game was required. Graphically impressive video games are quite demanding on computer resources. Adding the additional requirement of maintaining a consistent high frame-rate for stimulus presentation further stretches these computational demands. The C# graphics engine is capable of rendering the stimuli, together with the animated character and environment, at over 100 fps<sup>36</sup> on conventional hardware. With performance figures such as these, it would certainly be possible to perform signal acquisition and processing on the same PC that is rendering the graphics. The signal processing requirements of the feature extraction and classification stages are relatively undemanding and thus can be easily implemented in C#.

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<sup>36</sup> fps: Frames per second

## 5.5. Results and performance

This section presents the results and performance metrics for this study. The first stage involved an investigation to determine the optimum experimental conditions to elicit clearly distinguishable SSVEPs during attention to one stimulus over another. It was empirically found that the ideal stimuli were two flashing discs that flashed from yellow-to-black at 7 and 13 Hz for left and right respectively. In terms of visual angle, the discs were typically of diameter 7–10° and separation of 18–26°. The angles are guidelines to put the visual presentation in context. Subjects often moved their eyes to help with directing their complete attention to only one stimulus.

The next stage involved the feature extraction methods to characterise visual attention to a given stimulus from the EEG signals alone. As listed above in section 5.3.3, these methods were performed during the investigation stages of this study to empirically discover the optimum experimental protocol. For all five subjects, under the same aforementioned conditions, the features were extracted for the continuous recordings. These features were classified using linear discriminant analysis and employing an M-shuffle by N-fold cross validation to offer an unbiased estimate of accuracy. Table 5-1 presents the grand averaged accuracies for each feature, a combination of features 1, 2, 5 & 6 and finally a combination of them all.

Table 5-1: Classification results for various features or their combinations during the investigation stage

| Feature Combination | Mean test accuracy (%) | Test standard deviation (%) |
|---------------------|------------------------|-----------------------------|
| (1) MAXMIN          | 76.4779                | 0.1829                      |
| (2) MEAN            | 85.3553                | 0.1520                      |
| (3) STD             | 76.0350                | 0.1754                      |
| (4) MAX             | 83.3883                | 0.1539                      |
| (5) Pt_Ratio        | 88.7024                | 0.1194                      |
| (6) Pt_Diff         | 87.4253                | 0.1411                      |
| (1), (2), (5) ,(6)  | 89.8867                | 0.1737                      |
| All: (1) – (6)      | 89.9279                | 0.2318                      |

Figure 5-14 represents the distribution plots for various features in a matrix grid. The histograms of each feature are represented along the diagonal cells in the form of a 2-D distribution for both classes. The off-diagonal cells represent the distribution of the features relative to each other in the form of 2-D scatter plots. The tight diagonally linear scatter plots show the features *MAXMIN* and *STD* (1, 3) are highly correlated. This suggests that they both contain similar information. Due to the redundant information, inclusion of both will only add additional

noise and could decrease classification performance. Similarly for the features *MEAN* and *MAX* (2, 4). The ideal combination between the features would require the redundant features to be left out, hence the investigation in Table 5-1 of features 1, 2, 5 and 6 together. Figure 5-14 shows that the *Pt\_Ratio* and *Pt\_Diff* features, which are themselves quite correlated, discriminate most between the two control classes. Based on the performance of the *Pt\_Ratio* feature and the little improvement offered with the addition of other features, it was decided to use just the single dimension feature and employ a threshold based classifier. By not employing LDA as the classifier, it alleviated the computational needs on the classification task.

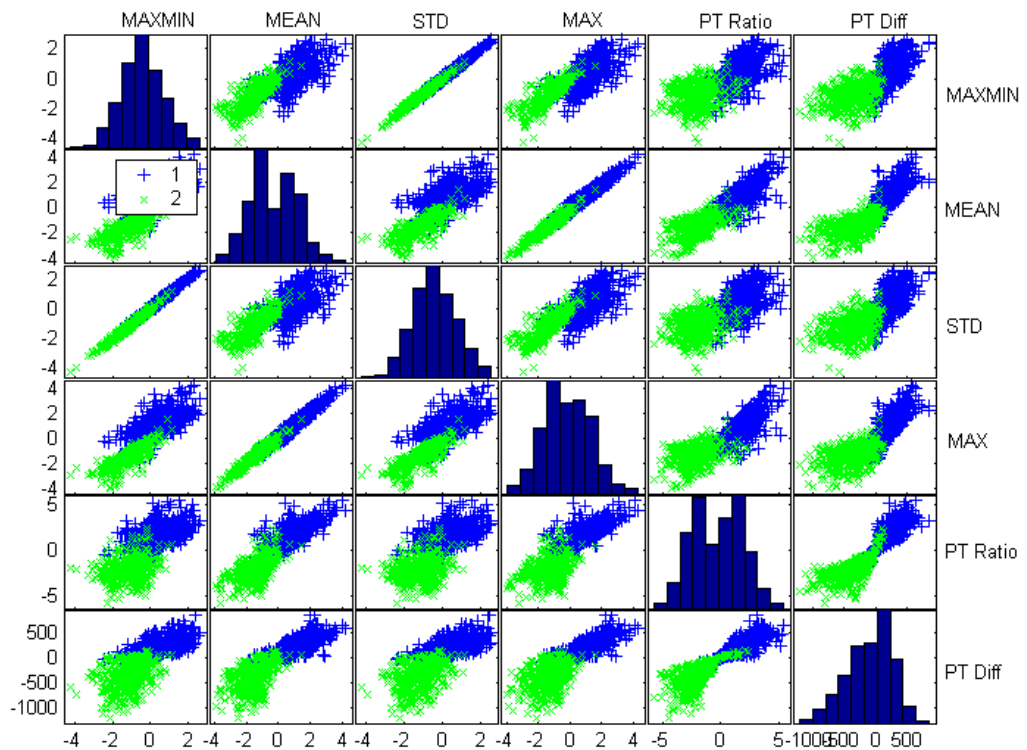


Figure 5-14: Distribution plots for various features with themselves (diagonal cells) in the form of 1-D histograms and with other features (off diagonal cells) in the form of 2-D scatter plots

Figure 5-15 shows the *Pt\_Ratio* feature value for two continuous sessions while attending a low frequency and high frequency stimulus separately. The mean feature values for each run are clearly distinguishable. The mid point that would be suggestive of the ideal classification threshold is noticeably located below 0 (approximately -0.3). This can be better viewed from the histogram in Figure 5-16. This confirmed the need to train the classifier in order to obtain the threshold that will offer optimum accuracy.

The online experimentation of the finished gaming application performed extremely well with all the subjects who participated capable of controlling the character Mawg by either ensuring his safe passage across the tightrope and completing the game or forcing him to an early grave.

