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ELLEN PEREIRA ZAMBALDE

SSVEP-BASED BCI WITH VISUAL STIMULI FROM LCD SCREEN APPLIED FOR WHEELCHAIR CONTROL: OFFLINE AND ONLINE INVESTIGATIONS

UBERLÂNDIA – MINAS GERAIS
JULHO – 2018

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Dissertação submetida ao Programa de Pós-Graduação em Engenharia Biomédica da Universidade Federal de Uberlândia, como parte dos requisitos necessários à obtenção do grau de Mestre em Ciências.

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Dedicated to my parents, Ana and André, and to my sister Érika, who have always support and believe in me more than I believe in myself.

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"...Tem vez que as coisas pesam mais do que a gente acha que pode aguentar
Nessa hora fique firme pois tudo isso logo vai passar
Você vai rir, sem perceber
Felicidade é só questão de ser
Quando chover, deixar molhar
Pra receber o sol quando voltar
Melhor viver, meu bem pois há um lugar em que o sol brilha pra você
Chorar, sorrir também e depois dançar
Na chuva quando a chuva vem
Dançar na chuva quando a chuva vem...".

Felicidade – Marcelo Jeneci

Resumo

As Interfaces Cérebro-Máquina (ICMs) têm se mostrado como tecnologias promissoras atualmente, especialmente para os usuários de cadeira de rodas afetados por lesões ou doenças de comprometimento motor. Os sistemas ICM baseados em Potencial Evocado Visual em Regime Permanente (PEV-RP) são amplamente utilizados para diversas aplicações, como o controle de um teclado de computador e robôs, devido ao seu baixo tempo de resposta e facilidade de uso.As ICMs baseadas em PEV-RP utilizam respostas cerebrais a qualquer estímulo visual piscando à uma frequência específica como comando de entrada para um dispositivo externo. Embora algumas ICMs baseadas em PEV-RP aplicadas ao controle de cadeiras de rodas tenham mostrado resultados promissores, existem características específicas do sistema que devem ser analisadas e discutidas com o objetivo de aumentar a precisão da classificação. Esta dissertação tem como objetivo desenvolver e investigar o desempenho de um sistema ICM baseada em PEV-RP utilizando um monitor LCD como estimulador visual e aplicado ao controle de cadeira de rodas. Dois experimentos foram realizados (offline e online). Através do experimento offline, realizado por 9 participantes, foi possível identificar os canais significativos do sinal EEG, e o tamanho adequado da janela para o processamento do sinal, além da localização do alvo no monitor LCD. No experimento online, 9 canais de EEG (PO3, PO4, PO5, PO6, PO7, PO8, O1, O2 e Oz) foram usados para registrar o sinal cerebral utilizando uma interface com 5 alvos de estímulo (15, 12, 6.67, 8.57 e 10 Hz) colocados na parte superior, inferior, direita, esquerda e centro da tela. Quatro participantes foram posicionados na frente do monitor LCD onde a interface foi executada. A interface foi desenvolvida em linguagem Python e, após a coleta do sinal, foi responsável por realizar filtragem, janelamento, extração de características (FFT) e classificação (SVM). Os resultados mostraram um bom desempenho ao utilizar um janelamento de 3 segundos com 250 ms de sobreposição. As taxas de precisão de classificação dos experimentos online foram altas, o que permitiu o controle de uma cadeira de rodas motorizada. Este sistema foi capaz de fornecer independência e aumentar a qualidade de vida dos usuários de cadeira de rodas. Trabalhos futuros envolvem adaptações e melhorias do sistema para aumentar a eficiência e fornecer mais confiabilidade ao usuário.

Palavras-chave: ICM baseada em PEV-RP, controle de cadeira de rodas, monitor LCD, localização de alvos, tamanho do janelamento, SVM

Abstract

Brain Computer Interfaces (BCIs) have been shown as a promising technology in the current years, especially for those wheelchair users affected by motor injuries or diseases. Steady-State Visual Evoked Potentials (SSVEP)-based BCI systems are widely used for many applications, such as keyboard and robot control, because of its short response time and ease of use. SSVEP-based BCIs use brain responses to any visual stimulus flickering at a specific frequency as input command to an external application or device. Although some SSVEP-based BCI applied to wheelchair control have shown promising results, there are specific features of the system that should be analyzed and discussed aiming to increase classification accuracy. This dissertation aims to develop and investigate the performance a SSVEP-based BCI system using LCD monitor as visual stimulator applied for wheelchair control. Two experiments were performed (offline and online). Through the offline experiment, performed by 9 participants, it was possible to identify EEG optimal channels, adequate window length for signal processing, and target location on the LCD screen. In the online experiment, 9 EEG channels (PO3, PO4, PO5, PO6, PO7, PO8, O1, O2 and Oz) were used to record the brain signal while using an interface with 5 stimuli targets (15, 12, 6.67, 8.57 e 10 Hz) placed on the top, bottom, right, left and center of the screen. Four participants were positioned in front the LCD screen where the interface was executed. The interface was developed in Python language and, after collecting the signal, it was responsible to perform filtering, windowing, feature extraction (FFT), and classification (SVM). The results showed a good performance while using a 3 seconds time-window with 250 ms of overlap. Accuracy rates from online experiments were high, which allowed the control of a powered wheelchair. This system can provide independency and increase quality of life of wheelchair users. Future works involve adaptations and improvements of the system to increase efficiency and provide more reliability to the user.

