Individual Diploma Thesis

EEG signal analysis for sending commands to external devices based on Brain Computer Interfacing

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Dear God, thank you for everything.

To my beloved grandpa, who always taught me that the only treasure we take with us when we leave this world, is the knowledge we have acquired.

Summary

Until recently, the idea of controlling one's surroundings with one's thoughts was limited in the realm of science fiction. Nevertheless, due to the technological advancements the old reality has been replaced by the new one. Nowadays, people can use the electrical signals from brain activity to interact with, influence or change their surroundings. This can be accomplished through Brain Computer Interfaces (BCI).

The main purpose of this dissertation is to acquire some EEG signals and then process them in order to categorize them. To accomplish this, an experiment based on Motor Imagery (MI) will take place where the subjects will have to imagine right and left-hand movements according to the instructions that will be given. Then, the brain signals will be processed and finally, using some classification algorithms, they will be classified in two categories: right and left hand movements. The aim of this categorization is to implement a desired action that the user wants by translating each pattern of signals to a specific command. Then this command will be sent to an external device to perform a specific task.

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Introduction

1.1 Motivation

A Brain – Computer Interface (BCI) is a computer-based system that builds an imaginary communication bridge between the human brain and the external world, trying to eliminate the need for traditional methods of information delivery. This can be achieved thanks to the ability of a BCI system to acquire brain signals, analyse them and finally translate them into commands that an output device will understand and therefore, perform a desired action. The biggest research on BCI focuses on helping users with severe mobility problems. BCI systems aim to replace or restore important functions of people who are disabled by neuromuscular disorders such as stroke, spinal cord injury, amyotrophic lateral sclerosis, or cerebral palsy. To help those people and make their lives easier, researchers try to create BCI systems in ordered to be used by disabled people to control wheelchairs, robotic arms, prosthetics, spelling and other devices. Brain-computer interfaces can also prove useful for rehabilitation after stroke and other disorders. Moreover, BCI systems can also be used by other people such as the elderly to improve the quality of their lives, by the military or even by healthy people to make their daily lives easier and to entertain themselves.

1.2 Thesis Structure

<u>Chapter 2</u>:

A basic introduction to the structure of the brain, the electroencephalogram, and the different brain signals (brainwaves) is provided in this chapter. It also discusses the different paradigms that exist based on mental control signals.

Chapter 3:

This chapter discusses who would use a BCI system and some of the applications that are currently available. More specifically, two key demands of individuals with disabilities are stated (communication through speech and mobility difficulties), as well as the need of entertainment (for both disabled and healthy people). Moreover, some existing BCI systems are presented based on these three areas. It also becomes clear that the purpose of these systems is to contribute to both the everyday tasks and the amusement of the users.

Chapter 4:

This chapter explains what a brain computer interface is and its components. It also discusses different pre-processing techniques as well as some popular classifiers that are used in these systems.

Chapter 5:

This chapter presents an overview of the equipment, infrastructure, and technologies employed in the experiments. An explanation of the experiment, from the placement of the EEG cap through the final scenario (testing phase), was also provided.

Chapter 6:

The scenarios that run in the background of the experiment are explained in this chapter. More specifically, each scenario's whole process is discussed, including the objective of each scenario and which algorithms are used. Finally, the results of the experiment are presented.

Chapter 7:

In the last chapter of this thesis, scenarios that were implemented but not used in the experiment at this stage are mentioned. Nonetheless, these scenarios are functional and can be used in the future for additional support of the current system. In conclusion, a description of the BCI system and its potential is provided.

Chapter 2

Theoretical Background

2.1 Brain Anatomy

"The brain is a world consisting of a number of unexplored continents and great stretches of unknown territory."

\- Santiago Ramón y Cajal

The brain is the body's command center. This specialized organ controls thoughts, emotion, memory, speech, motor skills and many of our actions. It receives messages through our five senses of hearing, sight, smell, taste, and touch.

From birth through adulthood, the weight of the brain changes. At birth, the average brain weights about one pound, and develops to approximately two pounds during childhood. The average weight of a grown-up female brain is around 2.7 pounds, while the brain of a grown-up male weights almost three pounds.

The brain, together with the spinal cord -that extends from it- constitute the central nervous system, or CNS. The spinal nerves, that branch from the spinal cord, and the cranial nerves, that branch from the brain, constitute the peripheral nervous system (PNS). Together, CNS and PNS form the nervous system which is a complex network of nerves and cells that carry messages to and from the brain to the rest of the body.
The brain is composed of the cerebrum, cerebellum, and brainstem [6].

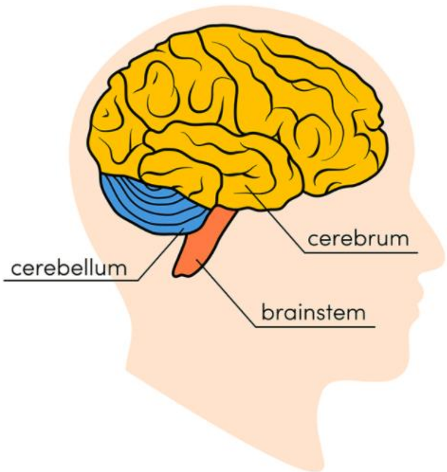


Figure 2-1: The main three components of the brain

2.1.1 Cerebrum

The cerebrum is the biggest part of the brain and is divided into two major parts: the right and left cerebral hemispheres. They are joined by a bundle of fibers called the corpus callosum that transmits messages from one side to the other.
Each hemisphere controls the opposite side of the body [1] [43].

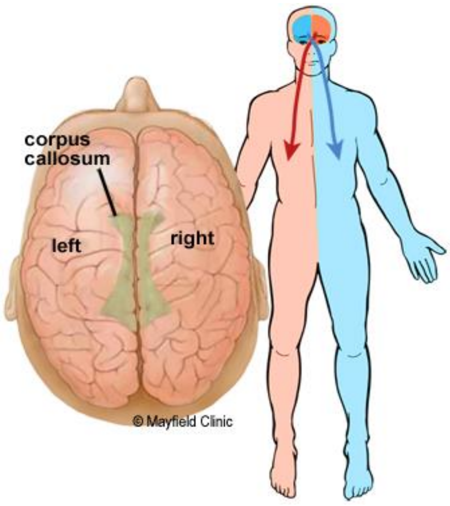


Figure 2-2: The left hemisphere controls the right side of the body and the right hemisphere controls the left side of the body.

While it is generally known that the left hemisphere is responsible for speech, writing, comprehension and arithmetic, and the right hemisphere controls creativity, artistic, musical skills, and spatial ability, both hemispheres are active in most cognitive tasks.

The cerebral cortex is the outermost layer of the cerebrum, and it is called the “grey matter” due to its grey-brown color. Beneath the cortex, long nerve fibers (axons) connect brain areas to each other and form a white-colored area called the “white matter”. The cerebral cortex -or surface of the brain- appears folded with hills and valleys. Each fold or bump is known as gyrus (plural: gyri) while each groove is known as sulcus (plural: sulci). These gyri and sulci serve as crucial markers for dividing the brain into functional areas [40].

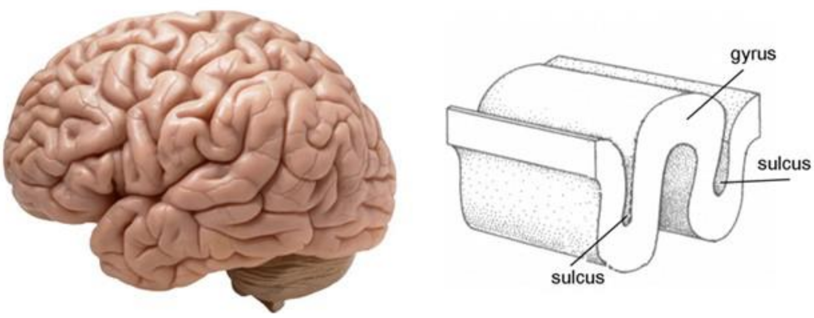


Figure 2-3: Image: (L) DJ / CC BY-SA 2.0 (R) Albert Kok / Public Domain

Thus, each hemisphere can be divided into four lobes: frontal, temporal, parietal, and occipital lobe. Each lobe does not work alone. There are complicated relationships between the lobes of the brain and the two cerebral hemispheres.

The various functions of the cerebrum are determined by the functions of each lobe as described below.

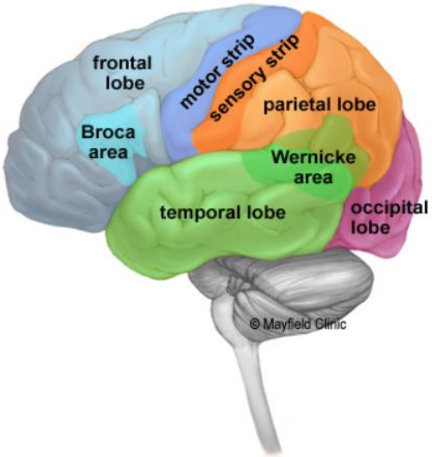


Figure 2-4: The frontal lobe is colored with light blue, the parietal lobe is colored with orange, the temporal lobe with colored with green and the occipital lobe is colored with pink.

The frontal lobe is the largest lobe of the brain and is in the front of the head. It is responsible for many different functions including motor skills (voluntary movement), speech (speaking and writing), emotional regulation, judgment, planning, problem solving and intelligence. It contains the motor cortex -which is associated with movements-, the prefrontal cortex that plays an important part in memory, intelligence, concentration and personality and it also contains Broca's area which is associated with speech ability [1].

The temporal lobe is located on the side of the head at about ear level, and is associated with memory, hearing, and some aspects of language. It contains the auditory cortex, which is responsible for processing auditory information, and the Wernicke's area that has an important role in speech comprehension [1].

The parietal lobe is located behind the frontal lobe and is involved in processing information from the body's senses and helps a person to identify objects and understand spatial relationships. It contains the somatosensory cortex, which is important for processing sensory information from across the body such as pain, pressure, temperature, and touch. The parietal lobe houses Wernicke's area as well and that helps the brain understand spoken language [1].

The occipital lobe is located at the very back of the brain and it contains the primary visual cortex that receives visual information from the eyes. This information is passed to secondary visual processing areas, which interpret depth, distance, and the identify of seen objects [1].

2.1.2 Cerebellum

The cerebellum is beneath the occipital lobes in the back of the brain. The cerebellum fine-tunes motor activity/movement and assists in maintaining posture, balance, and equilibrium by modulating muscle tone and limb position. The ability to execute rapid and repetitive movements, such as playing a video game, is dependent on the cerebellum [1].

2.1.3 Brainstem

The brainstem is the lower extension of the brain. It is positioned in front of the cerebellum and is connected to the spinal cord. The midbrain, pons, and medulla oblongata are the three structures that make up the brainstem. It has an important role as a relay station that passes messages back and forth between various parts of the body and the cerebral cortex. Breathing, heart rate, body temperature, waking and sleep cycles, digestion, sneezing, coughing, vomiting, and swallowing are some of the automatic functions performed by the brainstem [1].

2.2 Electroencephalography (EEG)

The EEG is one of the most widely used techniques for recording electrical brain activity due to its convenience and non-invasive implement. The EEG was invented by Hans

Berger in 1924 and has been used to address a variety of questions regarding the functioning of the human brain as well as a diagnostic tool to diagnose diseases like epilepsy and dementia. In order to acquire the brain signals, we place the electrodes on the scalp at specific positions according to the “International 10-20 system”. Electrodes of the EEG can be wet or dry. On the one hand, wet electrodes use a conductive gel or saline water to improve the conductivity between the scalp and electrodes. However, applying the substance (gel, saline water) can be time consuming and may leave residue in the subject’s hair. On the other hand, dry electrodes can be set up faster since they do not require the use of any substance. Nevertheless, without the use of a conductive substance, EEG signals can be noisy.

The amplitude range of the EEG is from 1 to 100μV. The electrical signals are measured as the difference in voltage between two electrodes. This is because EEG is recorded using the technology of the differential amplifier that takes as input two different electrical inputs and gives the output as their difference.

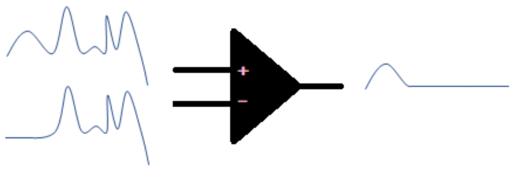


Figure 2-5 : Here is an example of a differential amplifier in order to get the general idea. Values are avoided.

EEG signals are collected and presented on the screen in particular montages / arrangements of channels (electrode pairs with waveforms expressing the potential difference between them). The most common are listed below.

- Bipolar montage: The difference in voltage between two neighboring electrodes is measured and then is recorded as a single value. This happens for all the channels.

- Referential montage: A single electrode is used as a reference point and for all the rest electrodes, the voltage difference is calculated between them and the reference electrode.

- Average reference montage: This montage is similar to the Referential montage. The average measurement of all EEG channels is used as the reference point and the voltage difference is calculated between each electrode and the average measurement. [19]

2.2.1 The 10-20 System

The 10-20 system is an international recognized method that is used to describes the locations on the scalp where the electrodes should be placed for an EEG exam, or lab research. The name of the system relates to the fact that the actual distances between neighboring electrodes are 10% or 20% of the entire front-back (Nasion-Inion) or right-left (pre-Auricular points) distance of the skull. This system is based on four primary positions of the head that are used as landmarks in order to mark the position of the EEG electrodes. These are:

1. Nasion: the area in between the eyes just above the bridge of the nose
2. Inion: the crest point of back of the skull, typically marked by a bump
3. Two pre-Auricular points: In front of each ear, they can be identified with palpation and if necessary, requesting patient to open his mouth slightly.

The measurements are made as follows:

1. From the nasion to the inion (front to back), the Fpz, Fz, Cz, Pz and Oz electrodes are placed at marks made at intervals of 10%, 20%, 20%, 20%, 20% and 10% respectively.
2. From the one pre-Auricular point to the other, the T3, C3, Cz, C4 and T4 electrodes are placed at marks made at intervals of 10%, 20%, 20%, 20%, 20%, 10% respectively.
3. Skull circumference is measured using the Fpz, Oz, T3 and T4 marks as a guide. The Fp2, F8, T4, T6 and O2 electrodes, measured above the right ear from Fpz (front) to Oz (back) are placed at intervals of 5%, 10%, 10%, 10%, 10% and 5% respectively. In the same way, the Fp1, F7, T3, T5 and O1 electrodes, measured above the left ear from Fpz to Oz are placed at the same intervals as on the right side.

4. The location of the F3, F4, P3, and P4 electrodes is measured differently. One way is to measure from front to back (Fp1-F3-C3-P3-O1 and Fp2-F4-C4-P4-O2 montages) and place the marks 25% “up” from the front and back points (Fp1, Fp2, O1, and O2).

Letters and numbers are used to symbolize each electrode. Odd numbers correspond to the left side of the skull, whereas even numbers correspond to the right side. Smaller numbers indicate that they are closer to the midline, which is symbolized by the letter ‘z.' The letters Fp, F, T, P, O and C are assigned to the electrodes to indicate at which lobe or area of the brain is the electrode placed. C is for the “center” and is used only for identification purposes, in other words, there is not a central lobe. The electrodes A1 (left ear) and A2 (right ear) are used for contralateral referencing of all EEG electrodes.

Extra electrodes are added using the 10% division when recording a more comprehensive EEG with additional electrodes, which fills in intermediate locations halfway between those of the original 10–20 system. [51]

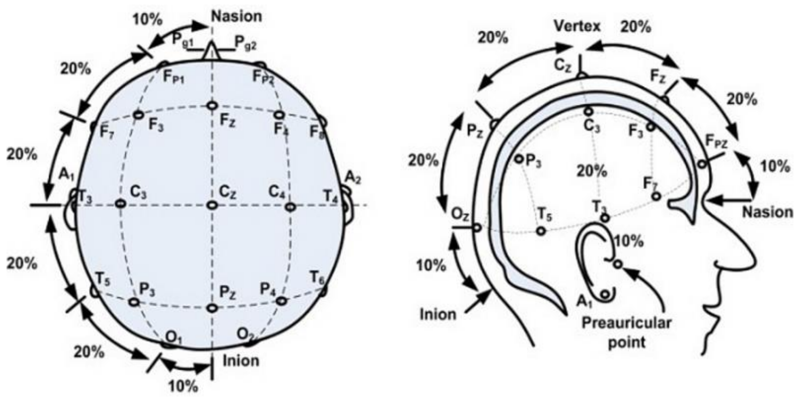


Figure 2-6 : The international 10-20 system, [Norani et al., 2010]

2.2.2 Brainwaves

When analysing EEG signals or brain waves, it is understood that some brain waves are more distinct than others due to some of their characteristics, such as the frequency of their emanations and the shape of their waveforms. Therefore, some of them are categorised according to those characteristics. There are five widely recognized brain waves: delta, theta, alpha, beta, gamma (from the slowest to the fastest). [28]

Delta brainwaves lie within the range of 0.5 to 4 Hz. These are the slowest of all brainwaves and have the greatest amplitude. They never go down to zero since that would lead to brain dead. Delta waves are associated with deep sleep.

Theta brainwaves lie within the range of 4 to 8 Hz. They can be detected when a person is dreaming in his sleep, during deep meditation, daydreaming, or doing an automated task (e.g., tying his shoes, brushing his teeth). Theta waves have also been linked to memory, creativity, and psychological well-being.

