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Brain-Computer Interface based on Motor Movement and Imagery Tasks for Controlling a Virtual Arm

Work presented in partial fulfillment
of the requirements for the degree of
Bachelor in Computer Science

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"We shall prove ourselves in glorious combat!"

— WILHELM, REINHARDT

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RESUMO

Ao longo das últimas décadas, os seres humanos buscam formas alternativas de se comunicar com máquinas ou sistemas a fim de superar as dificuldades impostas pelas limitações biológicas, deficiências ou apenas para criar um dispositivo vestivel útil. Essas motivações levaram cientistas e pesquisadores a desenvolver e melhorar dispositivos para registrar a atividade cerebral, abrindo, assim, inúmeras oportunidades na área de interface cérebro-computador (ICC). Essa área emprega sinais cerebrais (tipicamente, eletroencefalografia - EEG) para controlar ou se comunicar com diversos sistemas. Nesse sentido, este trabalho procura estudar, tanto quanto possível, os equipamentos disponíveis para registro de dados de EEG (OpenBCI), bem como sua aplicação em um ambiente de Realidade Virtual (RV). Neste trabalho, uma metodologia típica da ICC é empregada para avaliar o dispositivo em uma tarefa motora usando sinais de EEG e eletromiografia (EMG); esse procedimento é dividido em etapas como gravação, filtragem, extração de recursos e treino de um algoritmo de classificação. Após o treino, o sistema é testado em uma experiência de RV, onde o usuário pode controlar uma mão virtual usando movimentos reais ou imaginários. Os resultados obtidos demonstram o potencial do OpenBCI e o escopo que a tecnologia de código aberto tem dentro do ICC e RV; Da mesma forma que o desenvolvimento de sistemas que usam movimentos reais e imaginários como forma de interação, pode ser usado tanto com pessoas com deficiência quanto com pessoas sem deficiência.

Palavras-chave: EEG, EMG, BCI, OpenBCI, Neurológico, Paralisia, Redes Neurais.

ABSTRACT

Throughout of the last decades, humanity have sought for alternative ways to communicate themselves with machines or systems, in order to overcome difficulties imposed by biological limitations, impairments or just to create a useful wearable. Those motivations have lead scientists and researchers to develop and improve devices for recording brain activity, thus opening countless opportunities in Brain-Computer Interface (BCI) area. This area employs brain signals (typically, Electroencephalography - EEG) to control or communicate with many systems. In that sense, this work seeks to study as much as possible the recently acquired equipment for recording EEG data (OpenBCI) as well as its application in a Virtual Reality (VR) environment. Therefore, a typical BCI methodology is employed for evaluating the device in a motor task using both EEG and Electromyography (EMG) signals; this procedure is divided into recording data, filtering, feature extraction, and classification. Finally, after the training part, the system is tested in a VR experience where the user can control a virtual arm using either real or imagined movements. The present achieved results demonstrate the potential of OpenBCI and the scope that open source technology has within BCI and VR; likewise, the development of systems, which uses both real and imaginary movements as interaction way, can be used for both impairment and non-impairment people.

Keywords: BCI. OpenBCI. Neurological. EEG. EMG. Impairment. Neural Network.

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LIST OF ABBREVIATIONS AND ACRONYMS

BCI	**B**rain **C**omputer **I**nterface
EEG	**E**lectro **E**ncephalo **G**ram
CNS	**C**entral **N**ervous **S**ystem
ANN	**A**rtificial **N**eural **N**etwork
MLP	**M**ulti **L**ayer **P**erceptron
OpenBCI	**Open**-source **B**rain **C**omputer **I**nterface
fMRI	**F**unctional **M**agnetic **R**esonance **I**maging
MEG	**M**agneto **E**ncephalo **G**raphy
VR	**V**irtual **R**eality
LSS	**L**ow **S**ignal **S**trenght
OCD	**O**bsessive **C**ompulsive **d**isorder
DBS	**D**eep **B**rain **S**timulation
ICA	**I**ndependent **C**omponent **A**nalisys
SVM	**S**upport **V**ector **M**achine
RV	**R**ealidade **V**irtual
ICC	**I**nterface **C**erebro **C**omputador

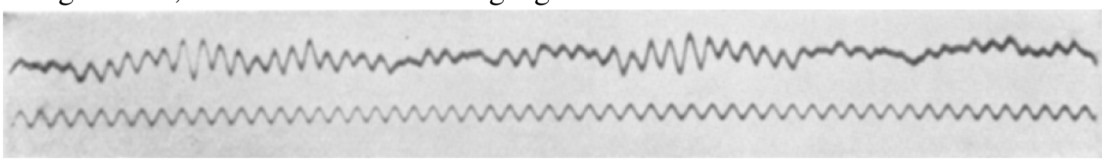
CONTENTS

1 INTRODUCTION

1.1 Neuroscience

The early studies about the electrical phenomena in the brain date much further from the modern days (G., 1987). However, for this work, it will only describe from the 19th century onwards, when a physician named Richard Caton presented his findings of such phenomena after exposing cerebral hemispheres of rabbits and monkeys. Later, in 1888, Adolf Beck published in a Polish scientific journal about spontaneous electrical activity including rhythmic oscillations. His experiments and findings lead to the concept of brain waves. Not so long after, in the 20th century, with numerous advances were discovered like, the Ukrainian physiologist Vladimir Vladimirovich Pravdich-Neminsky captured the first animal EEG in 1912, and two years later the first induced seizure was recorded. After that, in 1924, an invention described "as one of the most surprising, remarkable, and momentous developments in the history of clinical neurology" (MILLET, 2002) was created, the EEG machine, invented by Hans Berger, who also was the same who manage to obtain the first human EEG ever recorded (see figure 1.1). Colleagues first refuted his discoveries until they were confirmed by two British scientists named Edgar Douglas Adrian and Matthews in 1934 (HASS, 2003).

Figure 1.1: The first human EEG recording obtained by Hans Berger in 1924. The first tracing is EEG, and the lower is a timing signal.



Source: Ueber das Elektroenkephalogramm des Menschen, 1929

In 1935, three doctors (F. A. Gibbs, H. Davis, and W. G. Lennox) published a study called "The electroencephalogram in epilepsy and conditions of impaired consciousness" describing interictal spike waves and the three cycles per second pattern of clinical absence seizures, which began the field of clinical electroencephalography. A year later, Gibbs and Jasper reported the interictal spike as the focal signature of epilepsy, and in the same year, the first EEG laboratory opened at the Massachusetts General Hospital.

Franklin Offner, professor of biophysics at Northwestern University developed a prototype of the EEG that incorporated a piezoelectric inkwriter called a Crystograph (the whole device was typically known as the Offner Dynograph). Other important facts in later years in the neuroscience field were: the foundation of the American EEG Society, in 1947, the first International EEG congress. In the 1950s, two researches developed EEG topography as an adjunct to the already existing EEG, which allowed the mapping of electrical activity across the surface of the brain and the REM sleep was described by Aserinsky and Kleitman. All those cited facts had a place in history, enjoying a brief period of popularity and, in the 80s, such field seemed promising for psychiatry.

1.2 Brain-Computer Interfaces (BCI) and categories

A brain-computer interface (BCI) have its formal definition by: *"A system that measures central nervous system (CNS) activity and converts it into artificial output that replaces, restores, enhances, supplements, [informs], or improves natural CNS output and thereby changes the ongoing interactions between the CNS and its external or internal environment"* (WOLPAW; WOLPAW, 2012). Such device can do its measurements in several ways (Scalp, Epidural, Subdural or Intraparenchymal), operating in such a mode that we have two 'controllers'. Then the first one is the brain, whose produces an encoded activity in a wave and, the second, is a system that decodes this wave in commands. Brain-computer interfaces were divided into three major categories (MOORE, 2003; LEUTHARDT et al., 2009) :

- Invasive: Some particular devices are used to detect and capture a single area of the brain cells (Single Unit) or detect multiple regions (Multi-unit). Such devices are surgically inserted, obtaining the highest quality of signals, but this also came with a high risk to the patient, who has his brain exposed to the environment.
- Partially Invasive: Other than open the skull and expose the brain, devices are directly attached in the head. The signal strength is much weaker than the invasive option, but does not require extensive surgery.
- Non-Invasive: Most of BCI devices are in this category. They capture the brain waves through the human scalp. It is considered the best type regarding safety and cost because does not need any surgery and does not provide any immediate risk to the human life.

Also, many are the purposes that a BCI system can be used. Some of the proposed applications and paths throughout the years were(MOORE, 2003):

- Proposing new ways to interact with games with this non-usual input.

- Developing social applications can capture emotions and some nuances helping to filter the things that we most like.
- Helping partially or fully-disable people to interact with machines or other human beings with a prostatic device.
- Helping to understand more about the human brain and his neuron network activity, how it works.

1.2.1 Objectives and Challenges

The main objective of this work is to explore brain-computer interfaces, as well as possible benefits not only as an entertainment gadget but as an actual human improvement. Two main goals were set, one is investigative research upon the potentialities of the OpenBCI Hardware and Software, available at INF-UFRGS laboratories, seeking all its possible capabilities, hardware, and software limitations, etc. The second is a practical experiment using the previously cited divice to seek any possibility of impairment attenuation. To accomplish such objectives, this work will present a methodology, a set of experiments, achieved results, discussions and, future leads of what can be done. To establish a common environment for all subjects, the experiments will use the Unity engine to simulate the interpreted signal in real-time.

With these objectives in mind, it is essential to address the numerous challenges that exists in this field. Even with current technology and knowledge available, there are several challenges in the uses of BCI, primarily due to the natural complexity of the human brain, as well as the correct translation of the output, here, they are divided into four main aspects.

Hardware Challenges exist due to a physical limitation in the board, electrode or any part of the device. This limitation can also be a technological limitation in the current state of the art on the BCI field. There are a few important ones to address which can be attenuated at the moment, such as:

- Low Signal Strength (LSS): It is worth remembering that, the human brain waves are not very expressive, i. e., they are not naturally expressive since there is no need to be. Due to this natural occurrence, capturing these signals are quite tricky to noise and inner interference. Some devices have amplifiers to help with this issue.
- Inaccurate signal: As a consequence of the LSS, the signal can be misinterpreted

into another, leading to some problems such as low training confidence and high delay in application response.

- Transfer Rate(Bandwidth): Some studies (ABDULKADER; ATIA; MOSTAFA, 2015a; MOORE, 2003) discuss that the transfer rate of the BCI device is meager, serving as a bottleneck to what BCI applications can do.
- Autonomy: Ideally, anyone who wants to use such device or application could do it without any restrictions. However, people with severe disabilities need some caretakers. Nonetheless, the device needs to be turned on and off independently.

