Universidad Autónoma de Querétaro

Facultad de Ingeniería

Maestría en Instrumentación y
Control Automático

Computational system for biopotential processing focused on the detection of encephalopathies

TESIS

Que como parte de los requisitos para obtener el grado de
Maestro en Ciencias en Instrumentación y Control Automático

Presenta:

Ing. Luz María Sánchez Reyes

Dirigido por:

Dr. Juvenal Rodríguez Reséndiz

SINODALES

Dr. Juvenal Rodríguez Reséndiz
Presidente — Firma

Dr. Juan Fernando García Trejo
Secretario — Firma

MC. José Erik Rivas Araiza
Vocal — Firma

Dr. Luis Miguel Contreras Medina
Suplente — Firma

Dra. Gloria Nélida Avecilla Ramírez
Suplente — Firma

Dr. Manuel Toledano Ayala
Director de la Facultad

Dr. Juan Carlos Antonio Jáuregui Correa
Director de Investigación y Postgrado

Centro Universitario
Querétaro, Qro.
México.
Enero 2020

Universidad Autónoma de Querétaro

Facultad de Ingeniería

Maestría en Instrumentación y
Control Automático

Computational system for biopotential processing focused on the detection of encephalopathies

TESIS

Que como parte de los requisitos para obtener el grado de
Maestro en Ciencias en Instrumentación y Control Automático

Presenta:

Ing. Luz María Sánchez Reyes

Dirigido por:

Dr. Juvenal Rodríguez Reséndiz

SINODALES

Dr. Juvenal Rodríguez Reséndiz Presidente	Firma
Dr. Juan Fernando García Trejo Secretario	Firma
MC. José Erik Rivas Araiza Vocal	Firma
Dr. Luis Miguel Contreras Medina Suplente	Firma
Dra. Gloria Nélida Avecilla Ramírez Suplente	Firma

Dr. Manuel Toledano Ayala Director de la Facultad	Dr. Juan Carlos Antonio Jáuregui Correa Director de Investigación y Postgrado

Centro Universitario
Querétaro, Qro.
México.
Enero 2020

“Be the change you want to see in the world”

Acknowledgments

I dedicate this research work to God, to my parents, family, friends, and teachers who always supported me and motivated me to do my best.

Resumen

Un patrón de EEG (electroencefalograma) se define como una forma de onda que ocurren regularmente y tienen una morfología y duración similar. La identificación de patrones de voltaje y frecuencia para señales EEG se puede aplicar en diferentes áreas de la medicina, como por ejemplo en el desarrollo de herramientas de ayuda para el diagnóstico de enfermedades cerebrales, rehabilitación y/o comunicación con dispositivos de ayuda externos. De acuerdo a estudios realizados por la Organización Mundial de la Salud (OMS), más de 250,000 personas mueren cada año en México por enfermedades cerebrales tales como epilepsia o trastornos del sueño. Este proyecto tiene como objetivo desarrollar una aplicación para la clasificación de registros EEG anormales y normales mediante un análisis cuantitativo de potencias relativas. Un registro EEG anormal corresponde a la presencia de alguna enfermedad cerebral. El algoritmo se implementó en un lenguaje de programación orientada a objetos (Python). Se comienza por leer una base de datos, se envía la información mediante comunicación serial, la información es recibida, decodificada y se analiza en el dominio del tiempo. Posteriormente, se aplica técnicas de análisis en el dominio de la frecuencia (Transformada Rápida de Fourier y la Transformada de Wavelet), se realiza un análisis cuantitativo mediante un análisis de potencias, se muestran varias gráficas de ayuda (dominio en el tiempo, en la frecuencia, resultado del análisis cuantitativo) y los niveles de potencia encontrados en cada banda de frecuencia y la interpretación de los mismos.

Abstract

An electroencephalogram pattern (EEG) is defined as a waveform that occurs regularly and has a similar morphology and duration. The identification of voltage and frequency patterns for EEG signals can be applied in different areas of medicine, such as in the development of tools to help diagnose brain diseases, rehabilitation, and communication with external help devices. According to studies conducted by the World Health Organization (WHO), more than 250,000 people die each year in Mexico from brain diseases such as epilepsy or sleep disorders. This project aims to develop an application for the classification of abnormal and normal EEG records using a quantitative analysis of relative powers. An abnormal EEG record corresponds to the presence of some brain disease. The algorithm was implemented in an object-oriented programming language (Python). It begins by reading a database; the information is sent through serial communication, it is received, decoded, analyzed in the time domain, frequency analysis techniques are applied (Fast Fourier Transform and Wavelet Transform). After a quantitative analysis is performed through power analysis, several help graphs are shown (domain in time, frequency, the result of quantitative analysis) and relevant data is obtained in the identification of abnormal EEG in the which indicates the power levels found in each frequency band and the interpretation of them.

Contents

List of Figures

List of Tables

CHAPTER 1

Introduction

The WHO defines encephalopathy as a disease that alters the function or structure of the brain. Some examples are epilepsy, brain tumors, brain death, sleep disorders, migraine or dementia. Encephalopathies can present a full spectrum of symptoms; some complications can end in a coma, learning problems, mental retardation, autism, speech delays, attention deficit, mental confusion, seizures, dementia, death, among others. These occupy one of the first ten places in causes of death in countries of medium and low income of agreement with the WHO (Donald & Fernando, 2010).

The International Labor Organization (ILO) reports that more than 70% of people with brain diseases don't have medical coverage, compared to 22% of people living in urban areas. The ILO also establishes that there are inequalities in health coverage in most countries, whether rich or poor, although the highest rural/urban gap is found in developing countries. Specifically, in Mexico the number of patients with a brain disease corresponds to medium and low socioeconomic strata, corresponding to 77.1%. Therefore, the development of efficient, portable and inexpensive medical equipment is critical.

With the information provided by the EEG, it is possible to obtain clinically relevant information for the identification and monitoring of brain diseases. The conventional identification of brain disease by EEG is based on quantitative or qualitative analysis; in quantitative analysis, it is sought to identify abnormal frequencies and in a qualitative analysis paroxysms, which are waveforms that do not correspond to the nature of the signals.

The research aimed to implement a portable, low-cost computer system for the detection of encephalopathies, using EEG signal processing. For the analysis of the information, processing techniques are applied to work the signals in the frequency domain, a quantitative analysis of the relative powers is carried out and, with the data obtained and the frequency spectra, an interpretation of the information is made shown to the user.

1.1 Motivation

According to studies conducted by the WHO, more than 250,000 people die every year in Mexico due to encephalopathies. Encephalopathy has become one of the most common neurological disorders. Also, 80% of patients live in low and middle-income countries. Figure 3.3 shows the ten leading causes of death per 100,000 inhabitants, in this figure it can be seen that one of the main reasons is due to brain diseases (Audette, 2015; Dimitrios, Pierre, Marc, Jonathan, & George, 2014; Juti & Akinori, 2015; Christian & Julien, 2015; Hornero & Corralejo, 2016; Lisa, 2016).

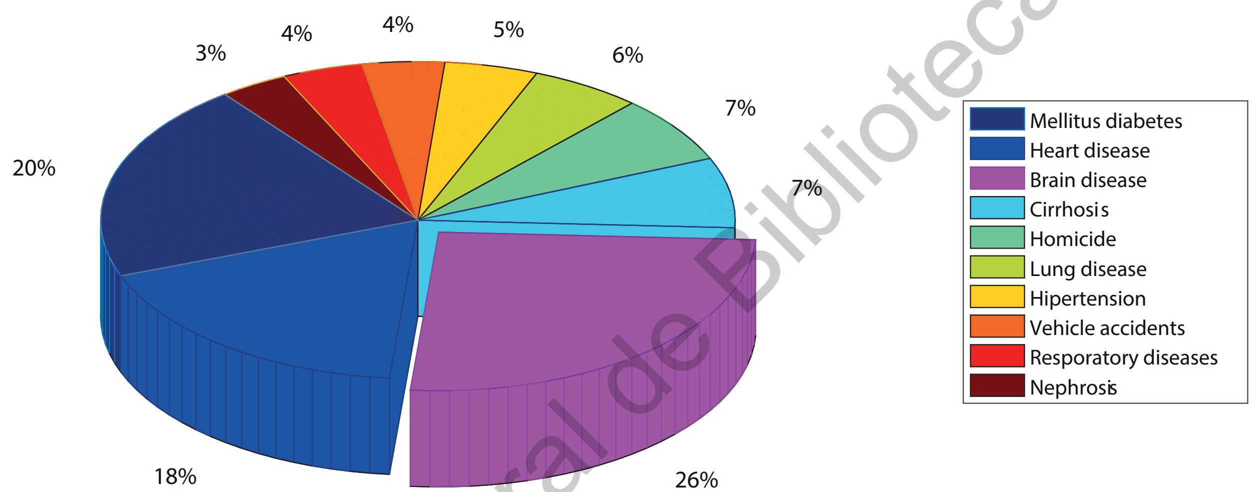


Figure 1.1: Top 10 causes of death in middle-income countries.

Brain diseases are a significant cause of mortality and on a global scale represent 12% of total deaths. Systems for the processing of EEG signals are critical in the field of medicine and specifically in the early detection of brain diseases since they contribute to the identification of patterns and, therefore, to the detection of brain diseases. With the early detection of brain diseases (secondary prevention), the number of severe cases that could end in death can be reduced up to 70% (Ferree, Luu, Russell, & Tucker, 2001; Lin et al., 2008; Muller, Scherer, Neuper, & Pfurtscheller, 2006; Vetter, Williams, Hetke, Nunamaker, & Kipke, 2004; Choi, 2015).

In medical centers, there are no systems that are used to detect brain diseases automatically, and in the literature, some have been reported, but their reliability is low, and they only detect one or two diseases. In the case of manual systems, their reliability depends on the specialist in the area. Another disadvantage of commercial systems operated manually is that they are costly, for example, Emotiv Non-Profit/Education License for Microsoft Windows has an approximate cost of

4300 dollars, but this is only considering the license, i.e., the cost of the software is still gone. Of the systems reported in the literature, for materials that use their approximate value is 2900 dollars considering only the use of the license for one year.

1.2 Problem Formulation

The computer systems conventionally used for EEG signal processing have the reliability that depends on the specialist in the area, and the methods reported in the literature have low assurance and only detect some diseases (Iman, Naser, & Alil, 2007; Sugi, Kawana, & Nakamura, 2008).

Also, both types of systems have a very high cost, which means that they are inaccessible for people with limited resources. Another disadvantage is that most of these are not portable, due to their design characteristics and equipment conditions, it is difficult to take them to remote areas. The higher the number of electrodes, the more expensive the equipment will be, and its processing and acquisition will require more advanced technology to achieve adequate sampling time.

With the development of portable modular systems, it is possible to adapt the equipment to different applications and take it to remote areas, since its power is through rechargeable batteries and, due to the modular architecture, the project is scalable.

1.3 Hypothesis and objectives

1.3.1 Hypothesis

A portable system for processing biopotentials focused on the characterization of voltage and frequency patterns based on filters using the FFT and TW, increases the reliability in the detection of encephalopathies in comparison with the conventional systems.

1.3.2 Objective

Implement a computer system for EEG signal processing focused on the identification of abnormal EEG.

1.3.3 Specific Objectives

The specific objectives of this project are as follows:

- Identify the design features for the EEG signal processing system.
- Determine the basic engineering for the design of the application (sampling time, processing techniques and their parameters).
- Build the graphical interface according to the specified design characteristics.
- Generate the database of the studies carried out with the computer system designed.
- Analyze the results obtained and validate the hypothesis.

1.4 Thesis Structure

The thesis is organized as follows:

- Chapter 1 is about the general panorama of the problem addressed in this project.
- Chapter 2 deals with the review of state of the art for analysis of EEG signals.
- Chapter 3 is about the development of the project, describes the steps taken to achieve the research goal.
- Chapter 4 shows the results obtained according to the objectives set.
- Chapter 5 is about the analysis of the results obtained.

CHAPTER 2

Literature Survey

2.1 Background

2.1.1 The human brain

The brain is an electrochemical organ, in Figure 2.2 is shown the essential parts of the brain. While the brain works, different regions of it emit different frequencies called brainwaves (Ormrod, 2005). The human brain is made up of specialized cells called neurons. Neurons are composed of a cell body, a nucleus, dendrites, and an axon.

Neurons are electrically excitable cells, process and transmit information via chemical and electrical signals, in Figure 2.3 is shown the necessary parts and interactions of neurons. The electrical signals are generated by changes in the electrical charge of the neuron membrane that covers the whole cell. Neurons have an electrical potential at rest, which is the potential difference between the inside of the cell and the extracellular space. The resting potential fluctuates as a result of impulses coming from other neurons through the synapses. The synapse is a specialized inter-cellular functional junction between neurons, where the transmission of the nerve impulse is carried out, which begins with a chemical discharge that causes an electric current in the cell membrane. The cell membrane contains ion channels where ions of sodium ($Na+$), potassium ($K+$), and chloride ($Cl-$) and calcium ($Ca-$) are concentrated during chemical processes in the cell. The concentration of ions creates potential differences in the membrane. Changes in membrane tension generate post-synaptic potentials that cause electrical flow along the membrane and dendrites (Gopathy & Karayiannis, 1997; Mohamad, Hashim, Khirotdin, & Mohamed, 2010).

When the potential difference is added in the area of activation of the axon reaches the range of -43 mV, the axon is triggered by the generation of an action potential in the $+40$ mV that goes along the axon to release the transmitters at the end of it. When the potential difference is summed and is below this threshold, the axon rests (Prieto, Pelayo, López, & Romero, 2013).

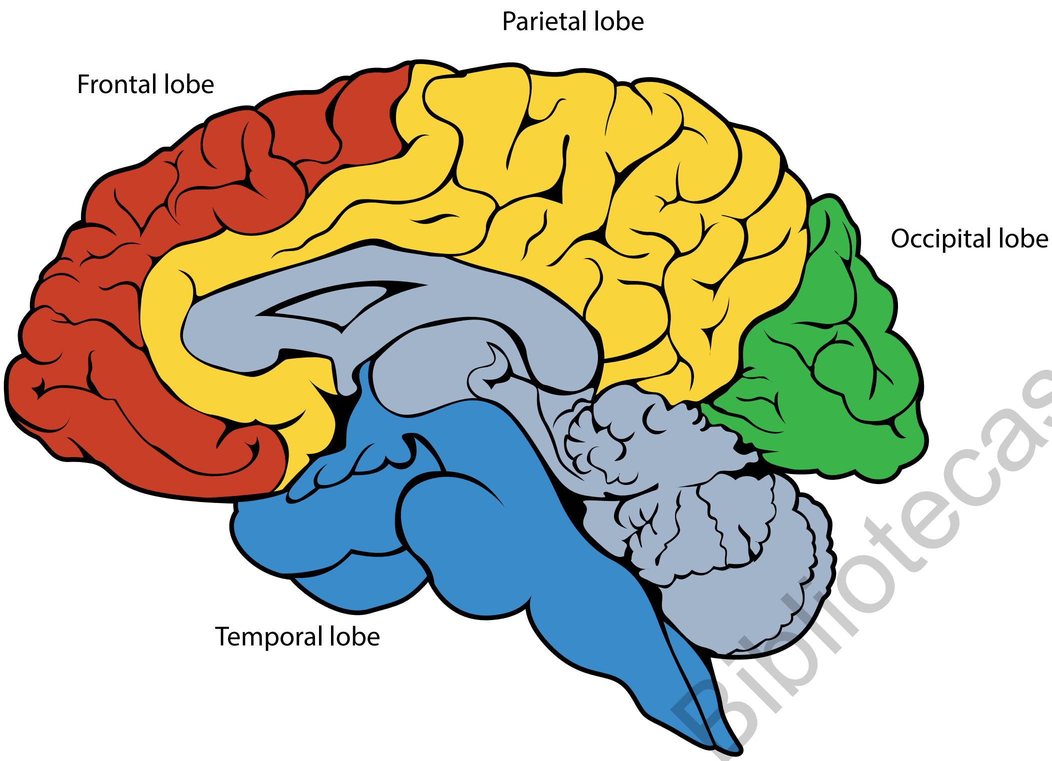


Figure 2.1: Parts of the brain.