Alpha brainwaves lie within the range of 8 to 13 Hz. They were the first to be found and are among the most easily observable brainwaves. Alpha waves are detectable when the eyes are closed. They can also be found if a person is in physically and mentally relaxed state.

Beta brainwaves range from 14 to 30 Hz. They are generated when the brain is aroused and actively engaged in mental activities. They are associated with problem solving, focusing on a task, learning new things and in general, when the person is in active thinking and alert.

Gamma brainwaves lie in the higher spectrum of frequencies, from 31 to 100 Hz. They are the fastest detectable EEG brainwaves and have been linked to heightened perception or a peak mental state in which information from many regions of the brain is processed simultaneously.

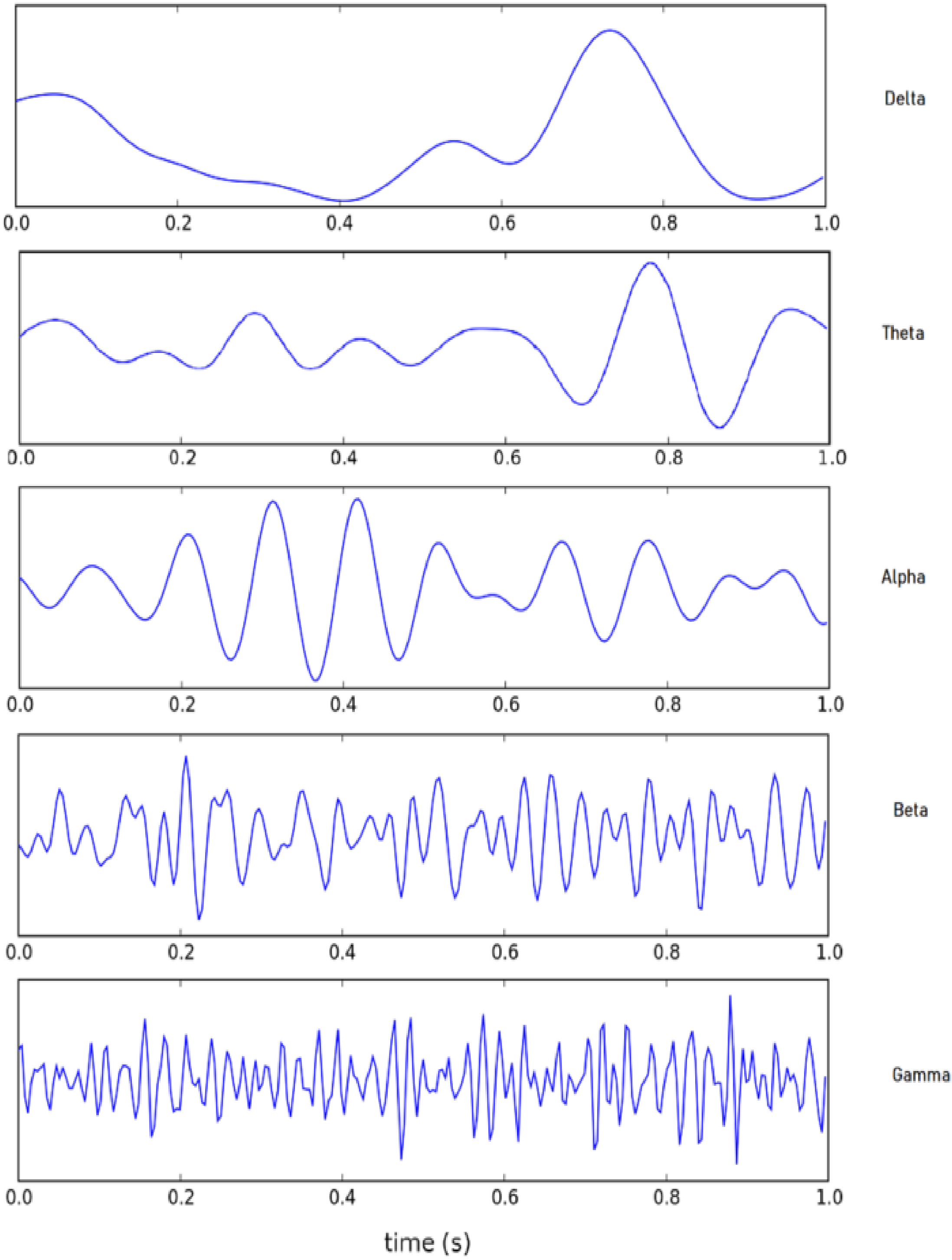


Figure 2-7: From the slowest to the fastest brainwave: delta, theta, alpha, beta, gamma. Image from Wikipedia.org

2.3 Brain Computer Interface Paradigms based on Mental Control Signals

EEG-based brain computer interfaces rely on control signals that come straight from the brain. There are three categories in which these signals can be classified into. These categories are known as: Evoked Signals, Spontaneous Signals, and Hybrid Signals

2.3.1 Evoked Signals

Evoked signals, also referred as Event-Related Potentials (ERPs), are created unintentionally by the subject when he experiences external stimuli. More specifically, an event-related potential, is the measurable brain reaction, response, to a given sensory, cognitive, or motor event. ERPs can be measured using electroencephalography (EEG) and in most cases it is hard to detect them since they are usually in the order of microvolts. Thus, a frequent technique to increase detectability is to average over numerous stimulus epochs and this will drastically improve the signal-to-noise ratio (SNR). Due to the averaging process, any brain activity that is not time-locked to the stimulus beginning would most likely vanish, leaving just the time-locked components. This method eliminates noise and spontaneous EEG while enhancing the voltage response to the stimulus allowing it to be clearly seen against the averaged-out background. Two of the most well-known evoked signals are the Steady State Evoked Potentials and P300.

2.3.1.1 Steady State Evoked Potentials (SSEP)

The term “steady-state” refers to the periodic stimulus. SSEP signals are brain signals that are produced when a participant is exposed to periodic stimuli such as a flashing image, modulated sound, or vibrations. When the subject feels a specific change at a certain frequency, his brain responds. Steady State Visual Evoked Potentials (SSVEP), Auditory Evoked Potentials (AEP), and Somatosensory Evoked Potentials (SSEP) are among the many varieties of SSEP signals.

<u>Steady State Visual Evoked Potentials (SSVEP)</u>

Visual Evoked Potentials are a type of evoked potential that occurs due to a visual stimulus and can be detected above the visual cortex. SSVEP is a paradigm in which different components flash steadily at different frequencies on a screen. The matching frequency in the EEG originating from the occipital lobe may get greater when the user concentrates on a certain aspect. The classifiers that distinguish different flashing frequencies are trained using machine learning.

Auditory Evoked Potentials (AEP)

An evoked potential in the brainstem that is induced by an aural stimulus (a sound) is commonly known as a Brainstem Auditory Evoked potential (BAEP) [27]. The electrodes that are placed on the scalp, record the responses to sounds and then they appear as electroencephalogram (EEG) readings. Moreover, the source of these responses, are the relay structures in the brainstem.

Somatosensory Evoked Potentials (SSEP)

The electrical activity of the brain that arises from the sensation of touch is known as Somatosensory Evoked Potential (SSEP).

2.3.1.2 P300

Another well known signal is the P300. In a P300 based on paradigm, the subject is asked to focus on something known as the target, such as a particular letter, a specific image, or a specific sound. At the same time there are presented more items of the same category that are known as non-targets. All of them, start flashing one by one and the subject is asked to count the number of times the target is presented. A particular weak EEG pattern -a little spike- is detected around 300ms after a target event happens. The system can determine what the user is focused on by repeating numerous target and non-target events. Machine learning is generally used to build a classifier that chooses if a signal is “P300” or “no-P300”. In order to provide a more reliable pick, the system is trained through several repeats, and this can be tiring and inconsistency to the subject. However, the subject does not need any training.

2.3.2 Spontaneous Signals

Spontaneous Signals are those signals that are generated by the subject's will. In other words, these signals do not require any kind of external stimuli. Slow Cortical Potentials, Motor and Sensorimotor Rhythms as well as non-motor cognitive tasks are the most widely known signals in this category.

2.3.2.1 Slow Cortical Potentials (CSP)

One of the categories of BCI systems are the SCP-based BCIs. These systems are implemented by taking into consideration SCP signals that have a low frequency potential (less than 1Hz) and are detected in the frontal and central portions of the cortex. Furthermore, there are positive and negative deflections of these potentials. According to [Birbaumer, Rockstroh, et al., (1990)], a positive deflection of this potential is related with lower cortical activity. A negative deflection, on the other hand, generally implies greater cortical activity which arises during movements and can last anywhere from milliseconds to many seconds. With operant conditioning, the individual can learn to regulate the exposure of these signals willingly.

2.3.2.2 Motor and Sensorimotor Rhythms

Motor and sensorimotor rhythms are rhythms associated with motor movements such as arm movement. These rhythms are detected over the motor cortex and their frequencies are between 8-13Hz (Alpha brainwaves) and 14-30Hz (Beta brainwaves). There are two different methods with which the subject can control these sensorimotor rhythms: Motor Imagery and Operant conditioning.

Motor imaging is a cognitive process in which a person imagines that he or she is making a movement without really doing so and without tensing the muscles. It's a dynamic condition in which the internal representation of a certain motor activity is activated but no motor output is produced. The user should envision the movement's "feeling" rather than its appearance. Typically, classifiers are trained to identify changes in spectral band powers between the two situations. A rising number of studies have found that brain regions involved in real movement execution are also active during motor imagining. Thus, people with motor impairments who are unable to accomplish a desired action on their own might utilize this motor imagination to communicate with various devices in order to do the desired action with the assistance of the external device.

Long-term training in operant conditioning allows the subject to intentionally adjust the amplitude of his or her sensorimotor rhythms. It's indeed up to the subject to determine which mental method is best for him or her. The training, on the other hand, may endure weeks or months. After all, the alpha and beta rhythms at various points might accumulate to form a control signal.

2.3.2.3 Non – Motor Cognitive Tasks

As understood by the term “Non-Motor Cognitive Tasks”, a BCI could also be driven by cognitive tasks. These tasks may be accomplished by musical imagining, mathematical computation, visual counting, mental rotation, etc. One of the examples on the non-motor cognitive tasks, is the pattern classifier with unknown parameters that had been utilized by Penny et al. [50], while the subject was performing some arithmetic (subtraction).

2.3.3 Hybrid Signals

The term "hybrid signals" refers to the utilization of a mix of brain-generated signals for control. As a result, rather than measuring and using only one type of signal in the BCI system, a mix of signals is employed. The basic goal of utilizing multiple types of brain signals as input to a BCI system is to increase dependability while avoiding the drawbacks of each signal type. The following table summarizes the current state of hybrid systems.

Reference	Signal Types	Purpose
K. Lin et al. [20]	EMG and SSVEP	Enhance the BCI system performance. It uses the speller application as a case study.
E. Yin et al. [12]	SSVEP and P300	Enhances the classification accuracy and increases the transfer rate.
Yuanqing Li et al. [56]	SSVEP and P300	Improving the performance of the BCI system in terms of detection accuracy and response time. A wheelchair control system is used for testing.

Table 2-1: Summary of the current state of hybrid systems

Chapter 3

BCI Applications and Related Work

There are people who face difficulties communicating and/or interacting with their surroundings, while there are others who are fully disabled. Thankfully, as technology advances, BCI devices have been developed, and they may be the sole surviving means of communication for such individuals. BCIs were first created with biomedical uses in mind, resulting in the development of assistive devices. They have aided in the restoration of movement function and the replacement of lost motor functions for physically challenged or locked-in people. However, the bright future of BCI has prompted researchers to investigate its role in the lives of non-paralyzed people and in non-medical applications. Following, are some of the most well-known BCI applications.

3.1 Spelling Devices

Spelling devices allow severely disabled people to communicate with their surroundings by picking numbers and characters from the alphabet in a sequential order. There are different types of BCI spellers according to the BCI paradigm that is being used or even their combination (hybrid). A BCI-spelling device is one of the earliest BCI applications to be released.

The first P300-based speller had been introduced by Farwell and Donchin in 1988 [15]. A 6x6 array of blinking symbols was presented on a monitor in this Spelling device. An "oddball" paradigm was created by arranging the objects in rows and columns that were enhanced in a random sequence. Because there were six rows and six columns in this matrix, at least 12 flashes were required in order to flash each column and row once. To improve concentration, the subject was told to count the number of flashes while focusing on the target character. A P300 wave would appear in the EEG readings when the row and column containing the desired target flashed. The sequential flashing of lines and columns caused an evoked potential in the user's brain activity and thus, it was detected and used to find the target character, and this allowed the user to type text.

Researchers were inspired by Farwell and Donchin's matrix and worked on several improvements to make it faster, more accurate and more user-friendly.

The basic Graphical User Interface (GUI) used in P300 based Spellers is shown in Figure 3-1. However, there are different GUIs as well.

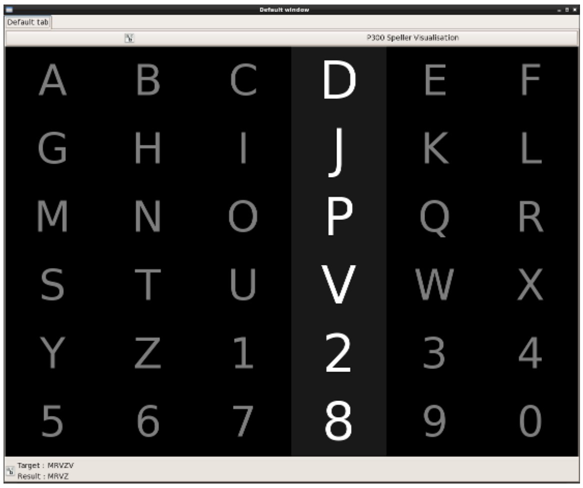


Figure 3-1: Basic Graphical User Interface of a modern P300 Spelling Device

Chroma Speller:

Among the many, one different P300-based interface, is the "Chroma Speller" that was developed by Acqualagna et al. [21]. The stimuli in this paradigm are six distinct colors projected on a large screen, and the character selection is done in two steps. Each color is assigned to a set of characters in the first phase (Figure 3-2 (a)), and single characters in the second (Figure 3-2 (b)). More specifically, for the initial selection, a total of 30 characters were divided into six colors, and when it started working, the colors flashed in a series manner. To choose a color, the participant had to focus on it, and then the ERP P300 signal was detected and processed. Following the initial selection of a group of characters, the selected group's individual characters were displayed independently on the second screen, with row colors identical to the first screen. The Chroma Speller was designed to be a gaze-independent speller with a low workload, since the user just had to concentrate on the target color that contains the desired character rather than the individual letter.

Figure 3-2: Chroma Speller GUI: (a) GUI for the first phase and (b) GUI for the second phase.

Bremen-BCI speller:

As previously stated, there are a variety of spelling devices based on the paradigm they employ. One of those spelling devices is the Bremen-BCI speller [49], which is a SSVEP-based BCI Speller. This speller's graphical user interface (GUI) consists of a virtual keyboard (with 32 symbols) and five flashing boxes at the screen's outer borders and upper left corner that are mapped to the commands "up", "down" , "left" "right," and "select,". The cursor is just above the letter 'E' in the center of the virtual keyboard at the start of each attempt. The user may move the cursor to the appropriate letter by focusing on one of the four vibrating boxes -left, right, up, or down-. The navigation can't go beyond the layout's limits. By emphasizing on the 'select' box, a letter is then chosen. Every acknowledged command is followed by audio feedback. The pointer automatically returns to the beginning letter 'E' after each selection. If the subject makes a spelling mistake, he can delete the final character or the whole text by pressing the special symbols 'Del' or 'Clr'. For example, to spell the word "BCI," the subject must implement at least 9 commands ("down, right, select," -> B , "right, right, right, select" -> C, "up, select" -> I), as seen in Figure 3-4.

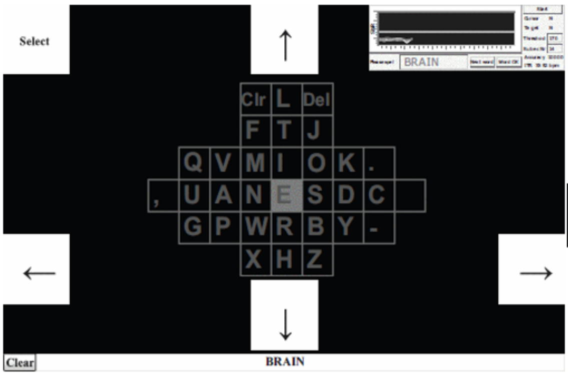


Figure 3-3: GUI of Bremen-Bci speller.

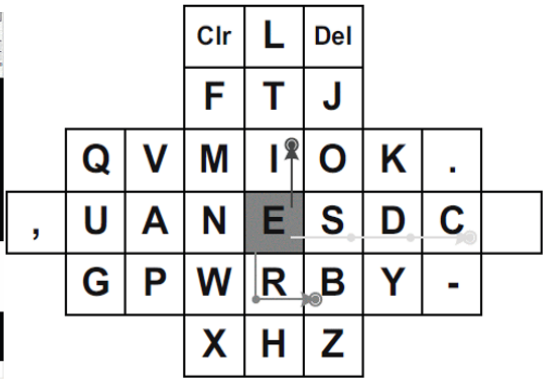


Figure 3-4: Minimum 9 Commands needed for "BCI" word.