Application Challenges occur as a direct consequence of the hardware limitations, like one of the previous mentioned, due to some application limitation or due to the existing knowledge (e.g., Machine Learning algorithms). Two of the main challenges that are existing are:

- Training process: The training phase of an application is the most critical and time-consuming activity, this happens due the fact that, for the application to be reliable to reality, the data set must be of a considerable size in order to cover the most substantial portion of cases, and the algorithm must be good enough to predict actions with some confidence.
- Application overhead: To ensure the accurate and constant data transmission, the developed application cannot have a significant cost inside itself. This can lead to an inaccurate measurement or a missed meaningful signal. Also, the signal filtering is one of the crucial steps in the data acquisition and can be as well the most costly in CPU power due to its complexity.

Biological Challenges exist because each brain is unique and have your own characteristics and own relation to the environment, this leads to a imprecision in the terms of conceiving a BCI system with the capability of generalization. Not only that, there are many other factors such as:

- Complexity: Talking only about humans, the human brain is somewhat complex. We do not know yet about every aspect of its behavior. We know that are some specialist areas in the brain, but the actual work the brain does, every facet and what means everything we do not fully understand.
- Disorders: Due to its complexity, the brain can have some behavior disorders. Some of them which have already been cataloged and studied by experts, but the brain does not work the same way we expect.

- Cognitive load: Most of the BCI studies are done in a controlled environment (MOORE, 2003) with not so many distractions, which allows the user to concentrate more on the task.
- Emotional load: There are some interference regarding emotions and, due to various factors, it cannot be filtered leading to interference in the interpretation of the actual input for the BCI device.

Environment Challenges exist mainly because BCI devices mostly use EEG technique as their path. The surrounding environment can have a principal role in the signal distortion. To put in some perspective, the device has to be powered, and the same device can cause electrical interference since it has its field of activity. Sound, light, nearby sources, everything can create a noise which can trouble the data collection. For that, many solutions were proposed. Noise canceling algorithms were made, rooms with a more confortable and calm atmosphere, and much more, but nothing cited removes all the noise, they attenuate it to an acceptable level.

1.3 Text Organization

This work has two main goals, which are complementary. Because of that, it has been divided into two 'phases'. The first phase contains the study on the OpenBCI Hardware and Software, and the second part the conduction of an experiment using that system. However, before diving into the methodology, experiments, discussions and such, there is the necessity to first focus on the theoretical background, giving the reader a brief explanation of the biology of the brain, which are the techniques to record the brain activity and such. After, in Chapter 3, it will be discussed what BCI can do in the various fields.

After the base knowledge being set, the first phase takes place in Chapter 4, when a methodology to use the OpenBCI will be discussed, how the data will be recorded, gathered, translated, used, and if any additional implementation had taken place. Chapters 5 and 6 will attack the second phase with experiments using the described methodology and the different parts of the hardware, what were the protocol of data acquisition applied in the volunteers. A full report with feedback and results will also take place in each one of these chapters. Chapter 7 will discuss the results, our impressions over the OpenBCI and its features, major difficulties and other important notes that were taken during the development of this work. Finally, the final chapter will summarize our conclusions, contributions, and suggestions for follow-up experiments.

2 BACKGROUND

This chapter introduces the biology of the brain, what is a brainwave, existing techniques to acquire these signals and devices that exist today.

2.1 Biology and the Brain

This section will focus on the biological structure of the human brain, like its components, what is a neuron, how information is transmitted, what are brain waves and their known meanings. Everything in this section will lean in the high-level explanation provided by khanacademy (AMGEN, 2018), since it is a biological approach.

Although the intuitive thought of we only have neurons in the brain, this is a mistake. They compose our entire nervous system, that goes across the whole body and can be divided into two main sections. The first one is the Central Nervous System (CNS) that consists of the brain and the spinal cord, where resides our information analysis. The second one is our Peripheral Nervous System which is made by neurons and parts of the same across the whole body. They are responsible for sending the environmental information and decoding information for the movement (sensory and motor neurons).

2.1.1 Neurons

Before explaining what forms a neuron, there is the necessity to classify them, since they have many duties in the body. The neurons can be classified into three different classes: Sensory, Motor, and Interneurons.

Motor neurons are those responsible for keeping the body in 'movement'. They are not limited only by the muscles, but also the organs and the glans. They also act to the immediate response of the sensory neurons.

Sensory neurons are the ones responsible for the feeling of things such as temperature, pressure, pain, etc. They send information about the status of the surrounding environment, telling the brain if they are safe or not.

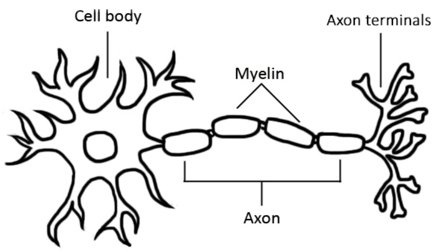
Interneurons exist only in the CNS part of the nervous system. They are responsible for creating the bridge which enables the brain to communicate with itself and get information from the sensory and send to the motor, and vice-versa.

With that in mind, the functions of the neuron can be summarized in: receive information in the form of signals, interpret it to perceive as good or bad information, and if it should be passed along, and communicate to other systems if the data is meaningful.

Anatomically speaking, a human neuron is composed of three parts (see in the Figure 2.1):

- **Cell body** which contains the input ramifications, called dendrites which are responsible for the first previously cites functions. The incoming signals can be interpreted in two different ways, divided in a fire/not fire trigger (excitatory/inhibitory response). Also, the cell body is attached to the second structure, and they are fundamental to our learning process, one time that new connections are made by them to create pathways.
- **Axon** arises from the cell body in a specialized area called axon hillock, and it is where the action potential in motor and interneurons takes a start. Axons also have a substance around them called myelin, which helps the fast convey of the nerve impulse.
- **Axon terminals** are the propagators of the signal. They condense the information in chemical reactions and send to a cell body dendrites.

Figure 2.1: A simplified view of the human neuron containing all the main typical structures.

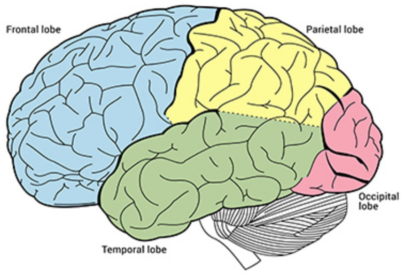


Source: Brain Facts Site

2.1.2 Brain Areas

Even the brain being composed by a high tangled network of neurons, it has its specialized areas as shown in Figure 2.2 which are:

Figure 2.2: Representation of the Brain divided in the four lobes.



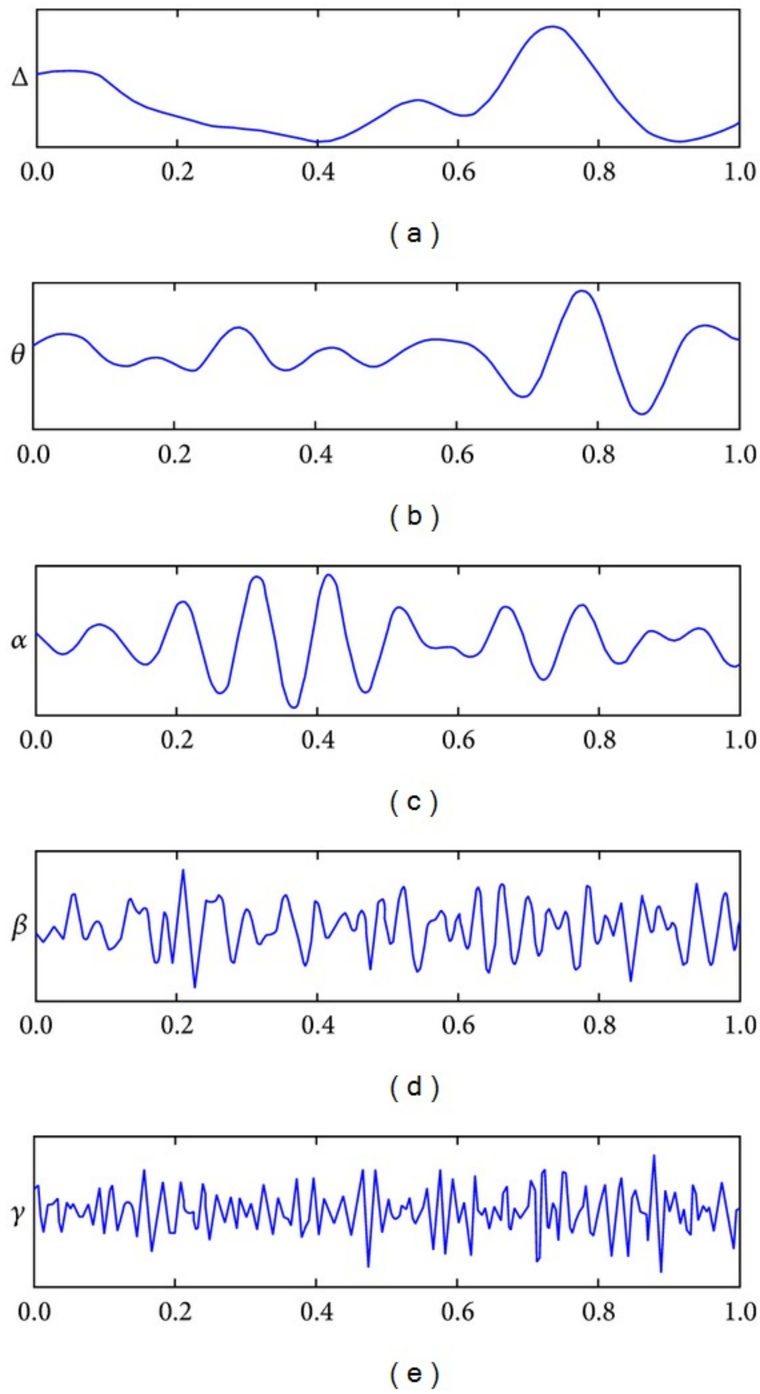
Source: Queensland Brain Institute Site

- **Frontal lobe** takes care of most of our cognitive tasks, also associated with language, motor skills, and reasoning.
- **Temporal lobe** is where our memories are formed, and the sound that we hear is processed. It is important to state that, even being this lobe responsible for forming memories, this is not stored. A lot is still to discover in this area.
- **Occiptal lobe** which duty is to interpret the visual signal of the eyes and decode it to brain information.
- **Parietal lobe** is associated with processing tactile sensory information such as pressure, touch, and pain.

2.1.3 Brain Signals

The electrical communication between the neurons, in their specialized areas, results in propagation of waves. Such phenomena were studied and, today, we have divided those waves into many spectrums. There are the five main spectrums (see Figure 2.3) which will be explained:

Figure 2.3: Representation of the five main spectrums of the brain wave being: (a)Delta (b)Theta (c)Alpha (d)Beta (e)Gamma



Source: (JIRAYUCHAROENSAK; PAN-NGUM; ISRASENA, 2014)

These spectrums can be broken in many sub-spectra but, to maintain the same level in detailing and the presented work. Only those five were presented.