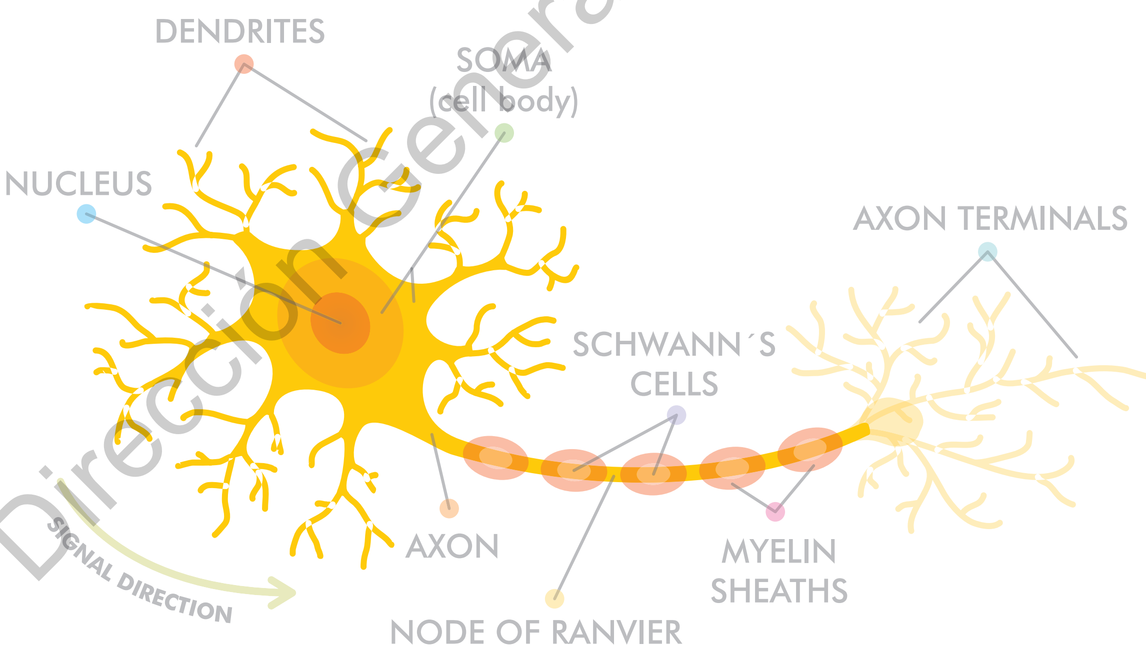


Figure 2.2: Neurons and their interactions.

Even though most electrical currents remain inside the cerebral cortex, a small fraction penetrates the scalp, causing different parts of the scalp to have different electrical potentials. These differences vary in amplitudes of $10-100\mu V$ (in the time) which are detected by electrodes (Martins, Selberherr, & Vaz, 1998; Ormrod, 2005; Prieto et al., 2013), these signals are called EEG signals. The EEG is a record of the brain of the individual through metal electrodes. The present research refers to the design and implementation of a platform for EEG signal processing, focused on the detection of encephalopathy.

2.1.2 Electroencephalogram

The electroencephalogram (EEG) is a record of spontaneous potential differences or brain waves measured on the surface of the brain through metal electrodes (lead, zinc, silver, platinum, aluminum, steel, etc.) scalp (Seijas, Caralli, Villazana, & Montilla, 2009; Barea, 2012). Brain waves are classified into four groups or bands depending on the frequency range and are identified by the Greek letters α, β, θ, and δ. Table 2.1 is shown the states of the brain and Figure 1.1 shows the brainwave pattern occurring when a person is in different states of arousal (Nicolaos & Gopathy, 2008; Mohamad et al., 2010).

Table 2.1: Brain states 2.3

Type of brainwave	Frequency(Hz)	State of consciousness	Normal amplitude(uV)
Beta β	13-30	A person in awake or alert condition.	<20
Alpha α	9-12	A person awakes up and truly relaxed.	20-60
Theta θ	5-8	A person feels depressed and tired.	<100
Delta δ	2-4	A person is in deep sleep.	<100

Current medical science has tools to monitor brain activity through the EEG technique. The development of this technology has allowed the appearance of devices that enable the communication of the brain with a machine (BCI), which fields of application are diverse and are increasing (Gopathy & Karayiannis, 1997; Nicolaos & Gopathy, 2008; Mohamad et al., 2010; Asadi, 2018; Hinault, 2016).

The EEG was applied for the first time by Hans Berger in 1924 although his study started before that year. The earliest descriptions of the existence of electrical brain activity were made by the English physiologist Richard Caton, professor of physiology at Liverpool's Royal School of Medicine. The English scientist hypothesized that peripheral stimuli could provoke focal electrical brain responses. This hypothesis allowed him to obtain in 1874 funding from the British Association of Medicine to be able to confirm it. In his historical publication on brain electrical activity in the British Medical Journal in 1875, he compared his work to that of an English neurosurgeon, David Ferrier, some years earlier. Figure 2.4 is shown a photograph by (A) Hans Berger and (B) Richard Caton, investigators of EEG signal analysis (Dimitrios et al., 2014; Audette, 2015; Brogger et al., 2018).

Approximately 15 years after the discoveries of Caton, Adolf Beck, medical students, and professor Cybulsky, their mentor at the University of Krakow in Poland, inspired by the works of Hitzig and Fritsch, made new proposals to try other methods of functional localization in brain. It is

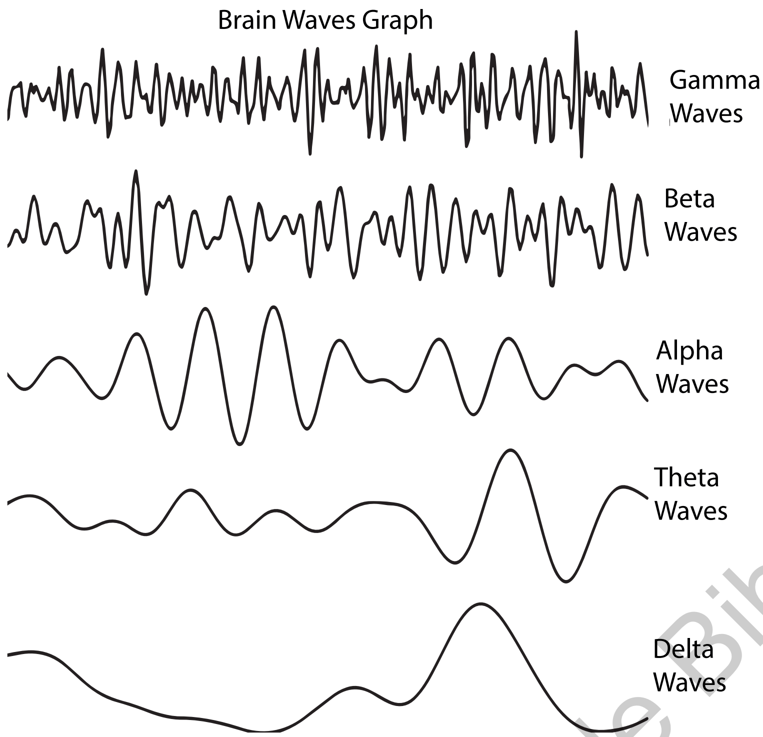


Figure 2.3: Brainwaves.

essential to mention that neither of them knew the works of Caton. Beck's thesis describes the observation of visual evoked potentials (Vetter et al., 2004; Heidmann et al., 2014; Christian & Julien, 2015; Hornero & Corralejo, 2016; Ruijter, Hofmeijer, Tjepkema, Tjepkema, & Putter, 2018; Maggioni, Bianchi, Altamura, Soares, & Brambilla, 2017; Ruijter et al., 2018).

Russians Pavel Kaufman (1912) and Pradvich Neminski (1913) were the first to establish that cerebral electrical potentials can be collected through the intact skull. Kaufman described the existence of two bioelectrical periods during anesthesia: the first to increase potentials (excitation phase) and the second to decrease potentials (depression stage). Neminski, using a string galvanometer, first described the different brain rhythms captured in dog brains according to their frequency (10 to 15, 20 to 32 cycles per second), baptizing these oscillations with the term "electroencephalogram."

Despite the many previous studies on brain activity and EEG performed by different researchers, the father of the human EEG was Hans Berger, Head of Psychiatry Unit at the University of Jena (Germany). He after a long series of studies on July 6 of 1924 recorded the first of the rhythmic oscillations of the brain of a young man of 17 years. For electroencephalographic recording in humans, he used needle electrodes and a cord galvanometer with a mirror that reflected light which in turn allowed the exposure of silver bromide photographic paper that moved at 3cm per second (the

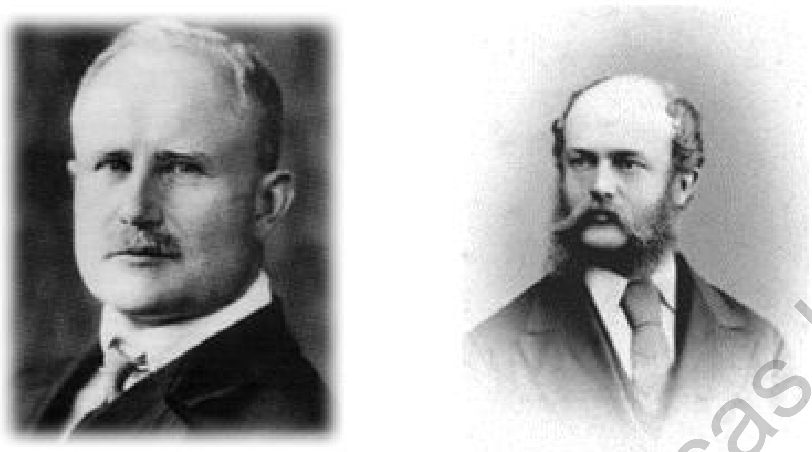


Figure 2.4: (A) Hans Berger; (B) Richard Caton

same speed that we use today).

In 1929, he published his discovery: spontaneous brain electrical activity in humans. As a careful investigator, he described in his publication the works of Caton, like those of Beck and Cybulsky. In his writing, he mentions: “Consequently, I believe that I have discovered the Electroencephalogram of man and that I reveal it here for the first time.” In 1930, he made 1,133 records in 76 people and prepared a second report. He designated with letters of the Greek alphabet the two types of waves that he had observed from the beginning in the tracings performed to human beings. The higher voltage and lower frequency were called alpha waves, the lower voltage and higher frequency, beta waves.

In 1931 they studied the frequency with which abnormal electroencephalography activity was observed in patients with epilepsy and recorded for the first time tip-wave activity.

Efforts to simultaneously record electroencephalography of signals EEG and intact events began in 1938 when at a meeting of the American Psychiatric Association Schwab showed moving images synchronized with an electroencephalographic tracing. Jasper and Hunter were able to perform a simultaneous recording of EEG and patient activity with a single camera with an ingenious system of mirrors placed on the patient and the electroencephalographic tracing. In the 1950s, television made the process less complicated. In 1960 the transistors that had been invented in 1947 replaced the amplifiers with vacuum tubes in the electroencephalogram obtaining a better photographic record. The same transistors made possible the computerized management of all aspects of electroencephalography (Palacios, 2002; Seijas et al., 2009; Barea, 2012; Kafiul, Rastegarnia, & Yang, 2016; Willems et al., 2018; Mu, Hu, & Min, 2016).

As well as Hans Berger, Schwab, and Richard Caton, currently hundreds of researchers around the world work to improve the techniques of processing and acquisition of EEG signals, which has allowed to expand the field of research, applications of these systems, and their levels of reliability.

2.1.3 Record of the electrical activity of neurons in the brain

Electrical signals are fundamental to the function of the nervous system, so it is essential to determine the electrical properties that propagate along with the excitable cells. However, despite the high diversity of recording techniques and experimental protocols, there are some common elements in all of them (Nicolaos & Gopathy, 2008). The steps for the acquisition of EEG signals are shown in Figure 2.5.

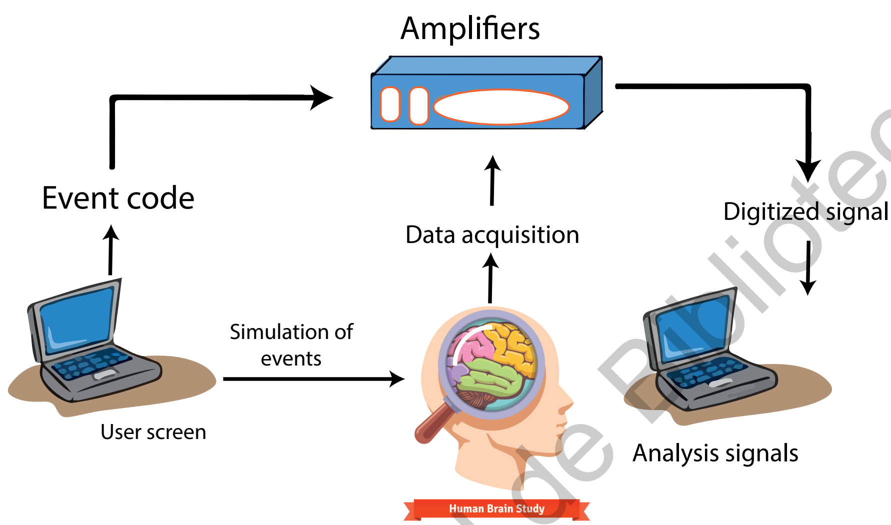


Figure 2.5: Acquisition and processing of EEG signals.

Several procedures can capture brain bioelectrical activity:

- On the scalp.
- At the base of the skull.
- In exposed brain.
- In deep brain locations.

Different types of electrodes are used to capture the signal:

- Surface electrodes: Apply to the scalp.
- Basal Electrodes: Apply to the base of the skull without the need for a surgical procedure.
- Surgical electrodes: The surgery can be cortical or intracerebral, and the advantage is that the surgical electrodes have more spatial precision.

2.1.4 Electrodes for recording biopotentials

Biopotentials are a critical branch for the area of medicine. It is that electrical signal emitted by the human body and that is acquired by medical measuring equipment to make it perceptible to the doctor's senses.

A biopotential is generated by the potential difference measured between the inside and outside of the cell.

In nature there are many types of biopotentials, these depend on the cells that generate them and in what organism they are, in the human body a great variety of biopotentials are presented, among them we have (Donald & Fernando, 2001; Seijas et al., 2009):

- ECG (electrocardiogram): measures the electrical activity of the heart.
- EEG (electroencephalogram): measures the electrical activity of the brain.
- ENG (electroneurography): study of the electrical activity generated in the anatomical structures of the peripheral nervous system, has among its central techniques reviews of motor and sensory neuro-conduction.
- EMG (electromyography): measures the electrical activity of muscles.
- EGG (electrogastrogram): it is the measurement of electrical changes that occur in the muscles of the stomach.
- EOG (electrooculogram): electrical potentials generated as a result of the movement of the eyeballs.

It is necessary an element that interfaces between the body and the measuring equipment to record biopotentials. This element is the electrode, i.e., an electrode is a transducer. Most bioelectrical signals are acquired from one of the following forms of electrodes: surface macro-electrodes, internal macro-electrodes, or microelectrodes. The electrodes can be classified into two types (Donald & Fernando, 2001):

- Polarizable: In this kind of electrodes there is no charge exchange at the electrode-electrolyte interface when a current is applied, in other words, the electrode behaves like a capacitor, and for this reason, there will be small scattering currents.
- Not polarizable: In this case, there is an exchange of charges at the electrode-electrolyte interface when we apply a current, in these will not require energy for the transition of charges.

The above is theoretically because, in reality, there are no materials for an electrode to behave in an ideal way, then in practice are used elements that resemble a behavior as required in theory. For the polarizable electrodes, noble metals such as platinum are used, while silver-silver chloride electrodes are used for non-polarizable electrodes.

Classification of surface electrodes:

- Adhered: they are small metal disks of 5mm in diameter. They are adhered with conductive paste and are fixed with collodion that is insulating, in Figure 2.7 (A) is shown an example of adhered electrodes. Correctly applied to give very low contact resistances (1-2kΩ).
- Contact: these consist of small tubes of chlorinated silver threaded to plastic supports, in Figure 2.6 (B) is shown an example of contact electrodes. A pad is placed at its contact end which is moistened with a conductive solution. They are fastened to the skull with elastic bands and connected with crocodile clips. They are straightforward to place but uncomfortable for the patient. It is why they do not allow long-term records.

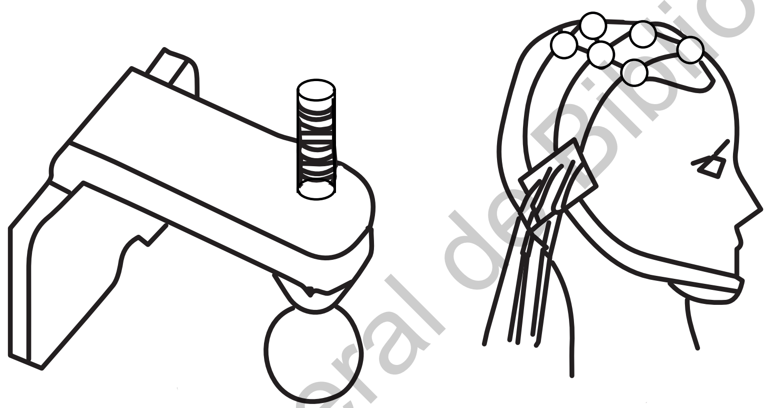


Figure 2.6: (A) Adhered electrodes; (B) Contact electrodes.