3.2 Robotic Control

Many BCI-based devices like brain-controlled wheelchairs and prosthetic devices have been developed as a result of advancements in research and technology to enhance, assist, and complement human movements in a paralyzed or partly handicapped individual. With these devices, researchers aim to support the society of disabled people in order to be able to accomplish their daily tasks.

<u>Wheelchair Control:</u>

Wheelchairs are mainly commonly used by disabled people. If a person still has control over certain muscles, he can utilize them to drive a wheelchair. There are devices that allow to an individual to control a wheelchair simply using a joystick or head motions, for example. However, if muscular control is lost, a BCI based wheelchair can possibly be used. Because guiding a wheelchair is a difficult effort and wheelchair control must be exceedingly dependable, the wheelchair's motions are severely limited in existing prototype systems. The EEG-based wheelchair system is a sort of brain–computer interfaces technology in which a wheelchair is controlled by electroencephalographic signals acquired from the human brain. By utilizing solely brain waves, the individual may achieve a specific goal using this technical method.

There are several existing applications of EEG-based wheelchairs which can be categorised according to the paradigm they use, such as MI, P300, SSVEP, Hybrid. As previously stated, the goal of these investments is to demonstrate the practicality and usefulness of a brain-controlled wheelchair in a real-world setting, with patients with limited motor abilities as the target group. As a result, among the four EEG control signal approaches utilized to drive BCI wheelchairs, those based on motor-imagery tasks may be deemed the best suited for accomplishing the intended goal. Furthermore, a motor-imagery paradigm does not rely on visual stimulation and thus, there is no chance of weariness. Moreover, MI-based brain control wheelchairs (BCW), is better suited for usage in unfamiliar environments and numerous typed of identifiable motor imagery output may be immediately communicated into the steering control of a driverless wheelchair. Some already developed applications of BCI wheelchairs follows.

In the paper [41], Swee et al. developed an electric wheelchair that could be controlled directly by the brain and did not require any physical feedback from the user as a controlling input. The EEG signals were collected by a commercial headset and were then analysed and translated into mental instructions/controls by whom the wheelchair was going to be controlled. In the hardware they used, a wheelchair, scooter motor, high current motor driver, Arduino Uno, HC-06 Bluetooth Module and Emotive EPOC Headset were included. The flowcharts of their programs both for the Microcontroller and the Microsoft Visual C# Application are presented in figures (a) and (b) respectively. There were 5 participants and their results revealed that the EEG data that had been processed did not deliver 100% accuracy when compared to the participants' mental commands, but they can attain a level of accuracy of up to 90%.

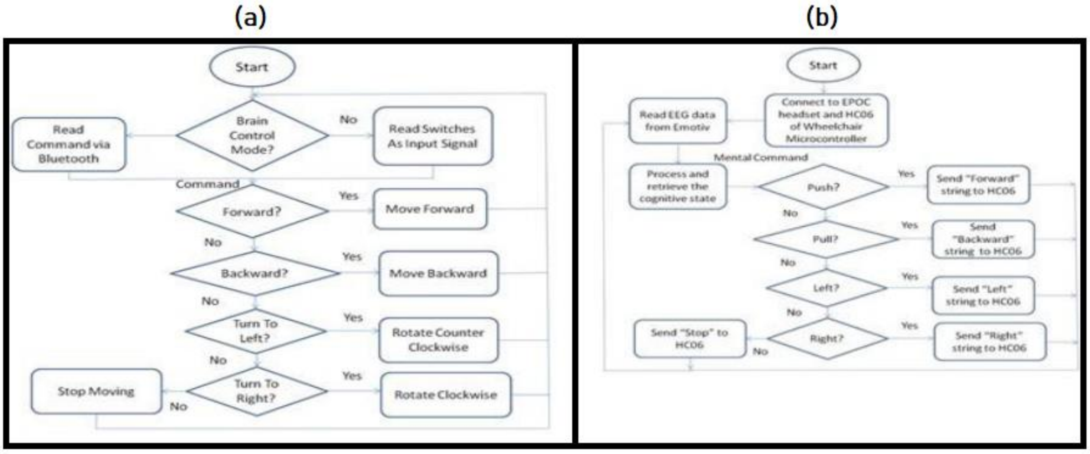


Figure 3-5: Flowcharts used for the Microccontroller (a) and the Microsoft Vicual C# Application (b).

Continuous wheelchair control based on inaccurate and noisy EEG readings is unreliable and places a substantial emotional pressure on the user. For this reason, Zhang et al. [33] integrated a brain-computer interface (BCI) with an automated navigation system. In their study, they describe a brain-controlled smart wheelchair that can navigate on its own. Candidate endpoints and waypoints are developed autonomously using an autonomous navigation system depending on the current surroundings. Moreover, using a motor imagery (MI) or P300-based BCI, the user chooses a location, and the navigation system generates a short and safe route in order to navigate the wheelchair at the specified destination. Despite this, the user can stop the wheelchair anytime he decides to, by sending a stop command. Furthermore, according to the authors, the user's mental stress can be significantly reduced by the utilizing their system and it can also be adapted in changes of the environment. Since they were confident about the effectiveness of their system, they made two experiments based on both MI and P300 and the success rate was 94.7 ± 2.3 (%) and 92.0 ± 4.4 (%) respectively. Figure 3-5 (a) depicts the system architecture and figure 3-5 (b) the wheelchair system with its equipment.

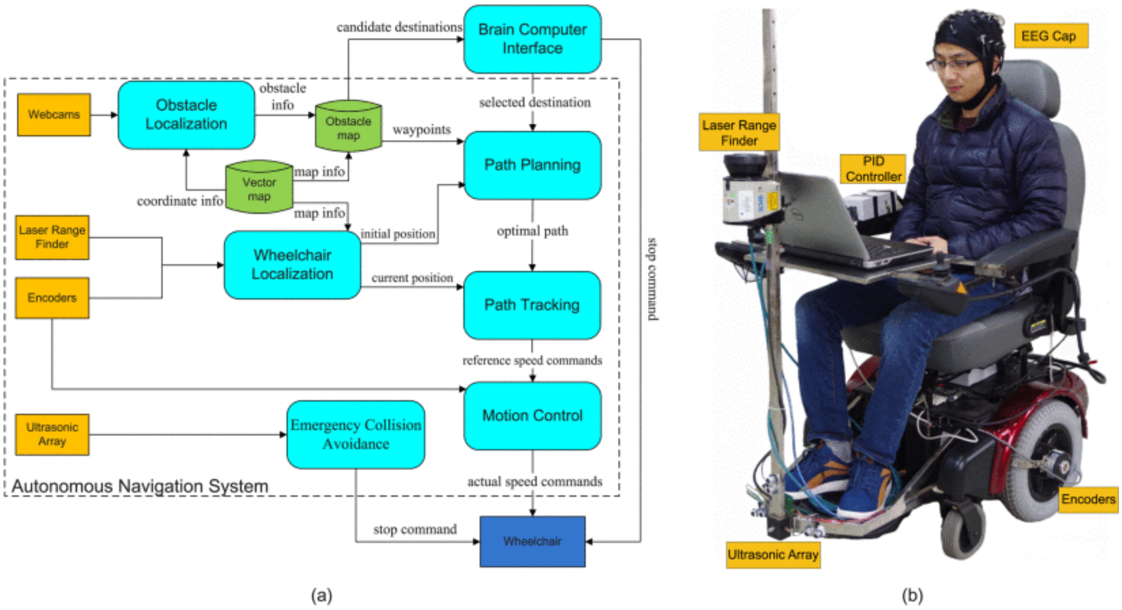


Figure 3-6: This figure presents (a) the system architecture, (b) the wheelchair with its equipment that was proposed by Zhang et al. [33]

Robotic Arm:

Bousseta et al. in their study [32], proposed a BCI system that is used to control a robot arm according to four mental motor tasks done by a user. The user has to imagine the movement of the left and right hand independently, as well as the movement of both hands and the movement of the feet. Each of these motor movements corresponds to the direction in which the robotic arm will be guided. The imagining movement of right hand makes the robot move right, the imagining movement of left hand makes the robot move left, while the imagining movement of both hands at the same time makes the elbow point up and finally, the movement of the feet make the elbow point down. Brain signals are recorded for each task using an acquisition device that captures EEG from the user's scalp, and then the signals are subsequently processed and classified. The classifier's result guides the robot arm's movement in the four directions: right, left, up and down. Moreover, with a monitor displaying the streaming of a camera mounted on the robot arm, the user can see the system's selections in real time. Bousseta et al., used 4 subjects in their experiment and the averaged accuracy they got was 85.45%.

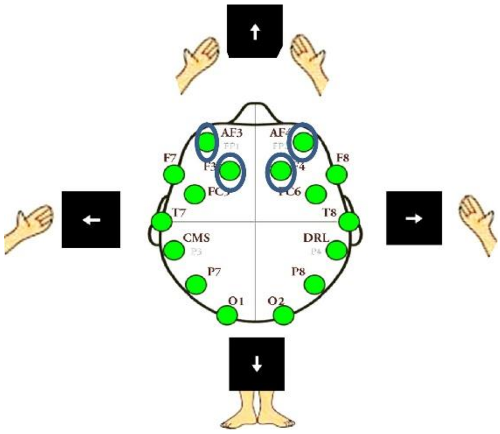


Figure 3-7: In this picture it is presented which imagination movements makes the robot arm to move in which direction.

3.3 BCI VR Gaming

The primary purpose of Brain–Computer Interface (BCI) research has always been, and continues to be, to develop communication, control, and motor alternative applications for individuals with severe disabilities. Nevertheless, new applications of BCI have lately arisen that can serve both handicapped and healthy users, particularly in the fields of multimedia and entertainment. The combination of BCI with Virtual Reality (VR) systems has quickly been viewed as highly promising on two different levels: how can BCI contribute to VE and what VE can provide to BCI. On the one hand, the VR community considers BCI as a novel input device that has the potential to dramatically transform how people engage with Virtual Environments (VE) [22]. Furthermore, BCI devices may be more user-friendly than long-standing devices. VR technologies, on the other hand, seem to be great tools for BCI research for a variety of reasons. To begin with, the virtual environment (VE) can provide BCI users with richer and more guiding feedback than conventional input which is often in the form of a basic 2D array presented on a screen. As a result, VR feedback might improve the system's learnability, reducing the amount of time required to learn the BCI skill while also improving mental state categorization accuracy. Furthermore, VR may be utilized as a pre-cursor to employing BCI applications in the real world. For example, in their paper [23], they used VR to train the user to guide a wheelchair and to evaluate alternative designs for wheelchair control, and these without putting them in danger and at a low cost. As an outcome, VE offers a secure, cost-effective, and adaptable training and testing environment for BCI prototypes.

Finally, combining VR and BCI technology might lead to novel applications for both disabled and healthy people. 3D video games, virtual visits, and virtual online communities are some examples of these applications that may be used to meet the social user's needs.

Researchers from University College Dublin and Media-Lab Europe proposed Mind-Balance [11], which is one of the most well-known videogames that uses VR and BCI. The game entails controlling an animated 3D figure in a virtual world. The goal is to use just the player's EEG to obtain one-dimensional control of the character's balance on a tightrope. The SSVEP generated in response to reversing chessboard patterns is used in the constructed BCI. The SSVEP greatly simplifies signal-processing approaches, requiring no or little training for users. A chessboard is placed on both sides of the avatar in the game. At 17 and 20 Hz, the checkerboards are reversed. There is short calibration time before each game. The individual must focus on the left and right checkerboards for 15 seconds respectively, as specified by arrows. The BCI is validated, and its settings are adapted to the current player's EEG using the data collected. This is done for 3 repetitions. The avatar that is walking a tightrope and is being exposed to random left and right movements, must be controlled by the user. In order to avoid the falling of the avatar, the user must be focused on the correct side. If he does not, then the avatar will lose balance (first degree) and if the user still does not precisely attention to the correct side, the avatar will go to a more perilous state of imbalance (second degree) and finally to an unfixable condition (third degree) where the avatar will collapse. If the user concentrates on the proper side, the avatar will adjust its balance until it is fully upright, enabling forward movement to resume. The user's file receives audio-visual feedback on the avatar's stability.

(a) (b)

Figure 3-8: (a) The training phase at which the chessboard that the user must be focused on is indicated by the arrows, (b) A moment in the game that the avatar loses balance.

Alshaimaa et al. [3] introduced a real-time rehabilitation system for post-stroke patients in their work. The system was made up of a Virtual Reality (VR) 3D game that was controlled by a BCI system, based on motor imagery, and they achieved a maximum accuracy of 79% with the combination of CSP and SVM. The aim of this system was to control the movement of an avatar in the 3D VR game in four different directions: up, down, right and left, regarding the imagined task. Each of these directions was considered as an individual class. There were 4 different imagined tasks one for each class. The imagination of a left hand movement corresponded to the first class, the imagination of a right hand movement for the second class, the imagination of movement of both feet for the third class and the imagination of movement of the tongue the fourth class. In their experiment, they used 8 electrodes with a sampling rate of 250Hz. Nine participants took place and each of them repeated the experiment for 2 sessions on two different days. Each session included 6 runs separated by short breaks and each run consisted of 48 trials (12 trials for each class) whereas each trial had a duration of 7 seconds.

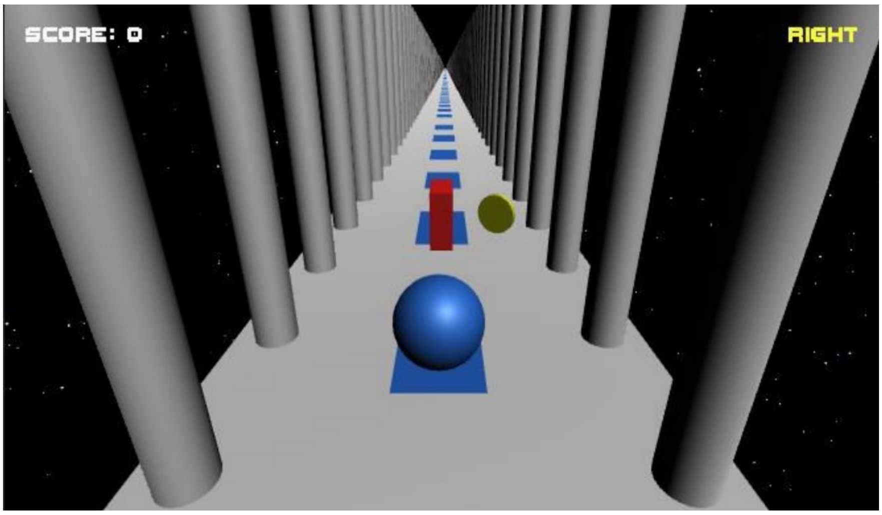


Figure 3-9: This figure shows the 3D VR game that is controlled by the user's imagination of the four different movements.

Chapter 4

Brain Computer Interface

4.1 The History and Definition of a Brain Computer Interface

Looking back to the time when Hans Berger, a German psychiatrist, first discovered the electrical activity of the human brain and invented electroencephalography, it can be seen as the event that started the history of brain-computer interfaces. Berger was the first person who recorded human brain activity by means of electroencephalography on a 17-year-old boy during a neurosurgery on July 6, 1924 [45]. Because of his concerns, he waited five years to release his first publication on EEG with title "Über das Elektrenkephalogramm des Menschen", in 1929 [4]. In his paper, he studied EEG recordings of patients with different genders and ages.

The composition Music for Solo Performer (1965) by the American composer Alvin Lucier was one of the first demonstrations of a functional brain-machine interface, even though the term had not yet been defined. To activate acoustic percussion instruments, the methodology utilizes EEG as well as analog signal processing equipment (filters, amplifiers, and a mixing board). To execute the music, alpha waves must be generated and used to "play" the numerous percussion instruments using loudspeakers positioned close or directly on the instruments. [39]

However, the first research on Brain-Computer Interfaces was made by Jacques Vidal at the University of California, Los Angeles (UCLA). Vidal was the one who coined the term "brain-computer interface (BCI)" in his paper "Toward Direct Brain-Computer Communication" which was published in 1973 [47].

There are several examples of handicapped people who have lost their capability to speak and connect with others. The loss of the capability to exercise language and physical function, restricts the range of communication options available. A Brain Computer Interface (BCI) is a system that uses the brain activity of its user, to identify his functional intent. In other words, a BCI system allows the operation of a device or application only with the user's thoughts and thus, restores the handicapped person's communication channel to the outside world. Typically, a BCI system consists of several components, and it can be divided into 3 main parts: signal acquisition, signal processing and application/device output. In the case of a closed loop online BCI system, there is another important part of a BCI which is the feedback.

4.2 Signal Acquisition

A signal acquisition system is responsible to collect brain signals, amplify them to levels appropriate for electronic processing, digitize them, and send them to a computer. It is made of hardware that measures the data (such as an EEG cap and an amplifier) and software that transmits the data to the computer.

