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Development of a Non-Invasive Brain-Computer Interface for Neurorehabilitation

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To my Friends and Family

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Abstract

Neurological disorders, in particular Stroke, have an impact on many individuals worldwide. These individuals are often left with residual motor control in their upper limbs. Although conventional therapy can aid in recovery, it is not always accessible, and the procedures are dull for the patient. Novel methods of therapy are being developed, including Brain-Computer Interfaces (BCIs). Although BCI research has been flourishing in the past few years, most rehabilitation applications are not yet suitable for clinical practice. This is due to the fact that BCI reliability and validation has not yet been achieved, and few clinical trials have been done with BCIs. Another crucial factor, is that modern BCIs are often comprised of inconvenient hardware and software. This is a major factor of aversion from both patients and clinicians.

This Master Dissertation introduces the *EmotivBCI*: an easy to use platform for Electroencephalogram acquisition, processing and classification of sensorimotor rhythms with respect to motor action and motor imagery. The acquisition of EEG is done through 8 channels of the *Emotiv Epoc* wireless headset. Signals are pre-processed, and the 2 best combinations of channel/frequency pairs that exhibit the greatest spectral variation between the rest and action conditions are extracted for different time frames. These features are then used to build a feature matrix with 2 sets of attributes and 2 class labels. Finally the resulting feature matrix is used to train 3 different classifiers, in which the best is selected. The EmotivBCI enables users to keep record of their performances, and provides additional features to further examine training sessions. To assess the performance of the EmotivBCI, two studies were conducted with healthy individuals. The first study compares classification accuracies between two different training paradigms. The second study evaluates the progress in performance of a group of individuals after several training sessions.

Keywords: Brain-Computer Interface, Emotiv, Neurorehabilitation, Signal Processing, Feature Extraction and Classification, Stroke.

Resumo

As doenças neurológicas, em particular o acidente vascular cerebral (AVC), têm um impacto em muitos indivíduos por todo o mundo. Alguns indivíduos ficam com controlo residual dos membros superiores. A terapia convencional ajuda a recuperar algum do movimento perdido, mas nem sempre é acessível e os procedimentos são monótonos. Novos métodos de terapia estão a ser desenvolvidos, incluindo Interfaces Cérebro-Computador (BCIs). A Investigação nesta área tem vindo a aumentar nos últimos anos, mas as aplicações relacionadas com reabilitação ainda não estão adequadas para a prática clínica. As BCIs ainda não alcançaram até à data um nível aceitável de confiança, além de que poucos estudos clínicos foram conduzidos. Outro factor crucial, é que BCIs modernos são compostos por equipamento e programas complexos, causando aversão por parte dos doentes e clínicos.

Esta Dissertação de Mestrado apresenta o *EmotivBCI*: Uma plataforma prática de aquisição, processamento e classificação de sinais de electroencefalografia (EEG), baseada em ritmos senso-motores com respeito a acção motora e imagética motora. A aquisição de EEG é feita a partir de 8 canais do equipamento wireless *Emotiv Epoc*. Os sinais são pré-processados e as duas combinações do par canal/frequência que exibem a maior variação espectral entre a condição de descanso e acção são extraídas em diferentes intervalos temporais. Estas características são depois usadas para construir uma matriz com dois conjuntos de atributos e duas classes. Finalmente, a matriz é usada para treinar três classificadores diferentes, do qual o melhor é seleccionado. O EmotivBCI permite aos utilizadores manter um registo do seu desempenho e tem funções adicionais de análise. Para avaliar o desempenho do EmotivBCI foram conduzidos dois estudos com indivíduos saudáveis: o primeiro estudo compara a precisão de classificações entre dois paradigmas de treino e o segundo estudo avalia o progresso no desempenho de um grupo de indivíduos após várias sessões de treino.

Palavras-chave: Interface Cérebro-Computador, Emotiv, EEG, Neuro-reabilitação, Imagética motora, Processamento de Sinal, Extracção de características e Classificação, AVC.

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Glossary

ALS Amyotrophic Lateral Sclerosis.

BCI Brain-Computer Interface.

CNS Central Nervous System.

DT Decision Tree.

ECoG Electrocorticogram.

EEG Electroencephalogram.

EMG Electromyography.

ERD/ERS Event-Related Desynchronization/ Event-Related Synchronization.

FES Functional Electrical Stimulation.

fMRI Functional Magnetic Resonance Imaging.

MEG Magnetoencephalogram.

NB Naïve Bayes.

PNS Peripheral Nervous System.

PSD Power Spectral Density.

SCI Spinal Chord Injury.

SVM Support Vector Machine.

VR Virtual Reality.

CHAPTER 1

INTRODUCTION

1.1 Motivation and Context

In the past, the idea of carrying actions only through the power of the mind was thought of absurd, even preposterous. However, about fifty years ago, a revolutionary idea was proposed, in which brain signals could be captured to trigger actions [1]. The idea showed promise, but the equipment and technology weren't appropriate at the time to show conclusive results. It has been in the past twenty years that more attention has been drown to Brain-Computer interfaces and their applications in gaming and entertainment, but above all else in Rehabilitation [2]–[4].

A Brain-Computer Interface (BCI) is a system that enables brain activity to manipulate external devices. The range of applications of BCIs is extraordinarily wide, going all the way from leisure to rehabilitation, with hybrids of both in between [5]–[9]. The scope of this work focuses mainly on neurorehabilitation. There is a significant number of disabled people worldwide that have lost function of one limb, or the ability to walk or speak due to neurological disorders. Amyotrophic Lateral Sclerosis (ALS) and Spinal Chord Injury (SCI) are prime examples of such disorders.

This section, however, will focus on one disorder that has the greatest impact worldwide: Stroke. Moreover, conventional methods of therapy will be discussed followed by a look at the future direction of these methods. Finally, the role of BCIs in stroke rehabilitation will be addressed, including what aspects need to be improved in order to make BCIs a legitimate rehabilitation tool in the future.

1.1.1 Stroke

Stroke is the second largest cause of death in the world and is also one of the leading causes of disability in adults [10], [11]. In the United States approximately 795000 people are affected every year [12]. In Portugal, from 2007 to 2011, the record of deceased people due to stroke was over 68500 [13];

Stroke, or cerebro-vascular accident (CVA), is defined as the abrupt onset of a non convulsive and focal neurologic deficit. There is a deep categorization of stroke types, but they fall under two main ones: *Ischemic* stroke or *Hemorrhagic* stroke. Cerebral ischemia can be caused by reduction in blood flow (hypoperfusion), by blockage of a blood vessel via thrombosis or arterial embolism. In the case of hypoperfusion, when blood flow is finally restored within several seconds to a few minutes then the symptoms are said to be transient. If hypoperfusion lasts more than a few minutes then *infaction*, or death of brain tissue, can occur. Cerebral hemorrhage is characterized by the accumulation of blood within neural structures [14].

The occurrence of stroke is characterized by several risk factors, some that are fixed, others that are modified[15], [16]. Examples of fixed risk factors are:

- Old age.
- Diabetes.
- Arterial fibrillation.

Modifiable risk factors include:

- High blood pressure.
- Tobacco smoking.

One of the most common non-hemorrhagic stroke is the *middle cerebral artery* stroke, which mainly affects the upper limb. Although available rehabilitation therapies help the limb regain some function, many individuals are still left with chronic hand paralysis [17]–[19]. It can also result in speech formulation or visual impairment due to the malfunction in the brain where the stroke occurred [10], [20]. Treatment to recover lost function is termed Stroke rehabilitation. The following section will discuss some conventional techniques and procedures to rehabilitate lost limb function due to Stroke.

1.1.2 Conventional Stroke Therapy

Recovery from stroke is a rather complex process that is thought to occur through the combination of spontaneous and learning-dependent processes [21], [22]:

- Restitution: Restoration of functionality of damaged neural tissue.
- Substitution: Reorganization of neural pathways to relearn lost functions.
- Compensation: Patient improves other skills to meet demands of their environment.

Stroke recovery and treatment depend on the individual, and has to be carefully assessed by specialists. The participation in formal rehabilitative therapy has been shown to improve stroke patients' ability over time. However, not all patients have access to therapy because of geographic or socio-economic status [23]–[25]. There are different types of strokes that lead to different consequences. Patients that are unable to walk and require more human assistance and are more dependent in other self-care tasks are often admitted in hospitals. If patients have a certain degree of self-care, therapy is carried at home simply to refine the skills that can improve their functional independence at home and community where they live [21]. There are specific therapists for the different skills that need to be improved. Some of these can be physical, occupational and speech therapists [10], [23]. Their role is to promote the practice of specific tasks that are important to the recovery of the patient. They do this by setting realistic goals within the limitations of residual reflexive and voluntary neural control. Moreover, they plan a regimen of daily skills practice of progressive intensity and difficulty [23], [26].

Therapy for upper limb disabilities vary depending on severity [10]. The therapy for the hemiparetic arm or hand involves at an early stage the attempted movement of single joints, and then it proceeds to more complex, multi-joint actions [23]. Finally, the patient engages in task-specific movements, known as *shaping*, which could be the grasping of a coffee cup [23]. Another popular technique is called constraint-induced movement therapy (CIMT) [27], and it consists of restraining the unaffected limb to promote the use of the affected one. This can ultimately lead to faster and improved movement of the affected limb.

The previous mentioned interventions have shown to be efficient only in patients that have a high enough degree of residual control in their affected limbs. For patients that have very weak hand movement and control, other methods of therapy are applied. These mainly consist of the use of commercially available forearm-hand orthotic devices with functional electric stimulation that can enable the grasping of the hand or finger pinch [23], [28], [29]. Mechanical devices are currently used as a supplement to standard care, and they have shown to be beneficial [30]. However, standard therapies with equivalent intensity can achieve the same outcome, and the use of these devices is more of a luxury, since they are generally expensive [23]. Ongoing research focuses on the use of mechanical devices with other rehabilitative therapies like non-invasive brain stimulation to achieve a higher efficacy in rehabilitation of patients after stroke [23].

1.1.3 Outlook of Stroke Therapy

As mentioned before, stroke therapy is highly specialized for a given patient and the severity of his condition. The neuronal mechanisms behind stroke recovery are still poorly understood, however, research in this field is prominent. It's a matter of time until the scientific community reaches conclusive results, which will result in better rehabilitation planning and consequently in better patient recovery.

Ideally, stroke therapy should rely less on therapists, and more on technology to achieve the same end. This is mainly due to the high number of stroke patients in comparison to the limited number of therapists [23], [24], [31]. Therapy itself should also be more engaging to the patient, instead of the conventional dull exercises. Motivation and engagement have been shown to be an important aspect in recovery success [32]–[34]. Fortunately, new approaches to therapy have surfaced in the last decade that have helped face this challenges.

The following sections will address a few of the new facets of stroke therapy, namely Virtual Reality (VR), Robotics and Functional Electrical Stimulation (FES). Finally, the current, and future, role of BCIs in stroke rehabilitation will be discussed, addressing its advantages and limitations.

1.1.3.1 Virtual Reality

Although Virtual Reality (VR) is often associated with gaming and entertainment, it has shown promise in helping to rehabilitate stroke patients [35], [36]. VR is a computer interface that allows individuals to interact with a three-dimensional (3D) environment by presenting simulated or artificially generated sensory information [37]. This interaction is made possible by the movement of the user/patient, which is captured through proper motion tracking equipment.

There are two main types of VR: *Immersive* and *Nonimmersive*. Immersion VR is characterized by the environment being viewed using a head-mounted display (HMD) with tracking systems [37]. This makes the user feel like he is within the virtual enviornment, with all the images being updated according to the movement of the user's head. Sometimes this results in what is called *simulator sickness*. Nonimmersive VR can be viewed in a computer monitor which projects a wide field of view, giving the perception of looking through a window. There are a variety of devices that allow interaction with the VR environment like data gloves, joysticks and force feedback technology [37].

The main focus of a VR rehabilitation system is to simulate real world tasks into a virtual platform so that stroke patients with motor impairments can practice such tasks safely and transfer the performance of the virtual task onto the real world. One example stated by Glendinning et al. [37] consisted of mailing an envelope into a "mailbox slot". The patient did this by matching the hand trajectory that was presented in the virtual environment, performing the delivery. Another forthcoming application involving a VR system is driving simulators. This will allow patients to practice safe driving trips, while the therapist can oversee and grade the task. There are plenty other applications and real-world task related activities being simulated on VR systems [38], [39].

Although VR systems show a lot of potential, there are still some factors that hinder its usage in clinical practice. Some virtual tasks, if not properly implemented may not help patients in the long run, and may actually delay recovery. Also, clinicians may be interested in developing specific programs, but so far it is time consuming and requires a high degree of expertise to develop such programs in a VR environment. Moreover, older people may have some reluctance in utilizing this technology [40]. All of these drawbacks, however, can be overcome in the future after further research and assessment. Ultimately VR can provide a cost-effective way of rehabilitation for patients with motor impairments, being convenient for both the patients and the therapist.

1.1.3.2 Robotics

Robotic systems have an important role in the rehabilitation of patients with stroke. Budget cuts and a limited number of physical therapists have propelled the development of new technologies to provide the same intensity of rehabilitation sessions to stroke patients [31]. Robot training can provide therapists the tools to increase productivity of training sessions, maintaining the same quality of care [41].

There is a deep categorization for upper limb robotic systems. There are robots designed for shoulder, elbow, wrist, and hand movement. According to their mechanical characteristics, robotic systems can be classified into *Exoskeletons* and *End-effectors* [31]. *Exoskeletons* have robot axes aligned with the anatomical axes of the user. They provide direct control of individual joints, which can correct abnormal posture and movement. *End-effector* type devices work by applying mechanical movement to the distal segments of the limbs. Even though they are easy to set-up, they offer limited control of proximal joints of the limb, and can result in abnormal movement patterns [42].

The use of robotic systems for rehabilitation has positively influenced the motor outcome of upper limbs in patients with stroke [41]. Their main advantage is that they can provide therapy for long periods of time, in a very consistent and precise manner. They can be designed to perform almost any type of functional therapy. This is highly beneficial for both the patient and the therapist, who has more time to assist other patients, without jeopardizing their rehabilitation process [31].

Ongoing research of robotic technology for neurorehabititation focus not only on enhancing their efficacy, but also in reducing the cost of these devices [42]. It is unlikely that robotic systems will ever replace therapists, but they have proven to be a useful support in the rehabilitation of stroke patients.

1.1.3.3 Functional Electrical Stimulation

Functional electrical stimulation, or FES, is a novel treatment that can be used to help chronic stroke patients with motor impairments to improve motor function [43]–[46]. FES consists in using electrical currents for stimulating nerves connected to the paralysed muscles with precise sequence and magnitude in order to emulate a real nervous impulse and facilitate movement of a paretic muscle. The frequency range of FES is between 10 and 50 Hz, and it directly stimulates nerves rather than muscle fibers [47]. The combination of FES and manual assistance allows the patient to feel and execute the desired muscle contractions and the associated arm motion [48].

There are several upper extremity FES devices available and the use of these devices have shown to have a positive effect in stroke therapy, specially when administered within the first 6 months after onset [46], [49]. The improvements in motor function due to FES have been attributed to a better ability of patients to voluntarily contract impaired muscles. Reduced spasticity, improved muscle tone in stimulated muscles and increase in joint range of motion were also resulting factors of FES therapy [46].

Besides the discussed functional effects, FES is believed to facilitate neural plasticity by increasing the strength of afferent inputs [49]. FES therapy can be even more advantageous when complemented with other therapies and devices. Particularly, FES used simultaneously with an EMG sensor as feedback, has shown that it can promote motor learning [49]. Thus, patients can actively participate in intensive and repetitive task-specific training, which is essential for recovery. The neural mechanisms underlying improvement in sensorimotor function by FES are still not fully understood [48].

1.1.4 BCIs in Rehabilitation

Brain-Computer Interfaces (BCIs) are emerging as a novel tool for rehabilitation therapy. There is growing interest and curiosity, not only restricted to the scientific community, but the public in general that soon this technology may improve the lives of many disabled people all over the world [50]. The primary goal of BCI technology is to establish a direct communication pathway between the brain and external devices, thereby enabling faster and more intuitive communication and control for individuals with motor disabilities caused by neurological disorders, namely stroke [51]. BCIs differ from the methods mentioned in the previous sections in that they can modulate brain signals to control an interface, without the need for users to execute any kind of muscular activity. In the Background Chapter (Chapter 2) a deeper review of how a BCI works will be presented.