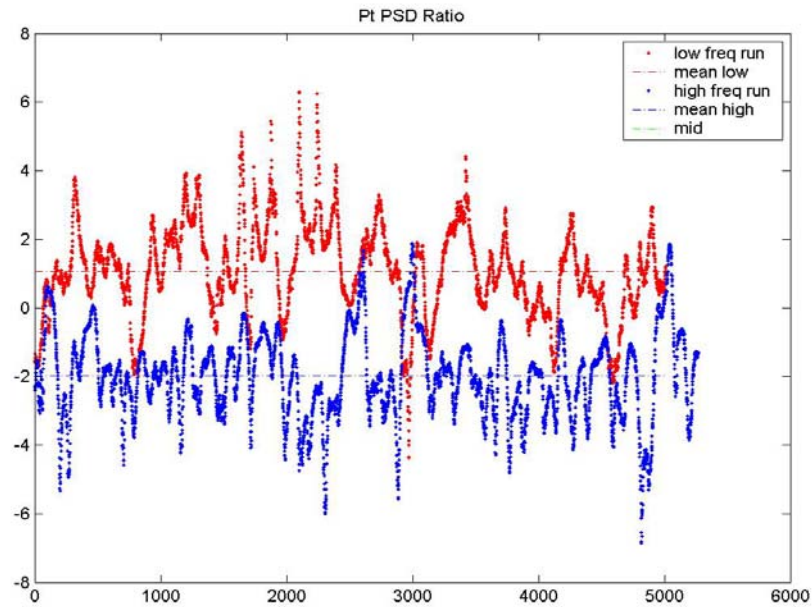


Figure 5-15: Plot of the Pt PSD Ratio for F1/F2 during attention to the low frequency stimulus (red) and high frequency stimulus (blue) in different runs. It can be seen that the former is predominantly greater than one while the latter is predominantly less than 1 one.

## 5.6. Discussion

This section is presented in three parts. Firstly it analyses the success of this study by reviewing the results and performance of the finished BCI gaming system. The second discusses some interesting findings uncovered during this study. Finally, the future potential of this BCI gaming framework is discussed, particularly focusing on areas of improvement for the Mind Balance game to offer a greater gaming experience and gain insight into the effects of biofeedback.

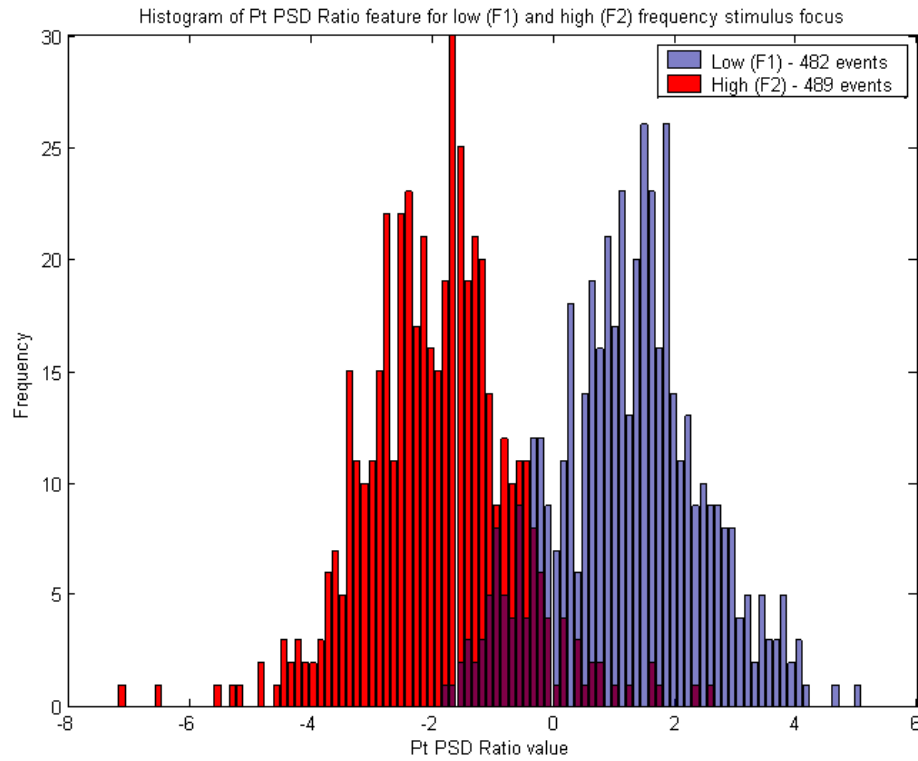


Figure 5-16: Histogram of Pt PSD ratio feature of F1/F2 during visual attention to low frequency stimulus F1 (blue) and high frequency F2 (red)

### 5.6.1. Performance analysis

The ease and accuracy of the online BCI implementation hinged on the efficient and robust feature extraction methods of the SSVEPs. The *Pt\_Ratio* feature, log of the power ratio at the two stimulation rates, was proven in the investigation stage to be more than adequate for distinguishing between the two classes by offering 82.7% accuracy across all subjects for the entire range of continuous data acquired. The later adjustment to average the last three one second EEG segments spanning 600ms and then inputting that to the threshold classifier further improved accuracy to 87%. The realisation that the classifier threshold for this feature was not typically zero and in fact varied between subjects, inspired the addition of the classifier training stage. Through its use, online accuracy moved closer to 90%. The online performance metric focused on the participants' ability to control the animated character Mawg. Every subject who took part successfully completed the game by ensuring his safe passage across the tightrope. Very few subjects, unless intentionally doing so, were unable to control Mawg after the first degree of imbalance but ultimately everyone prevented him from falling. It is worth mentioning that certain subjects

playing devil's advocate intentionally managed to throw the character more quickly from the tightrope by attending to the wrong stimulus (same side as which the character is falling).

In summary, the gaming application was an enormous success at the open day whereby participant's flawlessly controlled the character but more importantly enjoyed the gaming experience.

### 5.6.2. Interesting findings

During the investigatory stages of this study, some interesting findings resulted from experimentation and investigation. These can be summarised as follows:

- 1) The dominant SSVEP produces a sharp and precise frequency peak that is equal to the attended stimulation rate.
- 2) 7 Hz stimulus generated a greater parasitic SSVEP than the 13 Hz stimulus.
- 3) Hemispheric bias of visual cortex activity related to contra-lateral spatial visual attention.
- 4) Magnitude of the SSVEP response to the 13 Hz stimulus was greater than the 7Hz stimulus
- 5) Not windowing the EEG segments yielded on overall improvement of 5 % accuracy across all subjects for classifying the attended stimulus from 1s segments of continuous EEG data.

Refer to Figure 5-4 for the grand ensemble averaged frequency power estimate across all subjects in relation to the discursive expansion of the above points.

(1) It was found that the dominant frequency in an SSVEP occurs very precisely at the frequency with which the attended visual stimulus flickers. When the EEG data was zero-padded to 2048 (interpolation) yielding an estimated frequency resolution of 0.125 Hz, it was observed that even one FFT sample point either side of the attended stimulation frequency would result in significantly missing most of the power that the nearby SSVEP peak actually contained. In some cases, it was close to half the actual power allowing for the power of the SSVEP associated with the unattended stimulus to dominate and potentially lead to a misclassification. Care is needed in the feature extraction stage with high frequency resolution to correctly identify the FFT index of the peak associated with the attended stimulus. Despite the limited range for selecting the stimulation rates as discussed earlier, the precision and sharpness of the SSVEP frequency content clearly highlights the potential of using a SSVEP based BCI system with a lot more stimuli with closely packed stimulation rates to offer higher information transfer rates.