There are several ways to measure the brain activity and can be divided in two classes: invasive and non-invasive methods. For the invasive methods, electrodes are implanted either inside the user's brain or across the surface of the brain during a neurosurgery, whilst for the non-invasive methods, brain activity is monitored using external sensors. The first class, invasive methods, includes the Electrocorticography (ECoG) which measures the electrical current on the cortex and the Intracortical which measures current in the cortex. The other class, non-invasive methods, includes the Electroencephalography (EEG) which measures current on the scalp, the Magnetoencephalography (MEG) which measures magnetic fields induced by electrical currents in the brain and Functional Near-Infrared Spectroscopy (NIRS) as well as

Functional Magnetic Resonance Imaging (fMRI) which measure the metabolic processes by detecting variations in blood flow that are linked to brain activity.

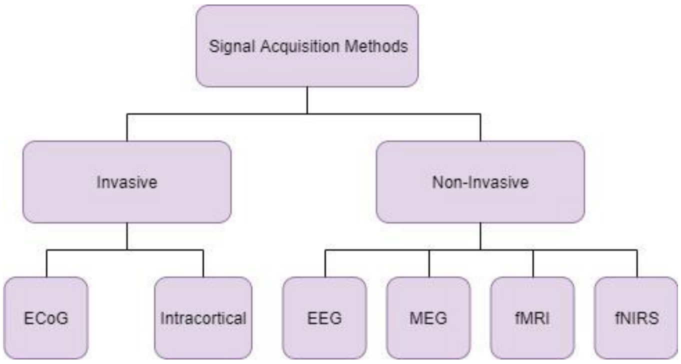


Figure 4-1: Signal Acquisition Methods

Each of the methods, invasive and non-invasive, have some advantages and disadvantages. The greatest advantage of invasive methods is that they provide high temporal (they can detect brain-activity as it happens) and spatial (they can pinpoint the location of activity) resolution. However, these methods may lead to infection or brain damage. On the other hand, non-invasive methods are more commonly used because they do not require surgeries or the implantation of external objects into the subject's brain, but at the same time, they are more sensitive to noise. In this thesis, we use the EEG method to acquire brain signals because of the convenience and non-invasive implement.

	Cortical surface	**Intracortical**	**EEG**	**MEG**	**fMRI**	**fNIRS**
Invasiveness and medical issues	Invasive	Invasive	Non-invasive	Non-invasive	Non-invasive	Non-invasive
Spatial resolution	High	Very high	Low	Mediate	High	Mediate
Temporal resolution	High	High	Mediate	Mediate	Low	Low
Portability	Portable	Portable	Portable	Non-portable	Non-portable	Portable
Recorded signal	Electrical	Electrical	Electrical	Magnetic	Metabolic	Metabolic

Figure 4-2: Characteristics of Acquisition Methods

4.3 Signal Processing

Signal processing is the part of the BCI system that identifies or classifies the brain signals that represent the intention of the user. Signal processing takes as input raw data from the signal acquisition and converts them into control commands which are sent to devices. Usually, the steps involved are preprocessing, feature extraction, classification and translation.

4.3.1 Preprocessing

Because of the poor signal-to-noise ratio, raw EEG data need to be preprocessed before feature extraction to achieve good classification accuracy. During preprocessing, the raw data are filtered and cleaned from the noise and artifacts. The main sources of noise and artifacts are 4 in total:

1. EEG equipment,
2. external to the subject and recording system electrical interference,
3. the electrodes and the subject’s electrical activity from his heart,
4. eye blinking, and in general all kind of muscle movements.

Moreover, when the data is as clean as possible from noise and artifacts, it is split in epochs of a few seconds. This enables us to extract a huge number of features from a single EEG recording for statistical purposes or to apply classifiers. Some of the most common preprocessing techniques are mentioned below.

4.3.1.1 Channel Selection

Some EEG sampling channels are strongly connected to sensorimotor rhythms in MI-based BCIs and thus, the spatial feature extraction can be improved by removing unrelated channels. [57] This depends on the tasks the user must do in the BCI system. For a MI-based BCI system that makes use of the left and right-hand movements, the target channels are C3 and C4. Therefore, any channel that is close to these channels should be taken into consideration whilst the channels that are not close to C3 and C4 should be removed. According to the 10-20 system that was explained in the subchapter 2.2.1, close to C3 and C4 channels can be assumed channels T3, Cz, T5, P3, Pz, F7, F3, Fz, F4, F8, T4, P4 and T6. However, if one wants to be more strict, he could only consider as close channels the ones that are exactly next to C3 and C4 and those would be T3, Cz, F3, P3, T4, F4 and P4. The right selection of channels that gives the best accuracy would be chosen after some experiments with different combinations.

4.3.1.2 Temporal Filters

A certain frequency band is used to extract the neurophysiological data. Temporal filters, such as band-pass, high-pass and low-pass filters are commonly applied to limit our investigation to the desired frequency range. Low-pass and high-pass filters take as a parameter a frequency and the former allow only frequencies that are lower than the parameter given to pass through while rejecting the higher ones. On the other hand, the later allows the frequencies that are higher than the parameter given to pass and reject the lower frequencies. The band-pass filter is a combination of the other two filters and what it really does, is to allow the frequencies between the 2 parameters to pass and reject the frequencies that are outside of that range. For example, the ERD/ERS can be detected over mu [8-13 Hz] and beta [13-30 Hz] bands in MI-BCI, hence the recorded EEG is band-pass filtered in the range of [8-30 Hz].

4.3.1.3 Spatial Filters

Spatial filtering, like temporal filtering, tries to limit the impact of unwanted information in the EEG. A spatial filter assigns weights to electrodes, with less weights going to electrodes that aren't relevant to the task. The Surface Laplacian (SL) and the Common Average Reference (CAR) are two of the most basic spatial filters used in EEG analysis. The former, subtracts the average activity of the other electrodes from each electrode, whereas the later, subtracts the average activity of the electrodes next to it. Another spatial filter is the Common Spatial Pattern (CSP) and is the most widely used. CSP’s purpose is to enhance signal discrimination between two classes by maximizing the variance of the signals for the one class while minimizing the variance of the signals for the other class. As a result, the signal intensity is increased, making it simpler to distinguish between the two classes.

4.3.1.4 Artifact Removal

Electrocardiography (ECG), electrooculography (EOG), electromyography (EMG) and technical artifacts like power-line sounds are examples of unwanted signals that might affect the efficiency of EEG-based BCIs. Since the most popular use of EEG frequency bands such as delta, theta, alpha, beta, and gamma concentrate the range from 4 Hz to 30 Hz, linear filtering is a typical way to eliminate artifacts. [57]

4.3.2 Feature Extraction

Feature extraction is the process of analyzing digital signals to obtain meaningful information. In order to accomplish this, it is needed to apply processing algorithms which will find important content in the data called “features”, such as the person’s intent. Usually, all the features that are extracted are arranged in a vector that is called as a feature vector. Because the understanding of neural activities is still limited, it is impossible to identify every intention of the subject. However, this can be bypassed in most BCI systems, since the practical BCI applications can be achieved by using the set of intentions that are recognizable (e.g., in a game, if the user wants to turn right or left, these can be achieved by imagining left -or right- hand movement).

Feature extraction is an essential step in signal analysis that must be done before classification due to the “curse of dimensionality”. According to this phrase, the quantity of data required to accurately characterize the various categories rises exponentially with the dimensionality of the feature vectors, according to this phrase [14]. It is suggested to use as many training examples as 5 to 10 times the number of the feature vector size. Having this said, we cannot provide the classifier directly with the EEG signals since this, in a concept of 16 EEG sensors and a sampling rate of 125Hz with one trial of EEG signal having duration of 1 second, would have a dimensionality of 16*125 = 2000 and thus a minimum of 10000 training examples (2000*5). This would mean that the user should do each mental task 10000 times in order to train the classifier and therefore the BCI system before its use.

The features of EEG signals are usually, but not only, extracted from 3 main sources of information, which are:

1. **Spatial Information**: the features extracted from this source will relate to the location of origin of the relevant signal. In fact, this would include choosing certain EEG channels or focusing more on some channels than others. This is analogous to concentrating on the signal arising from certain parts of the brain. [14]
2. **Temporal Information**: the features retrieved from this source of information will address the way that the relevant signal evolves over time. In reality, this involves employing distinct EEG signal levels at different moments or time windows. [14]
3. **Spectral Information**: the features extracted from here, indicate how the power fluctuates in various key frequency bands. In reality, this implies that the features will only consume the power in certain frequency ranges. [14]

4.3.3 Classification

After feature extraction, subsequent step is the classification. During this process, the classifier is trained with machine learning techniques, to assign a class to a feature vector that was extracted from the previous phase. This class relates to the type of mental state that has been defined. Throughout the training, it uses training data and labels, such as "target" and "not target", to recognize which feature predict the labels best. After the classifier is trained, given new data, it can recognize whether it belongs to one or another class. In our case, as we will discuss later, let us consider a Motor Imagery – based BCI system that is used with the imagination of left and right-hand movements. In this case, the two classes would be left and right respectively. To distinguish the mental states from the EEG signal and to assign them to a class, band power features, i.e., the power of the EEG signal in a certain frequency band, are the typical features used. In this case, band power features are commonly derived in the alpha [8-13 Hz] and beta [14-30 Hz] frequency bands for electrodes placed over the motor cortex sections of the brain (around C3 and C4 for right- and left-hand movements, respectively). Then, a classifier is used to classify those features.

There is a variety of classification algorithms that are used in BCI systems. In this chapter, four popular algorithms in the field of BCI are going to be reviewed: Linear Discriminant Analysis, Support Vector Machine, Multilayer Perceptron, k-Nearest Neighbours.

4.3.3.1 Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis classifier has been among the most popular classification algorithms for EEG-based BCI system since it is simple to use and has minimal computational need. As its name suggests, LDA is a linear model used for classification and dimensionality reduction problems. It was developed by Ronald A. Fisher, in 1936 and it was designed for a two class problem. However, C. R. Rao generalized it as 'Multi-class Linear Discriminant Analysis' in 1948 [46].

LDA aims to separate two or more classes using a plane or hyperplane (for high dimensionalities), also known as decision hyperplane. The separating hyperplane is found by looking for:

1. the projection that maximizes the distance between the means of the classes while
2. minimizing the interclass variance.

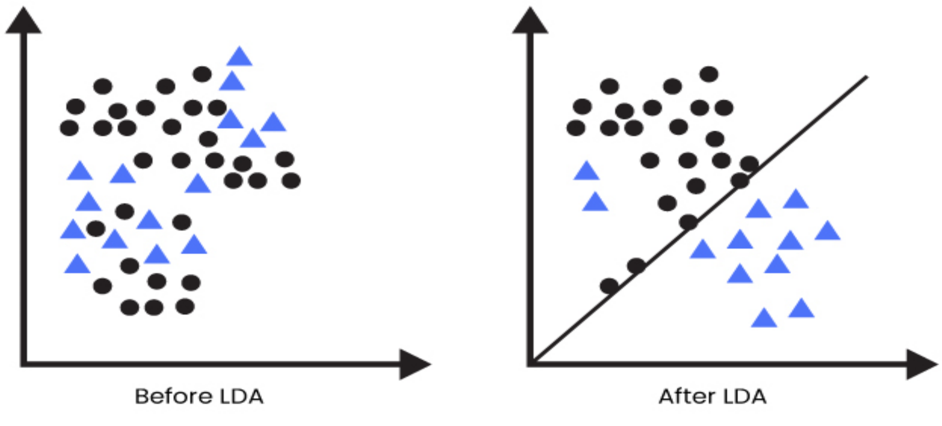


Figure 4-3: Left picture shows the objects before LDA was performed. Right picture depicts the categorisation of the objects (2-classes) after LDA was performed.

4.3.3.2 Support Vector Machine (SVM)

Support Vector Machine is another widely used classification algorithm. The purpose of SVM is to construct a hyperplane that separates the two classes and, more importantly, maximizes the distance between the hyperplane and the nearest samples. This distance is called the margin and the points that fall exactly on the margin are referred to as the supporting vectors [48]. Figure 4.2 depicts two alternative hyperplanes in a two-dimensional space. One can observe that the margins are wider in the second figure rather than in the first. In such situation, the SVM algorithm prefers the latter hyperplane over the former.

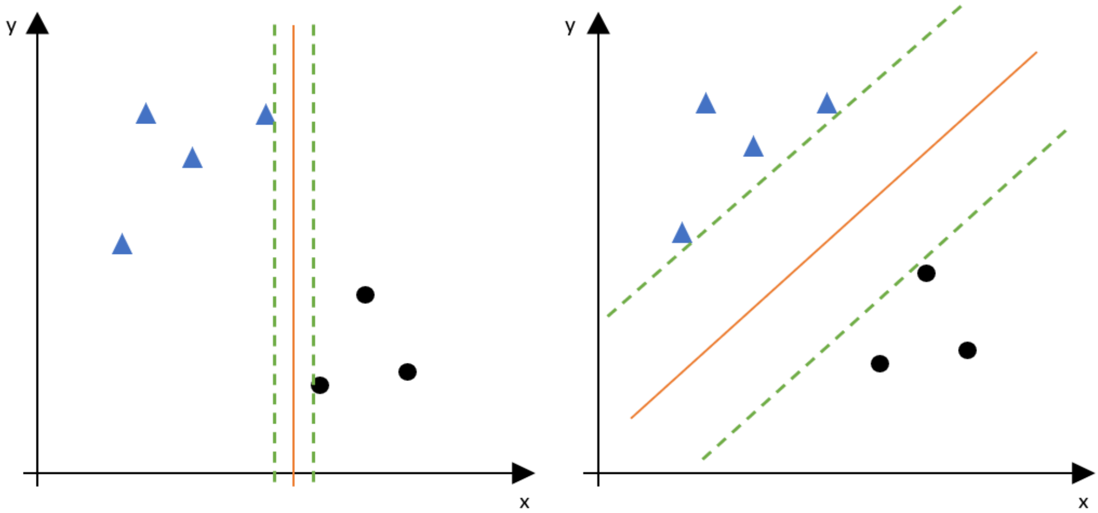


Figure 4-4: The figure represents two possible hyperplanes of SVM. In both plots, the orange line represents the hyperplane while the distance between the two green dotted lines represents the margin. The first plot has smaller margin than the left plot. Hence, the latter is preferred by SVM.

4.3.3.3 Multilayer Perceptron (MLP)

The Multilayer Perceptron is the most extensively used artificial neural network (ANN) for BCI. It is composed of several neurons that are organized in three or more layers: an input layer, one or more hidden layers and an output layer. The neurons in the hidden and output layers contain an activation function that turns weighted inputs into outputs, allowing MLP to categorize linearly inseparable data. Backpropagation is the learning process of an MLP; it is an iterative process in which the node weights are adjusted to minimize the output error [55].

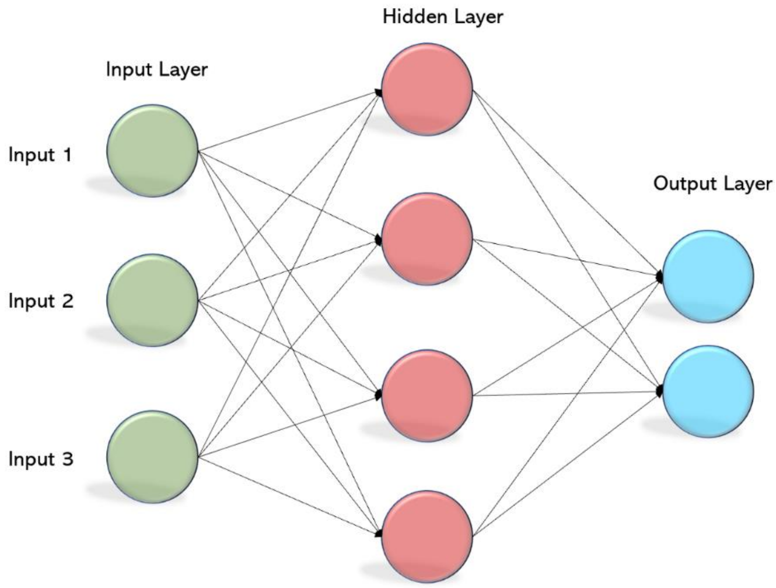


Figure 4-5: The structure of a Multilayer Perceptron ANN.

4.3.4 Translation

The following process is the translation. After a signal has been classified, the result of signal classification is sent to the feature translation algorithm. At this step, the features need to be translated into the appropriate action required, according to the user's intention.

4.4 Device Output and Feedback

The external device is controlled by the commands from the feature translation algorithm, which provide operations such as robotic arm movement, letter selection, a motorized wheelchair, cursor control, and so on. The device's operation gives the user feedback, closing the control loop.