A large number of BCI applications from varying complexity have been developed [50]. From basic control of cursors being displayed on a computer screen [52]–[54] to robotic arms [55], prosthesis [56] and even wheelchairs [57], [58]. Depending on the application of the BCI, different neural-recording techniques can be used. These include microelectrode recording of a single neuron activity [59], [60], Electrocorticogram (ECoG) [61], [62], Electroencephalogram (EEG) [63], Magnetoencephalogram (MEG) [64] and Functional Magnetic Resonance Imaging (fMRI) [65], all of which have their own advantages and drawbacks. For example, a BCI that serves as an assistive device would benefit from being highly portable, implantable, and capable of recording highly specific neural activity from a certain cortical area. In this sense, a micro-ECoG has the capability to decode hand movements in order to provide control signals for prosthetic hands or functional electrical stimulator to restore function of impaired limbs, enabling a user to easily perform basic daily tasks, that were difficult, or even impossible, before [51]. For BCIs that serve more as rehabilitation tools than assistive devices, portability is not so crucial, but they should be non-invasive and practical [50], [51], [66].

The main principle behind the use of BCI as a rehabilitation tool is that it can induce cortical plasticity by training through feedback [50], [51], [67]. When subjects are trained to operate a BCI system, visual or other sensory feedback is presented to subjects in real-time. Over time, subjects improve their performance in controlling the BCI system, and this is correlated with an enhanced modulation of the recorded brain signals. Moreover, there is evidence that combining BCI with functional electrical stimulation (FES) or assistive robotics may aid motor relearning in stroke patients [55], [68].

In particular, some research groups are focused on the feasibility and effectiveness of BCI systems that combine action observation and motor imagery to enhance neuroplasticity and facilitate motor recovery of disabled patients [69]–[71]. In essence, both action observation and motor imagery can induce a certain degree of motor cortical activity, even in the absence of actual movement. This way, BCI systems could better optimize their decoding algorithm to extract motor-related information from the patient's cortical activity, therefore allowing them to intuitively learn how to control and operate the BCI. Ultimately, the enhanced performance of the patient would translate into an improvement in motor function recovery, while keeping the patient engaged through real-time feedback of his or her actions. Additionally, BCI systems can also be used as a monitoring tool. Clinicians can monitor the level of attention directed towards the different tasks and the level of inter-hemispheric balance, which is an indicator of stroke recovery [67].

In spite of the groundbreaking achievements of BCI research, most of the applications are still limited to public demonstrations and laboratory settings [50]. Most studies and gathered data are often from healthy individuals or animals, and studies with disabled people have been limited to a few trials, closely supervised by research personnel. The use of BCI technology in a clinical setting is just beginning.

1.1.4.1 Current Limitations of BCIs in Rehabilitation

Shih et al. [50] clearly elaborates the three major areas that need improvement in order for BCIs to become a legitimate rehabilitation tool in the future. Summarily, they are:

1. Development of comfortable, convenient and stable signal-acquisition hardware;

2. BCI validation and dissemination;

3. Proven BCI reliability and adaptable for different user populations;

In fact, current BCI applications contain a high degree of technicality, that most clinicians and patients are not comfortable with. Also, current non-invasive BCIs are comprised of inconvenient and expensive hardware that takes a long time to set up and is not suitable for clinical settings. In the perspective of the patient there are also some aspects that need improvement. Most non-invasive BCIs use non-practical acquisition systems. These are generally electrode caps, which require conducting gel, and are comprised of one or more wires (Figure 1.1). Besides being a gruelling task putting it on and making sure all the electrodes are aligned, they are aesthetically displeasing and mildly uncomfortable. The present dissertation presents a new BCI prototype which tackles some of these drawbacks by using a commercially available wireless EEG headset: *Emotiv EPOC*. As this prototype undergoes further development, it may potentially become part of a clinical rehabilitation system in the future.

Figure 1.1: Conventional BCI system comprised of wired electrode cap and amplifier. Adapted from [1].

1.2 Objectives

This project has been conducted at the Instituto de Biofísica e Engenharia Biomédica and it consists of a **proof-of-concept non-invasive Brain-Computer Interface**: **EmotivBCI**.

The EmotivBCI is a simple, yet robust, BCI platform for EEG acquisition, processing and classification of sensorymotor rhythmical activity in the central to frontal cortex of the brain with respect to motor action and motor imagery of the upper limbs: in particular the Left and Right hands. The signal acquisition is done through the commercially available EEG headset: *Emotiv Epoc*. Moreover, the EmotivBCI provides additional features to analyse acquired data, and keeps record of users' performances.

In this Dissertation two studies will be presented to provide a general assessment of the EmotivBCI. The first aims at comparing two different training paradigms, and the second study aims at analysing the evolution in performance of a particular set of users after several sessions of training using the EmotivBCI.

The objective of this Master Dissertation is to provide the foundation of what can become a new methodology for rehabilitation of patients with motor impairment, after Stroke or other neurodegenerative disorders.

1.3 Dissertation Overview

The present dissertation is structured as follows:

- **Chapter 1:** Presents the motivation and context behind the topic, followed by the objectives and outline of this dissertation.
- **Chapter 2:** Provides the general background on the concepts that are closely tied to the scope of this dissertation.
- **Chapter 3:** Introduces the EmotivBCI and describes the materials and methods used to develop it.
- **Chapter 4:** Presents two different studies that were conducted to assess the performance of the EmotivBCI and summarizes relevant results.
- **Chapter 5:** States the conclusion and the direction of future work.

CHAPTER 2

Background

The field of Brain-Computer Interfaces (BCIs) embraces a myriad of different scientific areas ranging from brain physiology to electronic hardware and signal processing algorithms. Throughout this chapter, the most relevant concepts surrounding the scope of this dissertation will be reviewed. It will start by introducing the Human Nervous system, the Brain, and one of its most fundamental properties: Neuroplasticity. Next, the most common non-invasive technique to assess brain activity will be discussed, the EEG. Particular attention will be given to sensorimotor rhythms in the cerebral cortex, which is detected by EEG and that is tightly correlated to motor activity and motor planning. Finally, a detailed review of Brain-Computer Interfaces will be provided, as well as Signal Processing, Feature Extraction and Classification techniques which are an integral part of this project.

2.1 Nervous System and the Brain

The nervous system is responsible for communicating and processing information from the various body parts. It is divided into the Central Nervous System (CNS), which consists of the brain and the spinal chord, and the Peripheral Nervous System (PNS), which connects the brain and spinal cord to all the body organs and sensory systems. These systems work closely together since the sensory input from the PNS is processed by the CNS, and the responses are sent back by the PNS to the organs of the body. There is another important distinction within the nervous system based on functionality. The *somatic* nervous system and the *autonomic* nervous system. The somatic nervous system controls muscle activity in response to conscious commands and relays physical sensations. On the other hand, the autonomic nervous system regulates activities that are beyond conscious control, like cardiac activity. The autonomatic nervous system is further divided into the *sympathetic* and *parasympathetic* nervous system which dominate during physical activity and relaxation respectively [72].

2.1.1 Cerebral Cortex

From all the parts that compose the CNS, the cerebral cortex is by far the most important. Different regions of the cortex are responsible for processing different functions, such as sensation, learning, voluntary movement, speech and perception. The cortex is the outermost layer of the cerebrum and has a thickness of 2-3 mm. The cortical surface is characterized by having multiple ridges and valleys of different sizes that increase the neuronal area, which is comprised of about 10 billion neurons [72].

The cortex is separated by a deep sagittal fissure, called the *central sulcus*, into two symmetrical hemispheres: left and right. Each hemisphere is further divided into four lobes: the frontal, temporal, parietal and occipital lobes [72], [73].

The motor cortex, located in the frontal lobe, is the main responsible for voluntary movement. Sensory information is processed in other parts of the remaining lobes [73].

2.1.2 Neurons

The building block of the nervous system is a specific type of cell called *neuron*. Neurons are insulated, supported and nourished by another type of cells, called *Glia* [74]. There are many different types of neurons that differ in morphology and function, but the main types are *sensory neurons*, *motor neurons* and *interneurons* [72]. These are composed of a body, denominated *soma*, in which two structures extend: the *dendrites* and *axon*. The dendrites are the extension of a nerve cell, in the form of a branch that carries impulses to the cell body. The axon is the long projection of a nerve cell that conducts impulses from the cell body to other cells. The transmission of information from neuron to neuron takes place at the junction where a terminal part of the axon contacts another neuron, the *synapse*. The information is passed across neurons in the form of electrical impulses, which propagate along the axon membrane through ion-gated channel mechanisms [74].

2.1.2.1 Mirror neurons

Recently a new and special kind of neurons have been first found in monkeys and later in humans, called *Mirror Neurons* [75]. These are a particular kind of neurons that discharge not only when an individual performs an action, but also when he or she observes a similar action done by another individual [75]. The existence of mirror neurons was demonstrated in humans using non-invasive methods. It has been shown that other people's action triggers the activation of several cerebral regions. EEG studies showed that mere observation triggers the desynchronization of cortical motor rhythms, with less intensity than during active movement [76]. The EEG and sensorimotor rhythms will be discussed a few sections below.

These findings opened a new pathway for treatment of stroke patients, using mirror therapy and motion imagery. The idea behind it is that coupling motor imagery from the patient, meanwhile observing actual movement from another individual or segments of their own body, will promote the recruitment of mirror neurons and cortical reorganization that can reactivate motor neurons, resulting in the subsequent learning of new motor skills [77]. This is still a premature field, but the application of mirror therapies has shown good results when combined with other therapies showing promise in the better recovery of post-stroke patients [77], [78].

This is a key idea for the future of BCI rehabilitation techniques. Although the present project does not yet incorporate visual stimulus, it is a feature that is deemed essential in the future.

2.1.3 Neuroplasticity

The Central Nervous System (CNS) has a fundamental property that is responsible for its normal functioning, and how it responds to injury: **Plasticity** [79]–[81]. In simple terms, plasticity can be defined as the brain's capacity to adapt to changing circumstances throughout the lifespan of any individual. More specifically, it comprises all the structural and functional changes in the nervous system that occur due to a myriad of actions and experience of any individual [80].

The nervous system is dynamic, and it is constantly modifying associations among neuronal elements in response to changing stimuli and learning [73]. There are multiple complex mechanisms that mediate plasticity, including changes in synaptic strength, axon sprouting, neurogenesis, unmasking of latent neural assemblies and modulation of inhibitory circuits [49], [82]. All these processes occur in accordance to homoeostatic balance. In neurological disorders, this balance shifts in favour of plastic changes, resulting in the reorganization of network connectivity [49], [80], [83].

Practice is an underlying factor for the acquisition of motor skills. It's through repetition that movements are executed faster and more accurately [84]. Several animal studies have shown that motor learning leads to neuroplastic changes [81], [85], more specifically to long term potentiation in the primary motor cortex, also referred to as M1 [84]. Through non-invasive techniques, the same kind of neuroplastic changes after motor learning have been suggested in humans [84].

Motor Imagery (MI), can promote motor learning, through mirror neurons, as discussed before. Moreover, recent studies have shown that MI increases M1 excitability, resulting in motor learning by mental practice [84], [86], [87]. In other words, motor learning can be achieved by MI practice, leading to the development of neuroplasticity in the human primary cortex (M1). This knowledge can facilitate the development of pioneering techniques for neurorehabilitation.

All the mechanisms associated with neuroplasticity, and how they behave after injury of the CNS, like stroke, are still subjects under much research [22], [88]. Although animal studies have helped demistifying some of their behavioral patterns, it's more difficult, for ethnic reasons, to apply the same methodology in humans. Studies conducted with stroke patients, however, have shown that there is an optimal time frame of two to three months after injury where neuroplastic changes are more accentuated [85], [88], [89]. Therefore rehabilitation strategies should focus on this time window to capitalize on optimal plasticity recovery.

2.2 Electroencephalogram (EEG)

Electroencephalograms (EEGs) are recordings of electrical potentials produced in the brain with high temporal resolution. The EEG is able to record rhythmic electrical activity from the human scalp, and it is mainly used in clinical settings to detect pathologies and epilepsies. It can also be used in research facilities to quantify and evaluate effects of new pharmacologic agents [90]. In the past, the EEG was analysed visually by a specialized individual, but with the advancement of technology, there are now computerized and more efficient methods of quantifying EEG changes. New methods for analysing EEGs are emerging on a regular basis [91]–[93], resulting in a better understanding of how the brain works.

EEG acquisition systems vary in quality and complexity, but a basic system consists of electrodes, amplifiers and respective filters, and lastly a recording device. The signal obtained from the EEG comes from the potential changes over time between a signal electrode and a reference electrode. Unlike other biosignal measurements like the Electrocardiogram (ECG), the readings from the EEG are relatively more abstract and harder to interpret at the naked eye. This is due to the spontaneous neuronal activity in the brain that is recorded at the level of the scalp. The signal from the EEG is highly dependent on the positioning of the electrodes in the scalp. A slight misplacement may completely fail to detect certain patterns. To establish some consensus between the scientific community, a 10-20 electrode placement (Figure 2.1) system was adopted [90].

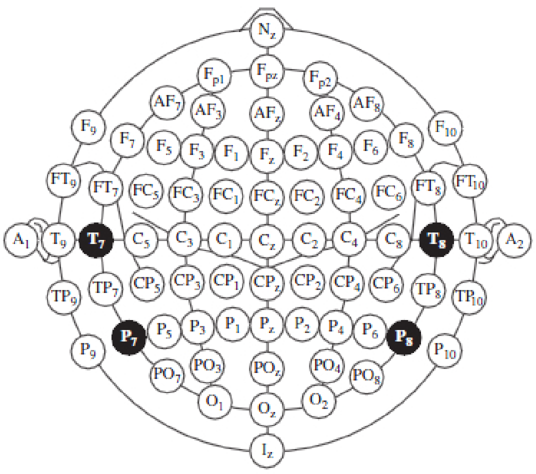


Figure 2.1: Diagrammatic representation of 10–20 electrode settings for 75 electrodes. Adapted from [94].

An EEG is mainly characterized by frequency and amplitude. These are highly diverse and depend mainly on the mental state of the subject [90]. The amplitude of the EEG is related to the degree of synchrony with which the cortical neurons interact, so a high amplitude signal is produced by a synchronous excitation of a group of neurons [74]. The frequency, or the oscillatory rate, of an EEG is partially sustained by the input activity from the thalamus. This part of the brain has neurons which possess pacemaker properties, so they have the ability to generate a self-sustained rhythmic firing pattern. Coordinated interactions between cortical neurons in specific regions of the cortex can also induce a rhythmic behaviour. Rhythms that have a high-frequency and low amplitude reflect an active brain (alertness or dream sleep). Low frequency and large amplitude rhythms are, on the other hand, associated with drowsiness and nondreaming sleep states [74], [90].

2.2.1 Desynchronization of Sensorimotor Rhythms

Two particular rhythms found in the central region of the frontal cortex are associated with sensorimotor activity: *Mu rhythm* (7-13 Hz) and *Beta rhythm* (15-30 Hz) [95], [96]. The planning and execution of limb movement has been shown to attenuate the spectral power in these frequencies. This phenomenon is designated **Event-Related Desynchronization** (ERD). Going from movement back to an idle state, the amplitude of the spectral power in these frequencies increase back to its previous intensity i.e. **Event-Related Synchronization** (ERS) [96], [97]. Event-Related Desynchronization/ Event-Related Synchronization (ERD/ERS) phenomena have also been observed during motor imagery and action observation [98], [99].

It has been demonstrated for quite a while that any given limb is mainly controlled by the contralateral hemisphere of the brain. Similarly, ERD/ERS is often stronger in the contralateral hemisphere of the brain as well. There is also some degree of activation on the other hemisphere also i.e. ipsilateral, which can be observed through imaging techniques and ERD/ERS. This knowledge makes it possible to detect the intention of moving each of the limbs, even if one hemisphere of the brain is lesioned.