- **Delta**: High amplitude waves with less than 4Hz, located in the thalamus (one of most inner part of the brain) or the cortex. The delta waves are associated (and only seen) with the slow-wave sleep (SWS) commonly named as Deep Sleep. Since BCI studies use their subjects awake, these waves are not useful.

- **Theta**: Theta waves are associated with daydreaming and the sleep state, have a frequency range from 4Hz to 8Hz, located far from any motor part. An interesting fact: If those waves are in abundance, it can be mean Attention Disorder.
- **Alpha**: With a frequency range from 8 to 15Hz, alpha waves are mainly located in the posterior region of the head. They are associated with the relaxing state when the eyes are being closed, for example.
- **Beta**: The beta waves have a frequency from 15Hz to 31Hz, are associated with our consciousness level, and have a symmetrical distribution along both sides of the brain.
- **Gamma**: These waves have a frequency between 32Hz to 100Hz and are located in the Somatosensory cortex. They have a strong association with the sensory processing and short-time memory in object recognition.

2.2 The 10-20 System

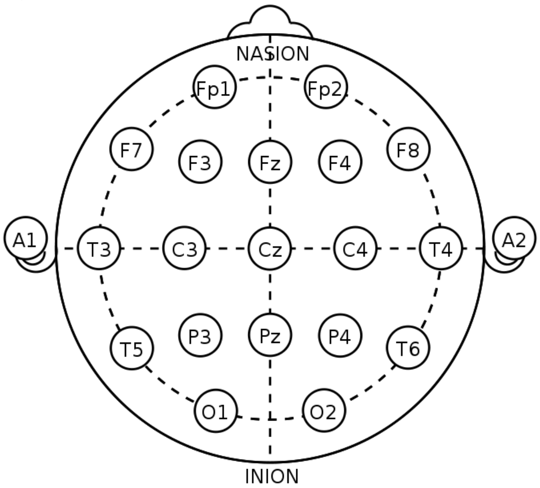
While the research on Neuroscience was getting more and more attention, the urge to make standardization of the human scalp for EEG to acquire and test data in a way that allowed the reproduction of tests. The work on the design of the system was led by Herbert Jasper and was presented at a conference in Paris, 1949 (THE..., 1961). Dr. Jasper established four guidelines:

- The positions of the electrodes should be measured from standard positions on the skull that can be easily detected in any subject, for example, the nasion, the point where the nose meets the forehead.
- All parts of the head should be represented with name-given positions.
- The names should be concerning brain areas instead of just numbers to make it possible for a non-specialist to understand.
- Studies should be made to determine the functionality of the part of the cortex underlying each electrode. The electrode should be named thereafter.

From these items, came the so-called 10-20 (the numbers are due to the percentage in the distance between the electrodes) system which respects all standardization as shown in

Figure 2.4.

Figure 2.4: Electrode locations of International 10-20 system for EEG (electroencephalography) recording



Source: Wikipedia: The 10-20 system

2.3 Recording Techniques

Many techniques can be used to map the brain activity, and they are used today in medical and research fields to seek any disorder or disease in the brain. Some of them will be presented here, such as:

MEG which is an abbreviation of Magnetoencephalography which is a device that allows measuring the ongoing brain activity with real-time resolution. Since the neuronal activity is detected by approximately 300 sensors distributed over the head, with a MEG device it is possible to identify where in the brain the activity is produced with reasonable accuracy. This makes MEG suited for studying the human brain as a network of interacting brain areas during performance of various tasks. The principal applications of MEG are clinical investigations and cognitive Neuroscience research. It should be the best BCI to use, but as shown in Figure 2.5, the machine is not portable due to its size and limited to a sealed and shielded room to nullify all interference. Also, the cost of acquiring and maintaining a MEG is high.

Figure 2.5: Representation of a MEG Machine

Source: Vendor Site

Functional magnetic resonance imaging or fMRI is a non-invasive neuroimaging technique which detects changes in local cerebral blood volume, cerebral blood flow, and oxygenation levels during neural activation utilizing electromagnetic fields. fRMI is mostly used in research projects than in the medical field. Like its name suggests this technique uses an MRI device (see figure 2.6), making impossible to use as a practical BCI device.

Figure 2.6: Representation of a fMRI machine

Source: NDCN Site

Electroencephalography (EEG) is the measurement of the electrical activity of the brain by using electrodes as shown in 2.7a. Each one of them represents a channel. These electrodes capture the electrical impulses from the scalp and transfer them to the measurement device like the one shown in 2.7b which amplifies the acquired signal and them records or show the resulting traces which are known as an electroencephalogram (EEG) and represent an electrical signal from a large number of neurons. Also, this is the most used technique for non-invasive BCI devices.

Figure 2.7: EEG Device Basic components

(a) The most commonly used electrodes in clinical EEG

(b) One example of EEG Device

Source: Medical material Vendor Site

2.4 Brain-Computer Interfaces

As previously said, many were the groups in the BCI-field that emerged in the recent years. In this section it will be discussed some of the works as well as some non-invasive BCI systems that already exist. These systems are critical due to its nature and possibility of use. Even with the weak brain signal, they capture the real-time data (i.e., they capture data with a minimum delay).

Started in the 70's with a paper discussing the possibility of a BCI-based system on an EEG by Vidal (VIDAL, 1973), this idea remained in the shadows for 15 years. Just in 1988 another researcher (FARWELL; DONCHIN, 1988), written an innovating paper demonstrating the development of a very primitive BCI. Then, other groups start to study more about BCI. In June of 1999, the first international BCI meeting was held, and a BCI definition was made *"A brain-computer interface is a communication system that does not depend on the brains normal output pathways of peripheral nerves and muscles"* (WOLPAW et al., 2002). This state that a BCI device should be able to identify and process his commands while remaining in silence and without moving.

The ability to use sensors to measure the brain-activity and it use as a path, based on an EEG, has been discussed for almost 50 years. The area in the past was not widely researched but, due to the advances in neurology and the reduced costs of computing power, the field, who in early 2000 had less than ten study groups, today counts with more than 200.

Also, while in the previous chapter, it was mentioned the types of BCI (invasive, partially invasive and non-invasive), this section will briefly explain the most common non-invasive devices and machines.

NeuroSky (see Figure 2.8) has a very delimited time-line. Beginning their work in 1999 and released a toy called MindFlex by Mattel, which uses the concentration level to trigger the game. A series of similar toys were made by the Company, as well a Hack Community to simple tasks, once the device have only one channel (now two channels in their new release) and have delimited signal output. Due to the acceptance of the product, the company started to sell the MindWave for multi-purpose tasks, including development in mobile applications.

Figure 2.8: Representation of a NeuroSky Helmet

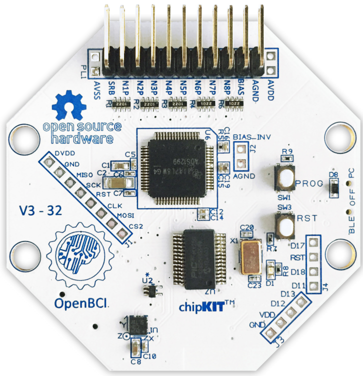
Source: Vendor Site

2.4.1 OpenBCI

OpenBCI stands for "Open-source Brain-Computer Interface" as they state *“Is a versatile and affordable biosensing micro-controller that can record brain, muscle, and heart activity"*(FOUNDERS, 2014). It began in 2014 with a Kick starter campaign aiming to create a low-cost, high-quality EEG sensor for non-traditional users. The campaign was a huge success leading the development of the V1 and V2 prototype, leading to their first sales board, the OpenBCI 32bit Board as shown in Figure 2.9. This board is composed of a 8-Channel with Ground (GND) and BIAS (i.e. reference pin to measure the signal), a EEG chipset, which can also takes measures of EMG and EKG and an acelerometer to measure the head movement.

Today, OpenBCI have a stable community with a great diversity of researchers (engineers, artists, scientists, designers, and so on), released another board with more channels and, because of the quality and cost, OpenBCI has been a good choice by re-

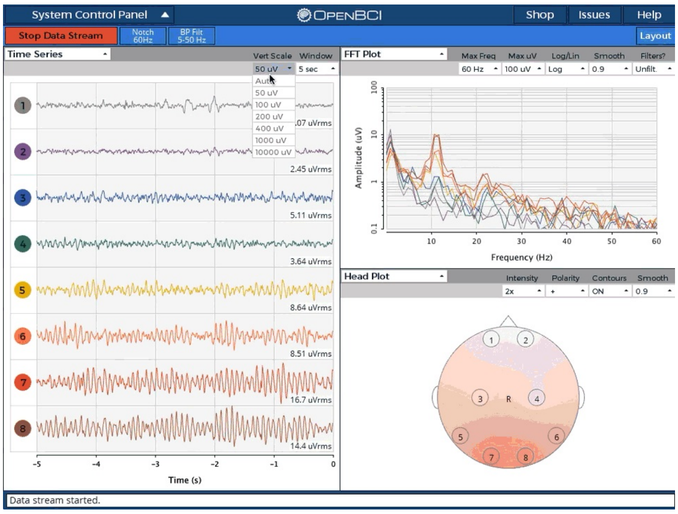
Figure 2.9: Representation of a OpenBCI 32 Bit Board, used in the work



Source: Vendor Site

searchers. It counts as well with an Open-Source Software; the OpenBCI-GUI like shown in the Figure 2.10. Such Software consists in the collaborative work of many developers to create a unique tool for study and test.

Figure 2.10: Screenshot of the OpenBCI Software showing brain signals from eight different channels



Source: Vendor Site

2.4.2 Epoc

Epoc (now Epoc+) is the most famous neuroheadset known. Created by the Emotiv company, initially released in 2009, the EPOC was demonstrated in the TEDTalks 2010 by Tan Le (LE, 2013). This device consists primarily of a 14 EEG Channels with two extra for reference, as shown in Figure 2.11, Epoc+ can detect 11 Facial expressions from scratch as well seven emotional states. Also, the same company has released another

BCI called Insight which is a reduced version of Epoc+ with only 5 channels and have the hability to monitor your cognitive health.

Figure 2.11: Representation of an Epoc+ Device

Source: Vendor Site

3 BCI APPLICATIONS AND APPROACHES

For decades, the humanity has imagined how it is to interact directly with machines, by making use of thoughts only, to control things, to manipulate the environment only with the emotions. Such ideas were translated in the fiction in many stories but, in the recent years, with the advances in cognitive neuroscience, the fiction is becoming more and more tangible, starting to provide some new abilities to interact with the ambient and monitor some of its processes through the use of sensors which enabled many areas that BCI can be used. In this chapter, they will be discussed.