(2) It was found that the parasitic presence of an SSVEP related to the unattended stimuli was more prevalent for the 7 Hz than the 13 Hz stimulus, i.e. while attending to the

stimulus flashing at 13 Hz the slower stimulus of 7 Hz had a greater parasitic effect than in the reverse case. It was strangely found that the parasitically induced unattended SSVEP for the 7 Hz had a spectral peak on average at a lower frequency than when it is being attended (6.3 compared to 6.725 Hz).

(3) It is well known that the functionality of the left side of the body affects the right hemisphere of the brain and vice-versa (except for the olfactory senses). Similarly for the occipital lobe with the generation of VEPs or SSVEPs, a visual stimulus change on one side of ones field of view has a greater affect on the contra-lateral side of the occipital lobe. For example, a stimulus in the right hemi field generates more brain activity on the left side than the right and subsequently the recorded activity difference at O1 and O2 respectively. There was a greater difference between O1 and O2 for the SSVEP response to the 13 Hz stimulus (where O1 was almost double that of O2) compared with the 7 Hz one (where O1 and O2 were similar). To remove any bias from knowing what stimulation rate is associated with a stimulus on a given side of the subjects' field of view, the spectral estimate for the EEG segments from O1 and O2 were averaged. It also helps cut the feature vector dimensionality requirements in half.

(4) The magnitude of the SSVEP response to the 13 Hz stimulus is much greater than the 7 Hz case. It was found to be typically double. This posed the question: 'is the relative magnitude of the SSVEP response associated with the chosen stimulation frequency and is it in fact the case that the greater the frequency the bigger the response?' It is the author's opinion that this is probably not the case and it is more closely linked with the non-linear superposition of repetitive VEP components that amass to the SSVEP. It was noticed that the harmonics of the 7 (6.725) Hz frequency could be clearly distinguished at 13.45 and 20.175 Hz. This was not as visible for the 13 (12.85) Hz stimulus.

(5) It was found that when the EEG segments were not windowed that the overall accuracy of the system improved by 5 % across all subjects. We compared the effect of windowing and not windowing the continuous EEG on the power spectral estimate averaged across an entire session. The SSVEP for the attended stimulus had greater magnitude at the associated stimulation frequency for the unwindowed EEG data compared with the Hamming windowed case. In review, windowing prevents the edge effects caused by discontinuities that occur at the start and end of a segment of continuous data. When converted into the frequency domain by means of an FFT, these sharp step-like discontinuities introduce high frequency components and their harmonics into the resulting overall spectral estimate. This is conventionally undesirable. In the case of the feature extraction methods employed within this study whereby a power estimate at only two specific frequencies (F1, F2) was required, windowing would appear unnecessary. This requires the assumption that the additional frequency components introduced by the discontinuities do not

occur at either of the stimulation frequencies (F1 or F2). To remove the discontinuities, windowing has the effect of decreasing the variance in the start and end of the segment of data while at the same time preserving the frequency content. If the segment of data has a dominant frequency throughout the segment, as would be prevalent during this experiment for an SSVEP, windowing

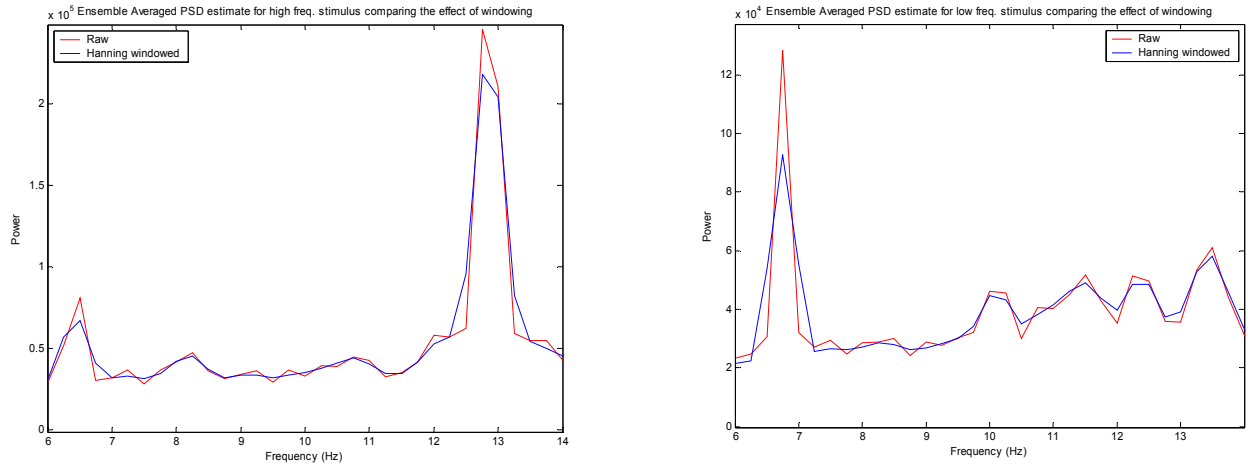


Figure 5-17: The effects of windowing the segments of continuous EEG on the power spectral estimate. It can be seen that the attended SSVEP has a greater response for the raw unwindowed case

would decrease the relative power at the start and end associated with that dominant frequency. It is in the author's opinion that this could account for the decrease in relative power at the attended stimulus frequency for the windowed case as can be seen in Figure 5-17. Assuming that the SSVEP can be represented by a single frequency sinusoid (~13 Hz), the effect of windowing on a similarly created spectral estimate was investigated. It involved taking 256 samples of the sinusoid, zero-padding to 1024 and then taking the square of the absolute of the FFT. It confirmed that windowing reduces the sharpness and peak amplitude of the spectral estimate for the dominant frequency as can be seen in Figure 5-18.

### 5.6.3. Future work

This intention of this study was to develop the BCI framework that could be extended to offer improved more natural and involving control. It was envisaged that this test bed would facilitate more rapid investigations into other neuro-control mechanisms and the effects of various forms of biofeedback.



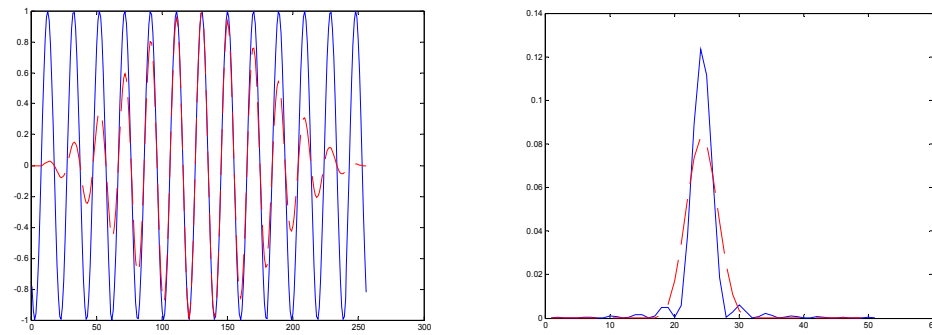


Figure 5-18: Comparison of windowed (blue) and unwindowed (red) spectral estimate for a single frequency sinusoid. The time and frequency domain are represented in the left and right graphs respectively. The unwindowed has greater power at the given frequency than the windowed case.