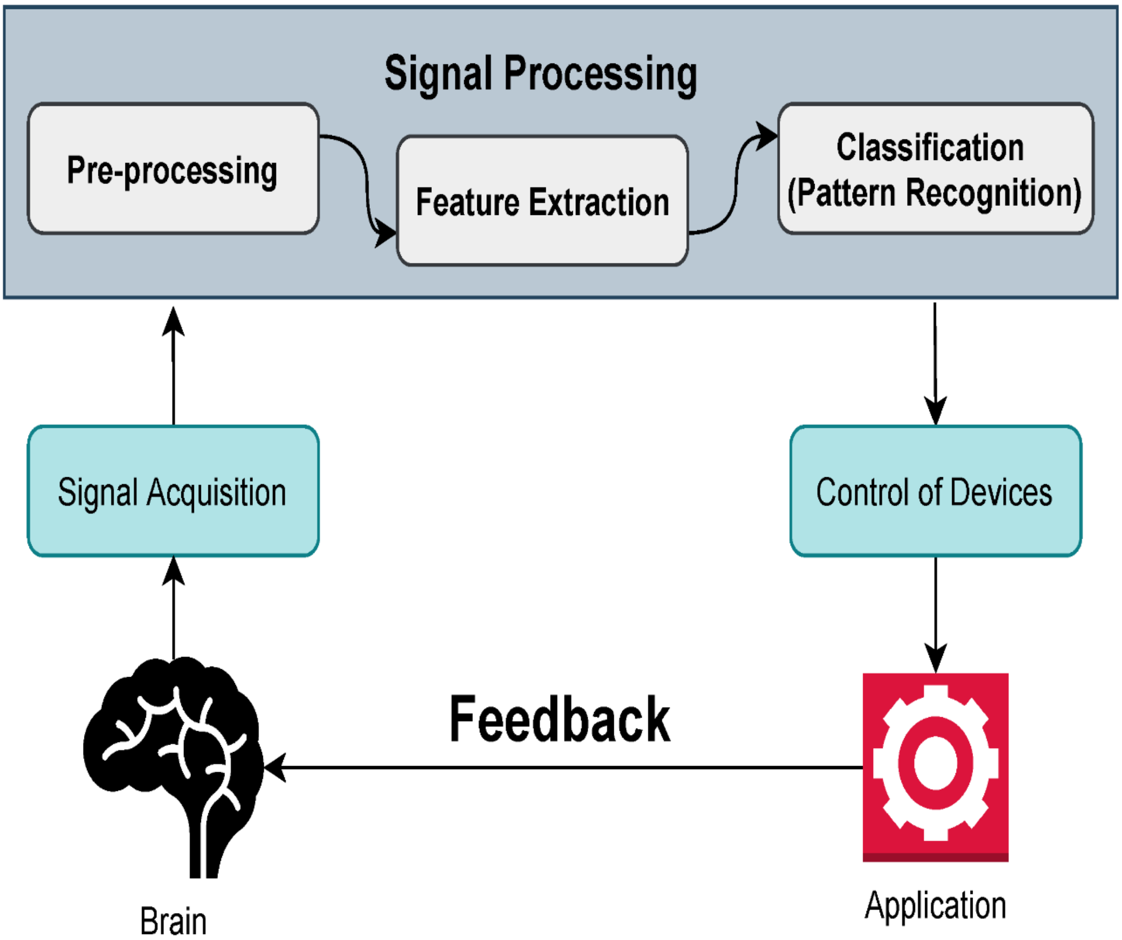


Figure 4-6: This picture shows the basic architecture of a brain computer interface system.

Chapter 5

Experimental Methodology

In the previous chapters, the background theory of Brain Computer Interfaces, along with effective methods and techniques for preparing and classifying the EEG signals have been discussed. As a result, the first objective of this thesis has now been met. In this chapter, the second purpose, which is the experiment, will be reviewed.

5.1 Hardware and Software Infrastructure

In order to accomplish the experiment, a variety of hardware and software tools were used. In this chapter, these tools are going to be briefly described.

5.1.1 EEG Electrode Cap

The whole experiment is based on the EEG signals acquired from the user and since the experiment is implemented by the use of a non-invasive EEG-based BCI, an EEG electrode cap is required. In the experiment, the "All-in-One EEG Electrode Cap Starter Kit" from OpenBCI's shop is being used. This kit is scientifically approved and is used in several research projects [2]. The kit includes the following:

1. Cyton + Daisy Biosensing Board 16-channel (x1)

2. OpenBCI EEG Electrode Cap (x1)
3. Header Pin to Touchproof Electrode Adapter (x2)

Cyton + Daisy Biosensing Board 16-channel:

The Cyton OpenBCI Board (Figure 5-1) is an 8-channel neural interface with a 32-bit CPU that is Arduino-compatible. Furthermore, the OpenBCI Cyton Board and the OpenBCI Daisy Module (which plugs into the OpenBCI Cyton Board) can sample up to 16 channels of EEG, EMG, and cardiac activity (ECG). RFDuino radio modules are used to communicate wirelessly with a computer using the OpenBCI USB dongle. It can also communicate wirelessly with any Bluetooth Low Energy-enabled mobile device or tablet (BLE). On each of its 16 channels, the CytonDaisy Board samples data at 125 Hz. However, if the "save data to microSD card" option in the OpenBCI GUI is enabled, the 250 Hz sampling rate can be used [9].

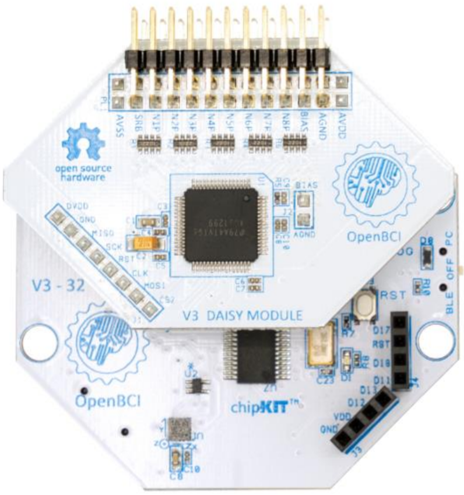


Figure 5-1: The Cyton and Daisy OpenBCI Board.

OpenBCI EEG Electrode Cap:

The OpenBCI EEG Electrode Cap (Figure 5-2) is designed for accurate EEG bio-potential readings with wet electrodes [13]. It comes in three different sizes (based on the circumference across the widest part of user’s head) :

- Small = 50-54 cm
- Medium = 54-58 cm
- Large = 58-62 cm

For the experiment purposes, because the dimensions of each participant may vary, both medium and large caps are available.

Figure 5-2: The OpenBCI EEG Electrode Cap.

Header Pin to Touchproof Electrode Adapter:

The OpenBCI Touch-proof Electrode cable Adapter belongs to the category of ribbon cables with ten touch-proof adapters for connecting a Cyton Board, a Cyton Daisy Board, or a Ganglion Board to the EEG electrode cap [16].

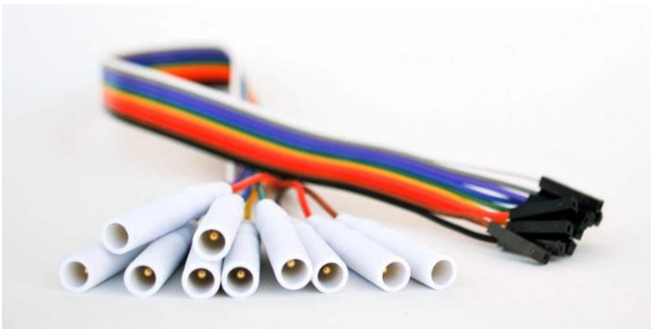


Figure 5-3: The OpenBCI Touch-proof Electrode cable Adapter.

5.1.2 Electrode Cap Gel

As it was mentioned in sub-chapter 2.2, wet electrodes use a conductive gel or saline water to improve the conductivity between the scalp and electrodes. In these experiments, the OpenBCI Electro-Gel is being used. To place the gel on the electrodes, a syringe is also used.

5.1.3 VR Headset

Throughout the experiment, the user is not only wearing the EEG Electrode cap, but he also wears a VR headset. More specifically, the VR headset that is being used in the experiments is the “Valve Index”.

Figure 5-4: The Valve Index VR headset that was used in the experiments.

5.1.4 OpenViBE and Unity

OpenViBE is an open-source software platform that consists of two main applications: the OpenViBE Designer (Figure 5-4: left picture) and the OpenViBE Acquisition Server (Figure 5-4: right picture). The former is used as a graphical programming language for creating and modifying BCI scenarios with the aggregation of linked boxes while the latter is used to acquire brain signals from a device and send the data back to the application that is connected with (OpenViBE designer). Moreover, it converts signals from a variety of devices into a common format.

As it is going to be mentioned below, the experiment is based on a VR game that was implemented with Unity. Therefore, another software that is being used in the experiment is Unity.

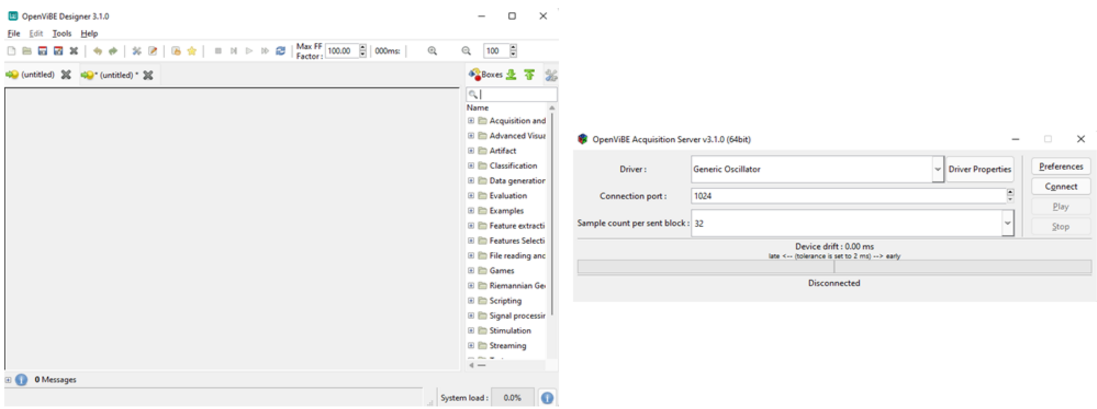


Figure 5-5: Left: OpenViBE Designer, Right: OpenViBE Acquisition Server.

5.2 Experimental Setup

Eleven healthy participants, of whom eight were female and three were male, volunteered to participate in this study. The subjects were aged 21 to 44 years, and none had a history of neurological disorder. The experiment was carried out in a silent room at CYENS Centre of Excellence (formerly known as RISE) in Cyprus. During the experiment, only the subject and two researchers were permitted in the room. The experiment was about a Motor-Imagery based BCI system where the user had to imagine left and right hand movements. Each subject, participated in one session which was consisted of two phases: the calibration phase, also known as the training phase, and the testing phase. Each of these phases had a duration of approximately 7 minutes and included 40 trials: 20 trials for left hand movements and 20 trials for right hand movements. However, the duration of the whole experiment was about one hour. In the beginning of the experiment, the participant was given information regarding the procedure that was going to be involved, and he signed the consent form. After this, the EEG electrode cap was placed on the user, according to the 10-20 system, and before he wore the VR headset, instructions about the following task were given once again to make sure he understood the relevant procedure. What he actually had to do, was to try feel the movement of left and right hand movements by imagining them, according to the relevant instruction that was given at each trial. Later on this chapter, the procedure will be clearly explained with details. By the end of the calibration phase, the acquired EEG signals were used to train both the CSP spatial filter and the classification algorithm. While the training was taking place, the participant was going through two cognitive tests on the PC which both together needed the same time as the training. The aim of these tests was to draw conclusions whether the accuracy of the system is depended by the user’s concentration. Nevertheless, this is not the case we are going to study in this thesis. The following phase was the testing. In that phase, the subject had to imagine left and right hand movements, just like in the training phase, but the differences between the two phases were that:

1. in the testing phase, there was another player that shoot the ball at the goalkeeper either on his left or on his right
2. the subject was getting visual feedback on his task as will be described in detail below.

5.3 Data Collection

The participant sat comfortably in an armchair and to acquire his EEG signals the OpenBCI EEG Electrode cap was used. Since both the medium and large size of the cap were available, the EEG cap that fitted him best was chosen. The electrodes were mounted on the cap by its construction and so according to the 10-20 system and having as reference the channel Cz, the cap was placed on the participant. After the cap's placement, the gel was placed on the electrodes using a syringe starting from the reference electrode (REF), then the ground electrode (GND - creates a common ground between the Cyton board and the user's body, while it also includes extra destructive interference noise cancellation techniques) and then continuing to the other electrodes. The channels that were used were 16 in total and those were C3, C4, Cz, O1, O2, P3, P4, Pz, T3, T4, F3, F4, F7, F8, T5 and T6. However, the target channels were C3 and C4 since they are located over the right and left hand representation areas and therefore are the main control channels of motor imagery hand movements. To check the quality of signals, the OpenBCI GUI was used. The VR headset was placed on the subject after ensuring that the electrode cap was properly positioned and that the channels were sending signals.

In the calibration phase of the experiment the training signals were acquired and, in the testing phase, the online BCI was performed where the user received feedback on his imagination movements.

5.4 Calibration Phase

The calibration phase, also known as the training phase, was the first part of the experiment. It consisted of 40 trials of which 20 trials was for right hand movement imagination and the other 20 trials for left hand movement imagination. The sequence of the trials was random. The subject was in a virtual environment behind an avatar that was a goalkeeper, and his task was to imagine either left or right-hand movement according to the highlighted hand of the avatar. In other words, if the left or right hand of the avatar was highlighted, then the subject had to imagine left or right-hand movement, respectively. In the beginning of the session, the participant was in a resting state and after the first 30 seconds, a flag was presented (let $t_0 = 0$) which signaled the beginning of the trial. Then, 3 seconds later, one of the avatar's hands was highlighted as a cue (let

t_{1_start} = 3) and was visible for 1.5 seconds (t_{1_end} = 4.5) indicating which movement the participant should imagine. After the highlighted hand went invisible, the flag was still presented until t_2 = 8 (end of trial). From the moment that the cue appeared (t_{1_start}) and until the flag had been disappeared (t_2), the subject was imagining the corresponding hand movement for a duration of 5 seconds (from t_{1_start} = 3 until t_2 = 8). A new flag appeared on screen (t_0 of the new trial) 3 seconds after the disappearance of the previous flag (at t_2) and indicated the beginning of the next trial. Moreover, it is important to mention that between the time that the previous flag disappeared (t_2) and until the new cue appeared (t_{1_start} of the next trial) the subject was in a resting state. In other words, the subject was not trying to imagine any hand movements for 6 seconds. This timing scheme is shown in Figure 5-6.

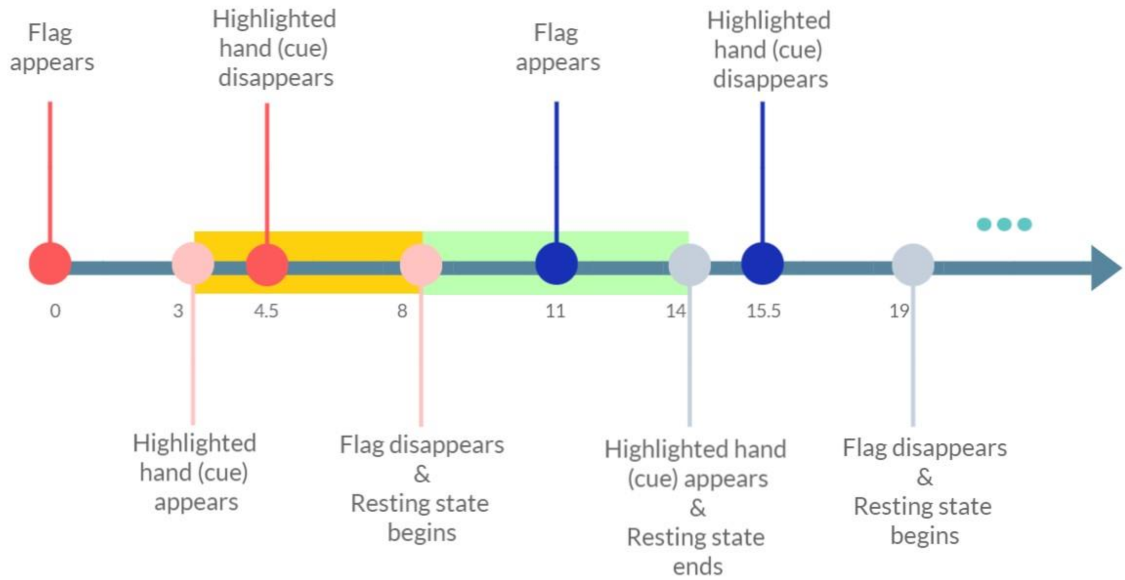


Figure 5-6: This figure shows all the events that happened in the calibration phase of the experiment. Each trial had a duration of 8 seconds and from t=0 until t=8 the first trial took place whilst the second trial begun at t=11 and ended at t=19. In addition, from t=3 until t=8 (duration of the orange box) the subject was imagining either left or right hand movement. The length of the green box, from t=8 until t=14, shows the duration of the resting state.

5.5 Testing Phase

The testing phase was the last part of the experiment and the one that intrigued most the interest of the users as they got feedback on each trial which made the process more interactive. This phase was also consisted of 40 trials: equally divided for left and right-hand movements that appeared in a random order. The task was exactly the same as the training's phase with the only differences being the other football player that was present in the field as well as the feedback that the participant received. More precisely, in the online game, the football player that was in front of the goalkeeper, shoot the ball at the direction of the latter's highlighted hand and the participant had to imagine the movement of the corresponding hand. During the participant's imagination task that lasted 5 seconds, like in the calibration phase, feedback was presented. The feedback was the moving hand of the goalkeeper trying to prevent the ball of getting into the net. If the subject was imagining of his left hand movement, then the avatar should extend his left hand and stop the ball while the corresponding act should happen if the participant imagined of a right hand movement.

Chapter 6

Data Analysis and Results

In this chapter, the process behind the experiment will be discussed. The details regarding the scenarios used in OpenViBE and the algorithms that were chosen will be explained.