- In a mesh helmet: the electrodes are included in a kind of elastic hull. There are helmets of different sizes, depending on the size of the patient. They are fastened with ribbons to a thoracic band. The most important features are the convenience of placement, patient comfort in long-term records, their immunity to artifacts, and the accuracy of their placement, which makes them very useful in comparative studies.
- Needle: its use is insufficient; It is only used in newborns and ICU. They can be disposable (single use) or multipurpose. In this case, their sterilization and handling must be very careful. All electrodes described so far only record the superior convexity of the bark. Particular electrodes such as pharyngeal, sphenoidal, and tympanic are used to study the basal face of the brain.
- Surgical: they are used during the surgery and are handled exclusively by the neurosurgeon. They can be dural, cortical, or intracerebral.

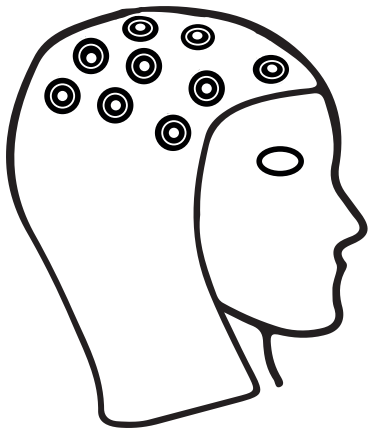


Figure 2.7: Principle of placement of electrodes in mesh helmet.

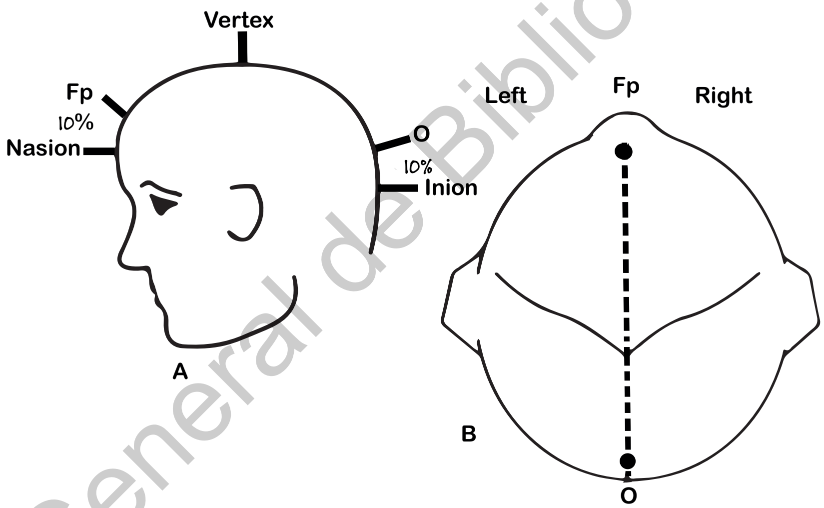


Figure 2.8: Position of the inion, nasion, Fp and O.

2.1.5 10-20 electrode system of the International Federation

The "Ten-Twenty" International System is the most used today for the EEG study. To locate the electrodes according to the system "Ten-Twenty" proceed as follows:

- The distance between the nasion and the inion is measured through the vertex. 10% of this distance on the nasion points to the point Fp (Polar Frontal). 10% of this distance on the inion points to point O (Occipital). Figure 2.8 is shown the position of the inion and nasion, as well as Fp and O.
- As a general rule, the electrodes on the left side are numbered odd while those on the right side

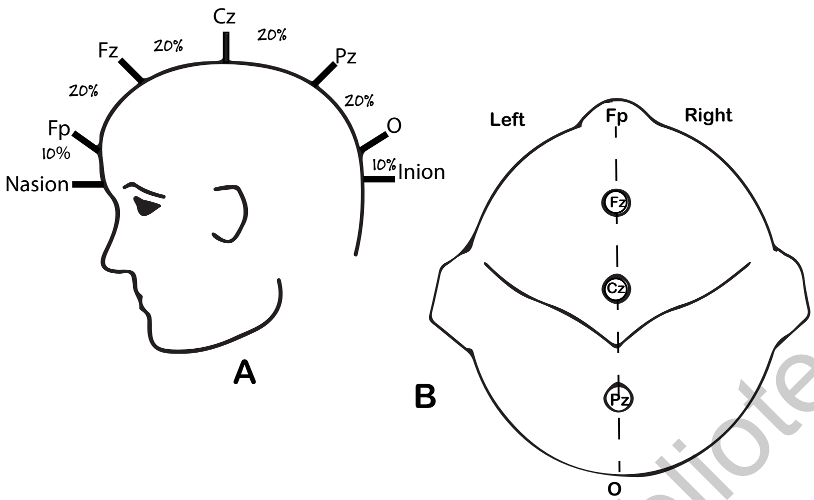


Figure 2.9: Position of Fz, Cz, and Pz.

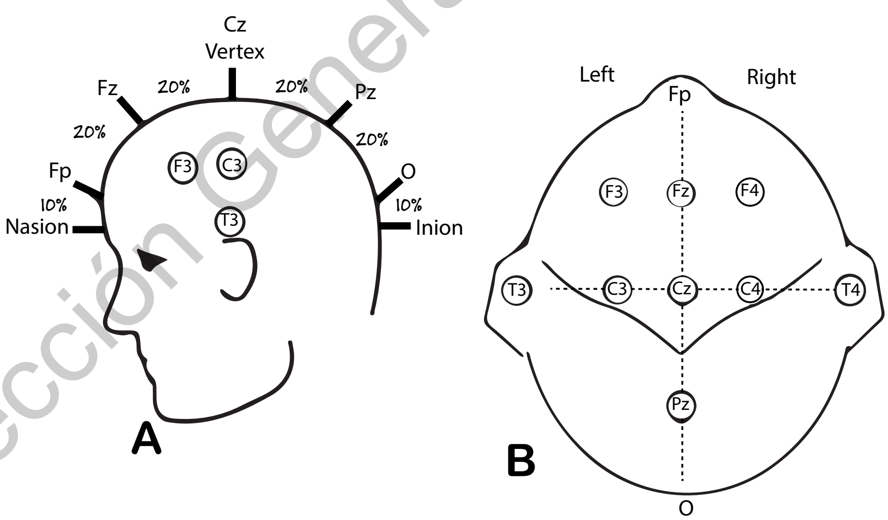


Figure 2.10: Position of C_3 and C_4.

are numbered even. Also, the midline electrodes are given the subscript "z."

- Between the points, Fp and O are placed three other points spaced at equal intervals (between each two the 20% of the nasion-inion distance). These three points are, from front to back, Fz (Frontal), Cz (Central or Vertex) and Pz (Parietal). Do not confuse Fz, Cz, or Pz whose subscripts mean "zero" (zero) with the letter "O" referring to the occipital electrodes. In Figure 2.9 (a) is shown the position of Fz, Cz, and Pz.

- The distance between the preauricular points (located in front of the auditory pavilion) and the vertex (Cz) is measured. The 10% of this distance marks the position of the medial temporal points, T_3 (left) and T_4 (right). Figure 2.9 (B) is shown the position of T_3, T_4, and previous ones.

- About 20% of the measurement above the mid-point are electrodes C_3 (left) and C_4 (right). The vertex is now the point of intersection between the anteroposterior line and the lateral coronal line. T_3 (left) and T_4 (right). In Figure 2.10 (B) is show the position of C_3 and C_4.

- The electrodes F_3 and F_4 (left and right, respectively) are located equally between the front mind point (Fz) and the line of temporary electrodes.

2.1.6 Considerations for mounting an EEG

- Long Distance Mounts are used when recording between non-contiguous electrodes.

- On the contrary, in the Mounts at Short Distances records are made between neighboring electrodes. On the other hand, the assemblies have also been classified by the International Federation of EEG and Neurophysiology in Longitudinal and Transverse.

- In the Longitudinal Assemblies, the activity of pairs of electrodes arranged in the anteroposterior direction of each half of the skull is recorded.

- Transverse Mounts record pairs of electrodes arranged transversely according to the anterior, middle or posterior sagittal planes.

- It is also recommended to follow the following guidelines in the design of EEG recording assemblies.

- Register at least eight channels.

- Use the ten-twenty system for electrode placement.

- Each routine EEG recording session should include at least one assembly of the three main types: referential, longitudinal bipolar and transverse bipolar.

The behavior of an electrode depends on:

- The model.

- The characteristics of currents passing through the electrode.

- The behavior of high and low currents.
- Waveform.
- The frequency.

Patient Preparation

- The patient should be alert and well rested.
- The patient will need to take his glasses.
- The patient will take his regular medications.
- Exam time: 30 minutes.

2.1.7 EEG Applications

The field of applications of an EEG is vast; it is a tool of great help for the diagnosis and monitoring of some pathologies, such as epilepsy, encephalopathies, alterations in the state of consciousness or infections of the central nervous system. Also, it is a diagnostic tool with applications that are in full expansion, in combination with other neurophysiological techniques, for example in the field of study and diagnosis of sleep pathology and intraoperative monitoring together with somatosensory evoked potentials. Examples of pathologies (Hoang, Pierre, Tatsuo, & Yasuhiro, 2001; Muller et al., 2006; Barea, 2012; Heidmann et al., 2014; Lahmiri, 2018; Rosenblatt, Figliola, Paccosi, Serrano, & Rosso, 2014):

- Brain Death: It is defined as the complete and irreversible cessation of brain or brain activity.
- Brain tumors: It is a growth of abnormal cells in the brain tissue. Tumors can be benign (without cancer cells) or malignant (with cancer cells that grow very fast). Some are primary, that is, they begin in the brain. Others are metastatic, that is, they started somewhere else in the body and reached the brain.
- Epilepsy: A disease of the nervous system, due to the appearance of abnormal electrical activity in the cerebral cortex, which causes sudden attacks characterized by violent convulsions and loss of consciousness.
- Multiple sclerosis: Pathological hardening of a tissue or organism that is due to the abnormal and progressive increase of connective tissue cells that form its structure; mainly applies to the blood vessels and the nervous system.
- Sleep disorders: Sleep disorders are a large group of conditions that affect the healthy development of the sleep-wake cycle. Some sleep disorders can be severe and interfere with the individual's physical, mental, and emotional functioning.

2.1.8 Encephalopathies

Encephalopathy is defined as a brain disease, damage, or malfunction. It can present a full spectrum of symptoms, ranging from mild, such as memory loss or subtle personality changes, to severe, such as dementia, coma, seizures, or death. In general, encephalopathies are manifested by an altered mental state that is sometimes accompanied by physical manifestations, for example, poor coordination of limb movements.

Some examples of types of encephalopathies and its main complications:

- Hepatic encephalopathy: cerebral edema with herniation, coma, death.
- Hypoxic-ischemic encephalopathy: loss of memory, lack of control of movements and increases in heart rate.
- Static encephalopathy: cerebral palsy, learning disabilities, mental retardation, autism, speech delays, attention deficit, hearing and vision problems.
- Transmissible spongiform encephalopathy: deterioration of brain function, including changes in memory, personality changes and movement problems that worsen over time.
- Wernicke encephalopathy: mental confusion, memory loss, decreased the ability to move the eyes.
- Limbic encephalopathy: memory loss, especially in long-term memory, variable, emotional and agitated behavior, seizures, difficulty controlling limbs, fatigue and vision problems.
- Neonatal encephalopathy: slowed reflexes, poor muscle tone, poor diet, convulsions and difficulty breathing.
- Metabolic encephalopathy: irritability, lethargy, depression, tremors, sometimes coma or death.
- Uremic encephalopathy: lethargy, hallucinations, stupor, muscle spasms, seizures, death.
- Hashimoto's encephalopathy: confusion, heat intolerance, dementia.
- Glycine encephalopathy: progressive lack of energy, feeding difficulties, weak muscle tone, abnormal spasmodic movements and life-threatening breathing problems.
- Hypertensive encephalopathy: severe hypertension, acute inflammation of the kidney or nephritis, and brain dysfunction.

The presence of encephalopathies in an EEG study generates abnormalities in the results, related to voltage peaks and abnormal frequencies. For example, when a person presents some type of epilepsy, electrical activity occurs between frequencies of 40 and 120 Hz, when the person shows some limbic encephalopathy anomalies appear in the activity record in the hypothalamus area, specifically in the frequencies theta.

2.1.9 Quantitative analysis

The changes in the EEG evaluated visually indicative of brain diseases are reflected in the price of paraxisms, which are abnormal waveforms in both amplitude and frequency. Reliable evaluation and accuracy depend on the skill and experience of electroencephalographs. The type, magnitude, and duration of changes in the EEG need to accurately predict brain disease have not been clearly established. Therefore, the precise EEG criteria for the referral requirement are still a matter of debate. The reasons for false positive or false negative EEG results have not been clarified either.

Since most EEGs are now performed using digital recording techniques, it is possible to perform quantitative EEG analysis using appropriate algorithms, either online or offline. These include the frequency analysis of the power spectrum, which consists of calculating the relative power for each frequency band.

With the quantitative analysis, it is expected that the results provide a more accurate and objective measure to reflect the subtle EEG changes indicative of brain diseases. This, in turn, is expected to reduce the false positive and false negative EEG findings. The Fast Fourier Transform (FFT) is used to generate the spectral power of specified or preselected frequency bands, Figure 2.5.

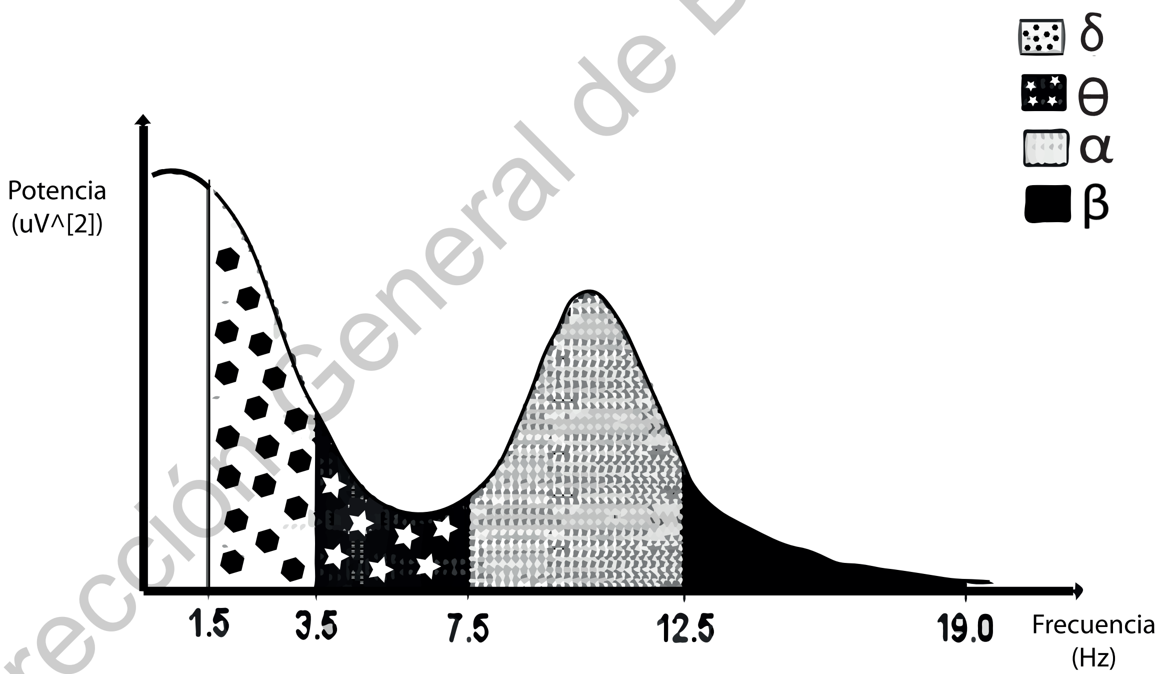


Figure 2.11: EEG power spectrum

In the frequency spectrum of the EEG, the abscissa shows the frequency (in Hertz) and the ordinates the power (in uV squared). In the range of 1.5 to 19 Hz approximately (this may vary a bit according to the reference consulted) the spectrum is divided into four bands mainly: Delta, Theta, Alpha and Beta, some authors also consider Gamma. The Absolute power of each band is the area under the course in the corresponding interval.