One of the most promising and important, if not the most, fields of study in BCI is the **medical**. The ability to use machinery as an alternative output for our brain communication, especially for those who lost the ability to use the primary interface (i.e., the own body functions) as the default way to communicate or execute a task. With this, the possible applications can target (ABDULKADER; ATIA; MOSTAFA, 2015b):

- Prevention: Applications can monitor brain activity and consciousness level, helping the user to prevent some condition that might injure him like an accident due to lack of attention.
- Rehabilitation: There are numerous conditions of the human health that he can have his mobility impaired. One of such conditions is commonly known as a stroke when the brain suffers damage, and the patient loses some abilities due to this condition. BCI devices can help the patient to gain movement again or even improve some other impairment (regain ability to communicate with others, move some bionic device and so on).
- Diagnosis: With prevention, comes diagnosis, applications that can monitor the user can also serve as feedback to doctors to help patients to discover any issue regarding the brain before it negatively affects him.

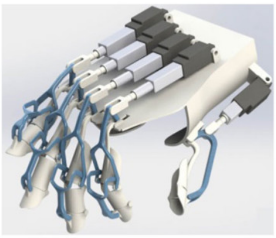
With those points in mind, the approaches that make use of one or more of the targeted applications are the most various, being a physical rehabilitation or a mental one

- Exoskeleton: An exoskeleton is something like armor (see Figure 3.1a), acting to help the damaged member, involving it. This approach has its complexity, and once many factors have to be taken in consideration, like the level of paralyzes or the percentage of impaired movement, if the patient still has its nervous system working in that area and so on. Regarding all of this, using an exoskeleton that is not too heavy and that can be used outdoor is the ’must have’ nowadays.

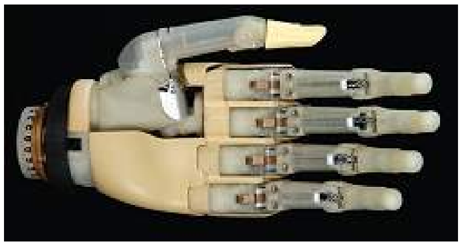
- Full prostheses: Different from the exoskeleton, this prosthesis is used attached to the body , instead of the actual member, as a metal hand (see Figure 3.1b). There are as many challenges in the replacement like in the exoskeleton, and there is no nervous system, so the patient cannot feel the bionic member. Therefore, the member cannot be too heavy, or demanding to be placed in a fixed location.

Figure (3.1) Representation of different equipament for physical rehabilitation

(a) Exoskeleton Hand



() Bionic Hand



Source : (CUI; PHAN; ALLISON, 2015) and Touch Bionics

Neurorehabilitation is engaged in helps the patient to live a better life with some neurological condition due to a genetic factor or trauma history. Some states come in the form of a degenerative or an erratic way that the brain works. Some devices can help to improve the patient lives, but, unfortunately, all of these brain conditions, demand an invasive solution of BCI.

One line of study is Deep Brain Stimulation or DBS (PERLMUTTER; MINK, 2015), which have many clinical applications like Parkinson’s Disease, Essential Tremor, Epilepsy, Dystonia, Tourette Syndrome, Stimulation for Pain, Depression, Obsessive Compulsive Disorded (OCD), and others. These clinical applications mainly consist of direct electrical stimulation inside the brain to stimulate specific areas too. For example, in Parkinson’s, relieve the tremors or in OCD, to attenuate the compulsive behavior.

Although BCI being primarily used in researches and medical approaches, there are those who seek an entertainment bias to such devices, like the use of the brain as an alternative input has opened a whole new opportunity to those who cannot use traditional methods to play games as well to experiment with new ways to play. There is some exploratory research on what it can be done regarding this, like for example, capturing the emotional state of the player and using it to create a more immersive environment (CHO; LEE, 2014) or in serious games like emotional control, attention rehabilitation, and interactive education. It is important to state that, no reliable study were found where a game could be entirely played with a BCI device. By any means, it is good to mention that this can be a line of study.

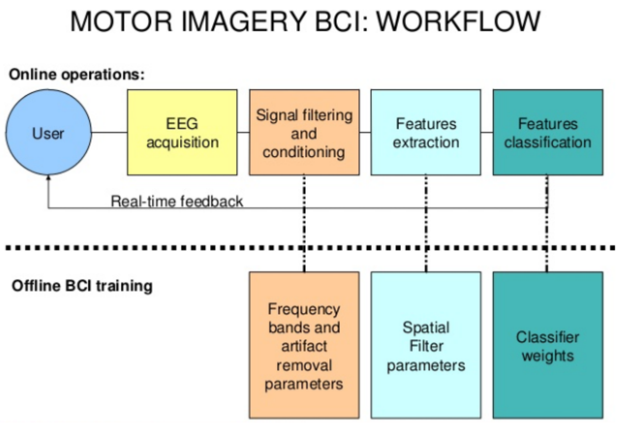
There is also work-related applications, which can be controlled remotely heavy and dangerous machinery. This concept already exists, but, stretching a little to the field of science fiction and placing in the reality, the use of a BCI remote-controlled machinery can be done to make the use of that machinery more intuitive and natural. Nonetheless, the worker will not be in an inhospitable/dangerous place, improving the job condition.

4 METHODOLOGY

This chapter introduces the BCI workflow, the device and preliminary findings concerning the first goal (the investigation of the Hardware and Software). It presents some workarounds to any software limitation, introduces the data acquisition, filtering and classification methods for the EEG and EMG as well as electrodes placement and why such locations were chosen. It also gives an overview of the volunteers that were invited to the experiment.

4.1 BCI Workflow

Figure 4.1: A Classical BCI Workflow on how to create a BCI system, showing the four phases to classify tasks



Source: adapted image from Brain Computer Interfaces & Haptics

The BCI workflow (exemplified in Figure 4.1), used to perform motor and imagery classification, consists in four main steps:

Data acquisition consists in using an EEG device to capture the data (brain waves) throught the scalp, in this case it will be used the OpenBCI Cyton-Biosensing (see Figure 2.9)

Signal filtering and conditioning are essential to this workflow, since the signal is weak (facing the low signal strength was one of the challenges) and prone to any noise or interference. The filtering can be spacial, in which we use the channel positions to filter the data (e.g. Laplacian Filter or Common Spacial Patterns) or we can make use of signal filters, that is, algorithms that can interpret a signal and clean it up (e.g. Infinite Impulse Filters or Butterworth).

Once the signal is filtered the **Feature extraction** phase took place. It consists, traditionally, in using proper algorithms to extract or use the squared signal amplitude (extracted by using Fourier Fast Tranform) as a set of features.

After the features are ready, the **Feature classification** processes begins, it consists in the training and of a classification algorithm (such as Support Vector Machine) or a machine learning algorithm (like Multi-Layer perceptron).

4.2 BCI Device

To extract the brain waves from the volunteers,we used a bio-sensing system called OpenBCI, which has triple functionality (EEG, EMG, and ECG). To achieve the first goal, which is investigative research of the OpenBCI Hardware and Software and its potentialities, a good review in the OpenBCI software was made, since it is an open-source software and the hardware was extensively tested.

Initially, some basic tests were applied in the OpenBCI board and OpenBCI-GUI (which is entirely made in the *Processing* coding language) to learn more about the use and the first impression were that, this device seems to be able to generate good results a priori.

The software has out-of-box features such as: four communication protocols including Lab stream Layer (LSL) which is a protocol designed for time-sensitive researches, widgets to visualize focus, EMG data, head plot activity and so on.

But, after an in-depth review, those early findings were more aimed to a common user than to a research purpose, i.e. the software does not reduce the complexity of a BCI system. One good example is the software relies a lot on the graphical user interface refresh window to update its data. Also, it was noticed that, the USB Dongle which makes the connection between the PC and the OpenBCI hardware looks very fragile.

Although the Software cannot do every step of the BCI-system workflow (exemplified in Figure 4.1), an auxiliary tool had to be developed.

4.3 BCI Data Manager

As previously stated, due to the lack of capabilities in the OpenBCI-GUI, it was noticed a necessity of manipulating the device data to achieve the desired results. Since the provided software does not have a classifier, additional filters (e.g., Independent Component Analisys or ICA) or classification tools (e.g., MLP or SVM), a new tool (BCI Data Manager or BDM). A new tool was developed in C++ which, in the moment of publication, can:

- Stablish a connection with the OpenBCI-GUI the BDM supports UDP connection;
- Parse Time Series, EMG or Band Power received data from the software in order to store or use them;
- Apply a data acquisition protocol without the intervention of the researcher, labeling the received information;
- Make a proper signal analysis, writing a raw data file and, also, another file with all the data conditioned to use in the classifier;
- Perform the classification phase using Support Vector machine implementation with libSVM (CHANG; LIN, 2016)
- Select a channel and band for writing only desired outputs in the file;
- Use signal filters such as IIR for visual analysis and comparison of the BDM aganist the OpenBCI filters.

Since it was exposed that OpenBCI-GUI only has signal filtering and this filter calculation is done by provided values using a Matlab function, it was implemented Signal and Spacial filtering in the tool with two primary purposes: The first one is to evaluate if the software filtering pre calculation is reliable and second to add value to the tool.

While all the code of the developed tool is publicly available in Bitbucket[1], the OpenBCI source code is not available in this repository, no branch or fork was made since this not an extension of their software is important also to address that OpenBCI is developed in Processing, a Java-Inspired language to "make it easier to develop visually oriented applications with an emphasis on animation and providing users with instant feedback through interaction.". And can be extended as the users will but, due to the insufficient scope of this language in classification and the high response overhead, it was chosen the C++ approach.

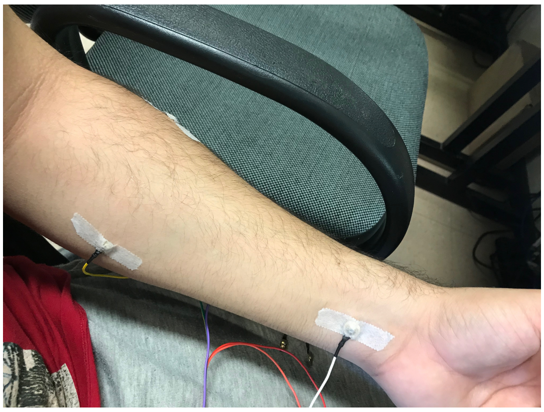
[1]https://bitbucket.org/Mandiow/tcc/src

4.4 Data - EMG

To acquire all the EMG data, two channels plus a third for the reference (or BIAS) were placed in the left forearm (see Figure 4.2) following (BALBINOT; JúNIOR; FAVIEIRO, 2013) to enable the OpenBCI Cyton Bio-sensing to be able to sense the muscular data. This placement and data capturing is performed to sense when the volunteer is opening or closing his hand. Due to the nature of EMG, it is not possible to distinguish between the open state and the closed state, because it can only sense the electrical signal that arrives in the muscles.

The choice to sense this kind of movement is to analize in a virtual environment the capability of using the hardware EMG function. Later, an analogous experiment will be performed with the EEG for comparison purposes.

Figure 4.2: A representation of the EMG electrode placement used to capture the signal data in the muscle.