ERD/ERS of sensorimotor rhythms, caused by motor imagery or actual movement can sometimes be difficult to observe in the EEG due to several factors. In particular, signal processing algorithms have to be efficient at capturing this change, while disregarding possible unwanted artefacts. Also, motor imagery detection depends greatly on the user's capacity to produce valid signals. Moreover, the brain's morphology varies slightly from individual to individual, therefore electrode placement may also be a factor preventing a clear detection of ERD/ERS in EEG signals [96].

Over time, the challenges have been surpassed due to advances not only in signal processing algorithms, but also in acquisition equipment, making it extremely convenient to use ERD/ERS of *Mu* and *Beta* rhythms to develop a BCI controlled by motor imagery [95], [99], [100].

2.3 Brain-Computer Interface

The human brain is the main organ responsible for coordination and movement, through electric impulses that travel from the brain to the peripheral nerves and back. When movement loss occurs due to stroke or other neurological disorders, the electric impulses are no longer propelled correctly. However, electrical activity of the brain can be acquired through the scalp and processed to trigger actions, through a BCI. A BCI, sometimes also referred as Brain-Machine Interface (BMI), is a set of hardware and software communications system that enables humans to interact with their surroundings, without the involvement of peripheral nerves and muscles, by using control signals generated from the brain's electric activity [96].

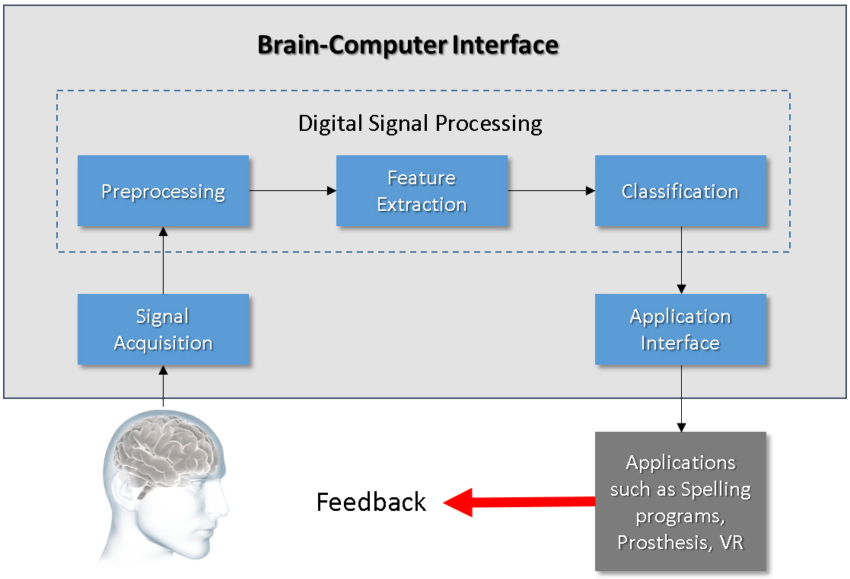


Figure 2.2: Block Diagram of a BCI system. Adapted and modified from [72].

A conventional BCI system is comprised of five consecutive stages:

1. Signal acquisition;
2. Pre-processing or signal enhancement;
3. Feature extraction;
4. Classification;
5. Control interface;

The signal acquisition stage records the brain signals, and depending on the acquisition system it may also perform some noise reduction and artefact processing. The pre-processing stage enhances the signal further so it is suitable for the feature extraction stage. This stage is where discriminative information is identified in the brain signals' recording. Afterwards, the signal is mapped onto a vector containing effective and discriminant features from the observed signals. This feature vector must be of low dimension, so that fast processing can be achieved with acceptable efficiency. The classification stage classifies the signals based on the feature vectors. Finally the control interface is where the classified signals are translated into actions and commands [96]. Figure 2.2 shows a diagram with the main building blocks of a standard BCI.

2.3.1 BCI: Synchronous and Asynchronous interfaces

A BCI can be generally categorized into two main types: *Synchronous* and *Asynchronous* interfaces. A Synchronous interface analyses EEG evoked potential signal resulting from stimuli received by the user from the system [101]. These can be visual, auditory or tactile stimuli. The processing consists of detecting responses from the brain activity to the stimuli, later transforming them into commands. An Asynchronous interfaces analyses the user voluntary activity in contrast to the user receiving any stimuli. In this case, the system continuously analyses the signals from the user's brain activity and classifies the mental state periodically [96], [101].

2.3.2 BCI: Invasive and non-Invasive

BCIs are also categorized according to invasiveness [1], [96]. If the electrical activity is acquired from the surface of the scalp using the EEG they are said to be *non-invasive*. *Invasive* interfaces require the installation of electrodes inside the skull, like electrocorticogram (ECoG) [61], [62], or the implementation of electrodes directly to a neuron [59], [60]. Non-invasive interfaces have a wider range of applications, in spite of being slightly harder to analyse and process EEG data due to the abundance of undesired artefacts and low Signal-to-Noise (SNR) ratio.

2.3.3 Performance of BCI systems

As it has been described throughout this document, BCIs are a groundbreaking technology. Enabling a user to interact with his or her environment through shear mind power is only possible because of BCI systems. However, even BCIs have limitations that are fundamentally derived from their nature. The whole range of motion an individual has of his or her body is virtually impossible to achieve through a BCI because they have low dimensional control [102]. This is mainly due to the complexity of the human brain and the limitations of an EEG acquisition system. Several studies have been able to successfully distinguish between two mental conditions using non-invasive BCIs i.e. two classes [4], [103], [104]. Current research is focused on distinguishing more than two mental conditions with an acceptable efficiency, usually 3 or 4 different classes [54]. Furthermore, research groups aim at being able to distinguish different mental intentions of the same limb [102], [105], [106]. For example, distinguishing different finger movements or distinguishing different arm movements, like elbow movement and hand grasping. This is especially more challenging, because this information reveals itself in the same regions of the brain [102]. BCIs that deal with 2 classes, for example rest condition versus imagined hand movement, classification accuracies should be higher than 70% [107]. State-of-art BCIs, however, can achieve accuracies above 90% for most test subjects with minimal training [63]. BCIs with more than two classes have accuracy ranges between 60% and 80%, with lower chance levels [102]. However, as it was mentioned before, some individuals have a greater ability to generate signals reflective of their motor imagery, therefore they can accomplish better classification accuracies. Consequently individuals that can naturally modulate their mental states can control devices more efficiently.

It's imperative for any worthy to mention BCI to have a decent acquisition system, be it EEG or any other acquisition techniques mentioned above, and also a meaningful feedback or control interface. However, it's the signal processing component of a BCI that dictates the overall performance of the BCI, including feature extraction and classification. The following section will discuss the importance of these two stages and give a brief overview of the techniques that are used to develop the current project.

2.4 Signal Processing and Feature Extraction

Signal processing and feature extraction are essential subjects in the field of BCI. As described earlier, the EEG is prone to many unwanted artefacts, and collecting valid information from it can be challenging. To acquire valid data, the equipment has to be proven efficient and the user must carefully follow the paradigms proposed. Besides, signal processing on the computer can take time, therefore analysis on real-time acquisition may be delayed and non-functional. Because of this, feature selection is a way to minimize the time and operations done while processing, by selecting only relevant portions of data. This greatly reduces processing time and makes it possible for real-time BCI applications to work.

Typically, the acquired EEG signals are pre-processed by a bandpass filter in the first stage, to obtain signals in the band of interest. Afterwards there is the feature selection phase in order to represent the vital components of the signal, or the **features**. The extracted features are then used to train a classifier in an offline phase. During the online phase, the trained classifier can identify the user's intent and output a command signal [108]. The objective of feature selection is to improve the prediction performance of the predictors, provide faster and more cost-effective predictors, and provide a better understanding of the underlying process that generated the data [109].

For a BCI to work efficiently, the mental state of the subject has to be recognized by the machine using a classifier. The optimal recognition process has to occur at high classification rates and be the least time consuming [110]. Therefore, the features and algorithms used have to simultaneously obey these two criteria. Another important aspect that should be considered is the individual particularities, such as native talent or sustained training of the user using the BCI. Classification accuracies vary significantly from user to user due to different individual cortical patterns for the same cognitive tasks [110].

There are a myriad of techniques used for processing, depending on the type of BCI and applications to be used on [111]. An extensive review of all of these techniques is beyond the scope of this project, however, all feature selection techniques and algorithms in EEG-based BCI aim at representing the EEG data in feature space, which can be later used to train the classifier [96]. The next subsections will review a few of the techniques and algorithms related to signal processing and feature extraction, which are used for the development of the proposed BCI system, the EmotivBCI.

2.4.1 Artefact Reduction

EEG signals are often contaminated with noise and artefacts. It is necessary to develop methods for detection and objective quantification of signal characteristics to minimize the influence of noise and artefacts to facilitate interpretation of relevant information [72].

One way to reduce artefacts is linear filtering. Linear, time-invariant filtering can be used for reduction of Electromyography (EMG) artefacts, and the 40/60 *Hz* power-line interference [72]. Filtering also allows to express a EEG signals in the frequency ranges where the relevant information is found. For example, ERD/ERS is observed in the *Mu* (7-13 Hz) and *Beta* (15-30 Hz) frequency ranges.

Although filtering can help in minimizing noise and artefacts, it is not bulletproof. Some artefacts due to muscular activity still overlap in EEG spectra.

2.4.1.1 Chebyshev Type 1 Filter

Chebyshev filters are used to separated one band of frequencies from another. The primary attribute of Chebyshev filters is their speed, since they are carried out by recursion. Unlike Butterworth filters, Chebyshev filters can maintain a constant amplitude value at cutoff frequency, which is beneficial to preserve the desired frequency content of the signal. The design of Chebyshev filters is based on a mathematical technique, the *z-transform*. The Chebyshev Type 1 Filter has the following transfer function:

$$|H_n(j\omega)| = \frac{1}{\sqrt{1+\varepsilon^2 T_n^2\left(\frac{\omega}{\omega_0}\right)}}. \tag{2.1}$$

The ε is the ripple factor, ω_0 is the cutoff frequency, and T_n is a Chebbyshev polynomial of the nth order, which can be defined as:

$$T_n(x) = \begin{cases} cos(ncos^{-1}x) & |x| \leq 1 \\ cosh(ncosh^{-1}x) & |x| > 1 \end{cases} \tag{2.2}$$

2.4.2 Power Spectral Density

Considering the oscillatory behaviour of EEG rhythms, including *Mu* and *Beta*, signal decomposition in terms of sine and cosine functions is extremely convenient. The *Fourier Transform* correlates the signal with sines and cosines of different frequencies, and produces a set of coefficients that define the *power spectrum*. From this spectrum, any particular frequency band can be readily obtained. The Power Spectral Density (PSD) is a natural quantity for characterizing a stationary signal. Therefore, spectral analysis is generally applicable to EEG signals of short durations (about 10 s), i.e. without major temporal changes [72].

2.4.2.1 Discrete Fourier Transform

The Discrete Fourier Transform (DFT) is the equivalent of the continuous Fourier Transform for signals known only at N instants. The discrete-time Fourier transform (DTFT) of a signal x_n is:

$$X(k) = \sum_{n=0}^{N-1} x_n \cdot e^{-2\pi ikn/N}, \quad k \in \mathbb{Z}\,(integers). \tag{2.3}$$

The simplest power spectral density estimate is the modulus squared of the DFT, known as *Periodogram*:

$$S(k) = \frac{1}{N}\,|X(k)|^2 = \left| \sum_{n=0}^{N-1} x_n \cdot e^{-2\pi ikn/N} \right|^2, \quad k \in \mathbb{Z}\,(integers). \tag{2.4}$$

2.4.2.2 Welch Estimation Method

The periodogram not always produces a consistent estimate of the power spectrum. This is mainly due to the fact that the variance of the periodogram does not decrease with the number of samples. Because of this, modifications have been applied to the periodogram, which consists of *windowing* and *averaging*. These techniques aim at reducing the variance of the periodogram [72].

Windowing is an operation in which a rectangular window $w(n)$ is applied to extract the segment of a signal that extends over a longer interval. There are different designs of windows. The most common are *Hanning*, *Hamming*, and *Blackman*. Windowing provides a trade-off between leakage and spectral resolution of the power spectrum estimate.

Variance reduction consists first of separating the signal $x(n)$ into K non-overlapping segments of length L:

$$x_i(n) = x(n + iL), n = 0, ..., L-1, i = 0, ..., K-1. \tag{2.5}$$

Then, the resulting periodograms resulting from each of the segments $x_i(n)$ is averaged. There is often a overlap between the segments.

The *Welch's method* is a nonparametric spectrum estimation technique that combines both of the above mentioned techniques: Windowing and averaging:

$$S(k) = \frac{1}{KLU} \sum_{i=0}^{K-1} \left| \sum_{n=0}^{L-1} x_i(n) w(n) \cdot e^{-2\pi i k n / KL} \right|^2 . \tag{2.6}$$

U is a normalization factor related to the characteristics of the window $w(n)$,

$$U = \frac{1}{L} \sum_{n=0}^{L-1} w^2(n). \tag{2.7}$$

2.5 Classification Algorithms

The classification stage is critical to guarantee the efficiency of a BCI system. The aim of the classification step is to recognize the user's intentions with respect to a feature vector that characterizes the brain activity [96]. Classification algorithms use the features extracted as independent variables that define the boundaries between the different classes in feature space [96].

The feature vector is extracted from training trials, which are then used to train a classifier.

2.5.1 Naïve Bayes

The Naïve Bayes (NB) classifier is a probablistic algorithm based on applying the Bayes' theorem with naïve independence assumptions. The Naïve Bayes classifier can probabilistically predict the class of an unknown trial using the available training trial set to calculate the most probable output. The most probable class C_{NB} of an unknown trial with the conjunction $A = a_1, a_2, ..., a_m$ is calculated by:

$$C_{NB} = \arg\max_{c \in C} p(c/A). \tag{2.8}$$

Where m is the number of discrete-valued features and C is the class.

2.5.2 Gaussian Support Vector Machine

The Support Vector Machine (SVM) classifier performs classification tasks by constructing the best hyperplane in a multidimensional space by finding the maximum possible margin, defined as:

$$f(x) = w^\top x + b. \tag{2.9}$$

where w is the weight vector, and b is the bias. In this case, the decision boundary defined by the hyperplane is said to be *linear*. Sometimes, non-linear classifiers provide better accuracies, depending on the input data. Support vector machines can be transformed into a non-linear method by using a non-linear *kernel function*. A kernel function defines a new vector for a given set of data x by calculating the similarity between the x and another set of data y. One particular kernel function is the *Gaussian* kernel, defined as:

$$K(x,y) = exp(-\frac{\|x-y\|^2}{2 \cdot \sigma^2}). \tag{2.10}$$

This function takes values between 0 and 1. If $x = y$ then $k = 1$. The parameter σ is the standard deviation, and it controls the width of the kernel function.

2.5.3 Decision Tree

The Decision Tree (DT) algorithm constructs a decision tree with branches and nodes based on a feature vector set. The decision tree begins with a root node r derived from whichever variable in the feature space minimizes a measure of the impurity of the two sibling nodes. The measure of the impurity at node r, denoted by $im(r)$, is defined as follows:

$$im(r) = -\sum_{i=1}^{m} p(w_i/r) \log p(w_i/r)). \tag{2.11}$$

where $p(w_i/r)$ is the proportion of patterns x_i allocated to class w_i at node r. Each none-terminal node is then divided into two further nodes, r_1 and r_2 such that p_1, p_2 are the proportions of entities passed to new nodes r_1, r_2 respectively. The most appropriate division is that which maximizes the difference:

$$\Delta im(d,r) = im(r) - p_1 im(r_1) - p_2 im(r_2). \tag{2.12}$$

The decision tree grows until a phase is reached in which there is no significant decrease in the measure of impurity when a further additional division d is implemented. When this phase is reached, the node r is not sub-divided further, and automatically becomes a terminal node. The class w_i, associated with the terminal node r is that which maximizes the conditional probability $p(w_i/r)$. Eventually, in testing phase, test samples are classified using the calculated optimal decision tree model.

Chapter 3

Development of EmotivBCI

The present chapter will cover the development of the project that is the topic of this Master dissertation: *EmotivBCI*. A full guide of usage will be provided in Appendix A. All the methods and algorithms that are not defined in this section, have been described in the section above.