2.1.10 Elements to consider in the clinical analysis of the EEG

- They have amplitudes ranging from $10uV$ in records on the cortex, to $100uV$ on the surface of the scalp.
- Its frequencies are between $0.5Hz$ and $100Hz$.
- They depend on the degree of activity of the cerebral cortex.
- Most of the time, they do not have any specific shape.
- Normal rhythms are often categorized as alpha, beta, theta, and delta:
  - Alpha waves (α) have frequencies between $9Hz$ and $12Hz$. They are recorded in normal subjects with no activity and eyes closed, especially in the occipital area; its amplitude is between $20uV$ and $200uV$.
  - Beta waves (β) have frequencies between $13Hz$ and $30Hz$, but can reach up to $50Hz$; are mainly found in the parietal and frontal regions. They are divided into two fundamental types, of very different behavior, beta1 and beta2. The beta1 waves have a double frequency to the beta waves 2 and behave in a similar way to them. Beta2 waves appear when the CNS is intensely activated or when the subject is under stress.
  - Theta waves (θ) have frequencies between $5Hz$ and $8Hz$ and occur in childhood, but adults can also present them in periods of emotional stress and frustration. They are located in the parietal and temporal zones.
  - Delta waves (δ) have frequencies lower than $4Hz$ and occur during deep sleep, in childhood, and severe brain organ diseases.

Recently a fifth band called gamma (γ) between $22Hz$ and $40Hz$ has been found, related to the result of the attention or sensorial stimulation; which has a very low amplitude of $2uV$ (peak to peak) (Nicolaos & Gopathy, 2008; Shih & Chang, 2008; Christian & Julien, 2015).

2.1.11 Works relations in advances of EEG and detection of encephalopathies

In medical centers, there are no automatic systems for detecting encephalopathies, but in the literature, a large number of investigations focused on this area have been reported. However, the reported results show low reliability and only focus on one or two diseases.

Iman et al. use the permutation entropy to identify normal EEG and EEG with the presence of epilepsy. The classification of EEG is improved using discriminant analysis; this allows them to more accurately eliminate noise in the signals and improve efficiency (precision between 97% and

85%). For validation, 200 segments of 23.6 seconds were used, using a sampling time of 173.61Hz. The software or the hardware used for the implementation is not mentioned (Iman et al., 2007).

Sugi et al. implemented an automatic method for the detection of EEG arousals in people with sleep apnea syndrome. For detection, the following parameters are evaluated: Resumption of ventilation, a rapid increase of EMG, and determination of threshold values. For signal processing, the FFT is used with Hanning-window and For training and validation, eight cases of patients with this condition (female, 46-58 years) are used, considering 8 hours of registration for each. Also, four channels were used. An efficiency of 86% was obtained in the detection of EEG arousals (Sugi et al., 2008).

Alaa et al. focused on invasive techniques, applied the electrocorticogram (intracranial implantation). Implantation of intracranial electrodes provides the most reliable source of neuroimaging but is considered an invasive technique since needles have to be embedded in the brain. For the processing and training, vector machines were used, and the frequency range of interest is between 0.5-25Hz. Effectiveness greater than 97% was found; there were ten patients and tests were performed for more than 875 hours. A sensitivity of 100% was achieved for eight of the ten patients of the validation. This algorithm presents a high precision but is invasive (Alaa, Ali, John, & Sydney, 2011).

Sally et al. perform the identification of epilepsy using neural networks and MATLAB as software for processing. They start by extracting parameters; once we have the necessary parameters, neural networks are applied and finally the classification. The databases are bipolar records using a sampling frequency of 400Hz. The best results in their experiments were obtained using the wavelet coefficients, the relative energy per frequency band. Efficiency is not mentioned, but two false positive cases of 23 were obtained (Sally & Mohamad, 2013).

Narendra et al. applied the Transforma S for the detection of epilepsy. A method based on the S transformation optimized in the width of the window for the detection of epileptic seizures compares their method with the Transformation S and the Fourier Transform of the short window. After the extraction of characteristics, neural networks are used for the detection of epilepsy. An efficiency greater than 82% was obtained (Narendra & Sharma, 2015).

Vladimir et al. worked in the detection of perinatal Hypoxic-Ischemic Encephalopathy (HIE), which is a disease that occurs more frequently in newborn children. The data records are obtained from 2 to 48 hours, using 17 or 13 electrodes and a sampling frequency of 256Hz. Its objective was to develop a system for long-term EEG monitoring of the neonatal HIE. For signal processing use discrete Wavelet. A reduction in the number of false-positive cases was obtained in comparison with traditional methods. Efficiency between 97 and 88% was obtained (Vladimir et al., 2016).

Zakareya et al. use three well-known techniques, which combined achieve a higher level of precision. They use neural networks, Support Vector Machine and K-Nears Neighbor to differentiate between a record with epilepsy and a normal one. It is an application that automatically monitors and detects epilepsy. The application can be carried on the cell phone. When values outside the ranges are detected, a message is sent to the doctor in charge and their relatives. To send the information to the cloud, they use Python as a programming language. An efficiency greater than 90% was achieved (Zakareya, Ramasani, & Khaled, 2017).

Quing et al. implemented a Wireless Help System, which is capable of detecting only some encephalopathies, was proposed. The device continuously monitors the electrical activity, sends warning messages to its relatives when it detects values outside the ranges, it is a headband that only uses four electrodes, for signal processing it uses Support Vector Machine, and the application can be carried in the cell phone. It was validated with 15 patients using various statistical techniques, and efficiency greater than 90% was achieved (accuracy between 91 and 93%, sensitivity 88%) (Qing et al., 2018).

Nikita et al. designed a system for detection and monitoring of epilepsy was reported. The application is mainly based on the use of Deep learning combined with a vector machine; an efficiency of 95% was reached. The deep learning part, in this case, was using recurrent neural networks. For signal processing and system training, a library called TensorFlow was used, which is an open source for deep learning. The system was validated with 100 segments of 2.5s each and statistical techniques such as t-student distribution were used (Nikita & Bryan, 2014).

According to the analysis of the results reported in the literature, the efficiency is between 80% and 90%; however, to have good reliability, at least 95% is required by medical standards. It is essential to continue improving this parameter as well as many others such as portability and cost.

2.1.12 Brain-Computer Interface (BCI)

A BCI is a means of communication that allows people to communicate with external help devices using the electroencephalogram or another technique. Parts of the BCI System: Acquisition of signals, pre-processing, extraction of characteristics, classification, interface, monitoring, and feedback. In figure 2.12 is shown the essential operation of a BCI. BCI systems are used with high frequency in combination with EEG studies for the development of biofeedback techniques that help us generate a reliable form for the same electroencephalographic pattern, since the EEG is a simple, non-invasive, portable, and low cost. The identification of patterns can be applied for the detection of brain diseases, encephalopathies, and pathologies.

BCI systems can be classified into two groups according to the nature of the input signal:

- Endogenous BCI systems.
- Exogenous BCI systems.

Endogenous BCI systems depend on the user's ability to control their electrophysiological activity, such as the amplitude of the EEG in a specific frequency band over a particular area of the cerebral cortex. BCI systems based on motor imaging (sensorimotor rhythms) or slow cortical potentials (SCP) are endogenous systems and require an intensive training period. The following two systems are described:

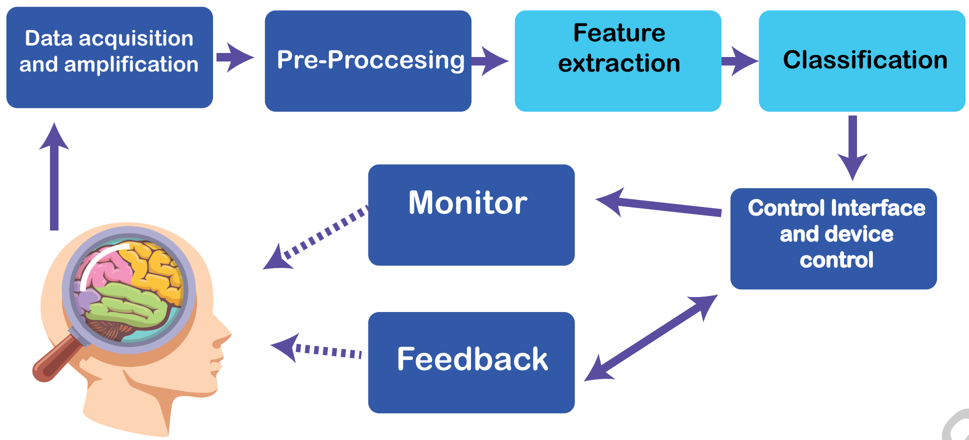


Figure 2.12: Block diagram of the basic operation of a BCI system.

- BCI based on slow cortical potentials: SCPs are slow changes of the voltage generated in the cerebral cortex, with a variable duration between 0.5 and 10 seconds. Negative SCPs are typically associated with movement and other functions involving cortical activation. It has been shown that people can learn to control these potentials.

- BCI based on motor images or sensorimotor rhythms (Nicolaos & Gopathy, 2008; Ali, Faesipour, Almuhammadi, & Moslehpour, 2016; Arunkumar et al., 2017): It is based on a paradigm of two or more kinds of motor images (movement of the right or left hand, of the feet, of the tongue, etc.) or other mental tasks (rotation of a cube, accomplishment of arithmetical calculations, etc.). These types of mental tasks produce changes in the amplitude of the sensorimotor rhythms ($8 - 12Hz$) and ($16 - 24Hz$) recorded in the somatosensory and motor zones of the cerebral cortex. These rhythms exhibit variations both for the execution of a real movement and for the imagination of a movement or the preparation thereof (Garcia, David, & Morari, 1989; Zhiqiang, 2006).

Exogenous BCI systems depend on the electrophysiological activity evoked by external stimuli and do not require an intensive training phase.

The processing of the signal in BCI systems is usually divided into four stages. First, an initial step of preprocessing is performed in which the EEG signals are filtered and some of the possible artifacts overlapping the signal of interest (blinking, eye movement, electrocardiogram, muscular movements, among others.). After that, a second step is performed, which involves the extraction of certain specific characteristics of the EEG signal. Next, we apply characteristic selection methods that choose the most significant within the extracted set, which encode the intention of the user. Finally, the classification algorithms translate the set of characteristics selected in a specific command, related to the intention of the user (Garcia et al., 1989; Hoang et al., 2001; Zhiqiang, 2006; Lin et al., 2008; Mohamad et al., 2010).

2.1.13 Programmable logic devices

Programmable logic requires hardware and software for its implementation. The devices can be programmed to perform specific logic functions by both the manufacturer and the user. One of the main advantages of the hardware description versus the fixed logic is that the devices useless space of the printed circuit board, besides that, with the programmable logic, the designs can be modified without having to rewire or replace components.

There are many types of programmable logic devices in the market, ranging from small devices that can replace some of the fixed-function tools to sophisticated, high-density devices that can replace thousands of fixed-function devices. There are two main categories of user-programmable logic devices: PLD (Programmable Logic Device) and FPGA (Field Programmable Gate Array), which are shown in Figure 2.13. The PLDs they can be SPLD (Simple PLD) or CPLD (Complex PLD).

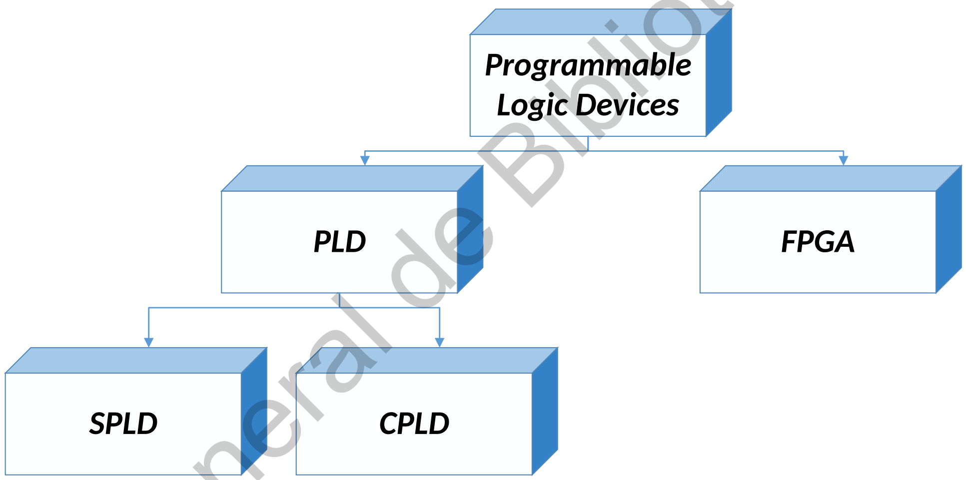


Figure 2.13: Programmable logic.

- SPLD (Simple Programmable Logic Device): A SPLD can replace ten fixed-function ICs and their interconnections, depending on the type of functions and the specific SPLD. SPLD devices can be divided into PAL and GAL, the difference being that the first can only be programmed once and the other can be programmed several times.
- CPLD (Complex Programmable Logic Device): It is a device that contains several SPLDs, and that can replace many fixed-function CIs.
- FPGA (Field Programmable Gate Array): An FPGA is more complicated, and has a much higher density than a CPLD, although sometimes its applications may overlap. The three basic elements in an FPGA are the logic block, the programmable interconnections, and the input/output (I/O) blocks. The logic blocks of an FPGA are not as complex as the blocks of logical matrices (LAB) of a CPLD, although they generally contain many more. These types of packages can have about 1,000 input and output pins.

2.1.14 Wavelet Transform (WT)

A Wavelet function can be defined as a small signal that its energy is concentrated over time and is a very useful method for the analysis of non-stationary and time-varying signals. Specifically, Wavelet analysis is based, like Fourier theory, on the concept of signal approximation using superposition of signals.

Wavelets are a time-frequency transform that improves the analysis of non-stationary signals compared to other techniques such as the Fourier Transform. The WT produces information blocks in scale and time of a signal. These blocks are produced from a single fixed function called Mother Wavelet $\psi(t)$.

Broadly speaking with the Wavelets a proper frequency resolution is achieved while at a low scale a good resolution is obtained in time. There are different families of Wavelets; there are no specific criteria for the selection, however, everything depends on the application and the criteria required for this, such as its support, symmetry, moments of fading, regularity, etc. The best-known families of wavelets are Haar, Morlet, Symlets, Mexican hat, Meyer, Shannon, Meyer, and Biortogonales.

When the Wavelet is used normally the noise reduction in the signals is carried out with the method called "Wavelet Shrinkage" or wavelet shrinkage, regardless of the type of discrete wavelet transform used. In this technique, the magnitude of each Wavelet coefficient is significantly reduced to a certain value depending on the noise level of a threshold.

2.1.15 Fourier Series and Fourier Transform

The Fourier Series are very useful in the study of periodic signals. However, this type of signals is not as frequent in practice as non-periodic signals. The basic idea of the Fourier Series is that every periodic function of period T can be expressed as a trigonometric sum of sines and cosines of the same period T. This tool is handy to analyze a periodic signal regarding its frequency content.

The Fourier Transform and some of its derivatives such as the FFT or the DFT are used to analyze the non-periodic signals. The incredible variety of applications that the Series and the Fourier Transforms have in different branches of mathematics and mathematical physics, from number theory and geometry to quantum mechanics. EEG signals are non-periodic signals that are characterized by specific frequencies for each state of consciousness and certain encephalopathies, so it is very common to use the EEG for the identification of patterns by applying some derivatives of the Fourier Series.

2.1.16 Digital Signal Processing (DSP)

Digital signal processing (DSP) is understood as the mathematical manipulation of an information signal to modify or improve it in some sense. Its representation is in the discrete-time domain, in the discrete frequency domain, or another discrete signal domain using a sequence of numbers or symbols and the processing of those signals. In Figure 2.14 is shown a general scheme of a DSP system.

One of the most important transformations is the Discrete Fourier Transform (DFT). The DFT converts the signal from the time domain to the frequency domain. The DFT allows a simpler and more efficient analysis on the frequency, especially in noise elimination applications and in other types of filtering (low pass, high pass, bandpass, band-rejection filters, among others).

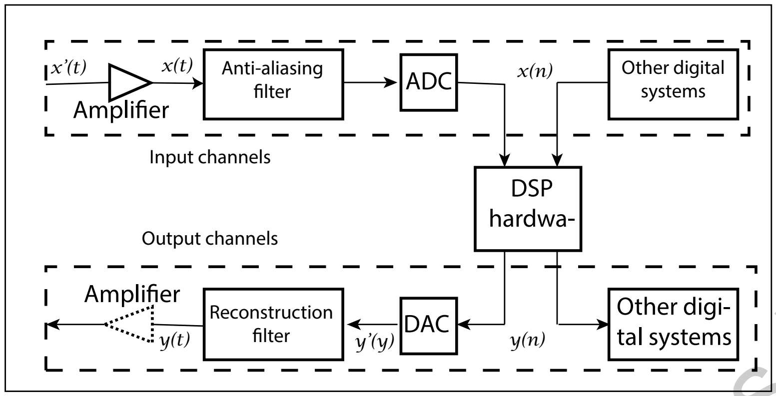


Figure 2.14: General scheme of a PDS system.