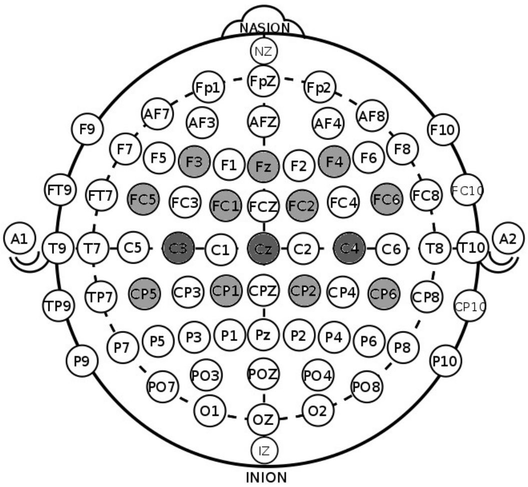


Source: Author

4.5 Data - EEG

All the EEG data that was used in this study was gathered using the OpenBCI Cyton Bio-sensing with 14 channels. The electrodes were positioned following the 10-20 system (THE. . . , 1961), placed in the following positions: FC5, F3, FC1, Fz, FC2, F4, FC6, CP6, CP5, C3, CP1, Cz, CP2, C3 as shown in the figure 4.3. After this placement the recording start and the data is filtered, the remaining channels that will be used in feature extraction are C3, Cz, and C4. The chosen channels come from numerous works (QIN; DING; HE, 2004; SLEIGHT; PILLAI; MOHAN, 2009; GE; WANG; YU, 2014; XIAO, 2012) whose experiments with motor and imagery leads to an assumption that this area of the brain is responsible for the motor task and is the one that we should extract data. The generated data will be filtered following two approaches to making a comparison, the first using OpenBCI software filters and the second one using BDM.

Figure 4.3: Representation of the EEG electrode placement used to capture the Brain data in the experiments, white represent unused placement positions



Source: adapted image from Wikipedia: The 10-20 system

4.5.1 Data Filtering

The OpenBCI software offers only three types of signal filter: Notch (Band-Stop) which cancels all the signal in a desired frequency; Band-Pass, which filters all data in a frequency range (e.g. in a band-pass of 5-50Hz all lower and higher frequencies are attenuated) and Power Density Spectrum (BandPower in the software) which is a FFT with mean square.

The data filtering process can take place in the developed tool or the OpenBCI software. But, to make the live testing and to achieve our first goal accurately, this process will be made by the OpenBCI software. It is important to note that this does not mean the filtering cannot be done by the BDM.

Also, to make a proper comparison, all the raw data gathered were filtered by the tool and the OpenBCI Software in the same way. Using a sample rate of 250.0Hz, band filter was set at 5 to 50Hz and a Notch filter in 60Hz.

4.5.2 Feature Extraction

Feature extraction is the last part before the feature classification, which is computed by the developed tool. Here we receive the data in the form of a JSON array from the software with all bands and all channels. Since we need only a selected numbered of channels, the tool is instructed to see those who were selected and extract from the whole package. Then, it is needed to multiply with the selected bands for those channels. Leaving something in the form of:

$X_{raw} = N * bands[]$

Being N the Array of numbers representing the selected channels, bands the array of selected bands on each channels and X is the total amount of features selected. Many references were researched to seek the better approach. Some relies on spatial filters (LOTTE et al., 2007), others uses machine learning algorithms (XIAO, 2012) to seek a better classification. But most of studies, relies on the more traditional approach, that is, using Independent Component analisys, band-power and Support Vector Machine(SLEIGHT; PILLAI; MOHAN, 2009). One that is worth a mention is a study (PALANIAPPA, 2005) that uses feature extraction as the power difference by the equation.

$$P_{diff} = \frac{P_1 - P_2}{P_1 + P_2}$$

Being P_1 the band power of one channel and P_2 the same band power of a different channel. This equation is performed in each selected band of the whole channel array.

Which raises the number of distinct features to a significant amount considering the number of channels. The experiment will consider training without the power difference, and it was discussed that, with this vast number of features, the classification process could be affected. But, for further discussion, this path was tested offline.

4.5.3 Data Classification

The data was classified following the criteria of the task:

- Baseline Task: The volunteer was asked to remain calm, be aware of its breathing, relax and clear the mind.
- Hand Movement: The volunteer was asked to open and close his hand.

- Hand Visualization: The volunteer was asked to imagine his hand opening and closing.

4.6 Classifiers

This section purpose is to give a brief explanation of the two algorithms studied to classify the extracted features, the first one was chosen following the line of study of (PALANIAPPA, 2005) and the second because is the most traditional algorithm used in BCI systems (LOTTE et al., 2007). By a classifier Its purpose is to receive the features in the data, analyze them and learn when each class of task happens.

The Multi-Layer Perceptron is a vast tangled network of Perceptrons (THE. . . , 1961) or neurons, with one or more layers between the input and output layer. The most common type of MLP is feedforward which means that the data flows in only one direction (Input to Output) with backpropagation method for training. Some studies pointed out that good accuracy percentage can be achieved with this implementation(FORSLUND et al., 2004; PALANIAPPA, 2005).

The Support Vector Machine is a classification technique developed by V. Vapnik (VAPNIK, 1995) and its the most traditional (GARRETT et al., 2003; BLANKERTZ; CURIO; MüLLER, 2002; RAKOTOMAMONJY et al., 2005) method for motor and imagery classification. An SVM is a discriminative classifier formally defined by a separating hyperplane, i.e., with the training data, the algorithm divides a decision plane with its boundaries, each plane with your classification.

4.7 Research questions

This work is based in three main Research questions:

- **Research question 1:** The OpenBCI Hardware has a good capability, enabling dense studies on the BCI field.
- **Research question 2:** The OpenBCI software is a good design and stable application that, combined with their hardware, remove much of the complexity, allowing not experts to perform experiments and researches in the area.
- **Research question 3:** The application developed shows that BCI applications can have a positive impact on people's lives, especially those who are impaired.

4.8 Volunteers

EEG and EMG signals from seven volunteers performing the mental and physical tasks were captured, being four males and three females (see Table 4.1) in the age range from twenty to thirty (see Table 4.2). All of them are at least a graduate student (see Table 4.3). One of them had an impairment in the left arm.

Table 4.1: Volunteer Men and Women distribution

Amount	Answer
3	Women
4	Men

Source: Author

Table 4.2: Age of the volunteers

Amount	Answer
2	23
1	26
1	30
1	21
1	20
1	24

Source: Author

Table 4.3: Educational Formation of the Volunteers

Amount	Answer
5	Bachelor in Progress
2	Bachelor degree

Source: Author

The reason of such small number of volunteers are many. Data acquisition is time-consuming, since the researchers are not experts in the field, there were a lot of wrong assumptions before the live testing and a lack of free-of-charge volunteers.

5 EXPERIMENT - EEG

In this experiment, the goal is to simulate, capturing the brain wave data, the motor and imagery left-hand movement and visualize it in a virtual environment using a Head Mounted Display. It is essential to address that, this experiment is vital to contemplate challenges and benefits of using EEG to perform the motor and imagery hand tasks as well as to seek any possibility of usability for people.

5.1 Protocol of data acquisition

To obtain a degree of reliability and consistency between tests, a protocol was implemented using the tasks explained in Chapter 4. The epoch (full experiment) consists in the volunteer being asked to sit in a chair in the most comfortable way possible with a notebook placed right in front of him. Then, the EEG is calibrated to make sure the measures are consistent, i.e., that is no problem with the device or the electrodes; this is visually done by asking the volunteer to open and close their eyes to see if there is significant changes in the electrical activity in the software interface. Once the device is checked, the test begins with the volunteer closing his/her and relaxing. The start of the protocol and each transition of a task is marked with a beeping sound. Each run consists in the following tasks and durations:

- **Baseline** One minute.
- **Hand Moviment** Two minutes.
- **Baseline** One minute.
- **Hand Visualization** Two minutes.

And, after this run being executed for at least three times to ensure a reasonable amount of data for the classifier and to off-line cross-validation, the data acquisition ends (epoch finishes). Each experiment lasts approximately 35 minutes with the task-run lasting 18 minutes and the rest being for training and live-testing in the virtual environment using a Head-Mounted Display.

5.2 Pre obtained Data-set

All data for the experiment were captured with the OpenBCI hardware. No previous data-set was used, most of that comes to the fact that even having some distinct parts in the brain, the same is unique and, to make more reliable to training, is recommended to apply the protocol while the data is being acquired.

5.3 Results

This section contains all noticeable findings during the experiment and additional findings in a further signal analysis as well as a brief overview of the whole experiment experience.

5.3.1 Accuracy of the algorithm

With all points being considered, we ran the Support Vector machine offline testing to gather data residing the accuracy of the algorithm. Since every human being is different, each one had its validation tested explicitly in the table with a mean of the overall accuracy.

Table 5.1 shows the accuracy achieved with each one of the volunteers, an intresting fact is like how the two subjects with the lowest accuracy were uncomfortable with the surroundings. Not only that, but the subject who the classifier managed to classify better was the disabled one. The overall accuracy shows a need for improvement.

Table 5.1: Achieved accuracy rate of the Support Vector Machine algorithm in the EEG experiment

Volunteer	Accuracy
A	43.0149%
B	54.4263%
C	40.9748%
D	40.0638%
E	33.2856%
F	33.4545%
G	40.0228%
Average	40.7489%

Source: Author

5.3.2 Report

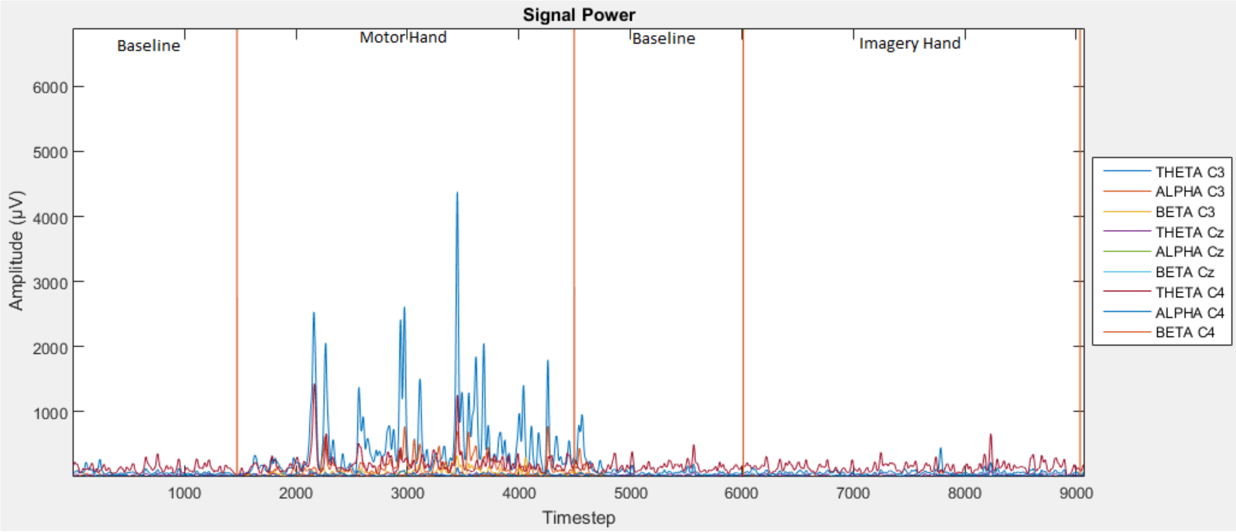
To make a proper analysis, a visual inspection of the captured waves was made. First to see if any problem occured during the data acquisition and second to document any significant finding. All visualization was done using the Raw OpenBCI data and timestamp combined with the timestamp in the written file by the tool and the desired output (see Figure 5.1). For example in Figure 5.2 there is a run (baseline, hand motor, baseline, motor imagery) of a volunteer with the transition of each task marked by a vertical line.