The figures of merit for any BCI are speed, accuracy and usability. The first two are described under the same category of information transfer rate capability which is the ultimate goal from the point of view of an alternative communication medium for locked-in patients. From a computer gaming application, the ease of interaction, user friendliness and the engaging use of biofeedback would be of equal importance in order to ensure an enjoyable gaming experience. The use of games in a rehabilitative context, as is the specialty of the Mind Games team, must grab the interest of the patient, particularly seeing as most rehabilitation sessions require the repetition of tedious exercises and may involve children.

The hopes for future development of this project was to extend the game with the additional controls of offering the forward and reverse control of the character as opposed to simply shifting his balance. This would require four visual stimuli of different flashing rates. Utilising the power ratio feature for all frequency combinations would result in a feature vector of dimension 6 thus requiring the use of multi dimensional classification methods such as LDA. This would offer the participant much more control over the character and hopefully as a result be more engaging. It was hoped that one could introduce a sense of progressive achievement by introducing levels of increasing difficulty. This would require an unresponsive band that separates the functional classes' distributions and widens with the progressive level. Therefore as the levels advance, the participant would be required to be more attentive to the desired control stimulus in order for the system to initiate the control. This could hopefully be used in a rehabilitative manner for patients suffering from attention deficit hyperactivity disorder (ADHD) to encourage better attention and focus. The gaming environment would offer the rewarding sense of achievement associated with progressing to further levels.

Having explored the full potential of this system using SSVEPs, it was hoped that other neuromechanisms such as the imagined limb movement paradigm as discussed earlier in chapter 4

could be investigated using the same gaming framework. Although MRPs are more difficult to elicit on a single-trial basis, it would bring to the game a more natural and involving method of exerting control.

### 5.7. Summary and Conclusion

This study successfully achieved the goal of employing a BCI system to offer real-time control within an immersive computer game application. The use of the SSVEPs in the multiple visual stimuli selective attention paradigm is commonly used as an input control in the area of BCI design. The power spectral correlate of the EEG activity with the attended visual stimulus, i.e. the fact that the generated SSVEPs have a dominant frequency component at the stimulation rate, facilitates the use of simple feature extraction and classification methods. The features concentrate on very specific frequencies associated with the stimuli and hence are very robust on a single trial basis amidst background EEG (acts as white noise). No such easily distinguishable characteristic exists with other ERPs such as the readiness or pre-motor movement potential as discussed in Study 1 (Chapter 4). In addition, the use of SSVEPs is computationally efficient and requires limited training for the purposes of online implementation. This BCI approach is capable of offering relatively high transfer rates compared with other implemented systems as quantified by Ming et al. [100].

The use of SSVEP based BCI systems is not as straightforward for completely locked-in patients who do not have the mobility of their eyes. The inability to move ones eyes seriously inhibits the ability to direct ones attention and focus on a particular stimulus over another. This would prevent the dominance of the desired SSVEP and ultimately will result in a control misclassification. Paradoxically for an SSVEP based BCI system, if a subject has the mobility of his eyes there exists eye-tracking means of communication with better speed, accuracy and usability than the SSVEP based BCI approach. Despite the wide application of SSVEPs in BCI designs, there remains much to understand regarding the dynamics of SSVEP creation.

It is with this in mind that the research collaboration hopes to use alternative neuromechanisms such as the MRP associated with imagined limb movement as the means to offer the control. The ultimate success of this study has been the development of a complete online BCI gaming framework with which to further investigate the electrophysiological functionality of the brain and develop more exciting applications.

## Chapter 6      Conclusions

The author hopes that this thesis will guide further BCI research and development within the DSP laboratory at UCD. This chapter firstly summarises the conclusions of the MRP and SSVEP based BCI studies as highlighted in sections 4.7 and 5.7 respectively. It then addresses the future of BCI technology and focuses on some key areas that require further research attention.

### 6.1.      Study 1 – MRP based BCI system

This study successfully submitted an entry into the BCI Competition 2003 with the goal of optimally identifying upcoming left or right finger movements from the EEG alone. A self-paced typing experimental paradigm was used within the laboratory in UCD to gather more experimental data to help in the training of a classifier. The data consisted of EEG recordings from the C3 and C4 electrode positions. The continuous recordings were segmented into epochs prior to the finger press. Three feature extraction methods were employed separately to establish distinguishable features that would identify with either a left or right movement. These included parametric modelling methods such as AR and ARX which yielded a performance accuracy of 51% and 64% on average. Frequency based features included spectral power band and STFT estimates which yielded classification accuracies of 69% and 66% respectively. It is worth noting that the spectral power band method used 8 channels from electrodes placed near motor cortex. LDA was uniformly employed throughout in conjunction with cross-fold validation.

The author is sceptical about the ability of AR and ARX methods to identify and more importantly distinguish the low SNR (~30dB) MRPs. Frequency and time-frequency based features, such as ERD/ERS methods, derived from a large montage of electrodes offers the most promising means of identifying actual and imagined limb movement on a single trial. There exist alternative BCI approaches that can offer more robust communication with higher transfer rates, such as in study 2.

### 6.2.      Study 2 – SSVEP based BCI system

This study successfully implemented an online BCI system to offer control within an immersive video gaming application. The robust nature of the control related brain activity feature and the adaptive classifier offered consistently good performance (>95% classification accuracy). The computationally efficient signal processing (feature extraction and classification) reduces the demands on the host computer for an online implementation. Further research needs to be carried

out to study the effects of the audio-visual neurofeedback offered by this BCI system. Video gaming is a billion dollar industry. There is continuous research into new methods of interaction or playing these games that includes joysticks, dance mats, cycling machines, skateboards, skis etc. The BCI system in this study demonstrated an innovative method of controlling a video game. This technology could provide an additional or replacement control input for the widespread computer gaming community. Further development of BCI technology could result in tapping into this lucrative industry.

The big discussion in the BCI research community is the level of dependence (as discussed in section 3.61 point 5) of SSVEP systems. Many BCI researchers regard SSVEP systems as ‘dependent’, i.e. the user must have the ability to move their eyes to successfully utilize the system. As there are many eye tracking communication systems that offer far higher information transfer rates than BCI systems, the future of SSVEP based systems is often dismissed. Others claim that it is possible to direct ones visual attention at different stimuli in the field of view without eye movement. Muller and Hillyard [361, 362] and Gao [43] both suggest, but do not substantiate, that subjects can modulate SSVEP amplitude without such gaze shifting.

SSVEP based BCI systems currently offer the highest information transfer rates (~27 bits/min Tsinghua BCI Group [100,116]). It is this author’s opinion that SSVEP BCI systems do not require gaze control but further research is needed with locked-in patients to qualify this. There may however be some adverse effects to ‘covert’ (out-of-focus) selective attention (i.e. without gaze shifting) such as producing a strain on the eyes that could result in headaches. The continued research by Lalor et al. further investigates the use of SSVEPs not only in the field of BCI research but also in the area of neurological rehabilitation.