3.1 Overview

The EmotivBCI (Figure 3.1) is a proof-of-concept BCI console platform developed in C# programming language. It acquires EEG signals from 8 electrode channels in the central and frontal cortices of the brain through the commercially available EEG headset: *Emotiv Epoc*.

Figure 3.1: Visual representation of the EmotivBCI and the main features it comprises.

The acquired signals are processed and relevant features are extracted to build a classifier based on ERD/ERS due to movement or imagery of upper limbs (left and right hands). It also implements real-time testing with the built-in classifiers. The EmotivBCI comes with a number of features, which will be described in the following sections.

3.1.1 Materials

The main core of the EmotivBCI is the software that was developed on the computer. For that, several other programs were used, which will be mentioned below.

3.1.1.1 Emotiv Epoc

The *Emotiv Epoc* is a wireless headset equipped with 14 sensors, and two reference channels (Figure 3.2). Prior to its usage, the electrode pads have to be moisturized with a saline solution. The battery duration is about 12 hours. The raw data from the headset can be accessed from the supplied SDK[1] [112].

(a) Emotiv Epoc wireless headset.

(b) Emotiv Epoc standard electrode placement.

Figure 3.2: The Emotiv Epoc: hardware and electrode positions. Adapted from [112].

The Emotiv Epoc internally samples at a frequency of 2048 Hz, and then it is down-sampled to 128 Hz. Moreover, the data is pre-processed in the hardware, with a low-pass filter with cutoff frequency at 85 Hz, a high-pass filter with cutoff at 0.16 Hz and a notch filter at 50 Hz and 60 Hz. The signal is then available through the API[2] [113].

3.1.1.2 Visual Studio Community 2013

Visual Studio Community is a free *Integrated Development Environment* (IDE) to create applications in various operating systems [114]. It allows to write and test code in a plenitude of languages. The EmotivBCI was developed in C#: An object oriented programming language. The class diagram of the EmotivBCI is illustrated in Figure 3.3.

[1]SDK - Software Development Kit
[2]API - Application Programming Interface

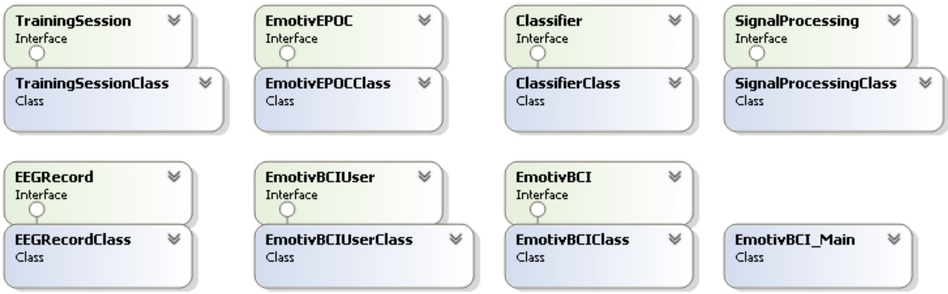


Figure 3.3: Class diagram of the EmotivBCI.

3.1.1.3 Matlab 2015

Matlab is a high-level programming language and interface developed by MathWorks[3]. Matlab is specially useful to develop signal processing algorithms, since it has implemented various functions to meet the users' needs. It is also extremely convenient to plot data and perform statistical analysis.

Throughout the development of the EmotivBCI, Matlab was an essential tool to develop some of the functions used for signal processing. Functions developed in Matlab were converted to a C# component in the form of *dll* (Dynamic Link Library), and then implemented in the main program developed in C#.

Table 3.1 summarizes the functions developed in Matlab.

Table 3.1: Functions developed in Matlab and used in the EmotivBCI for analysis and processing.

Function	Description
CalculatePowerValue	Calculates the logarithmic band power value for a band length of 1 Hz centered at the frequency given, for a single frame.
ExtractFeatures	Extracts the two best combinations of channel/frequency that exhibit the greatest action difference between the action and rest states.
GenerateFeatMap	Plots the power differences for each channel with respect to the frequency.
ChannelPSD	Plots the Periodogram and Welch Power Estimation for a given channel.
GenerateClassifierData	Plots the feature attributes used to build the classifier.

3.1.1.4 Accord.NET Framework

The Accord.NET Framework is a .NET machine-learning framework which is comprised of signal processing and classification libraries written in C# [115].

[3]The MathWorks Inc., Natick, MA, 2000

The classification algorithms used in EmotivBCI were implemented from the Accord.NET libraries. These algorithms yield a classification accuracy based on the respective input data: attributes and classes.

3.1.2 Getting Started

EmotivBCI was developed with the intent of serving as a personal platform, where users can register their personal information, perform tests, and keep track of their own progress. That being the case, a new user first has to register, by providing the name, age, a user-name and a password. After successfully logging in with the created user-name and password, the user can perform training sessions, and has at his or her disposition an array of commands to further analyse acquired data. In order to perform BCI tests, the user must be wearing the Emotiv headset. It is advised that the position of the headset is adjusted so the FC5 and FC6 channels are closer to the central cortex of the brain, in the C5 and C6 positions of the 10-20 EEG electrode system (Figure 3.4).

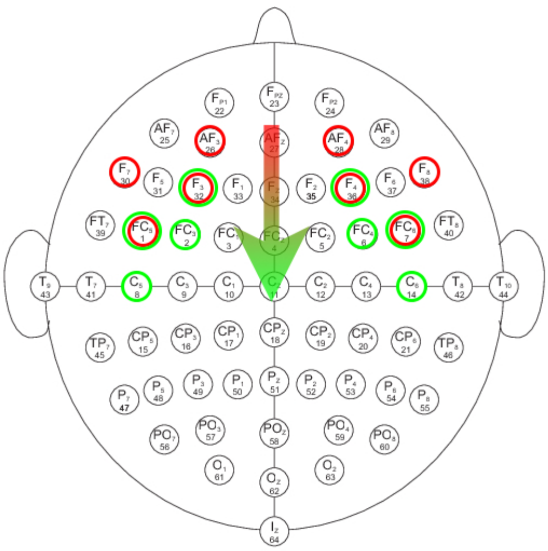


Figure 3.4: Adjustment of electrodes from the standard Emotiv position. The red circles mark the original positions, and the green circles mark the adjusted positions. Adapted and modified from [116], [117].

3.2 Training Session

The main feature of the EmotivBCI is the ability for a user to perform training sessions. They consist of two-minute EEG acquisitions, in which the user performs the action the screen display prompts him to do. At the end of the acquisition, a classification accuracy is given according to how well the classifier distinguished between the two tested conditions.

3.2.1 Training options

The EmotivBCI provides four different training options:

1. **Left hand motor action**: User repeatedly clenches left hand when prompted;
2. **Left hand motor action**: User repeatedly clenches right hand when prompted;
3. **Left hand motor action**: User imagines left hand movement when prompted;
4. **Left hand motor action**: User imagines right hand movement when prompted;

Depending on the selected option, the user will perform the respective action (**Action condition**) intercalated with an idle state, which from this point forward will be referred to as the **Rest condition**.

3.2.2 Training paradigms

Complementary to the training options, the EmotivBCI also offers two different training paradigms:

1. **Training Paradigm 1 - TP-1**: 5-second-rest-5-second-action;
2. **Training Paradigm 2 - TP-2**: 2-second-rest-2-second-action;

The training paradigm dictates the frequency at which the user is prompted to perform the chosen training option. The total time of the training session does not change (2 minutes). However, the number of repetitions change according to the paradigm. Table 3.2 summarizes the the parameters of both training paradigms. Both paradigms come with advantages and disadvantages, but these will be discussed in the next chapter.

Table 3.2: Comparison between TP-1 and TP-2. Repetitions represent the number of times a user has to perform the *rest condition* and *action condition* during the 2-minute training session. The number of features represents the total number of values available to train a classifier.

Training Paradigm	Repetitions	Number of Features
TP-1	12	48
TP-2	30	120

3.3 Processing Cascade

From the raw EEG data that was acquired through a training session, until a final classification is attributed, the signals from all the channels undergo a comprehensive processing cascade. From this cascade, the relevant features are extracted, and used to construct a feature matrix, which will then be fed to the classifier. Figure 3.5 gives a simple illustration of the processing cascade.

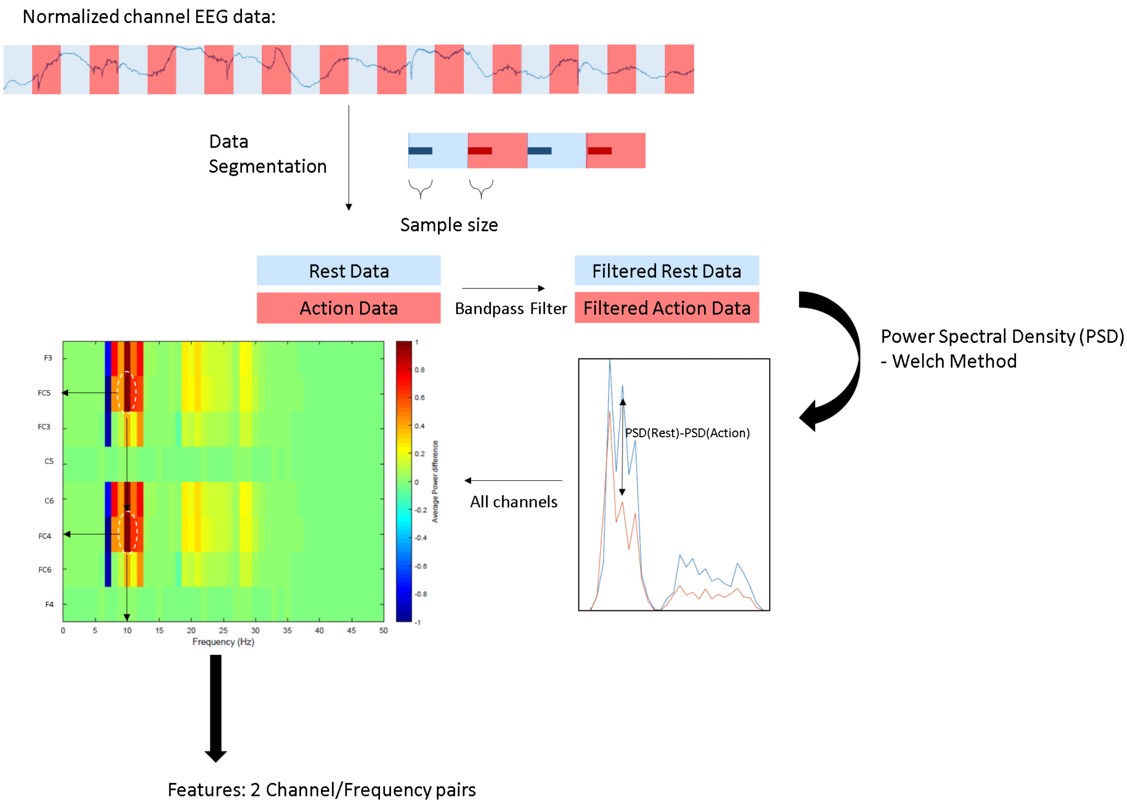


Figure 3.5: Diagram of the Feature Extraction processing cascade. Note that only one channel is represented for simplicity, however, all data from every channel is processed the same way.

3.3.1 Signal Processing

The signal processing is carried out with the support of *Matlab* wrapped functions in a non-parametric fashion. Once acquired, signals from each channel are pre-processed with the C# built functions that remove the DC component and normalize the signal for each of the channels. The offset of the signal is removed by subtracting the average over the time domain of the signal. The signal $x(k)$, in which k is the time instant, is then normalized between $[-1, 1]$ through:

$$x_n(k) = 1/max(|x(k)|) * x(k). \tag{3.1}$$

Next, each of the channels is separated into the **rest** and **action** conditions, but only the initial number of samples is selected, which corresponds to the initial instances of each condition (Figure 3.5). The reasoning behind this is further explained later, but essentially the initial instances of each condition are more likely to carry the greatest information value for feature extraction. There are 5 established number of samples that are selected:

- 13 samples ~100 ms;
- 26 samples ~200 ms;

- 39 samples ~300 ms;
- 69 samples = 500 ms;
- 128 samples = 1 s;

For each number of samples, the feature extraction cascade is the same.

3.3.2 Feature Extraction

After the signal is pre-processed and segmented into two distinct signal vectors: Rest and Action, the EmotivBCI extracts the 2 best combinations of channel/frequency that exhibit the greatest ERD/ERS over the respective number of trials between these two conditions. The first step in the feature extraction cascade involves filtering the signal. The filter used is a 10th-order double bandpass Chebyshev Type 1 filter (refer to 2.4.1.1) in the frequency bands that may exhibit ERD/ERS: 7 Hz to 13 Hz (*Mu*) and 15 Hz to 30 Hz (*Beta*).

Once filtered, the Power spectrum density (PSD) is estimated using the Welch method (Chapter 2.4.2.2) for each of the conditions in every channel: $PSD(rest)$ and $PSD(action)$.

The difference $PSD(rest) - PSD(action)$ is calculated to identify the channel and frequency pairs that show the greatest difference, hence the greatest ERD/ERS.

The two best combinations of channel/frequency are used to build the feature matrix to train the classifier. The best channels may be the same. If so they exhibit ERD/ERS in two distinct frequencies.

3.3.3 Feature Matrix Construction

The feature matrix is calculated for the best channels, by computing the logarithmic band power centered in the respective best frequency. The band power is computed as follows:

$$BP|_{f-0.5}^{f+0.5} = 10 \log \sum \left\| X(k)|_{f-0.5}^{f+0.5} \right\|^2 . \tag{3.2}$$

In this equation, $X(k)$ is the FFT coefficients between the delimited frequencies.

The data from each of the 2 best channels is again separated into rest and action conditions (this step is now computed in the C# framework), and buffered into frames of the same size as the respective number of samples.

For each frame, the logarithmic band power centered in the best frequency, with the range of 1 Hz, is computed.

The resulting matrix consists of a set of band power values for the rest state, which corresponds to output -1, and a set of band power values for the action state, which corresponds to output $+1$ (Figure 3.6).

Depending on the previously selected training paradigm, the number of values for the classes rest and action are different:

Training Paradigm 1: 12 repetitions x 2 conditions = 24 values per attribute;

Training Paradigm 2: 30 repetitions x 2 conditions = 60 values per attribute;

The resulting feature matrix will therefore consist of 2 sets of attributes: band power values for combination channel/frequency number 1, and band power values for combination of channel/frequency number 2.

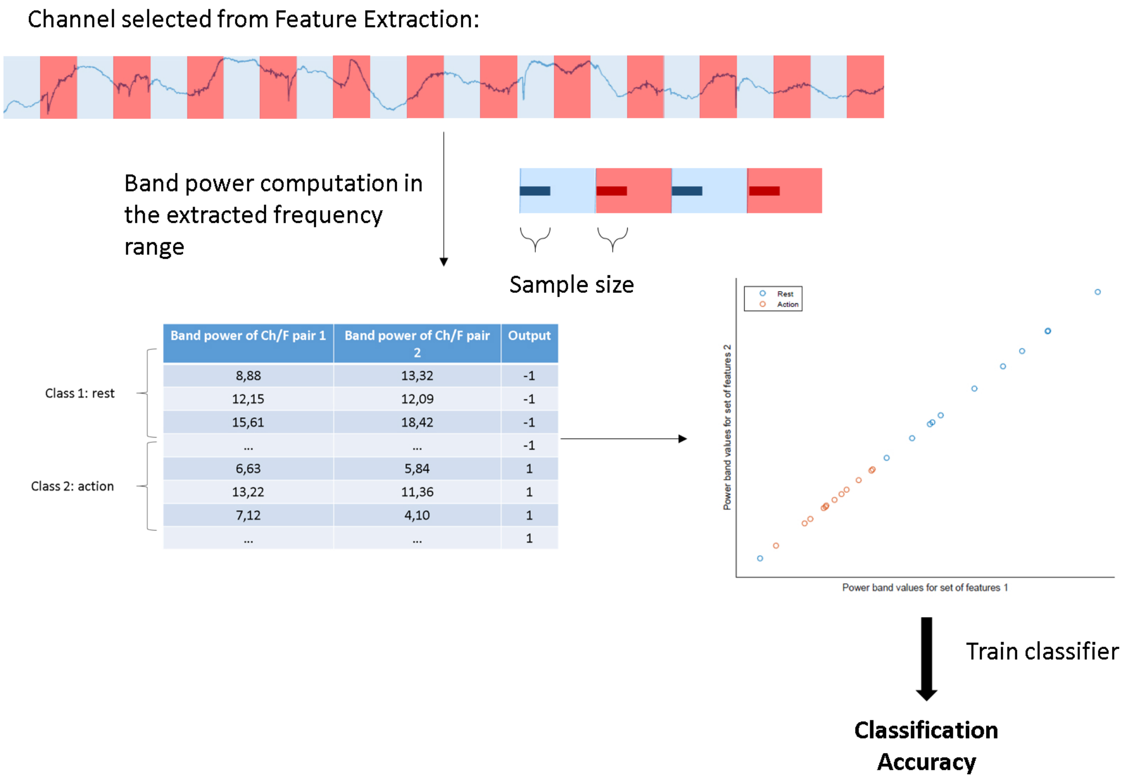


Figure 3.6: Diagram of the Feature Matrix construction. The features have been extracted prior to this stage. Both channel/frequency pairs go through this processing.