Figure 5.1: A representation of the generated file by the developed tool while capturing EEG data, showing the acquired outputs from the OpenBCI, the line that was written, the timestamp of the data and the label.

```
285.157930 149.356960 89.022070 31.540260 2.921941 1.570258 215.395280 15.254293 9.170323  4754 TS: 1529758597 2
280.600830 151.521580 88.576996 32.835556 2.906089 1.566028 222.596420 15.248517 9.321799  4755 TS: 1529758597 1
```

Source: Author

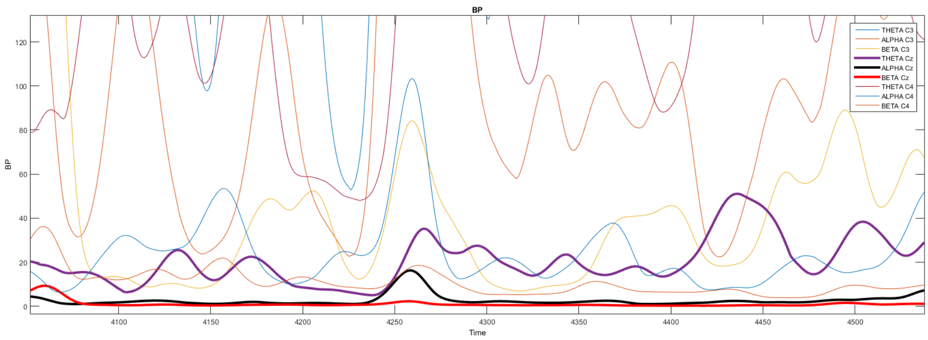
Figure 5.2: A graphical signal representation of one epoch of data acquisition, separated by task



Source: Author

It was noticed that the Cz channel of the volunteer's data does not have significant Band-Power values like shown in Figure 5.3, perhaps this channel is not the most advisable to use as one of the main for the selection of features but rather as filtering to remove noise from C3 to C4 and vice versa.

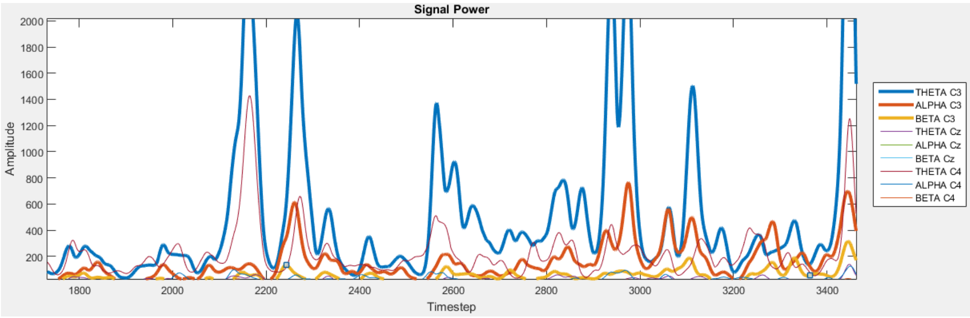
Figure 5.3: A visual observation on the electrode Cz signal, showing no expressive power in contrast with the other electrodes



Source: Author

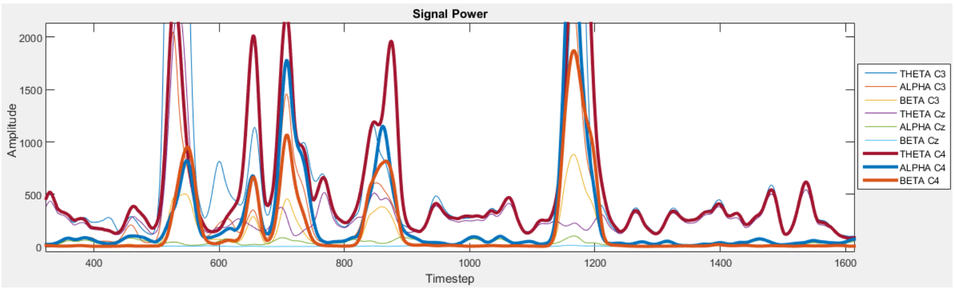
Also, one interesting thing that was noticed regards the data of the impaired subject, like shown in the Figure 4.3 of Chapter 4, the selected electrodes in the head were C3, Cz, and C4. But it can be seen in Figure 5.4 in contrast with a volunteer without impairment in Figure 5.5 that, the most active electrode was from the left side of the brain (C3) and not from the right side (C4). One possible explanation is, due to the damage to the brain caused by the impairment's cause, the brain reorganized itself to take care of the duties of the damaged area. A proper and more elusive explanation can only be given by an expert in this area.

Figure 5.4: Representation of motor left hand task being performed by a impaired volunteer, showing left brain activity



Source: Author

Figure 5.5: Representation of motor left hand task being performed by a healthy volunteer, showing right brain activity



Source: Author

Given the limited resources of time, subjects availability, and most knowledge in areas like neuroscience and signal processing, the classification algorithm could not correctly achieve its full potential in the experiment. Besides this limitation, the experiment was done without any significant complications, and the volunteers were assisted in the best way possible.

An important thing noticed during the experiment was the interference caused by the Head-Mounted Display in the EEG electrodes. It was visually seen that the captured digital signal is very different from the one obtained without the HMD. Several factors influence this. The HMD causes a lot of electrical noise, stimulates a lot the volunteer and can touch the electrodes. Due to that, the HMD could potentially be worsened the performance of the classifier. Also, this interference caused to the virtual application to not work properly with the EEG, being only able to perform the tasks without the HMD.

5.3.3 Goal Analysis

This experiment goal was the hardest to achieve, and many were the difficulties, assumptions, challenges. The volunteers were interviewed, and their opinion is that this possibility exists and its a matter of improving the methods. One interesting result was one of the volunteers, who has paralysis in the left part of the body. The accuracy achieved from this volunteer data were above in comparison to the others who do not have the same condition. Also, in the experiment, this same volunteer could simulate the movement without much problem.

5.3.4 Feedback

To gather volunteer information and feedback, a questionnaire was designed to collect meaningful information about them as well as any feedback that might help future experiments.

In this experiment, the opinions were a little mixed; As we can see in Table 5.2 the cap is actually not confortable. This maybe can be explained to the size of the cap being unique.

Table 5.2: How confortable is the use of the EEG cap

Amount	Answer
2	Confortable
2	Little Unconfortable
1	Very Unconfortable
2	Impartial

Source: Author

As can be seen in Table 5.3, many volunteers also reported dificulties while they tried to relax, the most weighty matter was the absence of a soundproof room, outside noise makes volunteers uncomfortable, suggestions of using white noise or another kind of sound were made. However, this could cause more noise that helps. These aspects were noted for further studies and experiments.

In the Table 5.4 the majority of the volunteers did not feel a fast response in the EEG experiment, unfortunately, for two of them, the EEG had some difficulties to run property, even without the Head-Mounted Display. Those were the same volunteers that

Table 5.3: Had difficulty to stay relaxed

Amount	Answer
4	Yes
3	No

Source: Author

reported not being able to relax at all.

Table 5.4: Fastest respose rate while performing the test

Amount	Answer
2	EEG
3	EMG
2	Impartial

Source: Author

And finally in Tables 5.5 and 5.6 we can see that, some of the volunteers reported that was hard to consistently perform the imagery task for the extend period of time and, due to the impairment in one of the volunteers, the motor task were the hardest one.

Table 5.5: Had difficulty on any task

Amount	Answer
4	Yes
3	No

Source: Author

Table 5.6: Which task the volunteer had difficulty

Amount	Answer
1	Move the Hand
3	Imagine the hand movement

Source: Author

6 EXPERIMENT - EMG

In this experiment, the purpose is to simulate the movement of opening and closing the hand by using the EMG part of the OpenBCI.

6.1 Dataset

All data for the experiment were captured with the OpenBCI hardware and software. No previous dataset was used.

The dataset was obtained following a pre-defined script, similar to the previous experiment but, since EMG cannot differ from imagery or baseline, only two tasks were performed:

- **Baseline** One minute.
- **Hand Moviment** Two minutes.

Since EMG data is easier to categorize, the experiments lasted for approximately 15 minutes, being three for the epoch, the rest in the training and virtual environment using the HMD.

6.2 Results

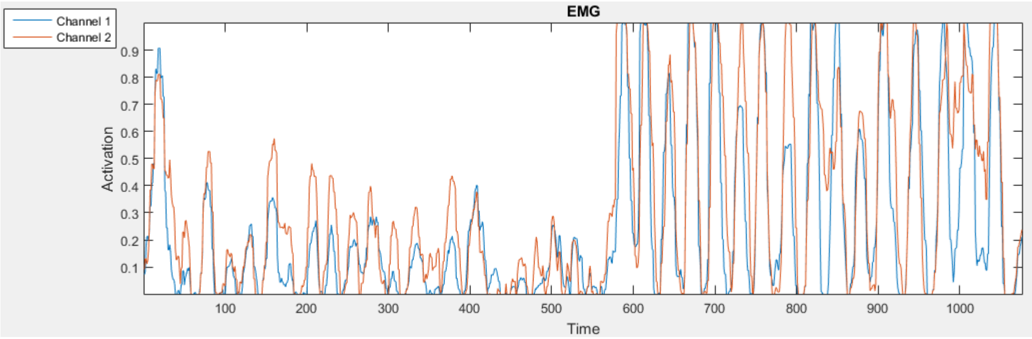
This section contains all noticeable findings during the experiment and additional findings in a further signal analysis as well as a brief overview of the whole experiment experience.

6.2.1 Accuracy of the algorithm

Since we used a threshold to separate the states (In movement, resting), there was no actual training in the SVM algorithm. The threshold was defined by analysing all the data and see which were the values peak while in the baseline activity, once this done, any activity that surpass this peak is accused as a movement. In Figure 6.1 shows a signal from a volunteer which was used to set a threshold.

As we can see, while the volunteer remained in the baseline activity, the both

Figure 6.1: A graphical representation of the two channels used in the acquisition of the EMG signals.