2.1.17 Discrete Fourier transform (DFT)

The DFT is one of the techniques applied for the processing of EEG signals. The DFT is not the same as the Discrete-Time Fourier Transform (DTFT). Both start with a discrete-time signal, but the DFT produces a discrete frequency domain representation while the DTFT is continuous in the frequency domain. So, these two transformations have much in common, so it is useful to have a basic understanding of the features of the DTFT, these properties are described in equations 1, 2 y 3.

Equation 1 DTFT: $x(t) <-> X(jw)$ where

$$X(jw) = \int_{-\infty}^{\infty} x(t)e^{-jwt}dx \tag{2.1}$$

Equation 2 Transform z: $x[n] <-> X(z)$ where

$$X(z) = \sum_{n=-\infty}^{\infty} x[n]z^{-n} \tag{2.2}$$

Equation 3 DTFT: $x[n] <-> X(j\Omega)$ where

$$X(e^{j\Omega}) = \sum_{n=-\infty}^{\infty} x[n]e^{-j\Omega n} \tag{2.3}$$

Periodicity: The DTFT $X = e^{jw}$, is periodic. One period extends from $f = 0$ to fs, where fs is the sampling frequency. Taking advantage of this redundancy, the DFT is only defined in the region between 0 and fs.

Symmetry: When the region between 0 and fs is examined, it can be seen that there is even symmetry around the central point, $0.5fs$, the Nyquist frequency. This symmetry adds redundant information. Figure 2.15 shows the DFT of a cosine with a frequency tenth the sampling frequency.

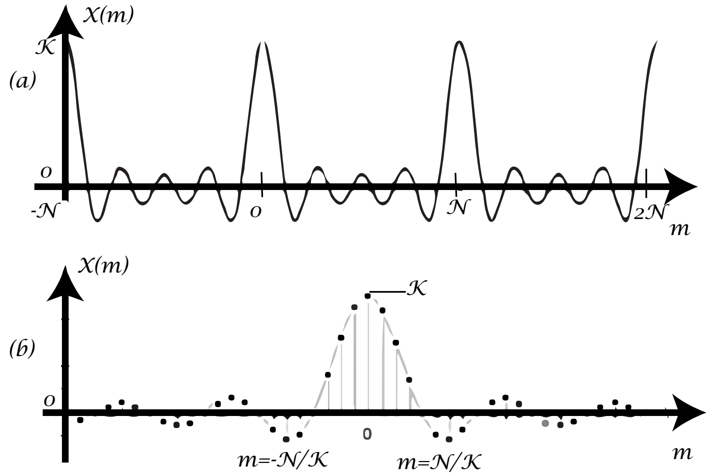


Figure 2.15: DFT symmetry.

2.1.18 Fast Fourier Transform (FFT)

The FFT is one of the techniques applied for the processing of EEG signals. Discrete Fourier Transformation (DFT) is used to obtain the components of a continuous signal, and there are many ways of calculating it. The most efficient is the Fast Fourier Transform, the FFT.

The FFT is a faster version of the Discrete Fourier Transform. The FFT uses some smart algorithms to do the same thing as DFT, but in much less time. While the order of complexity of the DFT algorithms is $O(N^2)$, that of the FFT is $O(Nlog(N))$, where N is the number of data to be processed.

The DFT is essential in the area of frequency (spectrum) analysis, as it takes a discrete signal in the time domain and transforms the signal into its discrete frequency domain representation. Without a discrete-time to discrete frequency transform, we would not be able to calculate the Fourier transform with a microprocessor or DSP based system. It is the speed and discrete nature of the FFT that allows us to analyze the signal spectrum with some software like Matlab.

The Laplace transform described in equation 4 is used to find a pole / zero, the representation of a signal or a continuous system over time, $x(t)$, in the s-plane. Similarly, the z-transform is used to find a pole / zero, the representation of a signal or system continues over time, $x(t)$, in the s-planes, $x[n]$, in the z-plane.

Equation 4 Laplace Transform: $x(t) <-> X(s)$ where

$$X(s) = \int_{-\infty}^{\infty} x(t)e^{-st}dx \tag{2.4}$$

The continuous-time Fourier transform can be found by evaluating the Laplace transform in

$s = jw$. The time of the discrete Fourier transform can be found by evaluating the z-transformed into $z = e^{j\Omega}$, equation 1.

For the analysis of EEG signals, it is not enough to do it with the Fourier Transform, because the signals change concerning time as well, so a Time-Frequency analysis is required that can be performed with the Short Window Fourier Transform (STFT) or with the Continuous Wavelet Transform (CWT).

2.1.19 Patents related to the project

Table 2.2: Patent 1

App/Pub Number	Year of publication	Name
CN101201696A	2008-06-18	Chinese input BCI system based on P300 brain electric potential

Summary: The Chinese input BCI system is based on P300 brain electric potential. The Chinese input BCI system can provide a way for the seriously disabled of physical paralysis and damaged linguistic function to communicate with others, can lead the disabled to realize to control a computer program and an electronic mechanical device after the peripheral function is extended, and has a plurality of values in medical rehabilitation, medical physiological experiments and brain function mechanism exploring. The device includes a brain electrical collection system used for collecting, enlarging and digitizing an EEG with P300 member, an EEG analysis module used for conducting enhancement processing for the EEG enlarged and digitized by the brain electrical collection system and detecting the P300 member, a user interface module used for inducing the EEG (CN101201696A, 2007).

Table 2.3: Patent 2

App/Pub Number	Year of publication	Name
CN203802460U	2014-09-03	BCI (Brain-Computer Interface) electroencephalogram helmet

Summary: The device is a BCI (Brain-Computer Interface) electroencephalogram helmet. The BCI electroencephalogram helmet comprises a slidable electrode, a non-sliding electrode, a toughened plastic bracket, a reference electrode clip and a reference electrode connecting wire, wherein the slidable electrode is positioned on the toughened plastic bracket; the non-sliding electrode is fixed on the slidable electrode; the reference electrode clip is connected with the reference electrode connecting wire; and the slidable electrode, the non-sliding electrode and the reference electrode connecting wire are respectively connected with a data processing chip (CN203802460U, 2014).

Table 2.4: Patent 3

App/Pub Number	Year of publication	Name
CN105022488B	2017-11-21	BCI input system based on wireless EEG potentials ssvep

Summary: Based on the potential SSVEP wireless EEG BCI input system, including a keyboard and a SSVEP EEG headband. The keyboard of the present invention SSVEP for EEG evoked potential SSVEP user, comprising key flashing in a particular frequency, the mask can be replaced by labeled keys; EEG headband comprising the EEG acquisition module, EEG an analysis module, a Bluetooth communication module, respectively, for collecting EEG user, thereby determining the potential of the input identification SSVEP intention of the user, the smart key sent to the mobile device to pair via Bluetooth. EEG headband according to the portable wearable devices, wireless keyboard with SSVEP mobile intelligent control devices. It provides a way to move between one human brain and intelligent devices can interact directly, though can assist incapacitated patient of sound mind but action also provides a convenient tool for hands-free control for healthy people (CN105022488B, 2015).

Table 2.5: Patent 4

App/Pub Number	Year of publication	Name
CN106419909A	2017-02-22	Multi-class motion imagination EEG signal classification method based on characteristic recombination and wavelet transformation

Summary: The device is a multi-class motion imagination EEG signal classification method based on characteristic recombination and wavelet transformation, mainly solving the problem of less classes and low classification accuracy of present technologies for classifying EEG signals. The method comprise following steps: 1) collecting motion imagination EEG signals and obtaining a training set and a test set; 2) training a two-grade classifier through characteristic combination, wavelet transformation and common space pattern algorithms; 3) extracting test characteristic classification vectors of the test set according to a method corresponding to step 2); 4) by means of the trained classifier, performing signal classification on test signals through the characteristic vectors of the test set to obtain the classifications of EEG signals of imagination left hand motion, imagination right hand motion, imagination feet motion and imagination tongue motion of the test signals. The method of the invention realizes classification on multi-class motion imagination signals and increases classification accuracy, and can be used in intelligent product control of on-line system containing motion imagination brain-computer interface BCI (CN106419909A, 2017).

Table 2.6: Patent 5

App/Pub Number	Year of publication	Name
US20120059273A1	2010-09-03	Process and device for brain computer interface

Summary: The process of the device provides substantial advantages over the similar systems/techniques known in the art, such as a 91 percent average hit rate, obtained in attempts to control a mobile robot. In other embodiment of the invention, there is provided an apparatus comprising: means for obtaining brain signals; an electroencephalograph (EEG); and means for transducing said signals into functional commands useful in several applications. The device is used to control a mobile robot, wherein the control is provided through four different mental activities, such as imaginary movements of a specific limb. These activities are correlated with four robot movements, respectively. The interface classifies the user's mental activity, sending the corresponding command to activate the mobile robot. Note that the user does not need to be able to perform any movement; just imagining them is enough to activate the robot (US20120059273A1, 2010).

Methodology

3.0.1 Material

- Computer
- Raspberry $Pi3$
- Touch screen for Raspberry $Pi3$ 7”
- Charger

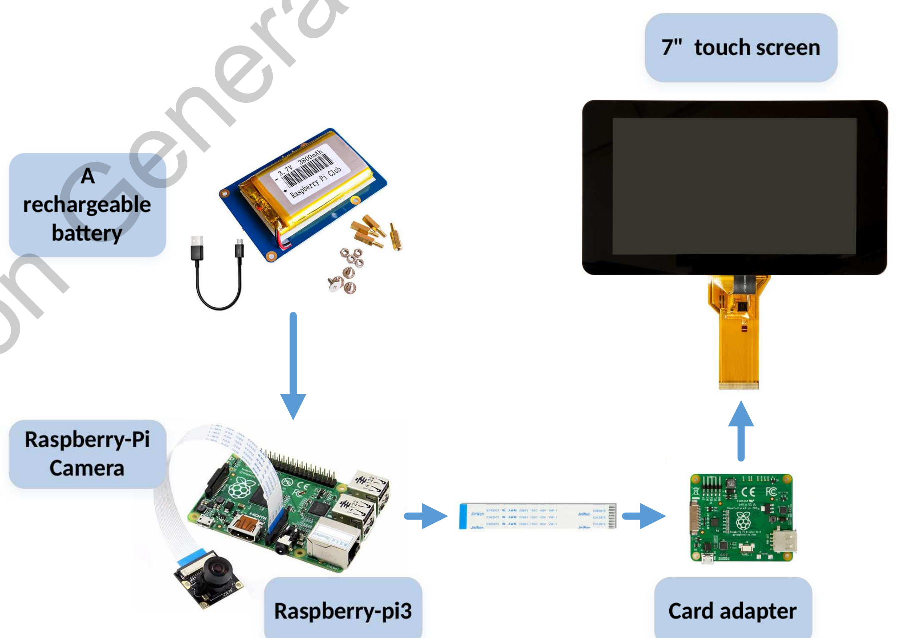


Figure 3.1: Diagram of connections in the Raspberry.

3.0.2 Methods

The methodology is divided in:

- Design data identification: An automatic system is required for the detection of brain diseases, it must be a technique based on the analysis of neuron properties, and it should not be to make use of data obtained with invasive techniques. It must be a system portable and scalable. Finally, the analysis of the information can be online or offline.

- Development of concepts, and basic engineering: Select database type, processing techniques, and materials to be used. Also, this will establish the technical properties for each part of the system.

- Implementation: The system is implemented according to the design characteristics.

- Validation: The validation methods for the hypothesis are applied.

Identification of the design data

Mainly these three different techniques are used: the electroencephalogram, the electrocorticogram, and the magnetoencephalography, from which the information can be obtained for the detection of cerebral diseases. The electrocorticogram cannot be used because it is invasive; it consists of embedding needles in the brain.

Magnetoencephalography is an extremely expensive method, only a study of it costs around 15 thousand dollars because superconductors are used, its maintenance is very expensive and must be very frequent. Therefore this technique is not widely used; besides that, this would raise the price and accessibility of the system extremely. The EEG is a non-invasive technique, cheap compared to the magnetoencephalogram, it can be portable, it is easy to apply to the patient, its analysis can be online or offline, and according to the literature the EEG is useful for detection, during treatment and even for the prediction of brain diseases. For which the EEG was chosen.

The most common techniques for processing EEG signals are the FFT in commercial systems and the STFT in the literature. The FFT has problems with stationary signals. The STFT (Fourier transform of Short Window) is a time-frequency map almost equal to the Wavelet Transform because it has the issue of resolution between time and frequency.

Wavelet Transform minimizes the effect by multiresolution analysis, so it has no issues with non-stationary signals. The implementation of a hybrid method composed of the FFT and the TW is proposed to improve reliability, with the application of a hybrid method it will seek to take advantage of each technique.

For the implementation of the algorithm, a Raspberry-Pi3 will be used, in combination with a 7” Touch Screen and rechargeable batteries. The selection of these materials was due to their processing speed, their dimensions, accessibility, and portability. Also, both the processing card and the screen are from the same family and allow us to develop and implement algorithms using Object-Oriented Programming (Python).

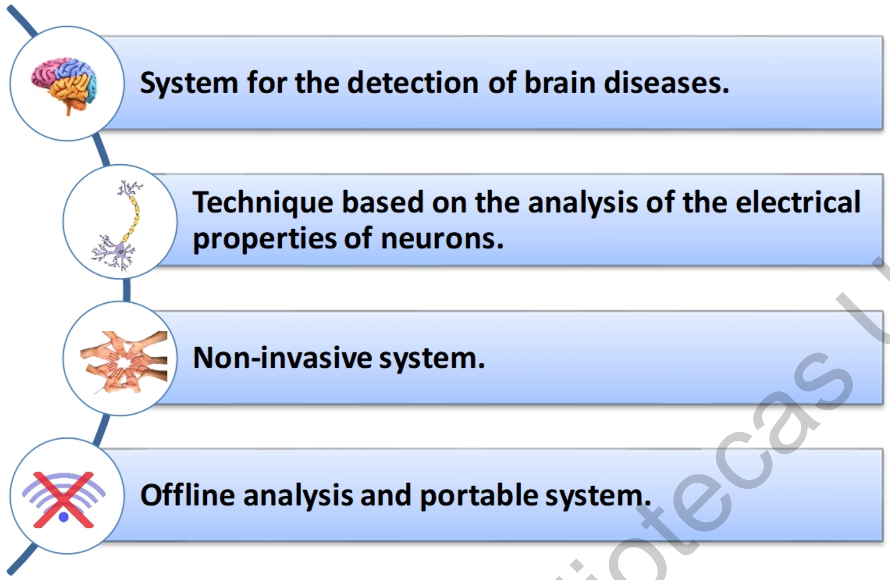


Figure 3.2: Design data.

Development of concepts and basic engineering

The design parameters for the application of the FFT and the TW were the following:

- $O(Nlog2N) = 70000$, reduction of more than 90% of processing time.
- FFT with 800 points.
- Wavelet Transform type Biorthogonal 1.5, with five levels.
- It is considered an SP of 500Hz.
- Validation of the interface with 54 segments.
- EEG signals 0-100Hz, with five frequency bands (alpha, beta, gamma, delta, theta).
- Its amplitude is of the order of the uV.
- We considered 19 channels and one channel as a reference (in addition to two earth channels in the ear lobes).

For the project implementation, the circuit of figure 3.3 was used, in which it is observed that five pins of the card were used, 2 and 6 for powering the screen, 9 and 4 for powering the push-button circuit and 11 for sending the push-button signal. The push-button is used to start reception.

The structure of the interface was designed with the aim of achieving a portable device with a focus for people of limited resources who can not access people specialized in the subject since the system can give a pre-diagnosis that helps in the identification of abnormal EEG records. The following figure 3.4 shows the block diagram that represents the operation of the application.