3.3.4 Classification

The feature matrix is used to train 3 different classifiers implemented using the Accord Framework:

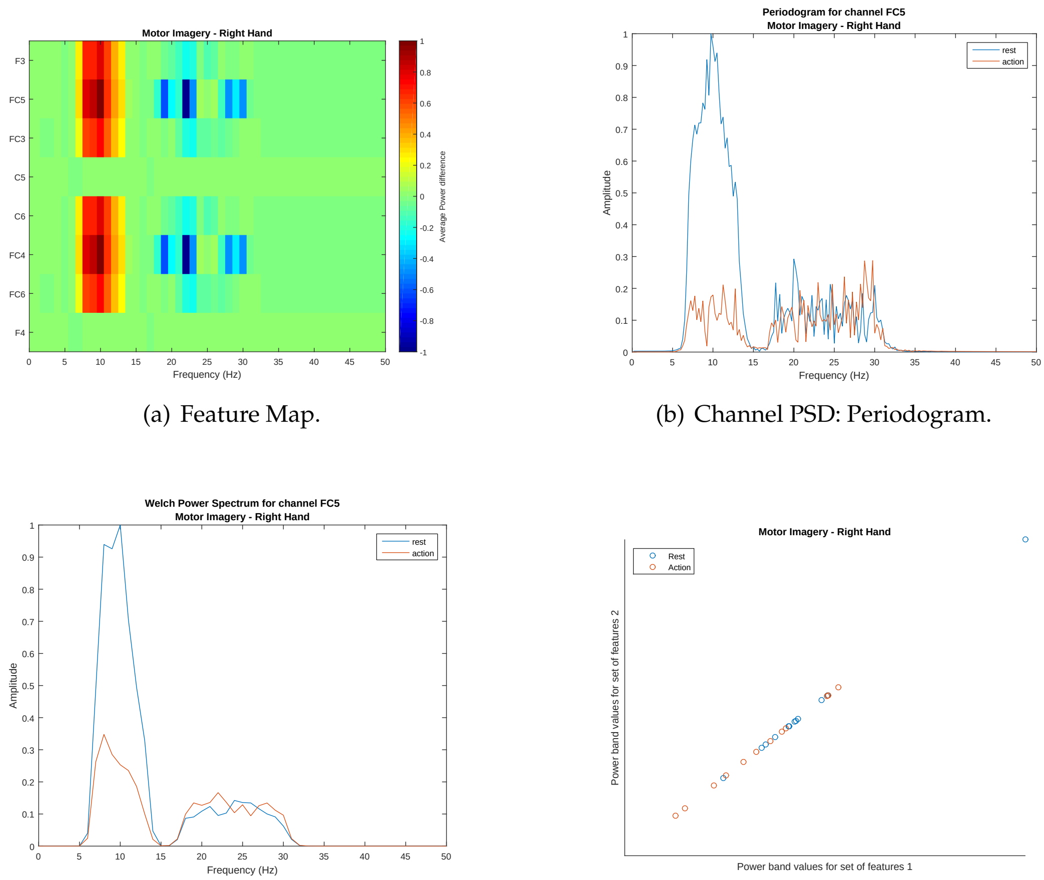
- Naïve Bayes
- Gaussian Support Vector Machine
- Decision Tree

The resulting classification accuracy represents the number of correctly classified samples over the total number of samples multiplied by 100%. The random classification accuracy is 50%.

The processing cascade will result in 3 classifiers for each number of samples, so in total 15 different classification values are computed. From these 15, only the one that yields the best accuracy is selected, along with the number of samples, to validate the training session, and posteriorly be used for real-time BCI processing. The relevant features extracted (2 best channel/frequency pairs)in respect to the best classification are registered for that training session as well.

3.4 Other Features

The ability to perform training sessions and subsequently classify data is the main feature of the *EmotivBCI*. It does, however, offer a few more features to round out and come close to a what a real BCI platform should be like (Figure 3.7). The next subsections will give a brief overview of such features.



(a) Feature Map. (b) Channel PSD: Periodogram.

(c) Channel PSD: Welch Method. (d) Classification Data.

Figure 3.7: Features of the EmotivBCI.

3.4.1 Online BCI - Real-time Testing

One of the most promising features of the *EmotivBCI* is the ability to perform BCI tests with live feedback. In order to perform real-time testing, a user has to first perform a training session, choosing the appropriate option for which he or she wants to test. During the training session, the appropriate features are extracted and a classifier model is built, so that it can classify incoming data from live acquisition. With classification accuracies above 90% it has yielded acceptable responses. With classification accuracies lower than 90% there seems to be no sufficiently adequate response. The way it is implemented, it computes a band power value (based on the respective features acquired from the training session) every 1 second, or 128 samples. The computed value is then classified as *Rest* or *Action* based on the training set. Because the features are extracted based on the initial samples, usually lower than 128, the data from live acquisition may not be fully compatible. This is an issue which should be addressed in further development of the *EmotivBCI*.

3.4.2 Generate Feature Map

Feature maps are density charts that show the activity of the channels with respect to frequency (Figure 3.7(a)). It is based on these charts that the features for a given training session are extracted i.e. 2 channel/frequency pairs. The user has the ability to visualize these feature maps and analyse the areas of the brain that showed grater variation between the *rest* and *action* conditions. The feature maps are generated according to the processing algorithms described above.

3.4.3 Generate Channel PSD

Although the feature map can show the power variation in all the channels, it is not very detailed. For this reason, the user can visualize the power spectrum of both the *rest* and *action* condition for any given channel. This command generates 2 power spectrum density plots: Periodogram (Figure 3.7(b)) and Welch Method Estimation (Figure 3.7(c)). Through these plots it is often possible to observe a clear desynchronization of the *action* condition.

3.4.4 Generate Classification Data

This command plots the attribute values used to train the classifiers in a plane i.e the values from the feature matrix. The y axis consists of the power values of the first channel/frequency pair, and the x axis consists of the second. The colors refer to the condition: blue is rest, and red is action. Through this plot it is possible to predict the accuracy of the classification (Figure 3.7(d)).

3.4.5 Miscellaneous

The *EmotivBCI* has a few other options that may be useful. Among these are the ability to export and import EEG data in *CSV* format, the ability to check previous training sessions and respective performances and other implemented functions that provide assistance on the usage of the platform. Aside from these, there are a few functions under progress to provide even more angles of analysis of acquired data, but that are not yet perfected to be mentioned.

3.5 EmotivBCI: Wrap-up

The EmotivBCI was developed in different stages. The signal processing stage was developed mostly in Matlab, with the support of a public available EEG dataset from Physionet [116], [117], which contains EEG data from motor action and motor imagery tests for 109 different subjects. During this stage different processing techniques were experimented in order to achieve the optimal processing algorithm used in this project. Meanwhile, the platform was being developed in C#. The final stage consisted of seamlessly implementing EEG data acquisition from the Emotiv Epoc and the functions developed in Matlab into the platform. Subsequently various tests were performed to validate if all the components were running smoothly. Throughout the development of the EmotivBCI, different methods and tests were conducted to reach the best performance possible. Special attention was given to speed and robustness of processing, not only so the user doesn't have to wait a considerable amount of time for his or her classification results, but so that real-time testing could then be feasible. The real-time testing functionality of the EmotivBCI is rudimentary at the time of this document. Different approaches should be taken in order to make it a viable feature. Further suggestions and commentary will be elaborated in the Conclusion chapter.

CHAPTER 4

ASSESSMENT OF EMOTIVBCI

In order to validate and analyse the efficiency of the EmotivBCI, two studies were conducted with a different number of volunteers. The participants consisted of healthy individuals between the ages of 23 to 37, who had no previous experience with BCIs. The aim of the first study was to analyse the performance of the EmotivBCI using the two training paradigms. The aim of the second study was to determine the evolution of the performance with continuous usage. With a few minor differences which will be mentioned below, the task formulation for both studies was similar. The group of individuals were different for each study.

4.1 Task Formulation

Although the group of individuals was different depending on the study, the task formulation was the same. Both studies consisted of the subjects performing the 4 different training options one after another. The subjects were asked to hand over their mobile phones, and then moved into a Faraday cage at the research center to perform the test. They were asked to sit on a wooden chair in front of a laptop. The *Emotiv* headset was placed on their head, with the electrode channels carefully located in the correct positions (the position of the electrodes was slightly different than the standard Emotiv channel position - Chapter 3.1.2).

It was certified that all the signals from every channel were being acquired with suitable quality using the *Emotiv* software *TestBench*, and by visual assessment. The subjects were then told to register in the EmotivBCI application and login. Before performing the training sessions, they were told to keep still as much as possible, including blinking, and just perform the movements indicated by the application. During every training session the subjects were alone in the Faraday cage. For both studies, the subject answered 4 survey questions after the test for futher analysis. The answers were to be given using a scale from 1 to 5, except for question 3. The questions were:

1. "How would you rate your mood?": 1 (very bad/exhausted) -> 5 (excellent);
2. "How comfortable was the Emotiv headset?": 1 (very uncomfortable) -> 5 (very comfortable);
3. "Which training paradigm did you consider less exhausting?"; 1 (TP-1), 2 (TP-2) and 3 (no difference);
4. "How hard was it to perform motor imagery?": 1 (very easy) -> 5 (very hard);

4.2 Study 1: Training Paradigm 1 Vs. Training Paradigm 2

The objective of this study was to assess the performances of 4 different subjects doing both training paradigms. For this, they performed all the training options twice, according to the task formulation. The first time they performed the training sessions using **Training Paradigm 1 - TP-1**: 5-second-rest-5-second-action. Shortly after they performed the training sessions using the **Training Paradigm 2 - TP-2**: 2-second-rest-2-second-action.

4.2.1 Motor Action Results and Analysis

The results from motor action performance are presented in Table 4.1, in which the channels correspond to the adjusted position, and not the standard Emotiv Epoc position. The channel positions are based on the 10-20 system. The features represent the two channel/frequency pairs which exhibited greater activity, and the samples used (Chapter 3.3.1). *T.O* stands for Training Option[1]. The classifier[2] used is displayed as well as the classification accuracy, which is the criterion for performance.

There is a clear variation in performance not only between the two training paradigms, but also from subject to subject. Among the 8 different tests, only two tests showed a better performance using the Training Paradigm 2. Figure 4.1 shows a box plot for each of the Training Paradigms with respect to motor action. Subject 2 reached a 100% accuracy in the left-hand motor action option, which enabled him to asynchronously control the BCI flawlessly in real-time. In most cases, the extracted channels are FC5 and FC4, which correspond to the pre-motor cortex on both hemispheres.

[1] LH - left hand; RH - right hand.
[2] NB - Naïve Bayes; GSVM - Gaussian Support Vector Machine; DT - Decision Tree.

Table 4.1: Study 1: Motor Action Classifications between TP-1 and TP-2 for 4 subjects. T.O: Training Option; LH: Left Hand; RH: Right Hand; NB: Naïve Bayes; GSVM: Gaussian Support Vector Machine; DT: Decision Tree.

Subjects	T.O	Training Paradigm 1: 5-second-rest-5-second-action			Training Paradigm 2: 2-second-rest-2-second-action		
		Features	Classifier	Classification (%)	Features	Classifier	Classification (%)
S1	LH	FC5/24Hz, F4/24Hz, 13 s.	DT	91.2%	FC5/10Hz, FC4/10Hz, 69 s.	DT	79.2%
	RH	FC5/9Hz, FC4/9Hz, 39s.	NB	83.3%	F3/9Hz, C6/9Hz, 39 s.	DT	70.8%
S2	LH	FC3/29Hz, FC6/29Hz, 128 s.	DT	75.0%	FC3/9Hz, FC6/9Hz, 39 s.	DT	83.3%
	RH	FC3/8Hz, FC6/8Hz, 39 s.	DT	100.0%	FC3/9Hz, FC6/9Hz, 26 s.	DT	79.2%
S3	LH	FC3/10Hz, FC6/10Hz, 128 s.	DT	83.3%	FC5/9Hz, FC4/9Hz, 13 s.	GSVM	83.3%
	RH	F3/10Hz, FC6/10Hz, 128 s.	DT	87.5%	FC5/9Hz, FC4/9Hz, 39 s.	DT	79.2%
S4	LH	FC5/8Hz, FC4/8Hz, 26 s.	GSVM	79.2%	C5/9Hz, F4/9Hz, 69 s.	DT	83.3%
	RH	FC5/13Hz, FC4/13Hz, 13 s.	GSVM	70.8%	FC5/9Hz, FC4/9Hz, 13 s.	DT	70.8%

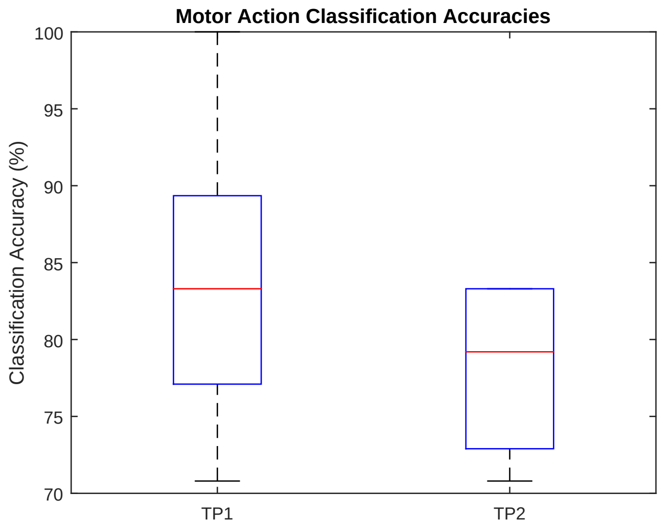


Figure 4.1: Box plot analysis between TP-1 and TP-2 for Motor Action: TP-1 shows overall better performance than TP-2.

4.2.2 Motor Imagery Results and Analysis

In a similar fashion to the Motor Action tests, Table 4.2 displays the results for the same subjects, but this time for Motor Imagery tests.

Table 4.2: Study 1: Motor Imagery Classifications between TP-1 and TP-2 for 4 subjects. T.O: Training Option; LH: Left Hand; RH: Right Hand; NB: Naïve Bayes; GSVM: Gaussian Support Vector Machine; DT: Decision Tree.