6.1 EEG Signal Monitoring

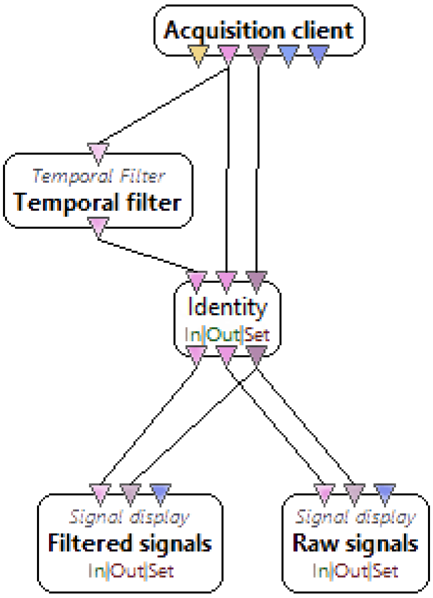


Figure 6-1: This figure shows a scenario that can be used for signal monitoring.

This scenario is used to check the quality of the signals before starting the experiment. First of all, the box named 'Acquisition client' receives the brain signals of the user through OpenViBE Acquisition Server which is connected to the EEG electrode cap.

Then, the input stream is being pre-processed by applying a temporal filter on the input signal. More specifically, a band pass filter (Temporal filter) is used with low cut frequency (high-pass) of 8Hz and high cut frequency (low-pass) of 30 Hz. This means that our signals are filtered, allowing only signals in the range of [8,30] Hz to pass through and reject frequencies outside that range. By doing so, unwanted noise and artifacts are removed. By displaying both the raw and filtered signals, the following results (Figure 6-2) are presented. It is obvious, from the following figure, that the filtered signals are clearer and in the Y axis it is immediately apparent that the signals are filtered in a smaller range (each channel has its own range, and the value in middle is 0Hz). However, to see the values of the filtered signals on the Y axis, one should zoom in.

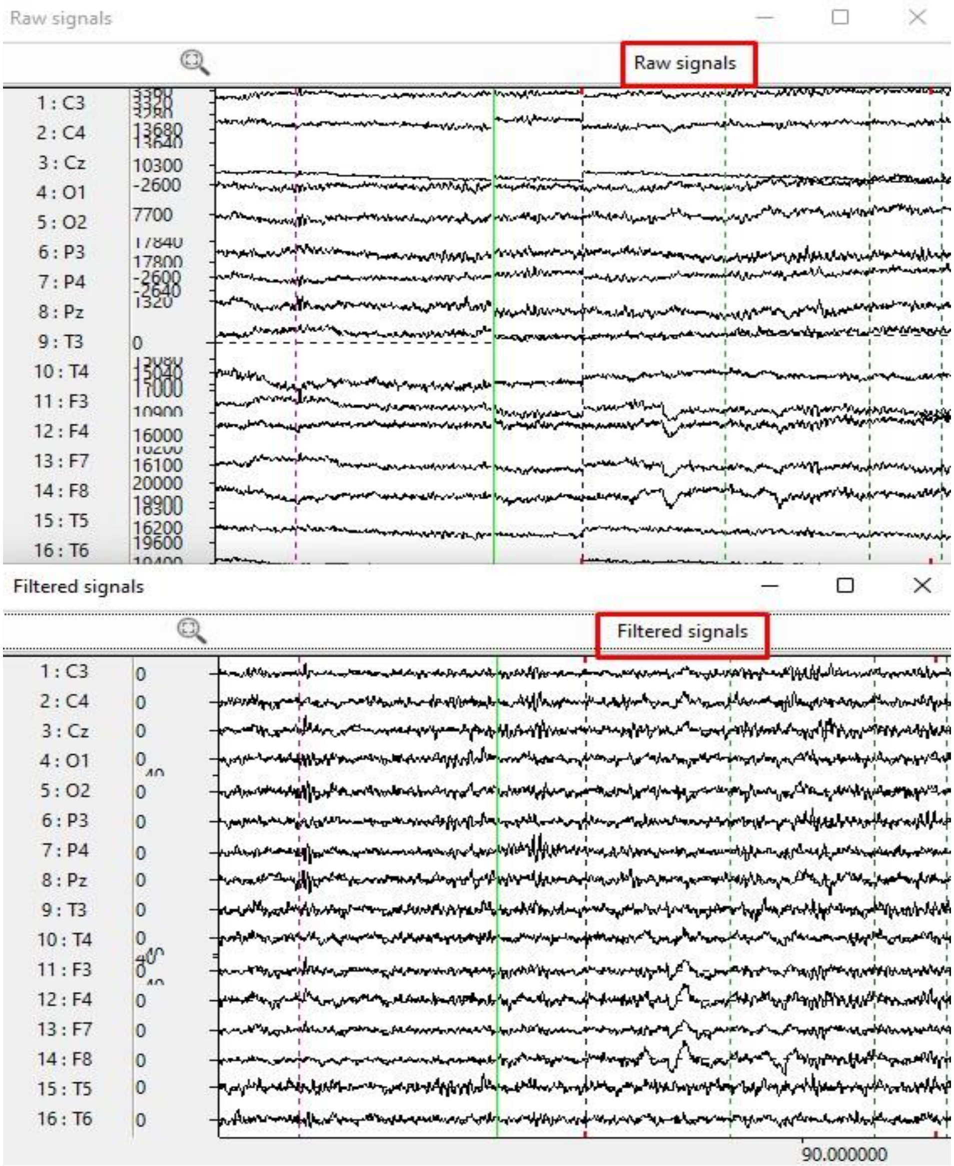


Figure 6-2: This figure depicts the raw signals at the top and the filtered signals at the bottom.

With slight changes, this scenario could be reused to study in detail specific channels or frequencies. For example, below a focus on alpha and beta bands is given, by applying separately temporal filters according to their frequency ranges (alpha band -> 8-12Hz, beta band -> 13-30Hz).

If this scenario is executed, the following window appears on screen, with the raw signals

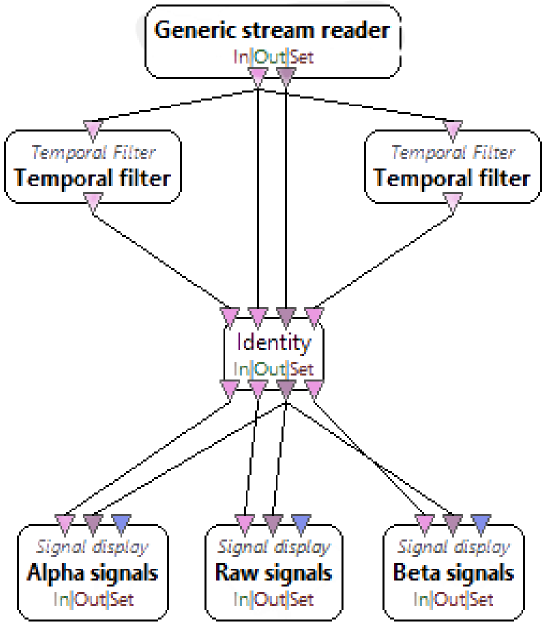


Figure 6-3: An alternative scenario that studies the Alpha and Beta bands.

on top, the alpha signals below, and the beta signals at the bottom. Since all of the 16 channels for all of the 3 cases – raw, alpha and beta – would not fit in the screen, only channels C3 and C4 was selected to be shown just for this case (Figure 6-4).

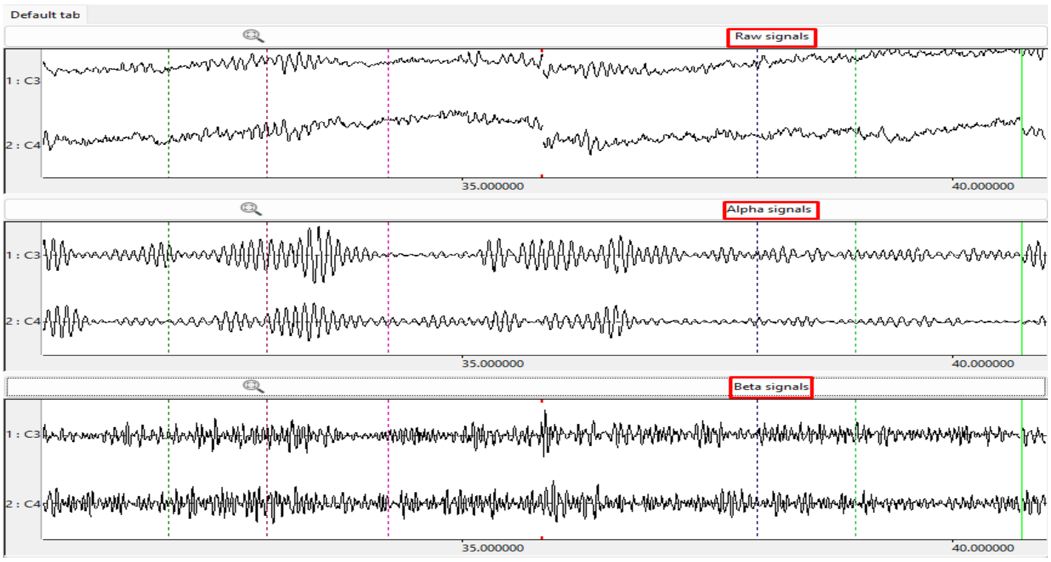


Figure 6-4: An alternative scenario to study in detail a specific range of frequencies and channels.

6.2 Signal Acquisition

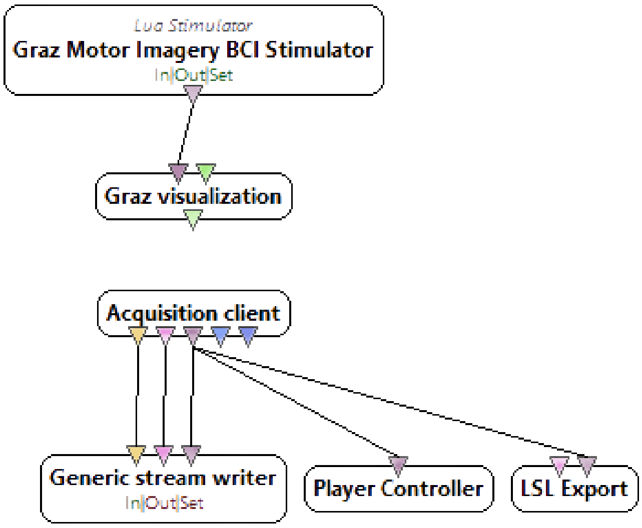


Figure 6-5: This scenario is used during the calibration phase to acquire the EEG signals of the participant.

This scenario is used in the calibration phase of the experiment to acquire the EEG signals of the participant. As explained before, the ‘Acquisition client’ box receives the brain signals of the user through OpenViBE Acquisition Server which is connected with the EEG electrode cap. These signals are saved and will be used to train the spatial filter and the classifier as will be discussed later. Behind the box named as ‘Graz Motor Imagery BCI Stimulator’, a program in Lua scripting language is being executed which is responsible of the events and the timing that those happen during the experiment, such as the appearance/disappearance of the flag and the stimulations (right or left cue). In order to receive the timing, the stimulations and the signals in Unity, this scenario is connected with Unity through the ‘LSL Export’. This must be accomplished in order to have the correct data presented on the right time in the VR game.

6.3 Pre-processing

As it was briefly explained above, the pre-processing is an essential step in BCI systems since it cleans the data and removes unwanted noise and artifacts. This step is done right after the acquisition of the signals (calibration phase). While the participant is busy performing the first cognitive test, the following scenario is being executed (Figure 6-6). The main purpose of this scenario is to pre-process the data. What really happens here is that the input signals are filtered by applying a bandpass filter in the range of [8,30] Hz (alpha and beta bands). Afterwards, the data are split in epochs based on the stimulation that was received, which might be left or right. Each epoch was set to have a duration of 4 seconds and the epoch offset was set to 0.5 seconds. That means that signal selection started after the actual stimulation. This offset was picked to prevent the initial half second (when the user started executing the activity) and the last half second (when the user finished the task) because it could reflect a phase when the user was not consertained well or was exhausted and did not perform the task optimally. A new epoch begun each time a new stimulation was received. Moreover, another pre-processing technique that was implemented, was the application of a spatial filter. For the purpose of this thesis, a focus on the Common Spatial Pattern (CSP) filter was given after running a few pilot experiments which proved that this filter, in combination of different classification algorithms, gave the best results. Thus, the CSP spatial filter was trained and the results it gave were saved in a configuration file that was used in the next scenario. The CSP-trainer took as input the stimulations and the two signal conditions (left and right trials) and computed the spatial filter coefficients according to the Common Spatial Pattern algorithm. This algorithm aims to enhance the discrimination of two types of signals by increasing the signal variance for one condition while limiting the variance for the other.

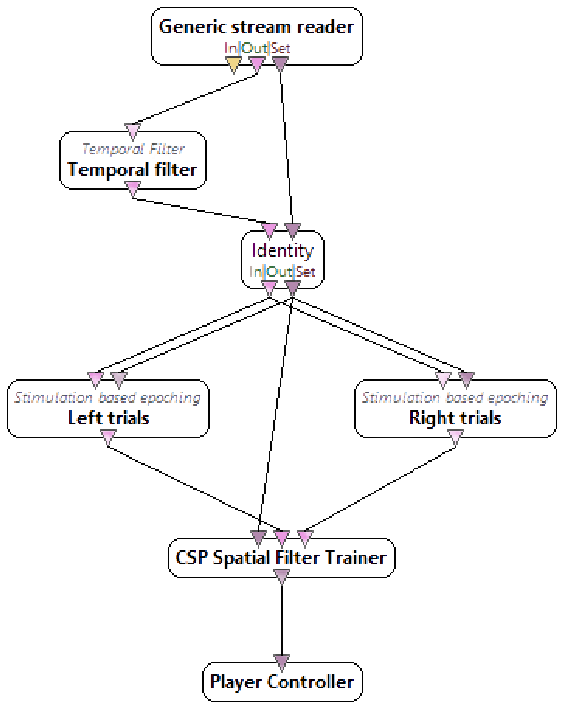


Figure 6-6: This scenario illustrates the pre-processing techniques that are used.

6.4 Feature Extraction and Classification

The feature extraction and classification steps come after the pre-processing. These steps are carried out in the same scenario (Figure 6-7) in OpenViBE, which is executed immediately after the previous scenario, when the participant attempts to complete the second cognitive task. The aim of this scenario is to train the classifier to detect left and right hand movements. At the end of this scenario's execution, an estimation of the classifier’s performance will be printed on the console.

In the beginning, the EEG data that were acquired in the first scenario are read, and then, a bandpass filter in the range of [8,30] Hz is applied to allow only the alpha and beta bands to pass while avoiding noise and artifacts. As a further action, the CSP spatial filter that was trained in the previous scenario, is applied and after that, comes the feature extraction.

In the feature extraction, the signals are sliced into chunks of 4 seconds length based on a stimulation event (left or right hand movement) and thus, we end up with 4 seconds signals which are further split in blocks of 1 second every 1/16th second. Then, the logarithmic band power is computed by squaring the signals, average them and finally calculating their logarithm. Finally, each chunk/feature is catenated into one vector which is then passed as input to the ‘Classifier trainer’ box. That said, the classifier takes 3 inputs. The first one is the Stimulation stream, with only one of its stimulations being important, the one that triggers the training process, while the second and the third inputs are the feature vectors, for left and right trials respectively. The behavior of this box is simple: it gets 2 feature vectors which are labelled depending on the input they arrive with and when a specific stimulation arrives (OVTK_StimulationId_Train), a training process is triggered and according to the parameters that were chosen, the classifier is being trained. The parameters include the classification algorithm and the number of partitions for the k-fold cross validation test. The classification algorithms that were used were LDA, SVM and MLP but with a small experiment that we illustrated, we concluded that LDA gives the best results and thus, we decided to use LDA over the other two. As for the number of partitions for the k-fold cross-validation test, it was set to 5. When the classifier trainer finishes its training, it saves a configuration file that is used in the next scenario (Real Time Classifier Processor).

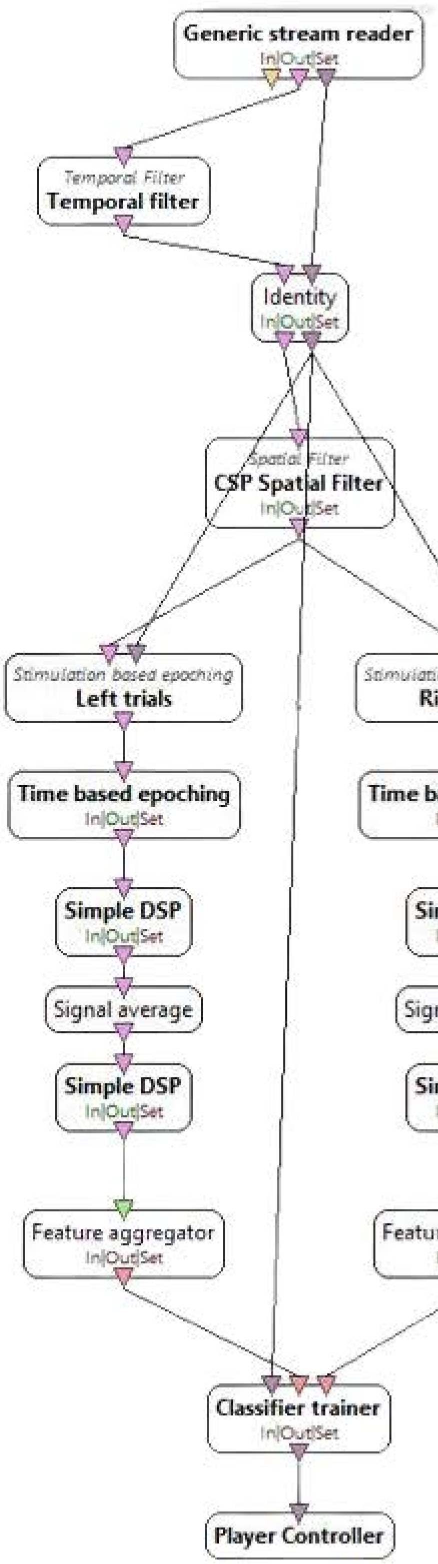


Figure 6-7: This figure shows the scenario that illustrates the feature extraction and classification.