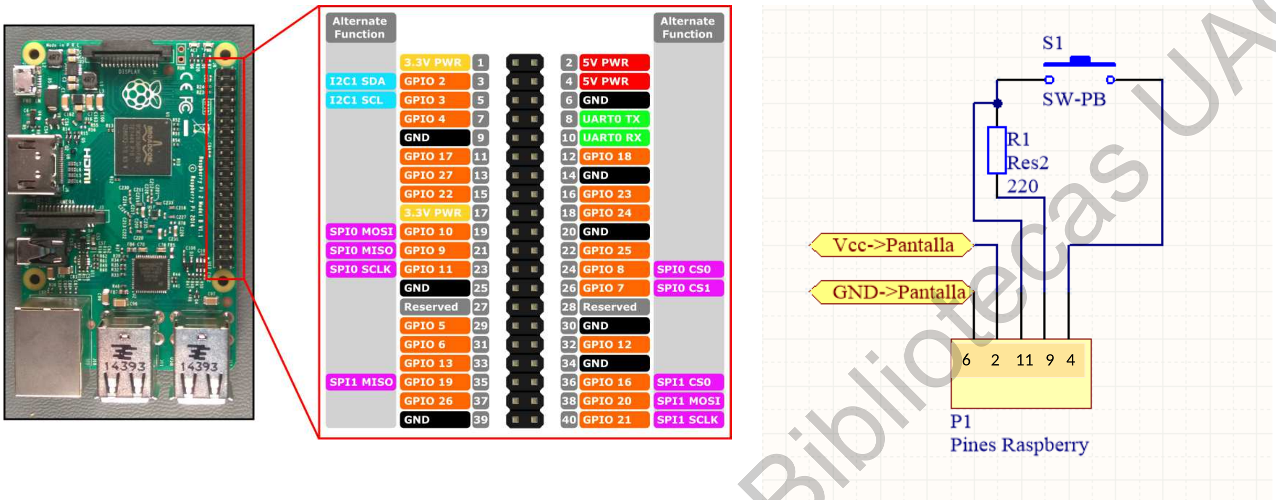


Figure 3.3: Diagram of connections in the Raspberry.

The application has two ways of receiving the data. The first is through the receiver function for serial communication and the second is to read the information from a txt file. After the information is received, we proceed with the decoding. Once the information is decoded, analysis is continued in the time domain, in the frequency domain (the FFT and TW were applied), and the quantitative analysis.

The received data is encoded with a frame start character and a frame end character and have a 16-bit format for each channel. When the transmitter begins with the sending of information, the receiver begins to receive the data and decodes it by adding an offset for its visualization in the time domain.

Once the signals are in the time domain, the FFT and the WT are applied to pass the information to the frequency domain. With the information in the frequency domain, a quantitative analysis is implemented. The quantitative analysis consists of the calculation of total relative powers and each band, the comparison of results and their interpretation. As intermediate steps between the information in the frequency domain and the quantitative analysis, several information operations are performed to adapt to the characteristics necessary for the power analysis.

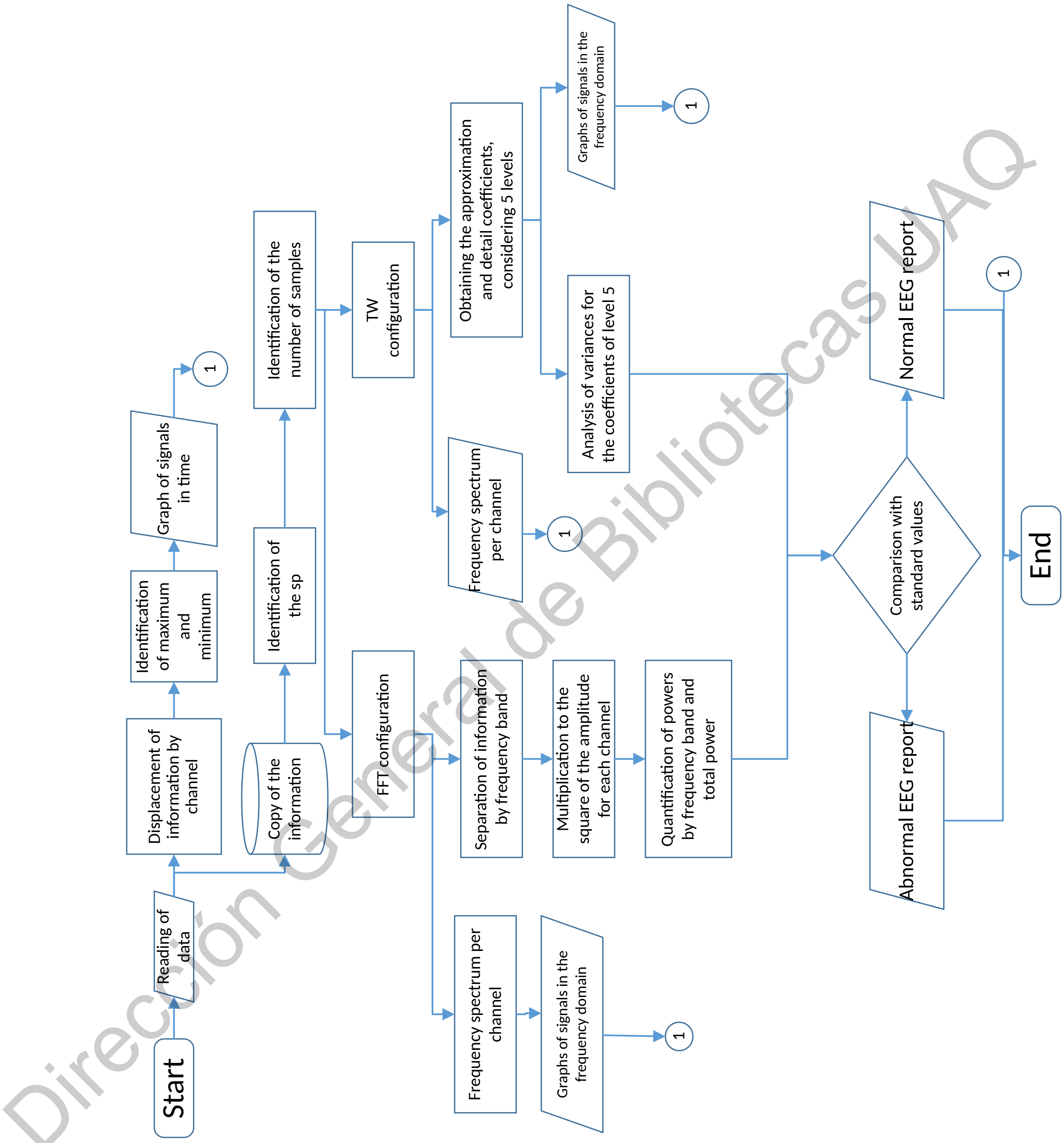


Figure 3.4: Block diagrams of the functioning of the algorithm.

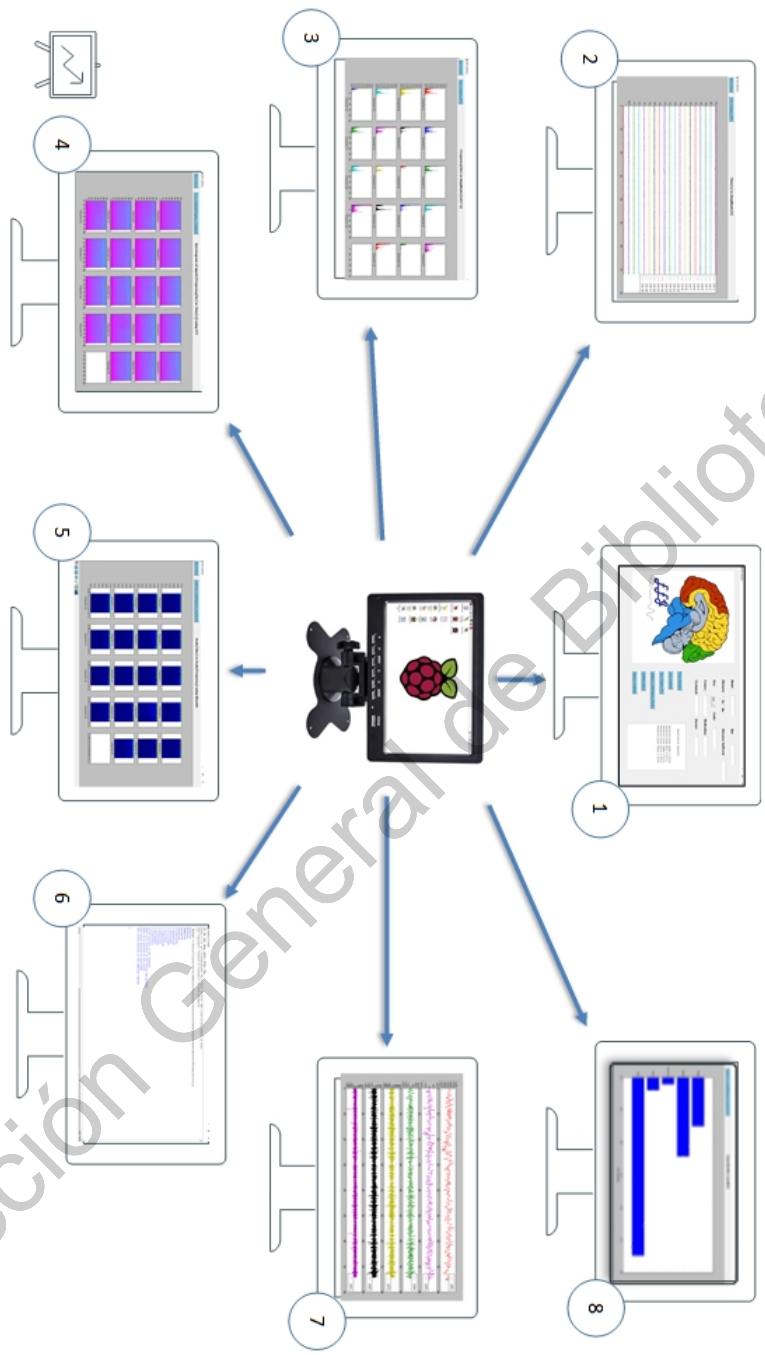


Figure 3.5: Windows containing the interface, (1) main window, (2) time-domain graphics, (3) frequency domain graphics, (4) spectra per channel using FFT, (5) spectra per channel using WT, (6) results of the quantitative analysis, (7) levels of decomposition using WT, (8) bar graph of the power analysis..

The graphical interface has seven windows plus the information that appears in the console. In the main window (1), you have the patient information, the technician data, patient history data, the buttons to enter the other windows, and the activity found by frequency band in the quantitative analysis. Patient data can be used as anonymous and only assign a patient number.

In window two, the signals are shown in the time domain, in the same graph all the channels are shown, each channel is identified by a specific color. In window three, the signals are shown in the frequency domain, a graph is used for each channel. In window four, a frequency spectrum is shown per channel, the Fourier Transform of Short Window is used. Window five is similar to window four, but Wavelet is used for calculations.

Window six corresponds to the console, in the console the data of the interpretation of the quantitative analysis and the results of the analysis of the coefficients for level five of the Biorthogonal Wavelet are shown. According to the analysis of the levels of the Wavert type biorthogonal, level 5 was the one that presented the best results to detect brain diseases. In window seven the results of the analysis of levels in the Wavelet are shown. Finally, in window eight a bar graph corresponding to the proportion of the activity found in the quantitative analysis for each frequency band is shown.

Each quantitative analysis of powers for the FFT is done by quantifying the magnitudes found over time, it is done by frequency band and in a total way to make a comparison. For the analysis of the wavelet coefficients, the maximum and minimum values for each channel are identified for level five; an average is obtained by the results and an analysis of variance.

Validation

Applications for validation of signal processing:

- NeuronicEEG

Databases:

- Internet data bases.
- Own design of databases.
- Digital electroencephalogram, UAQ.
- Digital electroencephalogram, UNAM.

Advice: Professors and researchers of the Faculty of Psychology, and Engineering.

Metrics:

1. For the application validation, the following equations will be used:

$$Precision = \frac{TP + TN}{TP + TN + FP + FN} \tag{3.1}$$

$$Specificity = \frac{TP}{TP + FN} \tag{3.2}$$

$$Sensitivity = \frac{TN}{TN + FP} \tag{3.3}$$

   Where TP are the true positive cases, FP are the false positive cases, TN are the true negative cases and FN are the false negative cases.

2. Comparison of the frequency spectrum obtained with the FFT, and the TW with those obtained from Neuronic.

3. Statistical analysis: A t-student test is applied to obtain the mean analysis, which is the most used to compare two means of two different treatments, since one of the things that is looked for is to demonstrate that statistically, the means are different between the treatments of patients with said disease and without said disease. Also an analysis of variance is made to determine the range in which the variances of the two treatments fall with a degree of reliability of 99%, finally an estimation of the detection ranges is made for each treatment with a 99% reliability by means of calculating the confidence intervals of means and variance of each treatment (patients with said disease and without disease).

CHAPTER 4

Results and Discussion

4.1 Results

The main objective of this research was to implement an efficient computational system focused on the detection of abnormal EEG, corresponding to patients with some encephalopathy. The system was implemented in an embedded system and developed in Python. The metrics for the validation were three, the first was the quantification of false positive and false negative cases, from these values the precision, specificity, and sensitivity were calculated. It was found that the WT reaches better levels in precision and specificity, but the processing time is 30 times longer than in the FFT. Figure 4.1 shows a bar graph of the percentage value of specificity, accuracy, and sensitivity. An efficiency of 100% was achieved for TW and efficiency of 90.55% for the FFT; the efficiency is the average of the specificity, the precision, and the sensitivity.

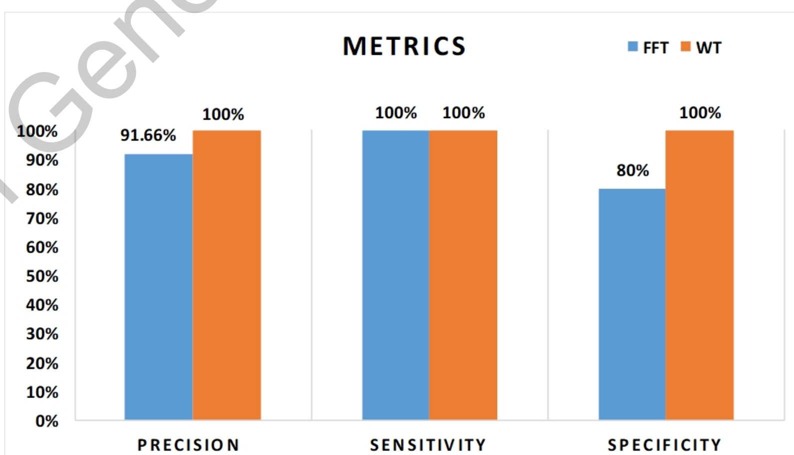


Figure 4.1: Bar graph of the percentage value of the calculation of the precision, sensitivity, and specificity using equations 3.1, 3.1, and 3.1.

The second evaluation metric was the comparison of frequency spectra, the spectrum of frequencies obtained with Fourier Short Window was compared with that obtained Wavelet, using the Wavelet of biorthogonal type. No significant changes were found in the frequency spectra; however, when analyzing level five of the Wavelet, it was found that there were substantial changes and that this helped us to improve efficiency levels. Figure 4.2 shows an example of the amplitude values obtained at level five of the Wavelet for seven of the channels; it can be seen that the amplitudes are very different between normal and abnormal EEG, the amplitudes of abnormal cases are at least twice as large as the amplitudes of normal cases.

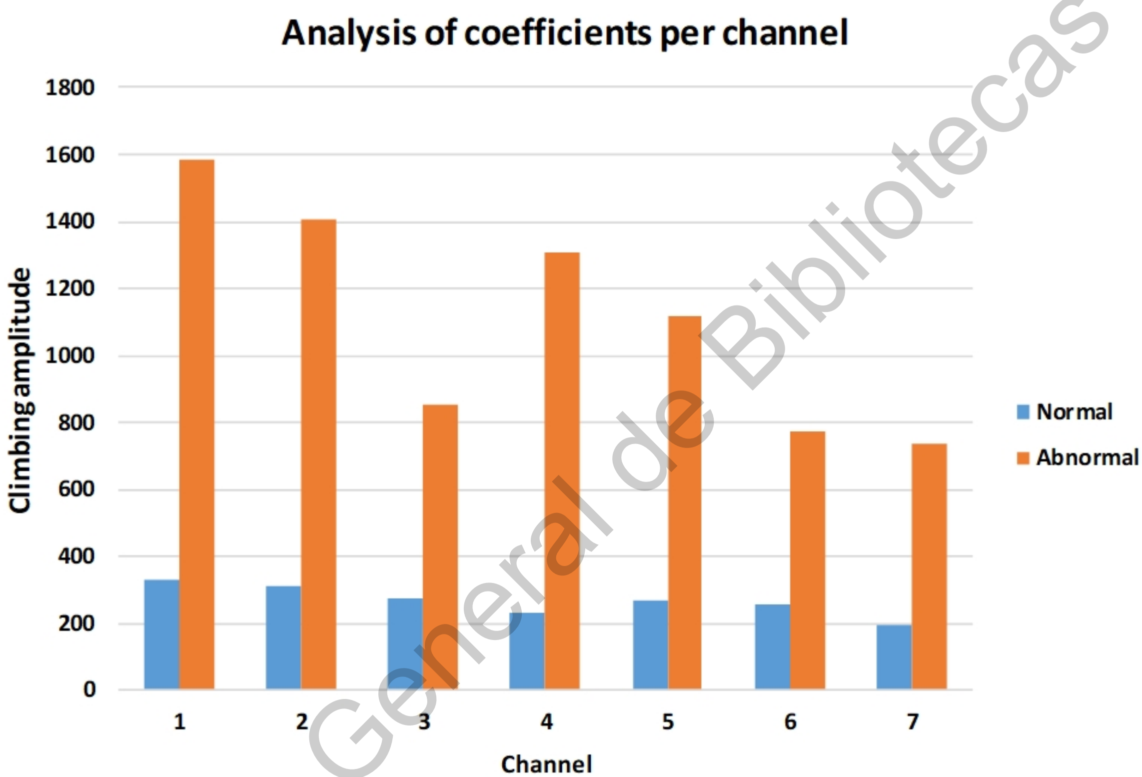


Figure 4.2: Bar graph of the comparison of the scaled amplitudes obtained from level 5 of the biorthogonal Wavelet decomposition for a normal and an abnormal case.