Source: Author

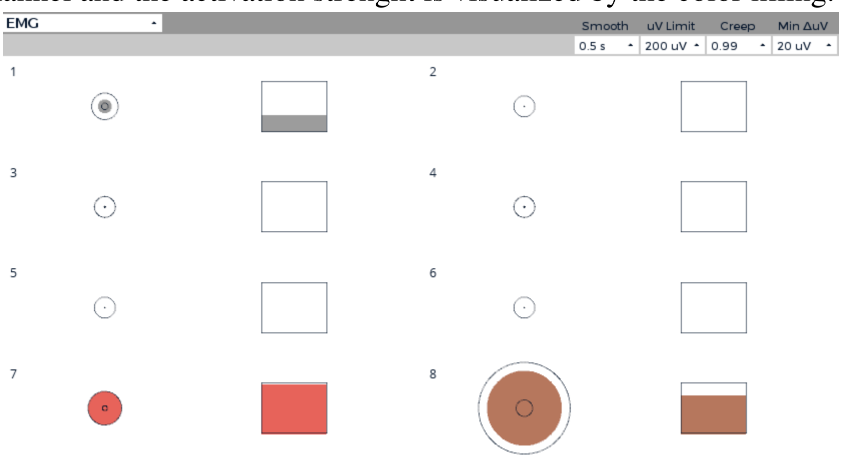
channels did not express activation signal greater than 0.5, due to that fact, this was the setted threshold.

6.2.2 Report

In contrast with the EEG experiment, this one was much easier to perform. Since the idea is to capture the strength of a signal without complex processing in it and classification is optional, it can work with the signal threshold without much of a problem, to help in the visualization, Figures 6.2 shows a live test was the volunteer closes and opens its hand.

In the technical perspective, the software records the electrodes signals and transforms it in power scaled signal (i.e., its peak it will always be 1).

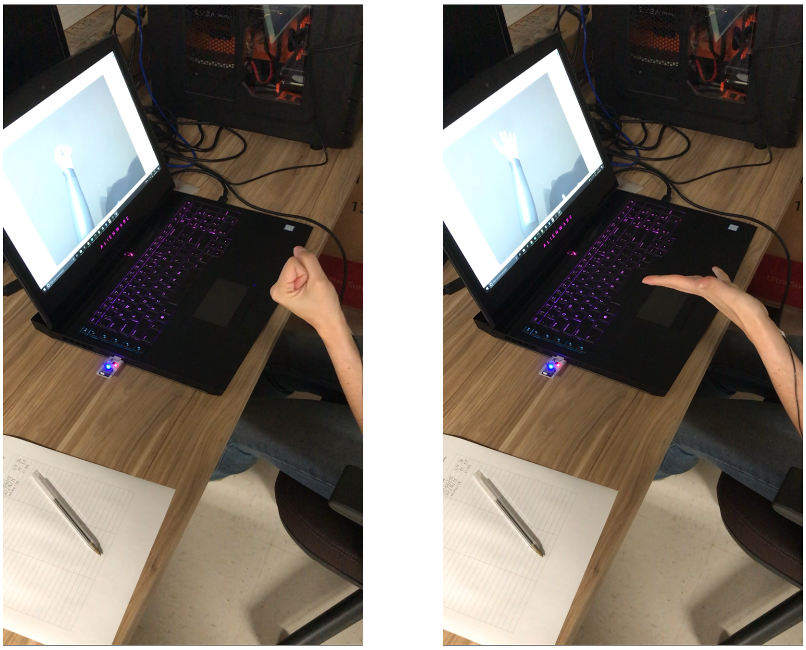
Figure 6.4: Representation of the EMG signal inside the OpenBCI-GUI, each circle represents a channel and the activation strenght is visualized by the color filling.



Source: Author

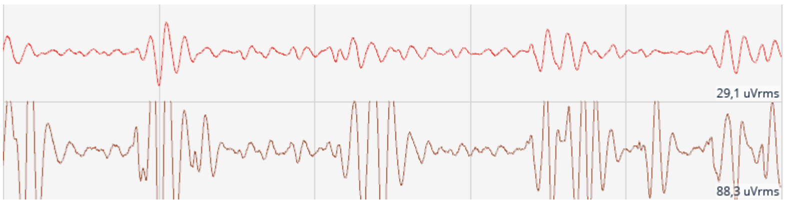
Figure 6.2: Representation of the Live testing using the OpenBCI EMG function, (a) shows the volunteer opening the hand and (b) shows the volunteer closing the hand and the simulation being activated.

(a) Volunteer Closing Hand (b) Volunteer Opening Hand



Source: Author

Figure 6.3: Representation of the muscular activity in the form of an oscilatory wave, visualized inside the OpenBCI-GUI



Source: Author

Figure 6.3 and 6.4 show, respectively, the oscillatory wave and the EMG module of OpenBCI-GUI which uses circles to represent the signal strength activity from a channel and Figure 6.5 shows the output captured by the tool. The experiment was a success in the terms of the goal (test OpenBCI EMG system and see usability in virtual reality), and all volunteers managed to experience the full potential of an EMG device.

6.2.3 Goal Analisys

The experiment goal was to capture the EMG signal and translate it to a virtual world application. Since EMG signals are quite easy to handle and translate, being a

Figure 6.5: A representation of the generated file by the developed tool while capturing EMG data, showing the acquired outputs from the OpenBCI, the line that was written, the timestamp of the data and the label.

```
0.071786 0.088601
0.080646 0.130219
0.180826 0.131071
0.212363 0.111193
0.212570 0.122867
0.198963 0.162065
0.232021 0.245703
0.323792 0.384316
0.323792 0.384316
0.408242 0.479468
0.408242 0.479468
0.482273 0.462357
0.482273 0.462357
0.756090 0.740382
0.831549 0.789947
0.814187 0.786318
0.814187 0.786318
0.907245 0.811270
0.907245 0.811270
0.906067 0.806751
```

Source: Author

movement discrete by a vertical oscillation in the signal strength, and when the threshold is passed, the action is executed. The goal was achieved without any complications whatsoever. Each one of the volunteers managed to successfully test the EMG in the virtual environment.

6.2.4 Feedback

The overall feedback was positive, all volunteers reported the use of EMG was more confortable than the EEG (see Table 6.1 and 5.2). This can be explained due to the EMG are only electrodes placed, unlike the EEG which the volunteer had to use a cap.

Table 6.1: How confortable was the use of the EMG electrodes

Amount	Answer
3	Confortable
3	Little Unconfortable
1	Impartial

Source: Author

After the two experiments, the volunteers were also asked if they would use a device with the tested technologies and, following the same pattern, most of the answers were directed to the EMG (see Table 6.2).

In the Table 5.4 showed that, the response of the EMG device were more faster than the EEG, mostly comes of the fact that, the EMG is less prone to interference, and even with this result, some volunteers also reported a sensation of weirdness due to the

Table 6.2: Which of technologies the volunteer prefer

Amount	Answer
2	EMG
1	EEG
2	Both
2	VR

Source: Author

imprecise movement, and this is due to the fact EMG can not discern between open and close hand.

Therefore, since a minimal threshold has to be achieved, gentle movements are more likely not to be captured, since the signal is attenuated over time, leading to a somewhat imprecision in the motor activity simulation.

7 DISCUSSION

7.1 OpenBCI

The newly acquired Hardware with no doubts have a lot of exciting features and capabilities, therefore is important to the point that, even being an open-source project, the cost to acquire the hardware is high and the application itself lacks a lot of stability, but this does not mean that there is no room for improvement.

One that was discussed for the software is a label marker for the raw file, to not be dependent on other tools. There are also a lot of recommendations for improvement in the software itself, it is overall stable, but a little annoying sometimes with networking.

7.1.1 Comments about the software

At first glance, the OpenBCI software is a fairly addequate application with a reasonable amount of pre-made widgets which allows the user to see out-of-the-box measurements happen. Provides connection adaptability with four different protocols, and also serves as a Notch and band-pass filters.

Although the software is good, it does a lot of calculations, is optimized by Matlab results and formulas, and have a useful and easy-to-use GUI, it is far from the optimal from usage, here are some of the recommendations that are good to take care.

Networking Widget its good for straightforward things like, make a connection, get packages and exit application. But, the continuous use of this widget can lead to a misbehave in the application, i.e., the port can not be closed and the application sends packages forever to that port.

Playback is a lovely part of the application which is the ability to reproduce later all the data that been recorded during a trial, but, be aware that the data recorded is imprecise, leaving the playback data slightly different from the actual brain signal caught in the EEG. Is recommended that you save your data right away, and by that the Networking can be used.

Processing language is an excellent Java-like language, but it has its downfalls such as: The code is interpreted, therefore the virtual machine has to decode and send to the processor, this leads to an overhead in the application; Usually, interpreted languages have a problem with floating points precision.

There were other problems that the software imposed, and this will be discussed further in a proper session but, even with those points, it is a good application, and for being open-source, someone is always improving the code and removing those minor problems. Also, the user can download the source code and do its customization.

7.1.2 Comments about the hardware

The Cyton bio-sensing is impressive, a versatile board which has comfortable and fast learning in its use. The Hardware allows its user to measure not only EEG and EMG data but also the ECG data, and head movement with accelerometers. Giving the user a good range of artifacts to study, gather data and create projects.

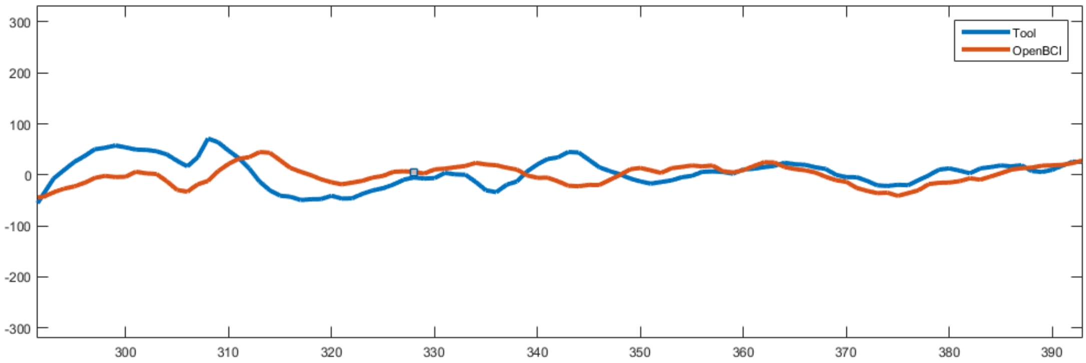
7.1.3 OpenBCI Software and hardware

Although the previous comments about the software, the same have a lot to improve or even to change. Its research purpose relays only in the hardware part, which can be impeditive for non-specialists.

As it can be seen in Figure 7.1 which represents a signal filtered by the tool and the OpenBCI Software using the same filters; Being the first one a Band-Stop Filter in 60Hz to remove AC interference and the second, a Band-Pass filter between 5Hz to 50Hz. It became visible that, even with the same input and filtering, the generated output was entirely different.