6.5 Real Time Classifier Processor – Online

This scenario (Figure 7-8) is used in the testing phase of the experiment in the background of the VR game. What happens here is a combination of the previous scenarios. More precisely, the first and foremost action is the acquisition of the EEG signals and then a temporal filter – bandpass – with low cut frequency of 8Hz and high cut frequency of 30Hz, is applied on the signals. After this, the CSP spatial filter is applied and then the signals are sliced into epochs of 1 second each $1/16^{th}$ second. Then, the band power is calculated as in the previous scenario and the signals are converted to feature vectors which are later passed to the classifier processor. The classifier processor uses the configuration file that was created by the classifier trainer in the previous scenario. Every time that a new feature vector arrives, it is forwarded to the classifier algorithm which predicts the class and sends it in the form of a stimulation while the algorithm status is sent in the form of a streamed matrix. Finally, the stimulation is sent to Unity and is used to present the feedback to the user.

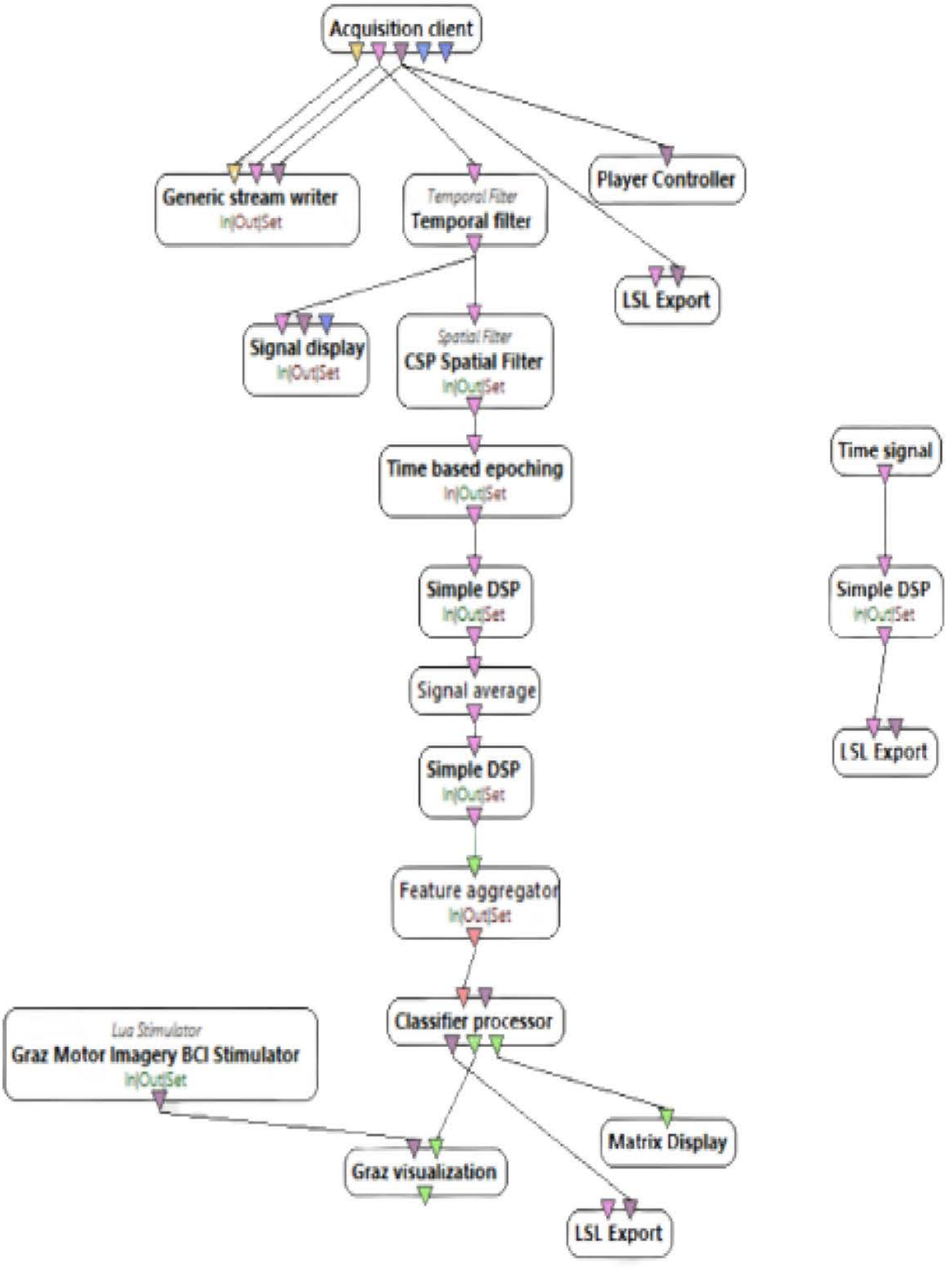


Figure 6-8: This figure presents the scenario that is used during the testing phase – the VR game.

6.6 Results

The experiment's outcomes will be discussed in this section. However, it is necessary to first clarify the measures that are applied. Various metrics and criteria are used to measure the performance of BCI systems, which is one of the primary reasons why different BCI systems cannot be compared. A classifier's performance is defined as its ability to properly predict or distinguish various classes. The most common measurements are precision, recall, false positive rate (FPR), true positive rate (TPR), classification accuracy, and confusion matrix, which are briefly detailed below.

The following metrics can be defined in a binary classification problem with classes labelled as 'positive' and 'negative':

- True Positives (TP): the number of positive examples that are labelled as positive.
- True Negatives (TN): the number of negative examples that are labelled as negative.
- False Positives (FP): the number of negative examples that are labelled as positive.
- False Negatives (FN): the number of positive examples that are labelled as negatives.

<u>Precision (p):</u> also known as positive predictive value, is the proportion of true positives to all positive findings, including true positives and false positives.

$$p = \frac{Tp}{Tp + Fp}$$

<u>Recall (r):</u> is the proportion of relevant occurrences that are recovered.

$$r = \frac{Tp}{Tp + Fn}$$

False positive rate (FPR): measures the likelihood that a trial would be incorrectly categorized as a user intention.

$$FPR = \frac{Fp}{Fp + Tn}$$

Classification accuracy is a standard metric used to assess the performance of any classification algorithm, and it is often defined as the ratio of successfully categorized trials over tested trials. The purpose of this thesis is for the user to complete the tasks using the proper hand imaginary movement, and so accuracy is measured as the ratio of the number of successes a subject achieves against the number of tries made.

$$Acc = \frac{Tp + Tn}{Tp + Tn + Fp + Fn}$$

A **Confusion matrix** is a prominent metric for classification problems. It may be used for both binary and multiclass classification problems. The confusion matrix used in this thesis is shown below. In the confusion matrix provided, element **C(i,j)** is the number of trials that belong to class **i** and were classified to class **j**.

		Predicted Condition	
		Left	**Right**
Actual Condition	**Left**	True Left	False Right
	Right	False Left	True Right

Table 6-1: Example of a Confusion Matrix

To discuss the results of this experiment, two different metrics will be used. The first one is the confusion matrix, and it will be used for the first phase (calibration phase) and the second one is the classification accuracy which will be used for the testing phase.

The following table summarises the results obtained from the calibration phase.

	Cross Validation Confusion Matrix (%)			Training Confusion Matrix (%)		
Subject 001		**Left**	**Right**		**Left**	**Right**
	Left	78.5	21.5	**Left**	80.3	19.7
	Right	6.5	93.5	**Right**	6.5	93.5
	Cross Validation Accuracy	86		**Training Accuracy**	86.9	
Subject 002		**Left**	**Right**		**Left**	**Right**
	Left	80.1	19.9	**Left**	85.6	14.4
	Right	31.6	68.4	**Right**	30.1	69.9
	Cross Validation Accuracy	74.3		**Training Accuracy**	77.7	
Subject 003		**Left**	**Right**		**Left**	**Right**
	Left	60.2	39.8	**Left**	67.4	32.6
	Right	38.6	61.4	**Right**	32.2	67.8
	Cross Validation Accuracy	60.8		**Training Accuracy**	67.6	
Subject 004		**Left**	**Right**		**Left**	**Right**
	Left	72.5	27.5	**Left**	74.4	25.6
	Right	45.8	54.2	**Right**	40.8	59.2
	Cross Validation Accuracy	63.3		**Training Accuracy**	66.8	
Subject 005		**Left**	**Right**		**Left**	**Right**
	Left	44.6	55.4	**Left**	67.2	32.8
	Right	45.6	54.4	**Right**	28.2	71.8
	Cross Validation Accuracy	49.5		**Training Accuracy**	69.5	
Subject 006		**Left**	**Right**		**Left**	**Right**
	Left	65.7	34.3	**Left**	70.4	29.6
	Right	36.2	63.8	**Right**	28.5	71.5
	Cross Validation Accuracy	64.8		**Training Accuracy**	70.9	
Subject 007		**Left**	**Right**		**Left**	**Right**
	Left	68.8	31.2	**Left**	74.4	25.6
	Right	15.6	84.4	**Right**	8.9	91.1
	Cross Validation Accuracy	76.6		**Training Accuracy**	82.8	
Subject 008		**Left**	**Right**		**Left**	**Right**
	Left	62.8	37.2	**Left**	65.8	34.2
	Right	25.7	74.3	**Right**	23.8	76.2
	Cross Validation Accuracy	68.5		**Training Accuracy**	71	
Subject 009		**Left**	**Right**		**Left**	**Right**
	Left	62.2	37.8	**Left**	71	29
	Right	48.2	51.8	**Right**	36.4	63.6
	Cross Validation Accuracy	57		**Training Accuracy**	67.3	
Subject 010		**Left**	**Right**		**Left**	**Right**
	Left	70.6	29.4	**Left**	71.8	28.2
	Right	36.9	63.1	**Right**	31.7	68.3
	Cross Validation Accuracy	66.8		**Training Accuracy**	70	
Subject 011		**Left**	**Right**		**Left**	**Right**
	Left	61.2	38.8	**Left**	72.3	27.7
	Right	29.8	70.2	**Right**	20.6	79.4
	Cross Validation Accuracy	65.7		**Training Accuracy**	75.8	

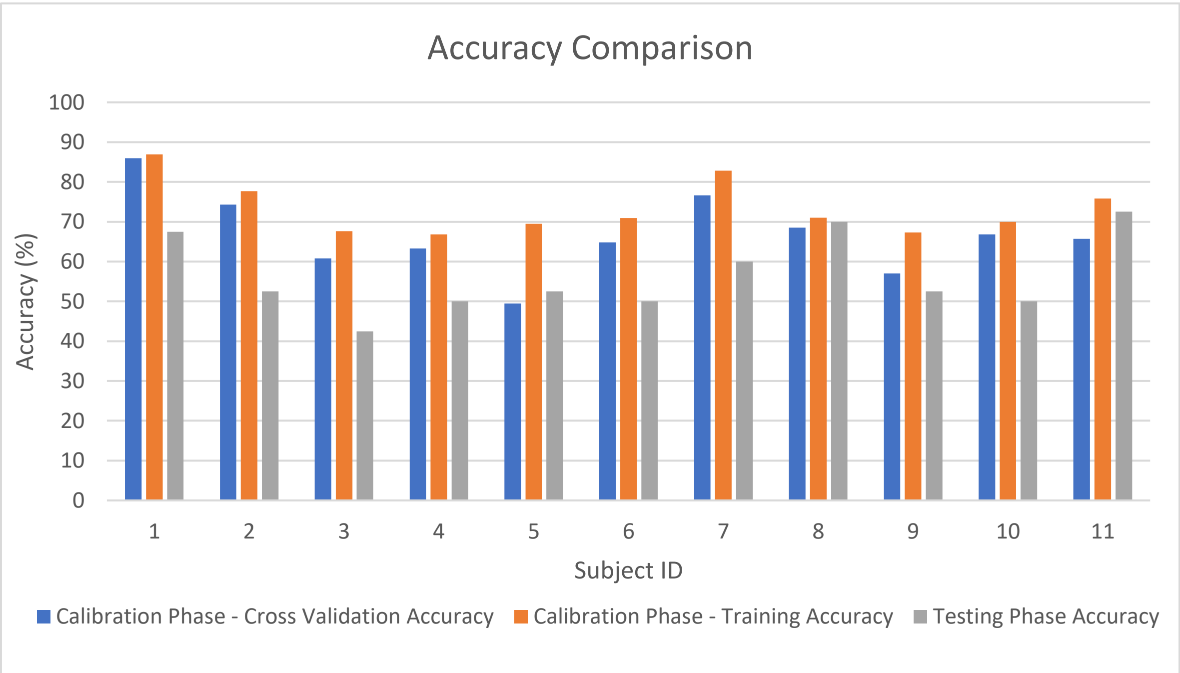
Table 6-2: Confusion Matrixes obtained from the calibration phase

The table that follows depicts the results obtained from the test phase.

	True - Target	False - Not Target	Accuracy (%)
Subject 001	27	13	67.5
Subject 002	21	19	52.5
Subject 003	17	23	42.5
Subject 004	20	20	50
Subject 005	21	19	52.5
Subject 006	20	20	50
Subject 007	24	16	60
Subject 008	28	12	70
Subject 009	21	19	52.5
Subject 010	20	20	50
Subject 011	29	11	72.5

Table 6-2: Accuracy obtained from the testing phase

The following bar char summarizes the results that are presented in the two tables above to make it easier to draw conclusions.



The graph above depicts the accuracy obtained throughout the calibration and testing phases. Because we used the k-fold test (k = 5) as previously mentioned, we have two accuracy values from the calibration phase: Cross Validation Accuracy and Testing Accuracy. As we know from machine learning, the accuracy in the calibration phase is higher than the accuracy in the testing phase, as was predicted. Moreover, we can see from the graph above that participant 1 showed the best performance in the calibration phase, with 86% cross validation accuracy, 87% training accuracy. However, participant 11, who had 66% cross validation accuracy and 76% training accuracy, achieved almost 73% accuracy in the testing phase while participant 1 who had better calibration accuracies achieved almost 68% testing accuracy. Despite the fact that the results of the other participants are not very good, we can argue that participants 1, 8 and 11 denies that the system may also provide good results. There are various elements that might impair the system's accuracy, as we are going to describe below. Calculating the average accuracy of each category yields the following results: cross validation accuracy = 66.7%, training accuracy = 73.3%, and testing accuracy = 56.4%. One of the key reasons why testing accuracy has reduced significantly when compared to training accuracy is that the EEG signals used in the testing phase are from a different session, and as we will see below, EEG signals are dynamic and change over time.

We find that the precision is insufficient but however, we know that the results in this domain are often roughly 80% accurate. There are several factors that could affect our results, and we will discuss them below. The reasons might be related to several components of a BCI system, such as the participant, the software utilized, and the nature of the EEG signals.

Let us begin with the participant – related errors that may occurred. One of the main reasons that the average accuracies are not as good as we would want them to be, is the participant’s skill and motivation. To be more specific, the individual is expected to perform some rigorous mental tasks that might be exhausting and difficult to concentrate on. Also, because the user may perceive the instructions differently, a good explanation of what the user had to accomplish was provided but, we couldn't tell if the imaginary task was completed correctly since we couldn't control what, when, or how they thought. For example, the participant, instead of visualizing the sense of movement, he could think the image of himself performing the action, resulting in visual imaging rather than kinaesthetic imagery. Also, the people who participated, did not have a motivation to continue the experiment in the right way even when they got tired. Moreover, another reason can be the physiological variation. Each participant has varying head shape, cortical volume and brain folding and so, there is difference in the electrical signal transmission from the generative sources inside the brain to the surface, from user to user. This is one of the reasons why some individuals do better than others. If we generalize this explanation, we may conclude that because the number of participants was small, the sample we picked might fall into the category of people whose brain physiology results in less-than-satisfactory results.

Another factor is the software, the techniques, and algorithms we use, as well as the algorithm parameters. We did try both CSP and Laplacian spatial filters as well as the LDA, CSP and SVM classifiers with different parameters and we found that the best combination was CSP with LDA. However, in a future work we could test other processing techniques and classifiers and compare them to decide which ones are the best.

Last but not least, the nature of EEG signals certainly affects the accuracy. EEG signals are non-stationary which means that time period and frequency are not constant but variable. Therefore, the features that are used in the training phase differ from those used in the testing phase. This is something that researchers who work on BCI systems have to deal with.