### **6.3. Future of BCI technology**

Current BCI systems can offer transfer rates of up to 25 bits/min. This is very limited in comparison to conventional human-computer communication mediums. The innovative means of communicating via thoughts alone has generated much research and media interest despite the relatively poor information transfer capabilities. For locked-in subjects, this technology offers the only possible means of communication. The social recognition of the needs of these people is the biggest driving factor behind this field of research.

The field of BCI research is in its relative infancy compared with other communication technologies such as internet, television, and mobile communications. In order for it to mature into an established research field there is a need for the BCI research community to take the system implementation stage out of the laboratory and integrate it into real-life situations. Only the

Tübingen group's TTD system, Kennedy's implanted electrode system and the Graz group's BCI have been tested to the author's knowledge outside of the laboratory.

To facilitate the further development of this technology in the future, the author has highlighted a few key issues which must be addressed. These are discussed as follows:

**1) *Improved understanding of cognitive neurophysiology***

Further investigation into the cognitive and psychological functionality of the human brain can develop a better understanding that can be exploited to improve BCI systems. It is also important to research the extent to which EEG activity control depends on the normal internal CNS structure and function.

**2) *More stable, convenient and affordable acquisition process***

The development of affordable, low-maintenance, less-invasive, and robust acquisition systems will be required for the deployment of this technology to the public. For the future progression of this technology, it is crucial that these systems can be set-up, maintained and cleaned by the general public without the need for specialized or trained staff. It requires the involvement of hardware specialists to attain these goals. Media Lab Europe has recently patented a wireless electrode cap, *Cerebus*, to facilitate convenient acquisition for future applications targeted at the general population. For the present however, the systems must first be of high quality and robust to facilitate the optimum recording of EEG activity for BCI input signals.

**3) *Improved identification and elimination of artifacts:***

Although the area of artifact removal is ripe, very few methods have been employed by current BCI implementations to eliminate artifacts. Most of the investigations performed to date have been performed offline due to the computational overheads. Artifacts are however a dramatic problem for real-time BCI performance in real-life scenarios. Further investigation is needed to arrive at methods of successfully removing artifacts such as EOG and EMG online and without contaminating the EEG signals or the need to discard single-trials. This requires a significant involvement from signal processors to develop the appropriate real-time algorithms.

**4) *Improved identification of features and the development of translation algorithms***

Once an in-depth understanding of the neurophysiological origins of the controllable EEG activity has been established, it is essential to derive signal features to robustly identify and distinguish the command-related activity. It is important to establish the EEG activity that users are best able to control, whether it is evoked potentials, spontaneous rhythms, or single-neuron firing rates. The translation of these features into a device command underpins the success of a BCI system. Adaptive algorithms are necessary in a BCI because the signals recorded change over time due to

technical, biological and psychological factors. This is the kernel of the BCI design challenge that requires the innovative involvement of engineers.

**5) *Development of standards to facilitate performance comparison***

It is important to adopt standard methods for evaluating short-term and long-term BCI performance to facilitate system comparisons within the community. To provide reliable and useful systems for consumers, BCI methods and applications should be systematically evaluated in target populations. Objective measurements are required to establish how successful individuals with various disabilities actually employ a particular technology and to what extent the technology has contributed to their communication and control abilities but more importantly on their quality of life.

Setting standards can however have an adverse effect on this line of research. An inevitable trade-off exists between encouraging innovation and finding an efficient method to compare systems. Since BCI technology is an early stage of development it is critical that the community does not constrict innovative advances by establishing too many standards and model frameworks. However, the development of standard data sets for the comparison of processing methods and algorithms is invaluable in the author's opinion. Collaborative studies such as the BCI competitions organized by the international BCI research community [141,142,146] is an excellent idea to encourage innovative approaches to solving the signal processing challenges involved in BCI design..

Although global standards may be useful in the future when the BCI field moves from exploration to application driven, the present state of BCI research requires the investigation of many alternative approaches to BCI design. It is too early to standardize BCI approaches as investigators need the flexibility and innovation to be free to conceptualize in many different ways.

**6) *Development of applications to optimize the use of the limited bandwidth***

We need to maximize bandwidth and to optimize how the limited bandwidth can be optimally used. Similar to the system-specific applications developed for low-bandwidth technology such as mobile phones, there is a need to develop applications tailored to the target population (currently communication and control devices for the severely disabled) that optimally utilizes the available bandwidth. Applications such as a spelling program with predictive word completion can make efficient use of the bandwidth and improve performance.

**7) *Study of the psychological and behavioural effects of BCI systems on user***

Research into the development of behavioural methods that can help users to gain and maintain feature control would be extremely valuable. A deeper understanding of the psychological and

behavioural affects of utilising a BCI system on the user would more importantly give an insight into the origins of the EEG control feature and the extent to which it can be independent of neuromuscular control.

#### **8) *Extension of goals to promote diverse application development***

The goal of current BCI technology focuses on developing a replacement communication medium for the severely disabled. If the systems can manage to boost the bit-rates then applications targeted at the widespread population such as multimedia, behaviour monitoring and video gaming applications may come to fruition. It is important that the community distinguish between the goal of aiding people with disabilities and the development of BCI systems and related applications. The undermining of BCI technology by incorporating it with partial muscular means of communication to aid the disabled will ultimately hinder progress but should remain a topic of research for the rehabilitation engineering field. The prime direction for BCI research for the present and near future will remain the improvement of the communication and control capabilities for people with severe neuromuscular disorders.

#### **9) *Recognition as an interdisciplinary challenge***

BCI research is a multidisciplinary endeavour that requires a broad base of skills from fields such as neuroscience, clinical rehabilitation, psychology, computer science, engineering and mathematics. To expedite the development of BCI technology requires the successful collaboration and promulgation of research from these disciplines. This realization has encouraged the establishment of broad-skill based BCI research groups, such as the Graz BCI group for example. The emphasis should be put more on peer-reviewed research publications and specialized workshops (e.g. [58,125]) to disseminate knowledge amidst the research community and less on sensationalised media hype.

### ***Concluding remarks...***

Several groups have now shown that rats and monkeys can learn 3-D robotic control from the invasive recordings of groups of motor neurons [204,205]. A 2-D control system was demonstrated with scalp recorded mu rhythms in [69] but the degrees of freedom required for adaptive automation of cognitive tasks, prosthetics and complex robots was reported to lie beyond the range of scalp recorded EEG activity and current BCI methodologies.

As BCI technology is in its infancy, no one neuromechanism or approach stands out as the most likely to succeed. In most cases the different BCI approaches are tailored for different needs and intended applications. It is the author's opinion that the biggest hurdle for making a dramatic

breakthrough in this field no longer resides with the signal processing. The author believes that a better understanding of the neurophysiology and the development of novel methods for acquiring the neuronal signals offers a greater potential of dramatically improving the information transfer rates compared with manipulating or interpreting the conventionally acquired signals.