Subjects	T.O	Training Paradigm 1: 5-second-rest-5-second-action			Training Paradigm 2: 2-second-rest-2-second-action		
		Features	Classifier	Classification (%)	Features	Classifier	Classification (%)
S1	LH	FC5/24Hz, C6/24Hz, 13 s.	DT	79.2%	F3/11Hz, C6/11Hz, 69 s.	GSVM	70.8%
	RH	FC5/9Hz, AF4/9Hz, 39s.	DT	75.0%	F7/11, F4/11, 128 s.	GSVM	79.2%
S2	LH	F3/9Hz, C6/9Hz, 128 s.	DT	87.5%	C5/27Hz, F4/27Hz, 69 s.	DT	83.3%
	RH	FC3/9Hz, FC6/9Hz, 69 s.	DT	83.3%	FC3/9Hz, FC6/9Hz, 26 s.	GSVM	79.2%
S3	LH	FC3/11Hz, FC6/11Hz, 128 s.	GSVM	83.3%	F3/12Hz, C6/12Hz, 39 s.	DT	79.2%
	RH	F3/12Hz, C6/12Hz, 128 s.	DT	87.5%	FC5/12Hz, FC4/12Hz, 39 s.	DT	83.3%
S4	LH	C5/8Hz, F4/8Hz, 26 s.	NB	70.8%	FC3/14Hz, FC6/14Hz, 13 s.	GSVM	70.8%
	RH	C5/9Hz, F4/9Hz, 128 s.	DT	79.2%	FC5/9Hz, FC4/9Hz, 128 s.	DT	79.2%

The results from motor imagery are more balanced between training paradigms than testing motor action. Motor imagery is more challenging to perform, and therefore performances were slightly lower than motor action also. However, there were some exceptions, namely subject 2 and subject 4 achieved a higher performance in certain tests. It is important to note that different features were extracted from motor imagery tests in relation to motor action. Yet, the channels still correspond to the two hemispheres of the brain. Overall, subjects performed better under training paradigm 1 than training paradigm 2. Figure 4.2 shows a box plot analysis between the two training paradigms, this time for motor imagery.

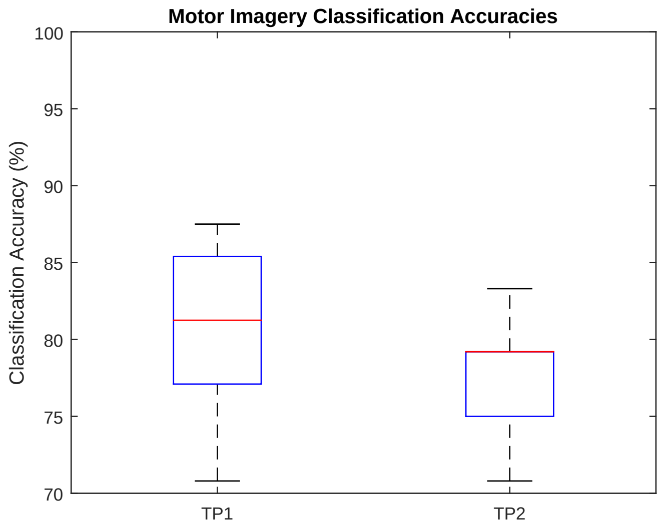


Figure 4.2: Box plot analysis between TP-1 and TP-2 for Motor Imagery: TP-1 shows overall better performance than TP-2.

4.3 Study 2: Evolution of Performance with Practice

The objective of this study was to evaluate if a group of four subjects improved classifications after several sessions of usage of the EmotivBCI. For this study, every subject performed 3 sessions of tests. Unlike the first study, where the subject performed each of the training options for both training paradigms, this time around the subjects performed each of the training options, with intercalated training paradigms. The training paradigms were intercalated between subjects too, therefore two of the subjects started with TP-1, and the other two with TP-2. Subjects 5 and 8 performed the tests in the span of 3 weeks, as subjects 6 and 7 performed the tests in 3 consecutive days.

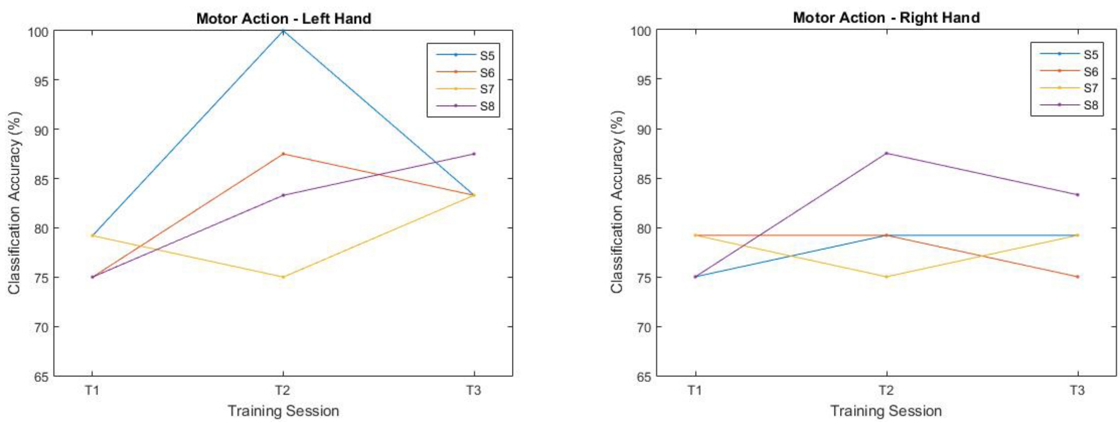


Figure 4.3: Study 2: Motor Action classification accuracies of 4 subjects over 3 training sessions.

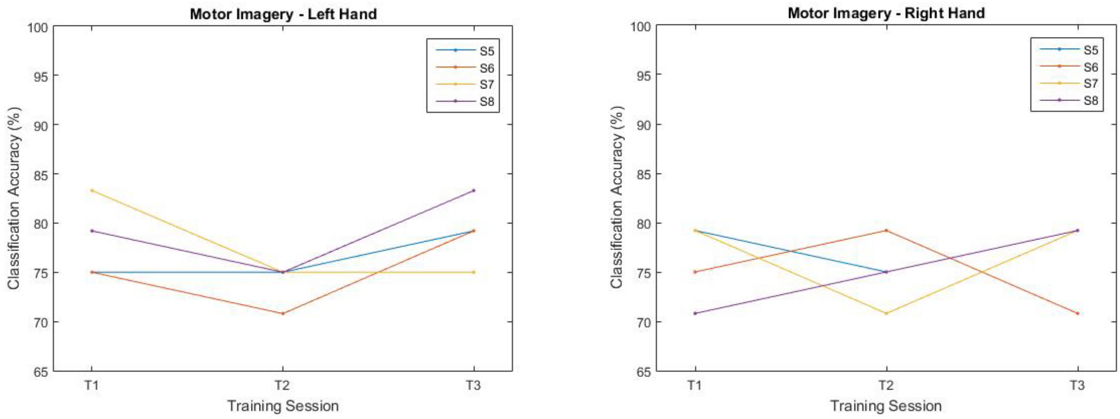


Figure 4.4: Study 2: Motor Imagery classification accuracies of 4 subjects over 3 training sessions.

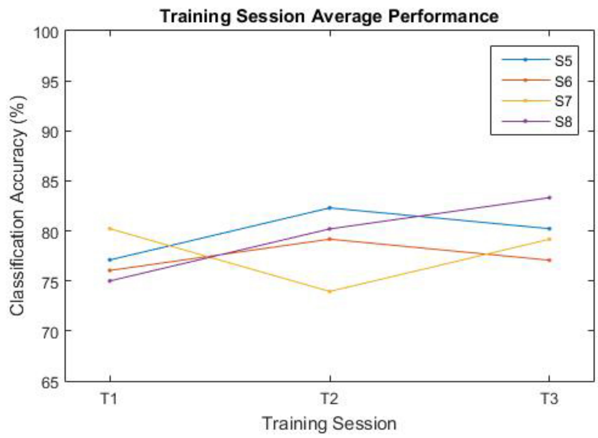


Figure 4.5: Study 2: Average subject performance over the 3 training sessions.

The results of the motor action and motor imagery tests for each subject are presented in Figures 4.3 and 4.4 respectively. Their average performance is showed in Figure 4.5. Subject 5 showed an improvement in performance between the first and last training session across all categories. His best performance, however, was the second training session, where he achieved a 100% accuracy in the left hand motor action test. Subject 7 reported he was tired and with few hours of sleep during his last two training sessions. Likewise, his performances were poorer. On the other hand, subject 6 reported to be light spirited and energetic during his second training session, in which he achieved his best performance. Due to these observations, a statistical analysis was done to observe how classifications changed with respect to mood, which will be presented in the following section. Only subject 8 showed a continuous improvement across all training sessions.

The details of each training session are presented on the next page in Tables 4.3 and 4.4. As in the first study, the extracted channels for each of the subjects correspond to the two hemispheres. As expected, most of the features are similar within the same training option over the 3 training sessions, however it is not always the case. This may be due to a slightly different placement of the headset from session to session.

Table 4.3: Study 2 - Motor Action classification accuracies across 3 training sessions for 4 subjects. T.O: Training Option; LH: Left Hand; RH: Right Hand; NB: Naïve Bayes; GSVM: Gaussian Support Vector Machine; DT: Decision Tree; TP1: Training Paradigm 1; TP2: Training Paradigm 2.

Subjects	T.O	Training Session 1			Training Session 2			Training Session 3		
		Features	Classifier	Classification (%)	Features	Classifier	Classification (%)	Features	Classifier	Classification (%)
S5	LH-TP1	FC5/9Hz, FC4/9Hz, 128 s.	GSVM	79.2%	FC5/11Hz, FC4/11Hz, 69 s.	DT	100.0%	FC5/8Hz, FC4/8Hz, 69 s.	DT	83.3%
	RH-TP2	FC5/9Hz, FC4/9Hz, 26 s.	DT	75.0%	FC5/8Hz, FC4/8Hz, 13 s.	GSVM	79.2%	C5/9Hz, F4/9Hz, 26 s.	DT	79.2%
S6	LH-TP2	FC5/9Hz, FC4/9Hz, 69 s.	GSVM	75.0%	FC5/9Hz, FC4/9Hz, 39 s.	GSVM	87.5%	F3/10Hz, C6/10Hz, 13 s.	GSVM	83.3%
	RH-TP1	C5/8Hz, F4/8Hz, 26 s.	GSVM	79.2%	C5/9Hz, F4/9Hz, 39 s.	GSVM	79.2%	FC5/9Hz, FC4/9Hz, 69 s.	DT	75.0%
S7	LH-TP1	FC5/9Hz, FC4/9Hz, 128 s.	GSVM	79.2%	F3/13Hz, C6/29Hz, 39 s.	NB	75.0%	F3/29Hz, C6/29Hz, 39 s.	DT	83.3%
	RH-TP2	C5/9Hz, F4/9Hz, 39 s.	DT	79.2%	F3/29Hz, C6/29Hz, 39 s.	GSVM	75.0%	F3/29Hz, C6/29Hz, 39 s.	GSVM	79.2%
S8	LH-TP2	FC5/30Hz, FC4/30Hz, 69 s.	DT	75.0%	FC5/9Hz, FC4/9Hz, 39 s.	DT	83.3%	FC5/8Hz, FC4/8Hz, 26 s.	DT	87.5%
	RH-TP1	F3/9Hz, C6/9Hz, 26 s.	DT	75.0%	C5/12Hz, F4/12Hz, 26 s.	DT	87.5%	F3/9Hz, C6/9Hz, 128 s.	DT	83.3%

Table 4.4: Study 2 - Motor Imagery classification accuracies across 3 training sessions for 4 subjects. T.O: Training Option; LH: Left Hand; RH: Right Hand; NB: Naïve Bayes; GSVM: Gaussian Support Vector Machine; DT: Decision Tree; TP1: Training Paradigm 1; TP2: Training Paradigm 2.

Subjects	T.O	Training Session 1			Training Session 2			Training Session 3		
		Features	Classifier	Classification (%)	Features	Classifier	Classification (%)	Features	Classifier	Classification (%)
S5	LH-TP1	FC3/10Hz, FC6/10Hz, 128 s.	DT	75.0%	FC5/10Hz, FC4/10Hz, 128 s.	DT	75.0%	FC3/10Hz, FC6/10Hz, 39 s.	DT	79.2%
	RH-TP2	FC5/9Hz, FC4/9Hz, 26 s.	DT	79.2%	F3/9Hz, C6/9Hz, 39 s.	DT	75.0%	C5/9Hz, F4/9Hz, 13 s.	GSVM	79.2%
S6	LH-TP2	C5/9Hz, F4/9Hz, 39 s.	DT	75.0%	FC5/27Hz, FC4/27Hz, 39 s.	DT	70.8%	FC3/10Hz, FC6/10Hz, 69 s.	GSVM	79.2%
	RH-TP1	C5/9Hz, F4/9Hz, 128 s.	GSVM	75.0%	FC5/9Hz, FC4/9Hz, 39 s.	DT	79.2%	C5/9, F4/9Hz, 13 s.	GSVM	70.8%
S7	LH-TP1	C5/11Hz, F4/11Hz, 128 s.	GSVM	83.3%	F3/13Hz, C6/13Hz, 26 s.	DT	75.0%	F3/27Hz, C6/27Hz, 26 s.	DT	75.0%
	RH-TP2	C5/11Hz, F4/9Hz, 128 s.	DT	79.2%	FC5/9Hz, FC4/9Hz, 39 s.	GSVM	70.8%	FC5/25Hz, FC4/25Hz, 13s.	GSVM	79.2%
S8	LH-TP2	FC5/11Hz, FC4/11, 69 s.	DT	79.2%	C5/30Hz, F4/30Hz, 128 s.	GSVM	75.0%	C5/11Hz, F4/11Hz, 128 s.	DT	83.3%
	RH-TP1	F3/9Hz, C6/9Hz, 39 s.	NB	70.8%	C5/24Hz, F4/24Hz, 13 s.	GSVM	75.0%	F3/9Hz, C6/9Hz, 128 s.	DT	79.2%

4.4 Miscellaneous Analysis

This section is devoted to provide further analysis, including data from all subjects, and also to present the results of the surveys. Figure 4.6 shows the overall performances with respect to each of the training options. As expected motor action tests yielded slightly better classification accuracies than motor imagery. This is due to the fact that motor imagery is generally challenging to perform.

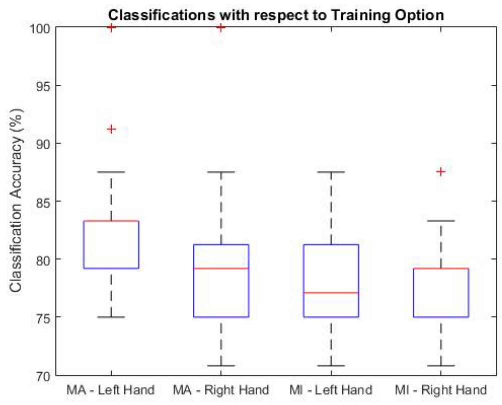


Figure 4.6: Performance with respect to training option for both studies.

Data from study 2 suggested that performance may be related to the mood and alertness of the subject, therefore a plot of classification accuracies with respect to mood is presented in Figure 4.7. The mood was assessed after every training session with the first question of the survey. It should be noted that data is distributed differently across mood, since most subjects reported to be "Just Fine" and "Good". Yet it is possible to see that classification accuracies were poorer when the mood was lower.