This can be explained by multiple factors; the C++ library might have some issue, which is unlikely because, not only it exists for more than six years, it is commonly wide used, such bug would be noticed before. Can be the micro-optimizations that the OpenBCI does to remove overhead caused by the virtual machine. But, can also be the aforesaid Network Widget one which has a lot of minor problems like the LSL protocol, which does not work, crashes the whole application, UDP port not being freed to ensure other connections, leaving an open port throwing wrong messages to whoever listens.

Figure 7.1: Comparison between the directly calculated wave and a value aproximated



Source: Author

Another late discovery involving the Cyton Bio-sensing is the Daisy module which enables 16-channels. It passed unnoticed for quite some time the fact that, when the module is attached, the sample rate drops to 125Hz and at the present moment. It is unknown if Daisy can work in upper-frequency rates, which can be a big limitation to work in such a low sampling rate, this can remove the possibility of removing noise, once it will become hard to detect it and also the feature extraction can be limited as well.

Those issues were addressed on the platform Github repository and documented for a further project not make the same mistake.

7.2 Obstacles faced

During the production of this work, many were the challenges that were primarily addressed. Some of them happened and new unexpected things appeared. This section is to discuss some of those obstacles, explaining them and seeking for some clarity in what could be better.

7.2.1 Environment

Since there was no proper room in the university to ensure interference containment the whole work had to deal with external noise, interruptions, interference of any kind. This probably led to an inaccuracy on the signal capturing, being by proper interference or even the external stimulus in the volunteers. One way out was to find an isolated place inside the university for the trials since it is complex to attenuate environmental interference due to the fact that it is not constant (e.g. voices, door slaming, etc.).

7.2.2 Knowledge

Although this was already mentioned, it is good to state that the author is not expert in many areas like biology, signal Processing and neuroscience, which imposed a hard to pass barrier which stalled the work for a little while. Due to this deficit, it is hard to tell when a studied work it leading to a dead-end. The solution for this is to study more and search for experts in those areas to address any doubts to seek good resolutions.

7.2.3 Accuracy

The accuracy that was achieved in fact was, in the average 40%. Many possibilities can be the possible cause: The work was not performed by an expert in the area, thus leaving some possible signal noises and any other problem impact in the signal. The OpenBCI software calculations can be imprecise enough to prejudice the signal, transforming the software a more cosmetic tool than a useful one. Lack of proper knowledge in neuroscience or the signal processing area placed a significant issue while performing the training process.

7.3 EMG vs EEG

Although being different by nature (EEG for brain waves and EMG for electrical activity in the muscles) both of them were used in the same experiment and it is nice to have a comparison in most efficient methods.

EMG is a very easy-to-use feature from the OpenBCI software, and the signal is sent already filtered and processed by the GUI. Not only that, but since is an activity detector, and a simple test is to use a threshold to detect if some activity in the channel happened or not, the first test that was made to verify if the channel, electrode, and hardware were working used EMG.

EEG, in other hand, is never simple. Process the data is somewhat complicated, feature extraction can be as well. The GUI is clean, and they are helpful in exposing a problem with a channel (showing 'railed' or by visually seeing the signal strength out of balance, those two happened in the experiments).

There are plenty of signal processing, feature extraction methods, classification techniques which helps, but there are also a lot of environmental things to account for such as amount of electronic devices nearby, nearby noises, etc. Acquiring data with a reasonable degree of reliability is complex. By that, if the experiment that is being made is simple, the tasks involve motor activity only, it is preferable to use EMG to that, but if the experiment requires a more complex bias, like the difference between right and left movement, this cannot be achieved with EMG only, an EEG approach is preferable.

7.4 MLP vs SVM

Arguably the MLP implementation did not perform as expected like in (PALANIAPPA, 2005), an explanation could be the MLP implementation not being robust to passage of time.

On other hand, the SVM approach, was able to generate meaningful results, even with the low accuracy the classifier was able change between classes.

Also, is worth a mention that this work tried to reproduce (PALANIAPPA, 2005) but it could not replicate the achieved results with OpenBCI, even following all the provided methodology, including data filtering, extraction, and classification.

8 CONCLUSION

In this final chapter, the objective is to settle the achieved goals during the production of this work, as well as validating or invalidating the proposed hypothesis.

As stated at the beginning of this thesis, this work started as an investigation over the OpenBCI hardware and software capabilities, experimentation seeking practical activities with it to show its potential for human improvement.

8.1 Research questions

This work lay firmly in the use of this hardware piece, a lot of tests, volunteers, stress in the hardware, and the acquisition remained stable, no problem was noticed in the equipment of any malfunction while performing any experiment. The only worth mention thing which could be different is the USB dongle that looks fragile. Thus, the OpenBCI hardware can be used in dense studies on the BCI field, respecting the physical hardware limitations.

The software as it was discussed in the previous Chapter have a lot of gaps that need to be fulfilled and fixerd, while this does not change, it is recommended that, for researches or works, the use of the software is limited only to the acquisition of data through a UDP package, and even by that, look to ensure the data is ok. Thus, the OpenBCI software is a good application to visualize and send data, it does not remove the complexity, and it is not a well designed and stable application.

The OpenBCI proved its aggregation value when the acquired data, independent of time of use and independent of how many people wear the cap, was able to be classified, even with the low accuracy, allowing each one of the volunteers to experience a simulated moving hand in the VR. In spite of that, with the EMG device, a sensation of weirdness was pointed, meaning that, it is essential to make better applications which handle the data latency.

In concordance with the research questions, one of our volunteers had a disability, and the classifier could differentiate the tasks, even with the EMG activity were recorded in the affected part, and he could successfully experience the VR. Thus, also being prominent to say, but there are some few indicators that, BCI applications, when correctly used, tested and applied can have a positive impact in people's lives, especially those who are impaired.

8.2 Contribution

This work's contribution lies first on the field of knowledge. An in-depth analysis of the OpenBCI capability of making a real-time experiment testing, what are its limitations, what we can or can not do with this board, combined with its software. It was all achieved with two practical experiments using different parts of the same device. Also, all the knowledge acquired in the development is documented here and in (FRAZAO, 2018), and a brand new tool born removing significant dependencies, a start point for future works with data acquisition protocol, an early virtual environment is also available for further improvements.

Additionally, it was possible to analyze volunteer activity and come out with an affirmative answer to the proposed questions and see that impaired and non-impaired people could potentially use a device.

8.3 Future Work

A full review of the work was done, including experiment, feedback that the volunteers provided, and a few observations and suggestions for improvement were pointed out and can be used in future works as well as an enhancement for ongoing ones.

One important point is, since the worst of our problems were the interference that the Head-Mounted Display caused, a **noise attenuation** study can be performed to nullify such problem, leading to a more promising work.

Another relevant point is to **bring to the real world** to do a **non-virtual experiment** and gather more data to be able to see any significant improvement in real life, like for example, helping people with some impairment. This point of development could be challenging due to several numbers of reasons like medical limitations, human anatomy and the type of disability.

Also, **enhance the methodology** to create more classes and improve the capabilities of the classifier in task execution, a good example is to enhance the methods for up to eight distinct categories to, for example, enable a 3D movement of a character and, finally, **increase the population** of testing to acquire more knowledge and understanding more about the human brain and its behaviors. One thing that occurred in this work was one of our volunteers having an impairment, and like it was discussed, his brain waves were quite interesting. An excellent way to go is to invite more people, especially those with some impairment.

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APPENDIX A — QUESTIONNAIRE GROUP ANSWERS

Although all the text inside this work is in English, the work was developed in Brazil, due to this fact, the questionnaire is all in Portuguese.

Figure A.1: Questionnaire Page 1

Questionário demográfico

*Obrigatório

1. **Qual sua idade? ***

2. **Qual seu sexo ***
   Marcar apenas uma oval.
   - Masculino
   - Feminino
   - Prefiro não dizer
   - Outro:

3. **Qual a sua formação?**

4. **Qual sua ocupação?**
   Marcar apenas uma oval.
   - Estudante
   - Professor
   - Administrativo
   - Outro:

5. **Se sua profissão for estudante, qual curso? ***
   Marcar apenas uma oval.
   - Ciência da Computação
   - Engenharia da Computação
   - Outro:

Experiência e relacionados

6. **Você já participou de algum experimento envolvendo essas tecnologias?**
   Marcar apenas uma oval.
   - Sim
   - Não

7. **Se a resposta for sim, o quão familiarizado você está com: EEG**
   Marcar apenas uma oval.

	1	2	3	4	5	6	7	
Muito Pouco								Trabalho com aparelhos

Figure A.2: Questionnaire Page 2

8. **Se a resposta for sim, o quão familiarizado você está com: EMG**
Marcar apenas uma oval.

	1	2	3	4	5	6	7	
Muito pouco	○	○	○	○	○	○	○	Trabalho com aparelhos

9. **Se a resposta for sim, o quão familiarizado você está com: Head-Mounted Display**
Marcar apenas uma oval.

	1	2	3	4	5	6	7	
Muito pouco	○	○	○	○	○	○	○	Possuo/Trabalho

10. **Você tem algum diagnóstico psiquiátrico medicado?**
Marcar apenas uma oval.

- ○ Sim
- ○ Não

11. **Como você mentalmente se sente agora?**

12. **Como você se sente fisicamente agora?**

Questionário após experimento

13. **Sobre o EEG, o quão confortável foi o uso?**
Marcar apenas uma oval.

	1	2	3	4	5	6	7	
Muito Desconfortável	○	○	○	○	○	○	○	Muito Confortável

14. **Sobre o EMG, o quão confortável foi o uso?**
Marcar apenas uma oval.

	1	2	3	4	5	6	7	
Muito Desconfortável	○	○	○	○	○	○	○	Muito Confortável

15. **Qual deles você teve uma sensação mais imediata de resposta? Sendo 5 como imparcial.**
Marcar apenas uma oval.

	1	2	3	4	5	6	7	8	9	
EEG	○	○	○	○	○	○	○	○	○	EMG

Figure A.3: Questionnaire Page 3

16. **Você utilizaria um dispositivo com as tecnologias testadas?**
Marcar apenas uma oval.

- Sim
- Não

17. **Se sim, qual tecnologia?**

18. **Durante o experimento, alguma atividade foi complexa?**
Marcar apenas uma oval.

- Sim
- Não

19. **Se sim, qual?**

20. **Teve alguma dificuldade durante o experimento para se relaxar?**
Marcar apenas uma oval.

- Sim
- Não

21. **Alguma dificuldade em imaginar os cenários?**
Marcar apenas uma oval.

- Sim
- Não

22. **Como se sente mentalmente após o experimento?**

23. **Como se sente fisicamente após o experimento?**

24. **Caso tenha alguma sugestão ou um feedback sobre o experimento, por favor, deixe no espaço abaixo:**