As the field develops it is hoped that transfer capabilities and user friendliness will improve dramatically to open the door for innovative applications targeted not only at individuals with neuromuscular impairments but also the general population. It is the hope of the author that some day in his lifetime, one would be capable of engaging in multimedia applications such as internet browsing or computer gaming via this technology. Can this technology advance to the stages where our brain signals can be decoded to the extent that this medium may offer a means of telepathy? Will it greatly benefit society? Although the author is extremely dubious of BCI technology extending this far, history has a terrible habit of exposing narrow-minds in science and hence the author concludes his work in this thesis with an optimistic view of the future of this technology.



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## Appendix A: List of BCI research groups worldwide

| No. | BCI Research Group and location   | Group Director / Principal Researcher     |
|-----|---|---|
| 1.  | Arizona State University, Neural Control Lab, AZ  | S. Tillery, D. Taylor                     |
| 2.  | Brown University, Providence, RI  | Black, J. Donaghue                        |
| 3.  | California Institute of Technology, Pasadena, CA  | M. Mojarradi                              |
| 4.  | Colorado State University, Fort Collins, CO   | C. Anderson                               |
| 5.  | Columbia University, New York   | L. Parra                                  |
| 6.  | DuPont Hospital for Children, University of Delaware  | Polikoff J.                               |
| 7.  | <b>EPFL, Federal Institute of Technology, Lausanne, Switzerland</b>   | <b>T. Ebrahimi, J-M Vesin</b>             |
| 8.  | Florida International University  | A. Barretto                               |
| 9.  | Georgia State University, Atlanta, GA   | M. Moore                                  |
| 10. | <b>Graz University of Technology, Institute for Biomedical Engineering, Department for Medical Informatics, Graz, Austria</b> | <b>G. Pfurtscheller, C. Neuper</b>        |
| 11. | Helsinki University of Technologie, Cognitive Science and Technology, Finland   | Mikko Sams                                |
| 12. | IDIAP, Dalle Molle Institute for Perceptual Artificial Intelligence, Switzerland  | Samy Bengio                               |
| 13. | <b>Intelligent Data Analysis Group, Fraunhofer-FIRST, Berlin, Germany</b>   | <b>K.R. Müller</b>                        |
| 14. | <b>Joint Research Centre of the EU, Ispra, Italy.</b>   | <b>J. del R. Millan</b>                   |
| 15. | NASA Ames Research Center, Moffett Field, CA  | L. J. Trejo                               |
| 16. | National Institute of Nervous System Disorders, Bethesda, MD  | W. J. Heetderks                           |
| 17. | National Chiao-Tong University, Taiwan  | Pei Chen Lo                               |
| 18. | <b>Neil Squire Foundation, Vancouver, Canada</b>  | <b>G. Birch, S. Mason</b>                 |
| 19. | Neuroprosthesis Research Organisation, Brooklyn, NY   | G. Gaal                                   |
| 20. | Northwestern University and the Rehabilitation Institute of Chicago, Chicago, IL  | W. Z. Rymer                               |
| 21. | <b>Oxford University, Great Britain</b>   | <b>S. Roberts, W. Penny</b>               |
| 22. | Reed Neurological Research Center, UCLA, Los Angeles, CA  | B. Dobkin                                 |
| 23. | Rochester Institute of Technology, Rochester, NY  | J. Bayliss, D. Ballard                    |
| 24. | San Francisco Brain Research Institute and SAM Technology Inc, San Francisco, CA  | A. Gevins                                 |
| 25. | Santa Lucia Foundation, IRCCS, Rome, Italy  | F. Cincotti                               |
| 26. | SUNY Health Science Center, Brooklyn, NY  | J. Chapin                                 |
| 27. | <b>Tsinghua University, Beijing, China</b>  | <b>G. Shangkai, G. Xiaorong, M. Cheng</b> |

|            |  |                                  |
|------------|--|----------------------------------|
| 28.        | Tulane University, New Orleans, LA                                       | P. Nunez                         |
| 29.        | UCLA Computer Science Department   | J. Vidal                         |
| 30.        | University College Dublin, Ireland                                       | A. de Paor, R. Reilly            |
| <b>31.</b> | <b>University of Alberta, Edmonton, Canada</b>                           | <b>M. Polak, A. Kostov</b>       |
| 32.        | University of Bielefeld, Neuroinformatics Group, Germany                 | H. Ritter                        |
| 33.        | University of Illinois Urbana-Champaign, IL                              | E. Donchin                       |
| <b>34.</b> | <b>Univerity of Tübingen, Germany</b>                                    | <b>N. Birbaumer, A. Kübler</b>   |
| 35.        | University of California at Los Angeles, Department of Neurology, CA     | J. Pineda, B. Allison, B. Dobkin |
| 36.        | University of California San Diego, Cognitive Neuroscience Lab.          | S. Makeig, B. Allison            |
| 37.        | University of Florida, Gainesville                                       | J. Principe                      |
| 38.        | University of Geneva, FBML and CVML                                      | Pun, Michel                      |
| 39.        | University of Malaga, Advanced Human Computer Interfaces, Spain          | L. Vazquez                       |
| 40.        | University of Michigan, Ann Arbor, MI                                    | S. Levine, J. Huggins            |
| 41.        | University of Rome "Tor Vergata", Rome, Italy                            | L. Bianchi                       |
| 42.        | University of South Florida, Department of Psychology, Tampa, FL         | E. Donchin                       |
| <b>43.</b> | <b>Wadsworth Center, New York State Department of Health, Albany, NY</b> | <b>J. Wolpaw, T. Vaughan</b>     |

## Appendix B: CD contents

- SSVEP based video gaming application demonstration (Study 2 – Chapter 5)

- SSVEP paper submitted

E. Lalor, S.P. Kelly, C. Finucane, R. Smith, R. Burke, R. B. Reilly, G. McDarby – “Steady-state VEP-based Brain Computer Interface Control in an Immersive 3-D Gaming Environment ”, *Journal of Applied Digital Signal Processing – Special issue on Brain Computer Interfaces*. See Appendix. (Submitted)



## Appendix C: Collaborative approach to our work in UCD

Prof. Ian H. Robertson

Trinity College Institute of Neuroscience (TCIN)