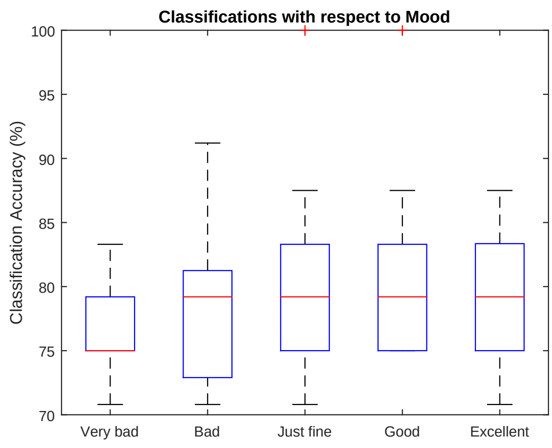
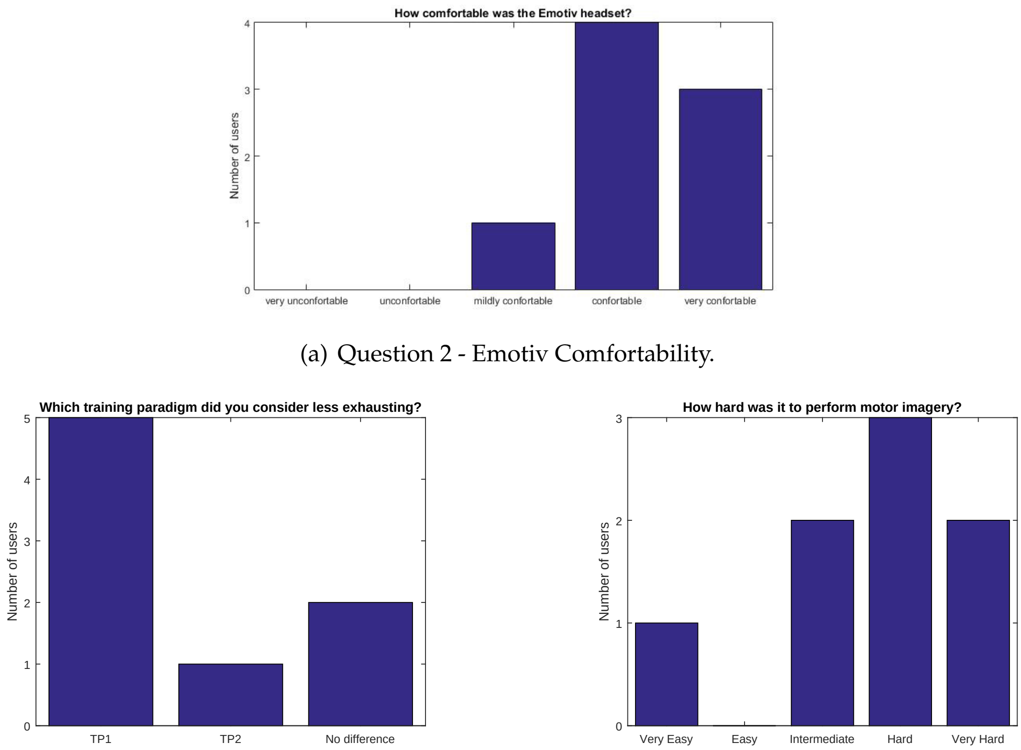


Figure 4.7: Performance with respect to mood.

Statistical information regarding the answers for questions 2 to 4 of the survey are displayed on Figure 4.8. No subjects reported that the *Emotiv* headset was uncomfortable

(Figure 4.8(a)). Most subjects considered training paradigm 1 to be less exhausting to perform (Figure 4.8(b)). Motor imagery was considered "hard" and "very hard" to perform according to most subjects. Only one subject considered it very easy to perform (Figure 4.8(c)).



(a) Question 2 - Emotiv Comfortability.

(b) Question 3 - Training Paradigm.

(c) Question 4 - Motor Imagery.

Figure 4.8: Results from survey.

Finally, Figure 4.9 shows a pie chart representing the best performing classifiers in all training sessions. Decision Tree was by far the most frequently selected as optimal, as opposed to Naïve Bayes, which was seldom used.

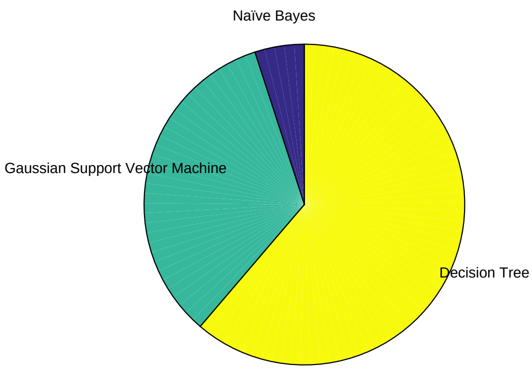


Figure 4.9: Pie chart of classifier usage.

4.5 Discussion

The presented data suggests the EmotivBCI can classify motor action and motor imagery up to an acceptable performance. Theoretically, the random accuracy of a 2-class problem is 50%, and the lower classification accuracy yielded by the EmotivBCI is 70.8%. However, it is important to mention that given the number of attributes used in classification, the practical random accuracy is around 70%, as suggested by Mueller-Putz et. al. [107]. Also, the way the EmotivBCI processes and classifies the signals is highly selective for patterns, which may not be directly linked to motor actions and imagery. The EmotivBCI generates 15 different classifiers based on different time frames as explained before, and selects the best one. This can sometimes lead to a dubious classification, specially if the time window is small (for example, 13 samples). However, it is possible to distinguish and observe patterns related to each individual. Based on the first study, it is clear that there is a difference in classification between both training paradigms. Subjects had generally better performances in TP-1 than in TP-2. Reasons for this may be that training paradigm 1 has less attributes to classify than TP-2, therefore classifications are slightly better. However, most users claimed TP-1 to be less exhaustive, and that may also contribute to better classifications.

It is difficult to take significant conclusions from the second study, which evaluates performance with respect to practice. This is mainly due to the limited number of subjects and training sessions. However, based on this study, 3 out of 4 subjects improved performance between the first and last training session. The subject which showed a drop in performance claimed to be exhausted and fairly inattentive during the last two sessions, which may have had an impact in performance. Based on this, a statistical study was made to assess user performance with respect to mood using data from all participants. The number of participants is not high enough to make a general conclusion, but based on the results, classification accuracies were worse under the intermediate level of mood ("Just Fine"), and constantly better above that.

Based on the survey, most subjects considered motor imagery to be hard to perform. They were told before training sessions to imagine movement to the best of their ability, be it visual imagination or tactile imagination. Some subjects imagined activities with their hands, like playing a musical instrument or playing with a gamepad or joystick. As mentioned in Chapter 2 motor imagery is an innate ability of an individual, and can be improved with practice. As such, some of the participants had better performances than others in the motor imagery sessions.

The Emotiv headset was considered comfortable by all subjects. It requires, however, frequent attention with regard to electrode pad moisture. In many cases the signals from the channels were not steady, most likely because of internal issues related to hardware. This resulted either in random spikes, or in a very attenuated signal at times. Although signals were normalized during the processing stage, these issues can still contribute to a wrong manifestation of an EEG signal.

CHAPTER 5

CONCLUSION

Neurological disorders have a meaningful impact in people's quality of life. Specially stroke, since it affects the greatest number of individuals. Rehabilitation and therapy are not overlooked. In recent years new methods have been developed and implemented in clinical settings, each with their own advantages and limitations. Nonetheless they have shown to have a positive impact. And they are not completely alternative to one another, but rather complementary. One of these methods is Brain-Computer Interfaces.

A BCI enables a subject to communicate and control the external world by using signals recorded from the central nervous system. Even though BCIs are not a new concept, it's undeniable its ongoing growth, as they may become an important asset in people's quality of life. Several applications have been developed using BCIs as the core of its functionality. Moreover, BCIs are continuously being researched as a mean of neurorehabilitation, showing potential to revolutionize how neurological diseases, mainly stroke, are treated in the future. Current limitations regarding reliability are being steadily overcome with better acquisition systems and more sophisticated processing algorithms. At the present time, non-invasive BCIs still suffer from having complex acquisition systems, which would be generally expensive and troublesome for a normal user, or even for hospitals and clinics. Therefore, they would benefit from being simple and practical.

This Master Dissertation consisted of the development of a practical, easy-to-use, non-invasive BCI: the *EmotivBCI*. The inspiration for the EmotivBCI is to be a user-friendly platform, not limited to research, in which users can perform BCI tests, based on motor action and motor imagery, and assess their performance. Furthermore, they can keep track of their progress and hopefully see a continuous improvement with practice. The EmotivBCI distinguishes between the idle condition and an action condition, based on the variation of sensorimotor rhythms.

The two studies conducted in the scope of this project provide a preliminary assessment of the EmotivBCI. The first study compares user performance between two training paradigms. The results suggest that fewer repetitions yield better classification accuracies. This is expected due to the fact that there are fewer attributes used for classification, and also most users considered it to be less exhaustive, giving them more time to perform each of the actions. The second study analyses the progression of performance after several training sessions. The number of training sessions and the number of users was suboptimal to take definite conclusions, however, an improvement pattern was recorded for 3 out of the 4 participants. A few complementary statistical studies were conducted with data from both groups of subjects. Data showed that motor action tests had higher classification accuracies than motor imagery, as it would be expected. Also a study of performance with respect to mood was carried out, and it showed that performance was lower with respect to lower mood states and exhaustion.

The EmotivBCI is a proof-of-concept BCI, which successfully implements most of the features it was intended to. There is, however, much room for further improvement, be it as a part of a doctoral project, or continuous master dissertation projects. The next section will discuss a few of the areas in which the EmotivBCI can continue to grow as a BCI platform, until it can be recognized as a legit rehabilitation tool.

5.1 Future Developments

The EmotivBCI is far from reaching its full potential. What was introduced in this Master Dissertation is the first prototype of what could potentially be an innovative rehabilitation tool. In this final section, it will be described and suggested a few of the ways in which the EmotivBCI can improve in respect to different areas:

5.1.1 Emotiv headset and Hardware

One of the innovative concepts developing the EmotivBCI was to use a commercially available, easy to use headset to perform the EEG acquisition. For this purpose, the Emotiv headset was selected, and it also gave the inspiration to the name of the BCI. Although it is aestheticly pleasing, and comfortable on the user, it comes with its drawbacks, as discussed before. Besides the electrodes not being designed to be placed on the central cortex, as adjustments were made for the studies, the necessity of constantly wetting the electrode sponges for acquisition can be a gruelling task for any potential user: a physician, or worse, the disabled patient. The fact that the electrode knobs are extremely fragile, and come off easily doesn't help either. Fortunately, new hardware keeps being launched. It is also worth noting that the computer where both the software was developed and the studies were conducted was 6 years old, and it caused the software to be unresponsive at times. In a couple of occasions, tests had to be repeated due to the computer lagging, and causing the training paradigms not to be timely. This is easily solvable, due to the fact that a newer computer could perhaps execute the code faster, without lagging issues.

5.1.2 Signal Processing

The EmotivBCI uses a simple and straightforward processing cascade, which provided acceptable results. For some users, it showed a clear distinction between the rest and action conditions, and for both motor action and motor imagery tests. There was some degree of correlation between the mood of the users and the results. A state-of-the-art BCI, however, should be able to classify and clearly distinguish the user's intent regardless of their condition, or even environment. To this end, new, and more sophisticated processing techniques should be investigated. Parametric techniques are an alternative, or complementary, approach that can be incorporated in the EmotivBCI. Ideally, it should be possible to detect patterns in EEG signal behaviour going from one condition to another, with respect to time. Wavelets and other time-related techniques may provide the means to study these patterns.

Some developed BCIs have the ability to successfully distinguish between four different conditions, while the EmotivBCI only does two: Rest and one action. However, for the majority of the conducted tests, the EmotivBCI showed different features for the use of Left and Right hand, for both motor action and imagery. So, theoretically the EmotivBCI could distinguish between 3 different conditions. But this remains to be tested in a paradigm where all the actions are involved.

5.1.3 Visual Interface and Visual Stimuli

The creation of a visual interface for the EmotivBCI is of a high degree of priority for two important reasons. The first is the obvious aesthetic aspect. Any user would prefer having a friendly interface to navigate through the options, instead of typing commands through a console. The use of visual cues to display the action the user has to perform would be more beneficial and be less exhausting than having to read tiny letters on the console display. The second, and more important reason, would be the incorporation of visual stimuli to the training paradigms. As mentioned in Chapter 2, mirror neurons have an important role in cerebral neuroplasticity. By combining visual stimuli with motor imagery, it is expected that ERD/ERS would be accentuated and hence, better classifications accuracies would arise. Moreover, most users reported that it was difficult to perform motor imagery, thereby the use of visual aid could facilitate this task. In the end, the user could perform motor imagery, and see a virtual hand moving in the computer interface.

Having the EmotivBCI platform built mostly on a C# environment was done intently for this purpose. A gaming engine software: *Unity3D* [118], operates by C# scripting, and it could be a viable option to create a visual interface. It has now been explored as a mean of Virtual Reality rehabilitation, and it is compatible with biomedical applications. Also, the creation of a virtual hand that opens and closes can be achieved using this software, thereby providing the Visual Stimulus mentioned before. Further ahead, it could even allow the creation of games or other entertaining activities associated with rehabilitation to captivate the enthusiasm of the patients and therefore promote their recovery.

5.1.4 Further tests and validation

The number of subjects used to perform the studies presented in this Dissertation was limited. A greater variety of subjects and studies should be conducted in the future. As mentioned, a new paradigm involving the use of 3 conditions as opposed to 2 conditions is fundamental. For example: Rest condition; left hand condition and right hand condition. Several paradigms should also be tested, with different durations, and triggered at random times, instead of following a pattern. If these studies show conclusive results in healthy individuals, then the EmotivBCI can proceed to be tested in real patients. At this point, the EmotivBCI should have a visual interface and visual stimulus implemented. Hopefully it should also perform the EEG acquisitions from a newer headset with dry electrodes. If it is well received by physicians and patients, and it is proven to be a useful tool in rehabilitation, then it should be disseminated across different clinical settings, and eventually be commercialized.

5.2 Outputs

The outputs of this dissertation are as follows:

- Participation in the 3rd Worksop on ICTs for improving Patients rehabilitation Research Techniques, held in Lisbon, on the 1st and 2nd of October of 2015 (workshop paper submitted and accepted)(Appendix B).

Future work may be prepared and developed for submission in journals and conferences related to BCIs and Neurorehabilitation.

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APPENDIX

A

EMOTIVBCI USER GUIDE

A.1 Getting started

Before launching the EmotivBCI application, place the Emotiv headset and make sure all the electrodes are in contact with the scalp. Verify beforehand if all pads on the electrodes are moisturized with a saline solution. Next, open *Testbench* and certify that all signals are steady. Wait a few seconds for the system to stabilize. After you have completed these steps, open the EmotivBCI application.

A.2 Registering and Logging in

If you have never used the EmotivBCI before, you will have to register. Type in the console *newuser*. Fill in your name, age, username and password. After registering you can login with your new credentials. Simply type *login* in the console and enter your credentials. If you had registered before you can skip the first step, and login right away.

A.3 New Training Session

Once you have successfully logged in, you can perform training sessions. Type *newtraining* in the console window. There are 4 training options to choose from:

1. Left hand motor action;
2. Right hand motor action;
3. Left hand motor imagery;
4. Right hand motor imagery;

Type in the number correspondent to the training option you want. Next, you are prompted to select the training paradigm:

1. 5-second-rest-5-second-action;
2. 2-second-rest-2-second-action;

Likewise, select the number that corresponds to the training paradigm you want. Once you have selected the training paradigm, sit back, relax, avoid facial movement and perform the action prompted by the console window. Depending on the training option and paradigm, the action and the repetitions' time will vary.

A.3.1 Training Session Performance

After 2 minutes, the training session concludes, and a classification accuracy will be displayed, along with the features and the classifier used. From here, you have several options to assess your performance. The following features generate plots in a pdf format.

A.3.2 Generate Feature Map

You can generate a feature map based on the acquisition, which shows the activity of each channel with respect to frequency. Type *generatefeatmap* on the console. Wait until the pdf document is generated displaying the feature map. You can close it whenever you want, it will be saved in your directory.

A.3.3 Generate Channel Power Spectral Density

You can generate a power spectrum density plot for any of the 8 channels used in the acquisition. For this, type *generatechpsd* on the console. You will be asked if you want to generate a PSD plot for the best channel extracted. Type *yes* if that is the channel you want. If not, type *no*, and type in the number correspondent to the channel you want. Again, wait until a pdf document is generated. A Periodogram and Welch Power Estimation will be presented and saved in your directory.

A.3.4 Generate Classifier Data

Finally, you can generate a plot with the data points from the attributes that were used for classification. Type *generateclassdata* on the console. As in the previous features, wait for the pdf document to open. You can close it whenever you wish, since it is saved in your directory.

A.3.5 Online BCI

If you achieved a classification accuracy greater than 90% you can attempt to perform real-time BCI testing. For this, type *onlinebci*. A different text will be displayed on the console with respect to your action.

A.4 Useful commands

Apart from the main features just mentioned, there are a few commands which you may find useful. You can browse through previous training sessions you performed, and see your performance. These are listed as records. To do so, type *listrecords*. If you haven't already, you can generate any of the plots mentioned for any of the records. To do so, type *loadrecord* and enter the *ID* of the training session you want. The *ID* is displayed at the top of each training session, and it specifies the training option and training paradigm you selected for that session. You can export the EEG data in CSV format by typing *exportrecord* on the console window. A CSV file will be generated in your directory, properly labelled. If you are unsure of any of the commands used to control the EmotivBCI you can simply type *help* and a full list of commands and respective descriptions will be displayed.