At this point, it is critical to note that when we conducted the pilot experiment through OpenViBE to determine the appropriate combination of spatial filter and classification algorithm, the results were better. This might be due to a tiny delay (in the order of 0.5 seconds) that occurs during the connection between OpenViBE and Unity (the transfer of the subject's classified signal and stimulation). As it was mentioned above, each epoch was set to have a duration of 4 seconds with 0.5 seconds offset (the first and last 0.5 seconds were not taken into consideration). Therefore, the remaining 3 seconds should be used. However, due to the delay occurred by the communication of the two platforms, the 3 seconds were not the entire window we wanted. More specifically, because of the delay, the timeline when the events happened (the presentation of the highlighted hand and the disappearance of the flag) were shifted right by 0.5 seconds in the Unity application. Thus, the user would start to imagine the movement when he saw the highlighted hand but this was 0.5 seconds after the actual stimulation through the OpenViBE.

Chapter 7

Other Scenarios Implemented for Future Work

In this chapter we will discuss other scenarios that were implemented but we do not use them in the experiment at this stage. However, the scenarios are functional, and we can, at any time, execute them through OpenViBE. Nevertheless, if we want to use them in the experiment via the VR game, then some changes need to be made in Unity.

7.1 Concatenation of Multiple Files

The first scenario we are going to discuss is the concatenation scenario (Figure 7-1). As it is commonly known, a classifier can predict better the class of a feature if it is trained with more data. Because the calibration phase in our experiment occurs in a single session during the first VR task, we only collect one EEG file for each subject. The idea behind this scenario is for each subject to complete three sessions of the first task and therefore acquire 3 EEG files for each participant. Then, we can merge these 3 EEG files into one and give this new file as input to all the scenarios that were explained above in order to have a bigger dataset and hence get a better accuracy.

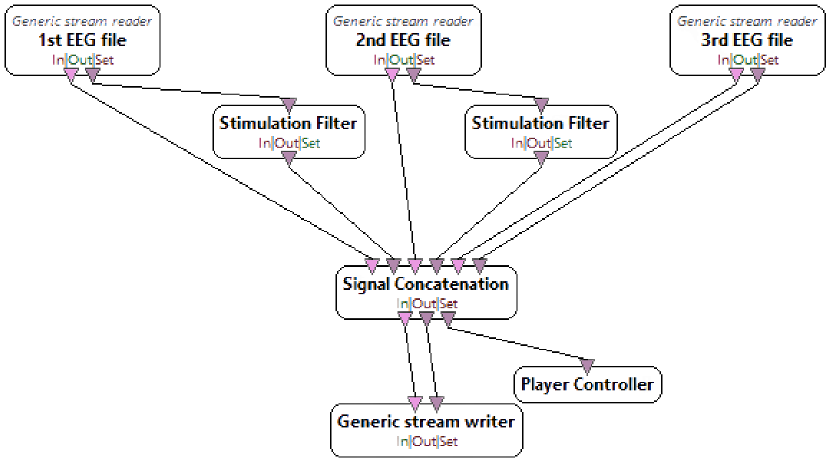


Figure 7-1: This figure shows the concatenation scenario.

7.2 Elimination of Fp1 and Fp2 Channels

In these scenarios (Figure 7-2 and Figure 7-3) , the channels used to acquire the signals were chosen. We observed that without the Fp1 and Fp2 channels, the results were better, with a 5% increase in accuracy. These two channels detect eye blinking, which we interpret to be noise. So, in the case below, we can observe the channels that were used. However, in our experiment, we simply chose not to use the relevant electrodes from the EEG cap, which is why this scenario was not executed.

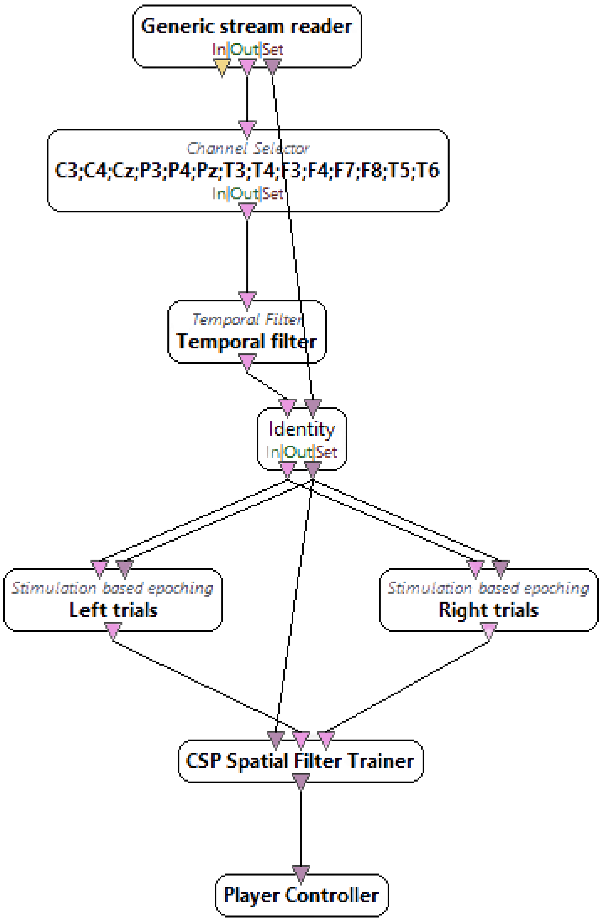


Figure 7-2: This is the scenario used to train the CSP spatial filter.

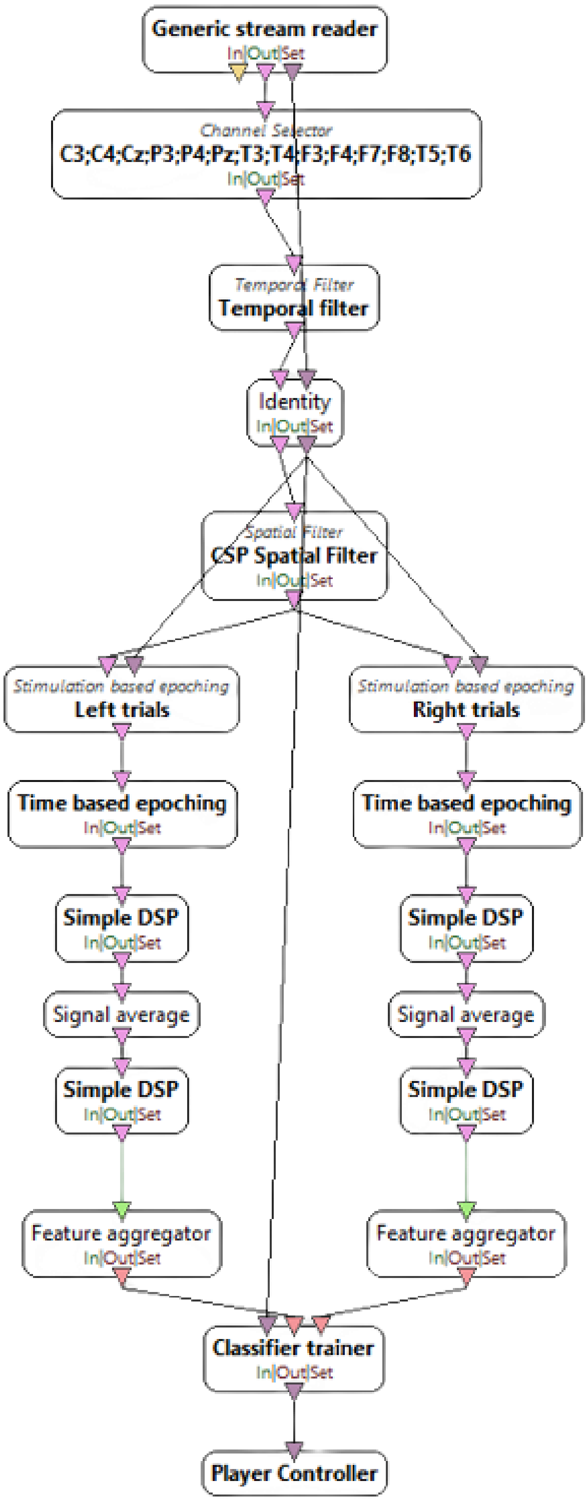


Figure 7-3: This is the scenario used to train the classifier.

7.3 BCI With Three Classes – Left Hand, Right Hand, and Feet

The next scenarios we will deal with are the implementation of a BCI with 3 classes. In the experiment we used 2 classes - right hand and left hand. Below, we will explain the alterations we made to the previous scenarios to accomplish the three class classification: right hand, left hand and feet.

Firstly, in the Signal Acquisition scenario (Sub-chapter 6.2) we modified the LUA file. What we actually did was to add a third class for feet and then make the appropriate additions and changes in the code to include another 20 trials for feet imagination. The que/stimulation used in OpenViBE to let the user know that he had to envision feet movement, was an arrow pointing up. Then, these 20 trials along with the trials of right and left hand movements, were presented in a random sequence.

In addition, we made some changes to the scenario where we train the CSP spatial filter (Figure 7-4). Instead of using only one CSP spatial trainer, we use three different ones, one for each combination of the three classes. As shown in the figure below, the class called "up" corresponds to the feet. The first CSP spatial filter is for the left and right classes, the second is for the left and up classes and the third is for the right and up classes. By doing so, we get three different configuration files, one for each CSP filter, which will be used in the scenario where the classifier is trained.

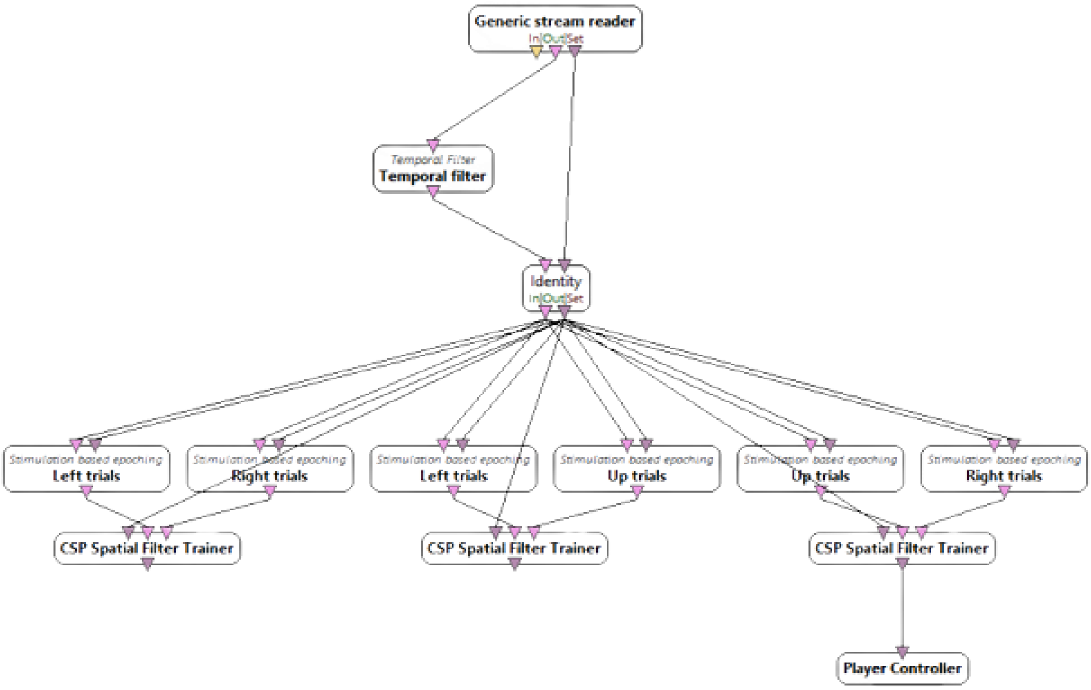


Figure 7-4: This figure shows the scenario in which the three CSP files are trained.

Finally, we also modified the scenario in which the classifier is trained (Figure 7-5). More precisely, we preserved the same structure as the initial scenario, but we repeated the same procedure three times, once for each of the three class combinations. We utilized the three CSP configuration files provided by the previous scenario, and then performed the identical approach as in the original example. As a result, instead of two feature aggregators, we had six (two for each spatial CSP filter) and we sent them into the classifier trainer.

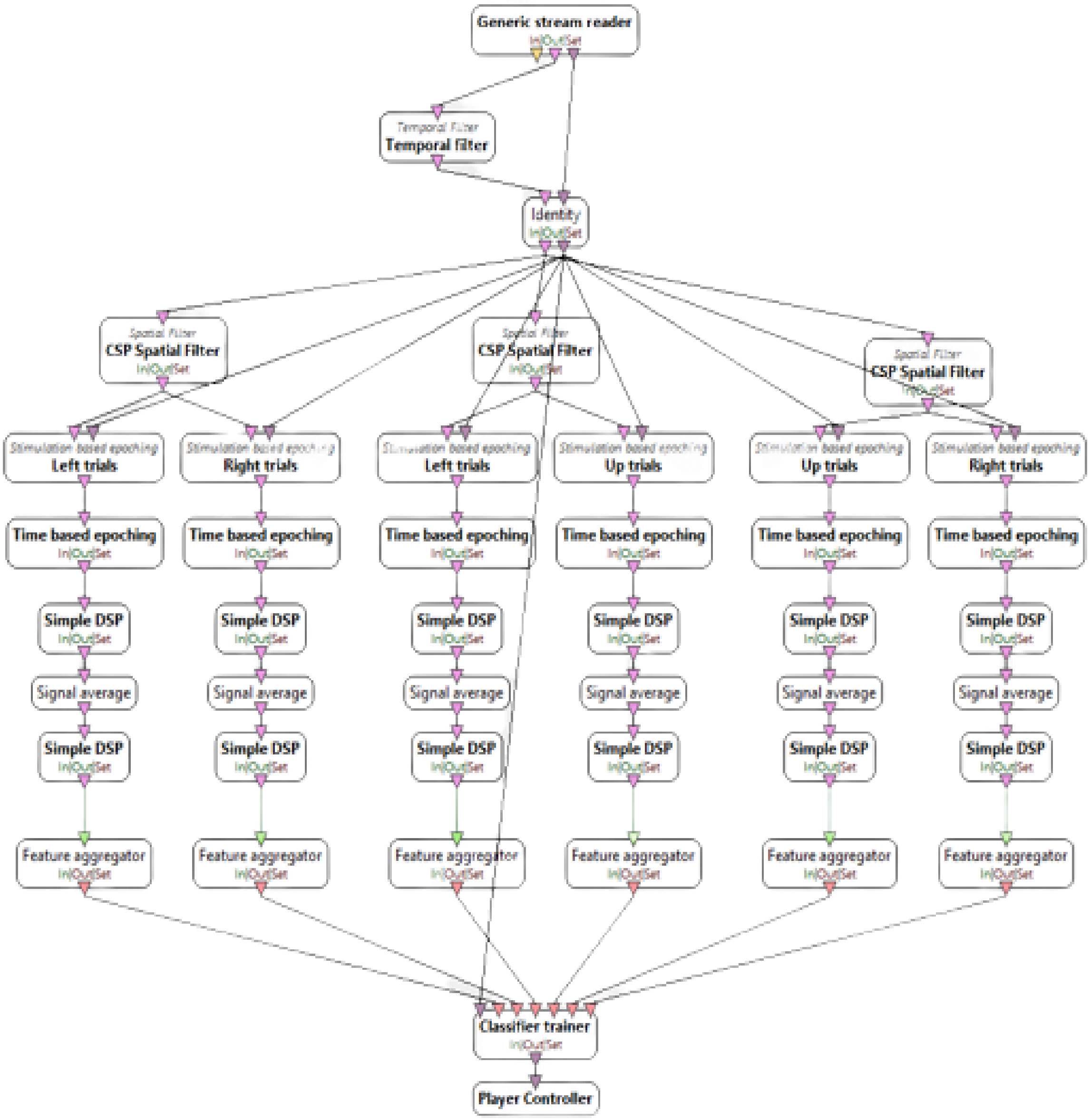


Figure 7-5: This figure shows the procedure followed to train a classifier with 3 classes.

These scenarios might be used in future work. The feet can be utilized for a variety of purposes. In our experiment, the class "feet" can be employed as a task for the goalkeeper to deflect the ball with both hands or with his feet.

7.4 Conclusion

EEG signals offer considerable promise for giving an alternate form of human-computer interface to people who are unable to use standard techniques for interacting with a computer due to medical reasons. In this thesis, we analysed the many tactics that are often utilized for enabling this type of interaction, as well as the algorithmic and technical aspects that are used in constructing such systems. Furthermore, we collected data from 10 different participants during our experiments and we draw the conclusions that were discussed above.

All in all, Brain Computer Interfaces has long piqued the interest of researchers. It has recently become a fascinating topic of scientific investigation and a promising way of showing a real connection between the brain and a computer. This idea has been utilized in several research and development initiatives, and it has also become one of the fastest growing sectors of scientific investigation. BCI research has been utilized effectively not just to assist the disabled, but also as an additional channel in games, augmented reality applications, domestic device management, as well as in other implementations.

In this work, we conducted an experiment on ten persons and obtained the results described above. As we mentioned, the result was unsatisfactory. This might be due to a variety of factors, including the participants chosen not having the necessary skills, the EEG signals being dynamic and unstable, as well as the signal processing and classification algorithms used. However, there is a scope for improvements and with the scenarios explained above and with the participation of more people in the experiments, we may be able to enhance the system's accuracy.

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