Dr. John J. Foxe

Nathan Kline Institute (NKI) for Psychiatric Research, NY

Dr. Richard Reilly

DSP Research Group, UCD

EEG team of 6 postgrads and postdocs

Dr. Sean Connolly, Neurophysiologist,

St. Vincent's University Hospital

Dr. Gary Mc Darby

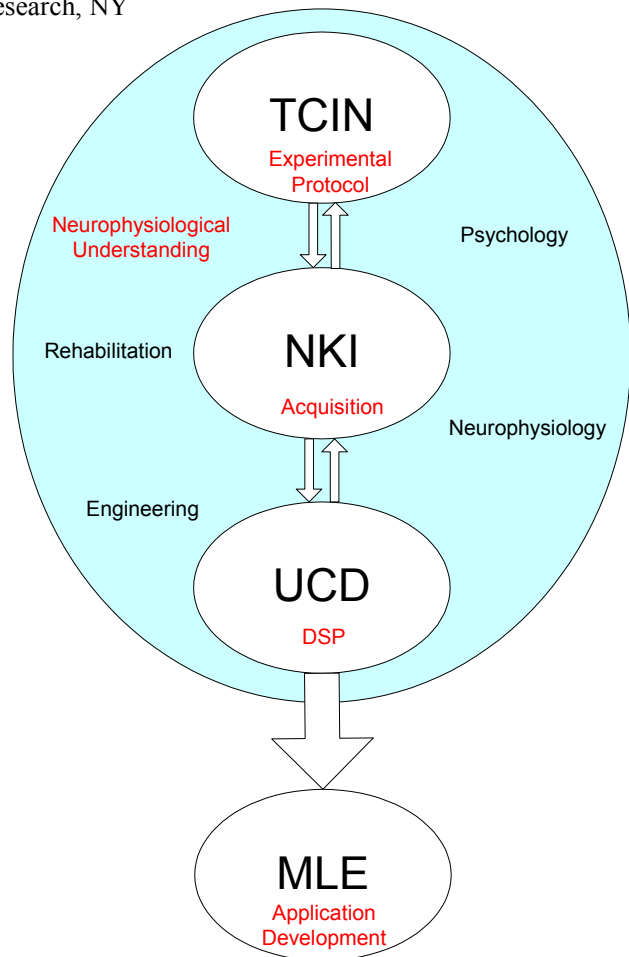
Media Lab Europe (MLE)

Dr. Nuala Brady

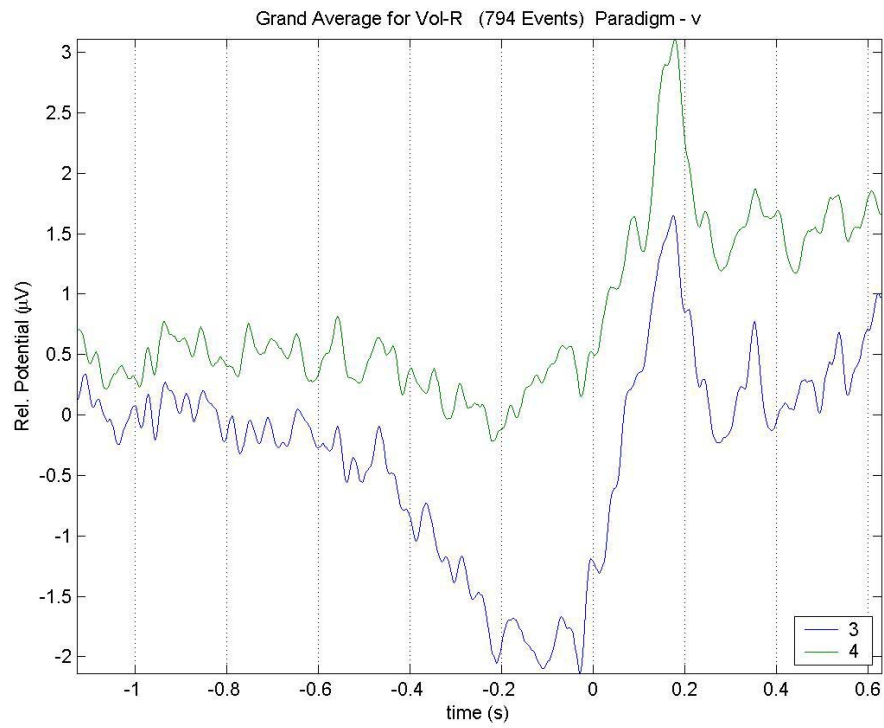
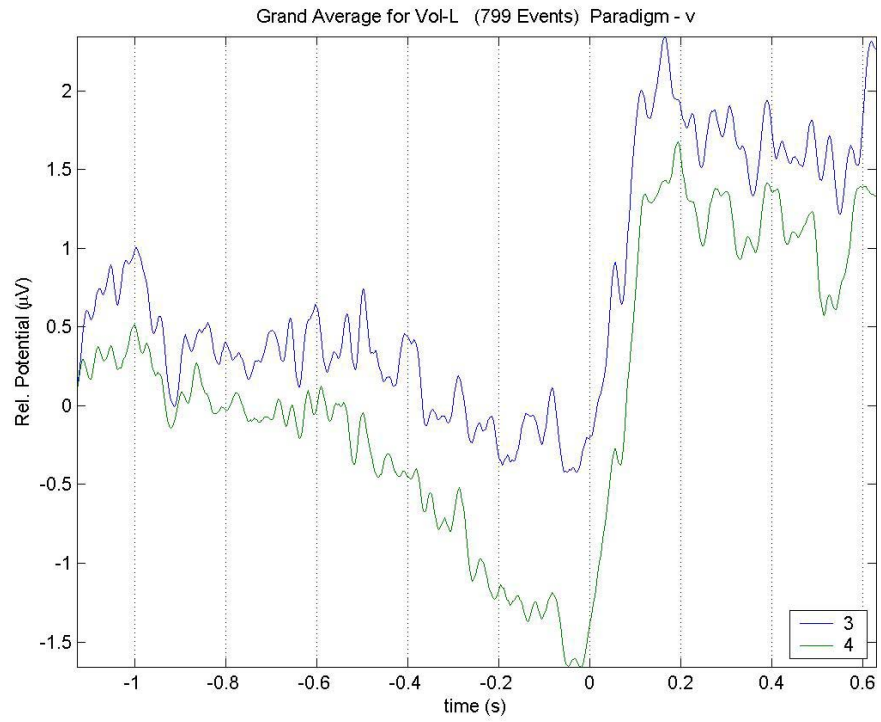
Dept. of Psychology, UCD