You can perform a new training session at any time, by typing *newtraining*. If you have concluded all the tests you meant to perform, just type *logout* and to close the application type *quit*.

Appendix B

REHAB 2015: Development of a non-invasive Brain Computer Interface for Neurorehabilitation

Development of a Non-invasive Brain Computer Interface for Neurorehabilitation

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ABSTRACT
Neurological disorders, in particular Stroke, have a substantial impact on a great number of individuals worldwide. These individuals are often left with residual motor control in their upper limbs. Although conventional therapy can aid in restoring some of the lost movement, it is not always accessible, and the procedures are dull and unappealing for the patient. Novel methods of therapy are being developed, including Brain-Computer Interfaces (BCIs).

This document introduces the EmotivBCI: a simple and accessible platform for EEG acquisition, processing and classification of brain signals with respect to motor action and motor imagery. The acquisition of EEG is done through 8 channels of the *Emotiv Epoc* headset. Signals are pre-processed, and the 2 best combinations of channel/frequency pairs that exhibit the greatest power difference between the rest and action conditions are extracted. These features are then used to build a feature matrix with 2 sets of attributes and 2 class labels. Finally this data is used to train 4 different classifiers.

As an early assessment phase, 6 healthy subjects tested each of the training paradigms. Although it is a project still in progress, it has shown promising results.

Keywords
BCI, Emotiv, EEG, Neurorehabilitation, Motor Imagery, Signal Processing, Feature Extraction and Classification, Stroke.

1. INTRODUCTION
Stroke is the second largest cause of death in the world and is also one of the leading causes of disability in adults. In the United States approximately 795,000 people are affected every year [1]. One of the most common non-hemorrhagic stroke is the middle cerebral artery stroke, which mainly affects the upper limb [2].

The therapy for upper limb disabilities varies depending on severity. If patients have a high enough degree of residual control, then techniques like *shaping* and constraint-induced movement therapy (CIMT) are applied. Patients that have weaker hand movement and control often use commercially available forearm-hand orthotic devices with electric stimulation [3].

Ongoing research focuses on the use of mechanical devices in combination with other rehabilitative therapies such as non-invasive brain stimulation to achieve a higher efficacy in rehabilitation of patients after stroke [1]. Among these, Brain-Computer Interfaces are also being explored as a mean of neurorehabilitation [4], showing potential to revolutionize how neurological diseases, mainly stroke, are treated in the future.

Brain-Computer interfaces (BCIs) are systems that enable brain activity to manipulate external devices. One type of BCI is the non-invasive BCI, which acquires brain signals from scalp Electroencephalography (EEG), for example [5]. EEG is a technique in which electrical potentials produced in the brain are recorded with high temporal resolution. The EEG is able to record rhythmic electrical activity from the human scalp. There are particular ranges of frequencies that are associated with sensory motor actions namely the Mu (8Hz-12Hz) and Beta (15Hz-30Hz) rhythms. The planning and execution of hand movement can be observed within these frequencies in the form of Event-Related Desynchronization/ Event-Related Synchronization (ERD/ERS) signals [6]. These consist of a difference in power in the Mu and Beta frequencies. Although these phenomena can be difficult to observe in EEG, due to the abundance of unwanted artefacts, advances in equipment and signal processing algorithms have made it extremely convenient to use ERD/ERS of Mu and Beta rhythms to develop BCIs controlled by motor actions, including motor imagery i.e. imagination of the movement of a limb.

To further validate the use of BCI in neurorehabilitation, studies have shown that motor imagery activates sensorimotor regions similarly to actual task performance, and repeated practice of motor imagery can induce plasticity changes in the brain [7]. This may be the key to a new rehabilitation methodology that aims at restoring lost function in a limb due to neurological disorders, such as Stroke.

There are, however, several factors that hinder the usage of BCI systems in clinical settings. Most non-invasive BCIs acquire EEG data from electrode caps with multiple wires, which are unattractive and uncomfortable. They also come with extra hardware for signal amplification, and take too much time to set up. Although these systems provide high resolution, they are often expensive, and end up disregarded as a rehabilitative solution. The EmotivBCI tackles these drawbacks by designing a highly portable, easy to set up BCI thanks to the *Emotiv Epoc* headset.

2. RELATED WORK
The following subsections describe a successful BCI application and the role of Virtual reality in rehabilitation.

2.1 Mechanic hand BCI
Fok et al, [8] designed an EEG-based BCI that drives a hand orthotic that opens and closes a patient's hand using ipsilateral activity of the brain. The purpose of the device is to aid in rehabilitation of stroke patients that are left with residual motor function in one hand.

The signals from the scalp were acquired through a portable EEG headset: *Emotiv Epoc*. After a calibration phase, we were able to determine relevant EEG features to distinguish movement from rest, and reducing the number of electrode channels and frequency bins to undergo further processing. Finally a pre-fabricated orthotic hand was modified to be controlled by the output of the classification algorithms, opening and closing depending on the output signal.

Through 10 sets of trials, consisting of moving a cursor to a target by imagining left hand movement, with healthy individuals, we were able to achieve an 81.3% success rate.

2.2 Virtual Reality

Virtual Reality (VR) is a computer interface that allows individuals to interact with a 3D environment by presenting stimulated or artificially generated sensory information [9]. Virtual Reality is an alternate or complementary rehabilitation method to BCI, which also promises to help rehabilitate Stroke patients. It differs from BCI because it doesn't usually take brain signals as an input, but rather movement that is captured through proper motion tracking equipment.

The main focus of VR rehabilitation is to simulate real world tasks into a virtual platform, so that stroke patients with motor impairments can practice such tasks safely and transfer the performance of the virtual task onto the real world.

3. TECHINAL DETAILS

3.1 Overview

The EmotivBCI is essentially a proof-of-concept of a simple BCI console platform developed in C# programming language. It acquires EEG signals from 8 electrode channels in the central and frontal cortices of the brain according to the 10-20 system (AF3, F7, F3, FC5, FC6, F4, F8, AF4) through the commercially available EEG headset: *Emotiv Epoc*. The Emotiv Epoc has 14 electrode channels, and a sampling frequency of 128 Hz. It also has built-in filters at 50 and 60Hz. Its wireless connectivity with a 2.4 GHz band makes it extremely portable and simple to use.

The acquired signals are processed and relevant features are extracted to build a classifier based on ERD/ERS due to movement or imagery of upper limbs (left and right hands). It also implements real-time testing with the built-in classifiers.

The EmotivBCI comes with a number of features, some of which will be described in the subsequent sections.

3.2 Operation

The way the EmotivBCI works is the following: A user registers and logs in with his credentials. Afterwards he or she can perform a training session.

3.2.1 Training Sessions

The EmotivBCI provides four different training paradigms: Left hand motor action, right hand motor action, left hand motor imagery and right hand motor imagery. All paradigms follow the same procedure: It's a 2-minute long run. Each run has 12 trials, which are 10 seconds long: 5 seconds of rest plus 5 seconds of action. The action is dictated by the chosen training paradigm. The user is prompted to follow the instructions that are displayed on the console.

3.2.2 Signal Processing

Signal processing is carried out with the support of *Matlab* wrapped functions in a non-parametric fashion. Once acquired, signals from each channel are pre-processed with C# built functions that remove the DC component and normalize the signal. The signal is then ready for feature extraction.

3.2.2.1 Processing Methods

The EmotivBCI has two different methods of processing the data. The first method uses the entire time interval (5 seconds) of each condition. The second method of processing consists of selecting only the initial number of samples for each condition, in contrast to the whole 5 seconds of method 1.

The number of samples implemented for extraction are:

- 13 samples ~ 100 ms.
- 26 samples ~ 200 ms.
- 39 samples ~ 300 ms.
- 69 samples = 500 ms.
- 128 samples = 1 s.

For each number of samples, the feature extraction cascade is the same as method 1.

3.2.3 Feature Extraction

The EmotivBCI extracts the 2 best combinations of channel/frequency that exhibit the greatest ERD over the 12 trials. For each channel the pre-processed EEG signal is segmented into two distinct signals for each condition: Rest and Action. Depending on the processing method the number of samples in the Rest and Action vectors are different.

The signals are then filtered using a 10^{th}-order double bandpass Chebyshev Type 1 filter in the frequency bands that exhibit ERD: 7Hz to 13Hz (Mu) and 15Hz to 30Hz (Beta).

Once filtered, the Power spectrum density (PSD) is estimated using the Welch method for each of the conditions in every channel: PSD(rest) and PSD(action).

The difference PSD(rest)-PSD(action) is calculated to predict the channel and frequency that show the greatest difference, hence the greatest ERD.

The two best combinations of channel/frequency are used to build the feature matrix for the classifier. The best channels may be the same. If so it exhibits ERD in two distinct frequencies.

3.2.4 Feature Matrix

The feature matrix is calculated for the best channels, by computing the band power centered in the respective best frequency. The data from each of the 2 best channels is again separated into rest and action conditions, and buffered into frames.

For each frame, the band power centered in the best frequency, with the range of 1 Hz, is computed.

The resulting matrix consists of a set of band power values for the rest state, which corresponds to output -1, and a set of band power values for the action state, which corresponds to output +1.

In the case of the first method of processing, the data after separation is buffered into 128 samples – 1 second. Since each trial has 5 seconds of each condition (rest and action), then the resulting feature matrix will have 60 band power values (12 trials x 5 band power values) for each condition, 120 total.

In the case of the second method of processing, the rest and action conditions are separated using the stipulated number of samples, and buffered into the same amount. It will therefore result in less number of inputs. 12 for each condition, and 24 total.

The resulting feature matrix will therefore consist of 2 sets of attributes: band power values for combination of channel/frequency number 1, and band power values for combination of channel/frequency number 2.

3.2.5 Classification

The feature matrix is used to train 4 different classifiers, implemented using the Accord Framework [10]. Accord Framework provides machine-learning libraries available for C#:

- Linear Support Vector Machine
- Gaussian Support Vector Machine
- Naïve Bayes
- Decision Tree

The resulting classification accuracy represents the number of correctly classified samples over the total number of samples multiplied by 100%.

3.2.6 End of training session

The processing cascade will result in a large number of classifiers built for each method: 4 for method 1, and 20 (5 sample sizes x 4 classifiers) for method 2. From these 24, only the one that yields the best accuracy is selected to validate the training session and posteriorly to be used for real-time BCI. The relevant features extracted and processing method are registered for that training session based on the classifier as well.

3.2.7 Real-time BCI

EmotivBCI offers the functionality of real-time BCI after a user has performed a training session. The data being acquired is processed every second, by computing the band power value in the channel and frequency extracted from the training session, and classified as rest or action, based on the selected classifier. In case of processing method 2, the data is still processed every second, but it's only selected the number of samples stipulated. At the moment, the EmotivBCI will display a different message based on the action the user is attempting to perform.

3.2.8 Other features

Besides classification of signals and real-time time testing, the EmotivBCI platform offers more features, some of which are worth mentioning:

- Feature map generation: Plot that shows the Power difference in each channel with respect to frequency. The extracted features are based on this feature map.
- Channel PSD generation: For any given channel, a Fast-Fourier, Burg PSD estimate, and Welch PSD plots are generated for conditions rest and action. These often show a clear representation of the ERD.
- Classifier data plot generation: Generates a scatter plot based on the feature matrix with the 2 classes used for classification.

4. EVALUATION AND RESULTS

In order to access the current state of the EmotivBCI, 6 healthy subjects, between the ages of 22 to 37, conducted a training session for each of the 4 training paradigms. The respective classification accuracies are presented below:

Table 1. Classification accuracies (%) of 6 different subjects for each training option. Avg = average

Training Option	Sub 1	Sub 2	Sub 3	Sub 4	Sub 5	Sub 6	Avg
Left hand motor	83.3	75.0	75.0	83.3	91.6	79.2	81.2
Right hand motor	75.0	79.2	75.0	70.8	83.3	79.2	77.1
Left hand imagery	79.2	75.0	87.5	83.3	79.2	70.8	79.2
Right hand imagery	75.0	79.2	87.5	75.0	83.3	75.0	79.2

For subject 4 that achieved an 83.3% accuracy in left hand motor classification, the typical Power Spectrum Density plot of the channel that was used for feature extraction is presented:

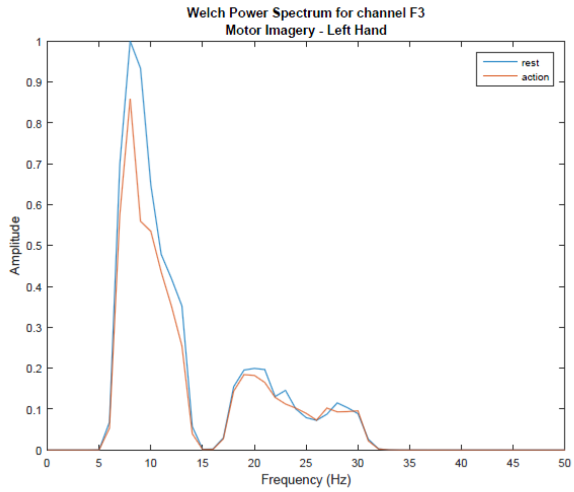

Figure 1: PSD plot for channel F3 of Subject 4

5. DISCUSSION

From the 2 processing methods implemented, all the best classification accuracies resulted from the second one, even though the number of samples varied within subjects and training options. This suggests that ERD is greatest at the start of the action condition. This may be due to the inability of the subjects to maintain a steady state of concentration during rest and action.

EmotivBCI can generate the PSD plot of any channel. This represents the Power characteristics of the rest and action conditions for the entire duration of the training session. Figure 1 shows the PSD plot for one of the subjects that achieved an 83.3%

classification accuracy. It can be observed from the plot a clear difference in the Mu frequency band between the rest and action conditions i.e. ERD.

The real-time BCI functionality has not been proven to be coherent as of this moment. The subject that achieved the classification accuracy of 91.6%, in the left motor action training, was able to successfully control the interface almost flawlessly for the first 10 to 15 seconds, becoming less responsive in the following instances.

The EmotivBCI is a work in progress, and several aspects are due to be improved. EEG signals are noisy and complex by nature, due to spontaneous firing of neurons in various directions. Because of this, event-related desynchronization is very subtle to observe, and can sometimes pass unnoticed. Muscular activity or natural reflexes, like blinking can greatly influence the results. Moreover, Event-Related desynchronization detection due to motor imagery depends a great deal on the individual. Fatigue and lack of concentration can significantly affect the results as well.

In order to overcome some of these obstacles, it is prudent to incorporate new training paradigms, in contrast to the 5-second-rest-5-second-action paradigm. These novel paradigms would consist of random cues, so the subject would not know what to expect, and shorter trial time, resulting in more data available to train the classifiers.

Even though the EEG signal is filtered to remove several unwanted artefacts, there are some that are still present, like blinking and other muscular activities. To prevent this it would be ideal to incorporate specific algorithms that recognize such irregularities and remove them.

The approach to signal processing has been mostly non-parametric. It would be interesting to couple this approach with parametric methods. Examining how the signal changes from rest to action in respect to time could provide invaluable information that could be used to help differentiate between the two states.

6. CONCLUSION

The EmotivBCI is a simple, accessible and yet robust platform for acquisition and processing of EEG data acquired from the *Emotiv Epoc*. It is now presented as a console application, but it can be the backbone to a more elegant graphic interface with a greater array of features.

Virtual reality and motor imagery show promise of a novel method of rehabilitation. Integrating the EmotivBCI in a virtual reality environment, like a virtual hand that opens and closes can be immensely beneficial. Not only by being more esthetically pleasing to the subjects, but more importantly by providing the visual stimulus that can better emphasize ERD/ERS and thereby improve classifications.

The long-term goal of the EmotivBCI would lie in neurorehabilitation. More specifically, in aiding to restore motor function of patients with neurological disorders such as stroke or ALS, by promoting the development of new cerebral cortex pathways through practice and observation. Ultimately giving autonomy to the patient, and be more engaging than conventional therapy. Unlike the common BCI systems comprised of multiple wires and complicated hardware, the EmotivBCI could one day be provide an affordable user-friendly system that can be incorporated in a clinical setting.

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