The last metric was a statistical analysis, first an analysis of means was made with the distribution of t-student, which is the most used to compare two means of two different treatments, since one of the things that was sought was to demonstrate that statistically, the means are different between the treatments of patients with said disease and without said disease both for the data obtained with Fourier and for Wavelet. An analysis of variance was also made to determine the range in which the variances of the two treatments fall with a degree of reliability of 99% for Wavelet and with 90% for Fourier, finally, an estimation of the detection ranges is made for each treatment with a reliability of 99% for Wavelet and 90% for Fourier.

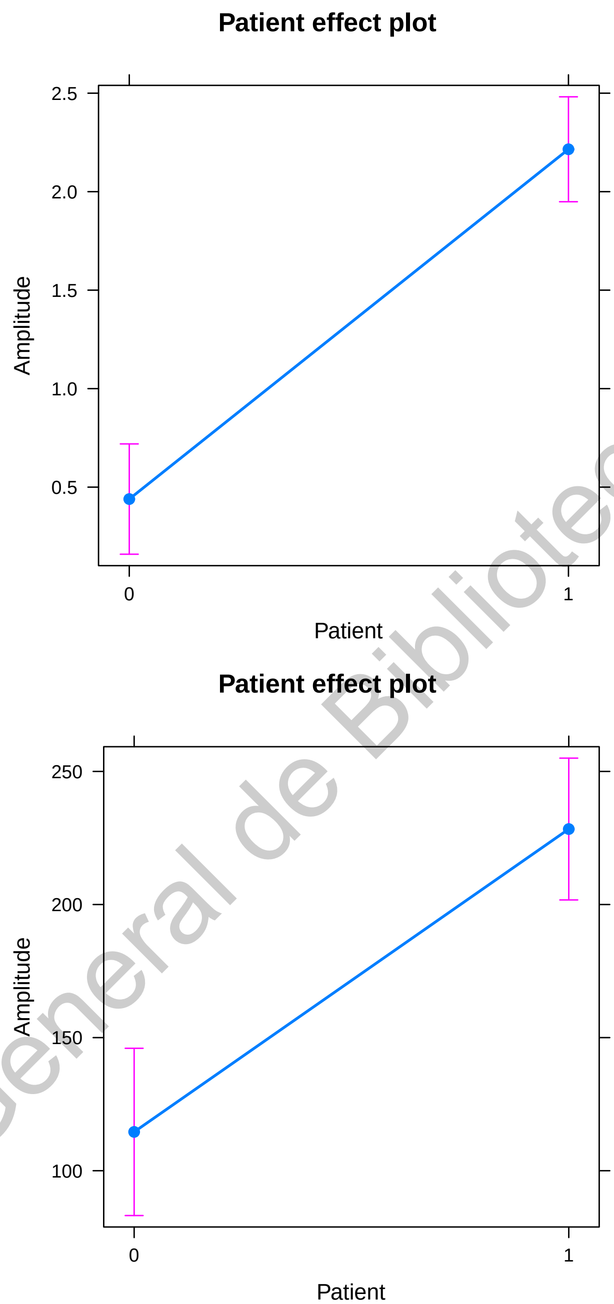


Figure 4.3: Ranges found for the FFT and the WT respectively.

According to the results obtained from the calculations, the treatments are statistically different with a reliability level of 99% or $1 - \alpha$, = 0.99 (for TW) and 90% or $1 - \alpha$ = 0.9 (for FFT), which is well, since we look for differences between them.

Subsequently the confidence levels of the mean were determined, according to the results of

TW it is said that the average of healthy patients will fall 99% of the time between a range of [94.9844, 161.4774], while the average of patients will fall 99% of the time between a range of [182.6948, 274.0163]. For the FFT it is said that the average of healthy patients will fall 90% of the time between a range of [0.2050, 0.54418], while the average of sick patients will fall 90% of the time between a range of [1.8529, 2.26177]. As we can see there is a slight overlap in the range of the FFT means, however, the reliability for which this was calculated is high, so it can be said that the confidence range is good and even more so in the WT where there is no overlap and in confidence level is very high.

Table 4.1: Results of the statistical analysis in WT for identification of the detection ranges for each group.

	Normal cases	Abnormal cases
Average Minimum	94.98	182.69
Average Maximum	161.47	274.01
Minimum variance	23.89	7.28
Maximum variance	53.16	14.20
Minimal standard deviation	4.88	2.69
Maxima standard deviation	7.29	3.76
Average Minimum - Maxima standard deviation	87.69	178.92
Average Maximum + Maxima standard deviation	168.76	277.78
Overlap	0	

Table 4.2: Results of the statistical analysis in FFT for identification of the detection ranges for each group.

	Normal cases	Abnormal cases
Average Minimum	0.20505	1.8529
Average Maximum	0.54418	2.2617
Minimum variance	0.29285	0.6887
Maximum variance	0.48561	1.0520
Minimum standard deviation	0.54116	0.82980
Maximum standard deviation	0.69686	1.0256
Average Minimum - Maximum standard deviation	0	0.82720
Average Maximum + Maximum standard deviation	1.2410	3.2874
Overlap	0.41378	

Table 4.1 and 4.2 shows the results of the statistical analysis for the identification of the detection ranges for each group using the software developed. It was concluded that the means are statistically different between both groups of people using these methods with a reliability range of 99% for WT and 90% for FFT. It is excellent because what is sought is that there are differences to establish detection range. It is concluded that, if a normal distribution is followed in the data series which is normally followed for several biological phenomena, and the range where the variances fall is calculated, a detection range can be found between a normal EEG and an abnormal EEG. With a 99% confidence level in which most of the data of healthy and sick people fall, this range has an overlap of 0 for the case of the WT and less than one for the FFT.

Figures 4.4 and 4.5 show four images that illustrate the start-up of the system, the wait status (the screen shows the word ”Waiting” that tells us that you are waiting for the reception to start), and console results. Figure 4.6 shows examples of the windows that can be observed in the interface, the signals in the time domain, the components for Wavelet levels, the frequency spectrum, the main window.

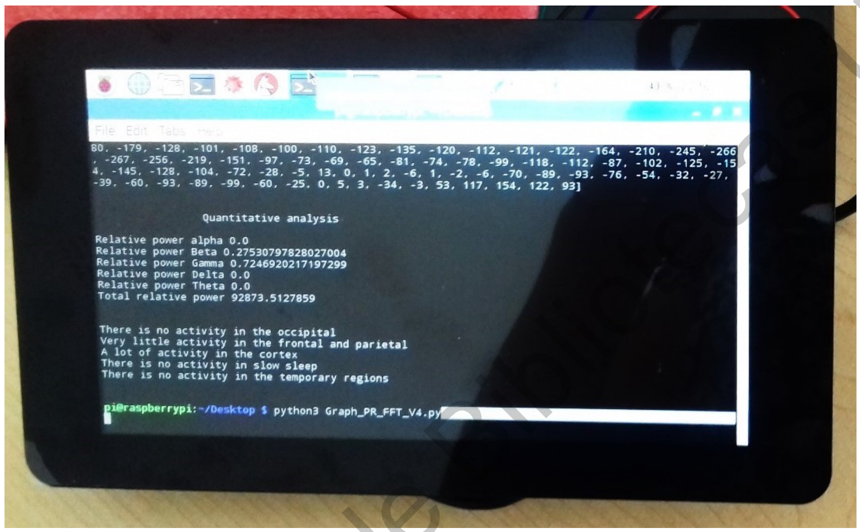


Figure 4.4: The figures show the start-up of computer software. The screen shows the wait status.

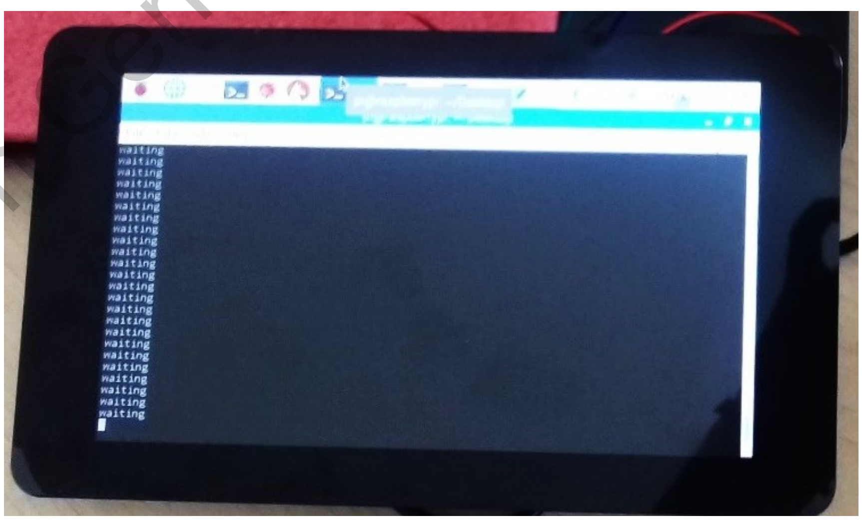


Figure 4.5: The figures show the start-up of computer software. The screen shows the comparison results of relative powers by frequency rhythms.

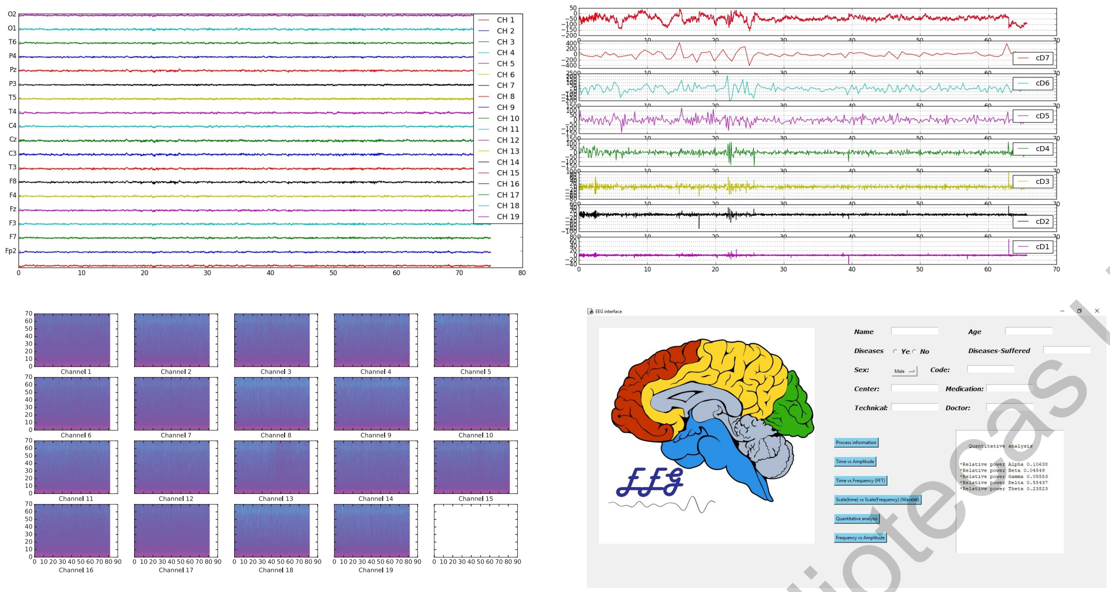


Figure 4.6: The figures show some of the windows offered by the computer system developed. (A) signals in the time domain, (B) biorthogonal Wavelet decomposition for a channel, (C) signals in the frequency domain, (D) main window.

An example of the results obtained for a normal EEG and for an abnormal EEG is shown in Table 4.3. As can be seen, in a normal EEG activity is concentrated in the alpha frequency band, when an EEG is abnormal depending on the disease is the frequency region where the activity is concentrated and the magnitudes are much larger.

Table 4.3: Comparative table of a normal case and an abnormal EEG, signals in the time domain.

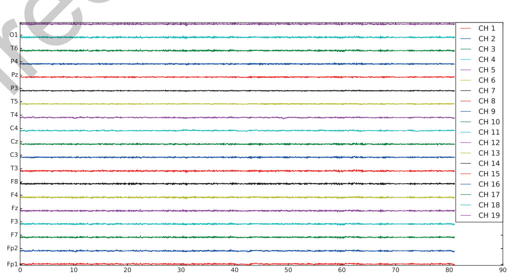
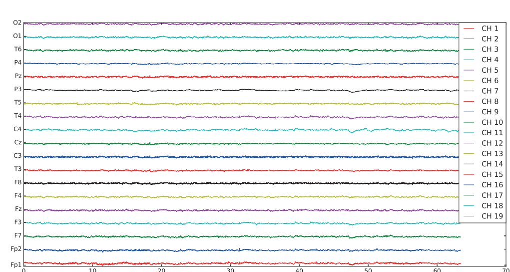
Healthy	Sick
	

Table 4.4: Comparative table of a normal case and an abnormal EEG, signals in the frequency domain and frequency spectrum.

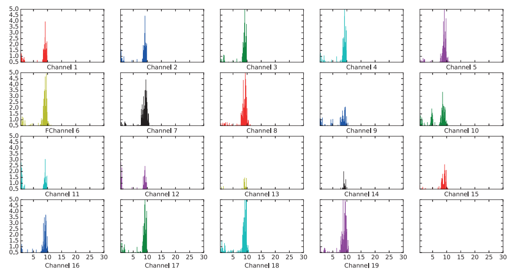
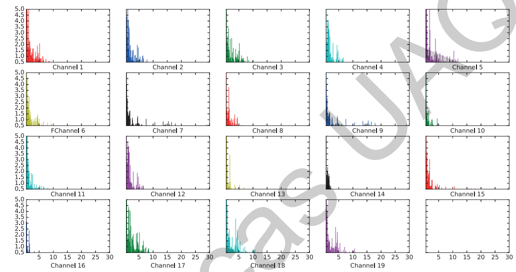
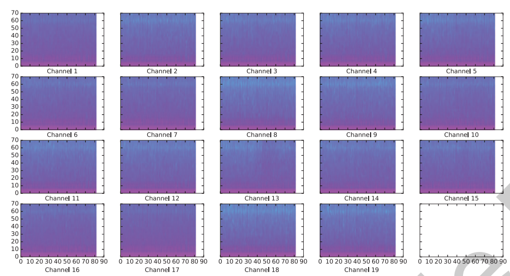
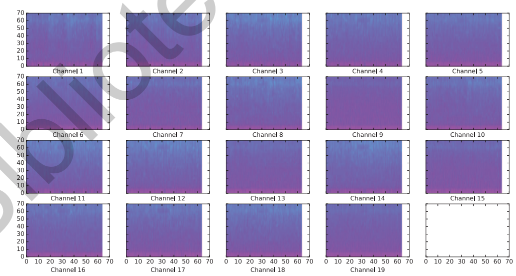
Healthy	Sick
	
	

Table 4.5: Comparative table of a normal case and an abnormal EEG, biorthogonal Wavelet decomposition considering five levels for a channel.