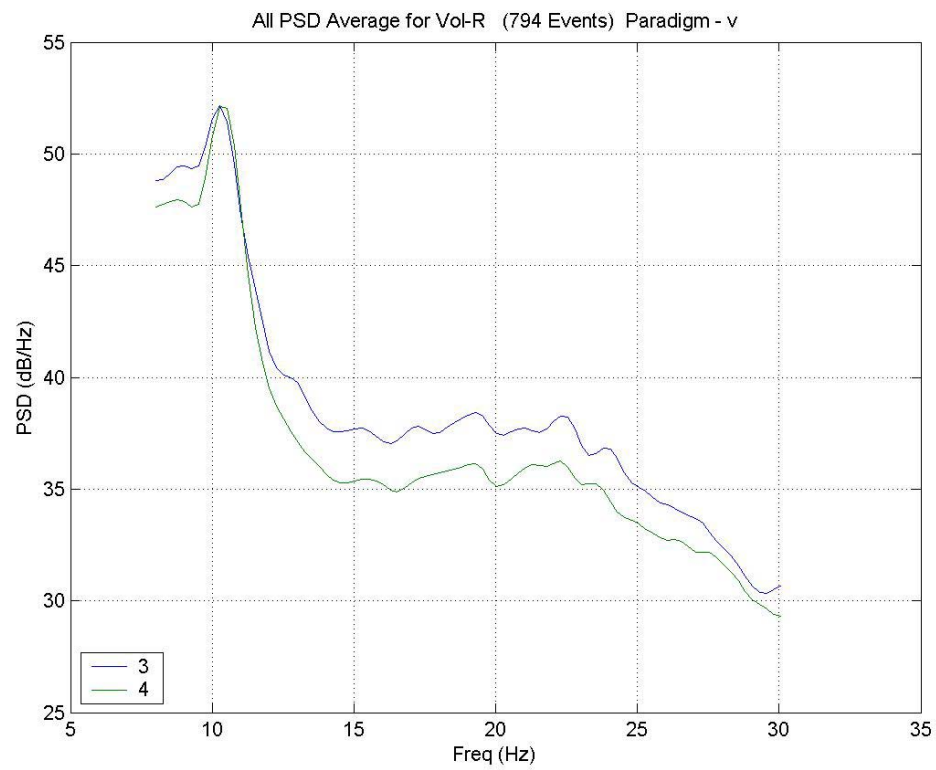
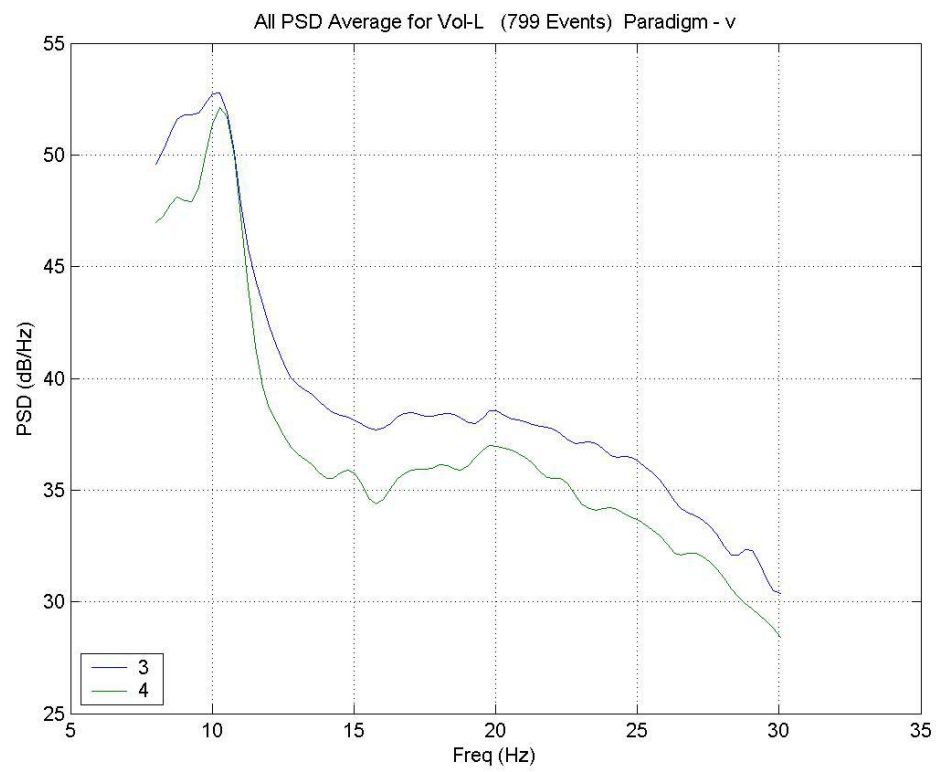
Dr. Gary Donohue

Dept. of Psychiatry, TCD

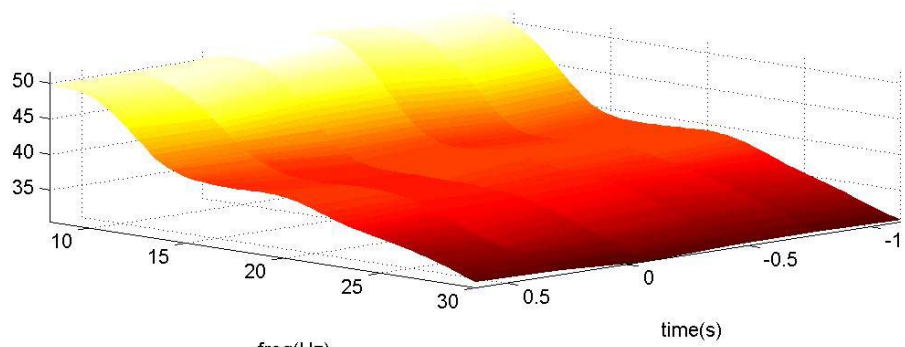


## Appendix D: Additional plots in MRP study

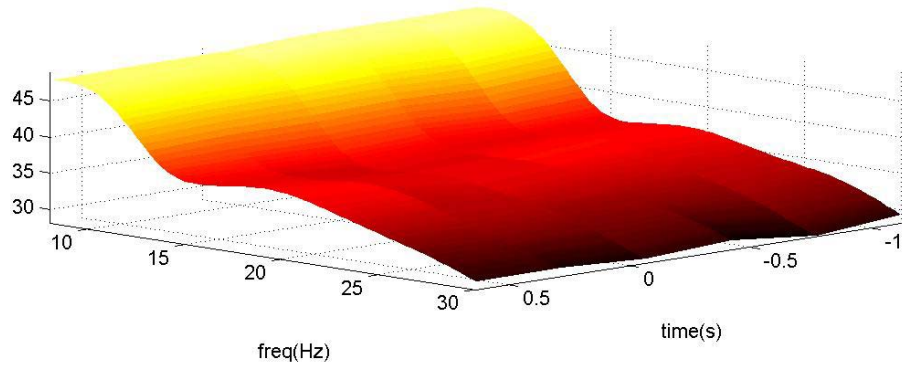




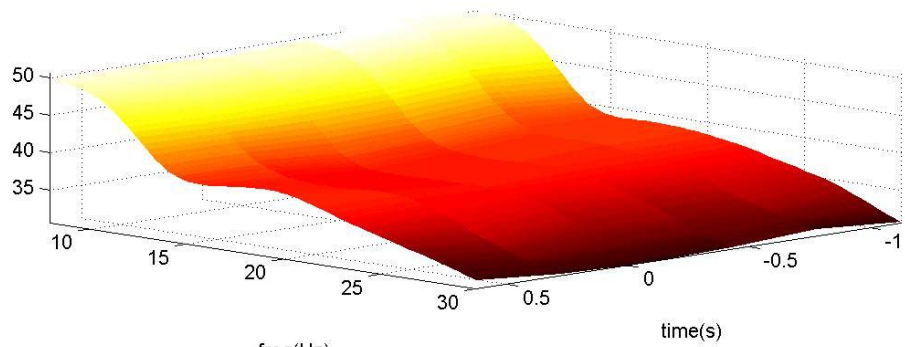
All TF Average for Vol-L @ 3 (799 Events) Paradigm - v



freq(Hz)  
All TF Average for Vol-L @ 4 (799 Events) Paradigm - v



All TF Average for Vol-R @ 3 (794 Events) Paradigm - v



freq(Hz)  
All TF Average for Vol-R @ 4 (794 Events) Paradigm - v