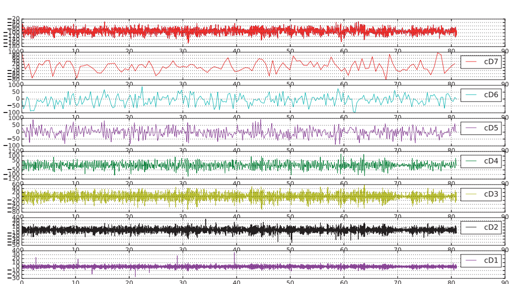
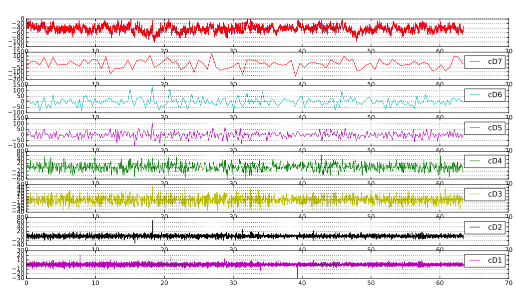
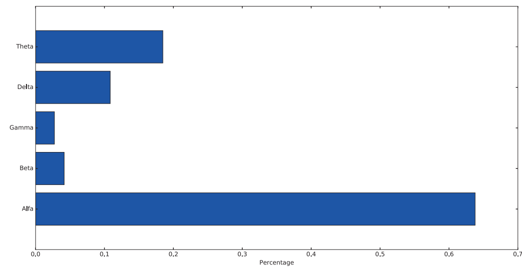
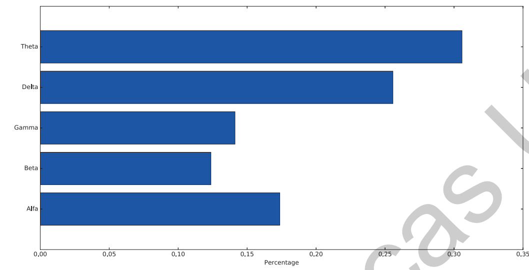
Healthy	Sick
	

Table 4.6: Comparative table of a normal case and an abnormal EEG, results of the analysis of the relative powers for each frequency rhythm.

Healthy	Sick
	
Quantitative analysis *Relative power Alpha 0.63799 *Relative power Beta 0.041530 *Relative power Gamma 0.027 *Relative power Delta 0.10838 *Relative power Theta 0.18474	**Quantitative analysis** *Relative power Alpha 0.17367 *Relative power Beta 0.123710 *Relative power Gamma 0.141 *Relative power Delta 0.25567 *Relative power Theta 0.30577

4.2 Significance/Impact

4.2.1 Social Impact

1. According to studies carried out by the WHO, systems for EEG signal processing are critical in the field of medicine and more specifically in the identification of encephalopathies, since they contribute to establishing a communication channel for the identification of voltage patterns and frequency. The improvement of the processing systems for EEG signals contributes to the development of more reliable equipment. In the market, there are no processing systems like the one that will be developed, for which there is a significant technological contribution.

4.2.2 Environmental Impact

1. With the implementation of new techniques for signal analysis, the reduction of waste can be achieved since during the selection of materials it was sought that the materials to be used were non-disposable to avoid generating significant impacts to the environment. In addition, it is intended that the device to be designed is low energy consumption and thus make the most of resources.

4.2.3 Economic Impact

1. When designing and implementing improvements in an EEG signal processing system, it is possible that in future investigations the device will be more accessible for people with limited resources, since most devices on the market are expensive and increase significantly with the number of channels and the type of communication it contains.

4.3 Publications

- 1 Paper in a local magazine, NTHE magazine.
- 1 Local conference at the international brain week event.
- 3 international conferences, International Engineering Congress 2018 (CONIIN2018) (María & Juvenal, 2018) and 2019 (CONIIN2019) (María, Juvena, Jesus, & Gloria, 2019), Biomedical Engineering Congress 2018 (IECBES2018) (María, Juvenal, & Gloria, 2018).
- 3 International indexed papers, International Engineering Congress 2018 (CONIIN2018) (María & Juvenal, 2018) and 2019 (CONIIN2019) (María et al., 2019), Biomedical Engineering Congress 2018 (IECBES2018) (María et al., 2018).
- 1 A prototype of a computer system for EEG signal processing.
- 1 Poster presentation.

4.4 Future Work

Future work is divided into two parts:

- Improvements for the computer system: Increase the number of databases used to achieve greater software robustness.
- A processing system for the acquisition of EEG signals: Complement the computer system with the acquisition of signals so that we can generate our databases.

48

CHAPTER 5

Conclusion

According to the analysis of the results, the proposed objective was met since the implementation of a computational system for processing EEG biopotentials was achieved, focused on the detection of abnormal EEG records. During the development of the project, several challenges related to the calculation of the FFT and the interpretation of the results for the analysis of relative potentials were presented.

When a person has an abnormal EEG, the proportions or activity levels change drastically in the frequency bands, so the magnitudes for the relative powers also change. These variations are reflected in the bar graph, and in the graphs of the frequency spectra.

The quantitative analysis using a hybrid method integrated by the FFT and the TW improve the characteristics of the EEG signal processing software in comparison with the conventional systems, so it can be concluded that, according to the analysis of the results, the device presents a High efficiency and sensitivity compared to conventional methods.

By having a scalable and modular architecture for electroencephalogram signal processing, it is possible to perform research related to BCI systems, both for diagnosis, as well as for rehabilitation and communication with external devices.

As future work, we will work in the electronic and reading part of the ADC to complement the part of the programming in which we were working so that in future results we have a system that can record and detect the existence of encephalopathies by using signal processing of EEG.

References

Alaa, K., Ali, S., John, G., & Sydney, S. (2011). An algorithm for seizure onset detection using intracranial eeg. *Elsevier, Epilepsy and Behavior*, *25*, S29-S35.

Ali, K., Faesipour, M., Almuhammadi, W., & Moslehpour, S. (2016). Sleep stage clasification using eeg signal analysis: A comprehensive and new investigation. *Entropy, MDPI*, *18*, 2-31.

Arunkumar, N., Ramkumar, K., Venkatraman, V., Enas, A., Steven, L., Seifedine, K., & Segal, S. (2017). Classification of local and nonfocal eeg using entropies. *Pattern Recognition Letters, Elsevier*, *94*, 112-117.

Asadi, A. (2018). Yield of eeg monitoring in children with developmental disabilities is high. *Epilepsy and Behavior, Elsevier*, *84*, 105-106.

Audette, C. (2015). Mind control. *IEEE Spectrum*, *52*, 21-22.

Barea, R. (2012). Electroencefalografía. *Instrumentación Biomédica*.

Brogger, J., Eichele, T., Aanestad, E., Olberg, H., Hjelland, I., & Aurlien, H. (2018). Visual eeg review times with score eeg. *Clinical Neurophysiology Practice, Elsevier*, *3*, 59-64.

Choi, Q. (2015). A brain computer interface that lasts for weeks. *IEEE Spectrum*.

Christian, F., & Julien, N. (2015). Parameters analyzed of higuchi of fractal dimension for eeg brain signals. *2015 Signal Processing Symposium (SPSympo), IEEE*, 1-5.

CN101201696A. (2007). *Chinese input bci system based on p300 brain electric potentiald.* url-https://patents.google.com/patent/CN101201696A. (Accessed 03-20-2018)

CN105022488B. (2015). *Bci input system based on wireless eeg potentials ssvep.* url-https://patents.google.com/patent/CN105022488B/en?oq=CN105022488B. (Accessed 03-20-2018)

CN106419909A. (2017). *Multi-class motion imagination eeg signal classification method based on characteristic recombination and wavelet transformation.* url-https://patents.google.com/patent/CN106419909A. (Accessed 03-20-2018)

CN203802460U. (2014). *Bci (brain-computer interface) electroencephalogram helmet.* url-https://patents.google.com/patent/CN203802460U. (Accessed 03-20-2018)

Dimitrios, A., Pierre, L., Marc, R., Jonathan, R., & George, G. (2014). Organic electrochemical transistors for biomems applications. *IEEE International Electron Devices Meeting*, 31.4.1-31.4.4.

Donald, L., & Fernando, H. (2001). Electroencephalography: Basic principles, clinical applications, and related fields. *Lippincott Williams and Wilkins*, *6*, 500-1179.

Donald, L., & Fernando, H. (2010). *Niedermeyer's electroencephalography: Basic principles, clinical applications and related fields* (Sixth ed.). LWW.

Ferree, T., Luu, P., Russell, G., & Tucker, D. (2001). Scalp electrode impedance, infection risk, and eeg data quality. *Clinical Neurophysiology, Elsevier*, *112*, 536-544.

Garcia, E., David, M., & Morari, M. (1989). Model predictive control. *Elsevier*, *25*(3), 335-348.

Gopathy, P., & Karayiannis, B. (1997). Quantum neural networks. *IEEE Transactions RANSACTIONS on Neural Networks*, *8*.

Heidmann, N., Hellwege, N., Hohlein, T., Westphal, T., Drolshagen, P., & Paul, S. (2014). Modeling of an analog recording system design for ecog and ap signals. *Automation and Test in Europe Conference and Exhibition (DATE)*, 1-6.

Hinault, T. (2016). What does eeg us about arithmetic strategies? a review. *International Journal of Psychophysiology, Elsevier*, *106*, 115-126.

Hoang, T., Pierre, A., Tatsuo, N., & Yasuhiro, Y. (2001). Parameterized linear matrix inequality techniques in fuzzy control system design. *IEEE Transactions on fuzzy systems*, *9*(2), 324-332.

Hornero, R., & Corralejo, R. (2016). Brain computer interface (bci) aplicado al entrenamiento cognitivo. *Grupo de Ingeniería Biomédica (GIB)*.

Iman, V., Naser, P., & Alil, K. (2007). Fast and robust detection of epilepsy in noisy eeg signals using permutation entropy. *IEEE 7th International Symposium on BioInformatics and BioEngineering*, *226*, 200-203.

Juti, N., & Akinori, N. (2015). Eeg based analysis of auditory stimulus in a brain computer interface. *6th International Conference of Information and Communication Technology for Embedded Systems*, 1-4.

Kafiul, M., Rastegarnia, A., & Yang, Z. (2016). Methods for artifact detection and removal from scalp eeg: A review. *Neurophysiologie Clinique/Clinical Neurophysiology*, *46*, 287-305.

Lahmiri, S. (2018). An accurate system to distinguish between normal and abnormal electroencephalogram records with epileptic seizure-free intervals. *Biomedical Signal Processing and Control, Elsevier*, *40*, 312-317.

Lin, C., Ko, L., Chiou, J., Duann, J., Huang, R., Liang, S., ... Jung, T. (2008). Noninvasive neural prostheses using mobile and wireless eeg. *Proceedings of the IEEE*, *96*, 1167-1183.

Lisa, H. (2016). *Neuroscience and machine learning restore movement in paralyzed man of hand.* urlhttps://blogs.mathworks.com/headlines/2016/04/20/neuroscience-and-machine-learning-restore-movement-in-paralyzed-mans-hand/. (Accessed 10-10-2017)

Maggioni, E., Bianchi, A., Altamura, A., Soares, J., & Brambilla, P. (2017). The putative role of neural networks synchronization as a potential biomarker for bipolar disorder: A review of eeg studies. *Journal of Elsevier*, *212*, 167-170.

María, S. L., Juvena, R., Jesus, P., & Gloria, A. (2019). Non-invasive system for the detection of malignant melanomas. *2019 XV International Engineering Congress (CONIIN)*, 1-6.

María, S. L., & Juvenal, R. (2018). Neural monitoring system for the characterization of voltage and frequency patterns. *2018 XIV International Engineering Congress (CONIIN)*, 1-6.

María, S. L., Juvenal, R., & Gloria, A. (2018). Trends of clinical eeg systems: A review. *2018 IEEE-EMBS Conference on Biomedical Engineering and Sciences (IECBES)*, 571-576.

Martins, R., Selberherr, S., & Vaz, F. (1998). A cmos ic for portable eeg acquisition systems. *IEEE Access*, *47*, 1406-1410.

Mohamad, W., Hashim, H., Khirotdin, S., & Mohamed, Z. (2010). Vision system for quantifying eeg brain wave histogram images. *IEEE Symposium on*.

Mu, Z., Hu, J., & Min, J. (2016). Eeg-based person authentication using a fussy entropy-related approach with two electrodes. *Entropy, MDPI*, *18*, 2-12.

Muller, G., Scherer, R., Neuper, C., & Pfurtscheller, G. (2006). Steady state somatosensory evoked potentials. *Neural Syst. Rehabil, Eng. IEEE Trans.*.

Narendra, K., & Sharma, S. (2015). Detection of epileptic seizure in eeg signals using window width optimized s-transformed and artificial neural networks. *IEEE Bombay Section Symposium (IBSS)*, 1-6.

Nicolaos, B., & Gopathy, P. (2008). Methods in cognitive neuroscience. *Pax*.

Nikita, G., & Bryan, H. (2014). Drowsy driving detection by eeg analysis using wavelet transform and k-means clustering,. *Elsevier, Computer Science*, *34*, 4400-409.

Ormrod, E. (2005). Aprendizaje humano. *Pearson*.

Palacios, L. (2002). Breve historia de la electroencefalografía. *Facultad de Medicina Universidad del Rosario*.

Prieto, A., Pelayo, F., López, M., & Romero, S. (2013). Brain computer intefaces (bci). *Centro Mediterráneo de la UGR*.

Qing, Z., Pingping, W., Yan, L., Bo, P., Yufu, Z., Zhiyong, Z., … Yakang, D. (2018). A real-time wireless wearable electroencephalography system based on support vector machine for encephalopathy daily monitoring. *Sensor Networks, International Journal of Distributed*, 1-9.

Rosenblatt, M., Figliola, A., Paccosi, G., Serrano, E., & Rosso, O. (2014). A quantitative analysis of an eeg epileptic record based on multiresolution wavelet coefficients. *Entropy, MDPI*, *16*, 15977-5989.

Ruijter, B., Hofmeijer, J., Tjepkema, M., Tjepkema, M., & Putter, M. (2018). The prognostic value of discontinuous eeg patters in pastanoxic coma. *Clinical Neurophysiology, Elsevier*, *129*, 1534-1543.

Sally, A., & Mohamad, K. (2013). Classification of eeg signals to detect epilepsy problems. *IEEE, 2nd International Conference on Advances in Biomedical Engineering*, 5-8.

Seijas, C., Caralli, A., Villazana, S., & Montilla, G. (2009). Detección de patrones patológicos en electroencefalogramas usando maquinas de vectores de soporte. *Facultad de Ingeniería, Universidad de Carabobo*.

Shih, C., & Chang, H. (2008). An intelligent brain computer interface of visual evoked potential eeg. *IEEE Access*, *1*, 343-346.

Sugi, T., Kawana, F., & Nakamura, M. (2008). Automatic eeg arousal detection for sleep apnea syndrome. *Elsevier, Biomedical Signal Processing and Control*, *4*, 329-337.

US20120059273A1. (2010). *Process and device for brain computer interface.* url-https://patents.google.com/patent/US20120059273A1/en?oq=US20120059273A1. (Accessed 03-20-2018)

Vetter, R., Williams, J., Hetke, F., Nunamaker, E., & Kipke, D. (2004). Chronic neural recording using silicon substrate microelectrode arrays implanted in cerebral cortex. *IEEE Transactions on Biomedical Engineering*, *51*, 896-904.

Vladimir, M., Perumpillichira, J., Katrien, J., Ninah, K., Gunnar, N., Renate, M., … Maarten, V. (2016). Improving reliability of monitoring background eeg dynamics in asphyxiated infants. *IEEE Transactions on Biomedical Engineering*, *63*, 973-981.

Willems, L., Reif, P., Spyrantis, A., Cattani, A., Freiman, T., Seifert, V., … Strzelczyk, A. (2018). Invasive eeg-electrodes in presurgical evaluation of epilepsies: Systematic analysis of implantation-video-eeg-monitoring-and explantation-related complications, and review of literature. *Epilepsy and Behavior, Elsevier*, 1-8.

Zakareya, L., Ramasani, P., & Khaled, E. (2017). Smart phone application development for monitoring epilepsy seizure detection based on eeg signal classification. *2017 IEEE 8th Annual Ubiquitous Computing, Electronics and Mobile Communication Conference (UEMCON)*, 83-87.

Zhiqiang, G. (2006). Active disturbance rejection control. In *American control conference* (p. 7-15).

UNIVERSIDAD AUTÓNOMA DE QUERÉTARO

FACULTAD DE INGENIERÍA

The Querétaro State University through the Engineering Faculty grant the present acknowledgment to:

Sánchez Reyes Luz María

FOR THE COLLABORATION:

ORAL PRESENTATION: " Neural Monitoring System for the Characterization of Voltage and Frequency Patterns."

QUERÉTARO, MEX.
MAY 2018

Dr. Manuel Toledano Ayala
PRINCIPAL
ENGINEERING FACULTY

Dr. Gonzalo Macías Bobadilla
GENERAL COORDINATOR CONIIN
ENGINEERING FACULTY

Figure 1: Conference International Engineering Conference 2018.