Keywords: SSVEP based BCI, wheelchair control, LCD screen, target location, window length, SVM

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Abbreviations and Symbols

Abbreviations

WHO: World Health Organization

IBGE: Brazilian Institute of Geography and Statistics

BCI: Brain Computer Interface

SSVEP: Steady-State Visual Evoked Potential

ITR: Information Transfer Rate

LCD: Liquid-Crystal Display

AT: Assistive Technologies

ALS: Amyotrophic Lateral Sclerosis

MPT: Matching Person and Technology

PSD: Power Spectral Density

FFT: Fast Fourier Transform

SVM: Support Vector Machines

CCA: Canonical Correlation Analysis

LDA: Linear Discriminant Analysis

ANN: Artificial Neural Network

EEG: Electroencephalogram

MI: Motor Imagery

SMR: Sensory Motor Rhythm

LED: Light-Emitting Diode

CRT: Cathode Ray Tube

SNR: Signal-to-Noise Ratio

LASSO: Last Absolute Shrinkage and Selection Operator

MEC: Minimum Energy Combination

SFT: Spectral F-Test

PCA: Principal Component Analysis

CSP: Common Spatial Pattern

EMD: Empirical Mode Decomposition

MSI: Multivariate Synchronization Index

SDK: Software Development Kit

LSL: Lab Streaming Layer

CAR: Common average reference

OAA: One-Against-All

RBF: Radial Basis Function

SMB: Seat Mobile do Brasil

Symbols

Na^+: Sodium

K^+: Potassium

Chapter 1

1. Introduction and Objectives

In this chapter, the contextualization of this document is introduced followed by the objectives, justifications, contributions, and the structure of the dissertation.

1.1. Overview and Motivation

Disability is a human condition that originates from one type on impairment that can be physical, cognitive/intellectual, mental, sensory, or a combination of these [1]. This impairment can be temporarily or permanently, and it may be present from birth or appear during a person's lifetime caused by an external injury or pathogens (disease), specially at old age [1, 2].

The disability induces restrictions on person's body functioning and structures, and it can affect the person's ability to socialize and interact with the environment and/or other people [1, 3]. A disability can be classified into mild, moderate, or severe [2]. A person with mild disability characterized the one with none or mild difficult to perform a task. The person that has some difficult to perform an action is diagnosed with a moderate disability. In addition, severe disability means the person has a lot of difficult or is unable to perform a task.

There are some environment and technological adaptations and/or new developments that have been done to help improve the quality of life of people with any type of disabilities. For example, sidewalks and transportation with accessible design, assistive technologies, devices aids (wheelchair, hearing aid, etc.), and signage for people with sensory impairments. Specifically, the development of device aids has been growing in recent years, aiming to assist people with disability [2].

According to the World Health Organization (WHO) [2], it is estimated that about 15% of the world's population live with some type of disability. Based on 2010 global population estimates, it represents more than a billion people. In Brazil, the Demographic Cense of 2010 performed by the Brazilian Institute of Geography and Statistics (IBGE) [3] expressed that approximate 23.9% (45.6 millions) of the Brazilian population declared experiencing any kind of deficiency. Figure 1 represents data referred to visual, hearing, motor, and mental/intellectual disability of Brazil's population in 2010 divided by its level of impairment (mild, moderate or severe).

The part of the population with severe disability consist of the main target of public policies directed to the population with disabilities [3]. People with severe motor disability are not able to move around by themselves, they represent approximate 0.39% (734 thousand) of the Brazilian population, which are the target users of the developed system in this master dissertation.

Wheelchair is one of the most known and used mobility aid. It promotes empowerment, independency, and overall well-being for those people with difficulty in walking or moving around. According to WHO (2011), there are more than 70 million of people in the world needing a wheelchair; however, only 5 to 15% of them have access to one. Mostly, wheelchair users may be people with motor (physical) or mental disability. A physical or mental impairment restrains the activity of cells (neurons, muscle fibers, etc.) which reduces the person's motor skills [1], leading to difficulty in lower and/or upper limb movements. Furthermore, people with restrains in upper and lower limb movements may not be able to walk and operate a manual wheelchair or a joystick on a conventional powered wheelchair [4]. These people should to be dependent from someone for the rest of their lives.

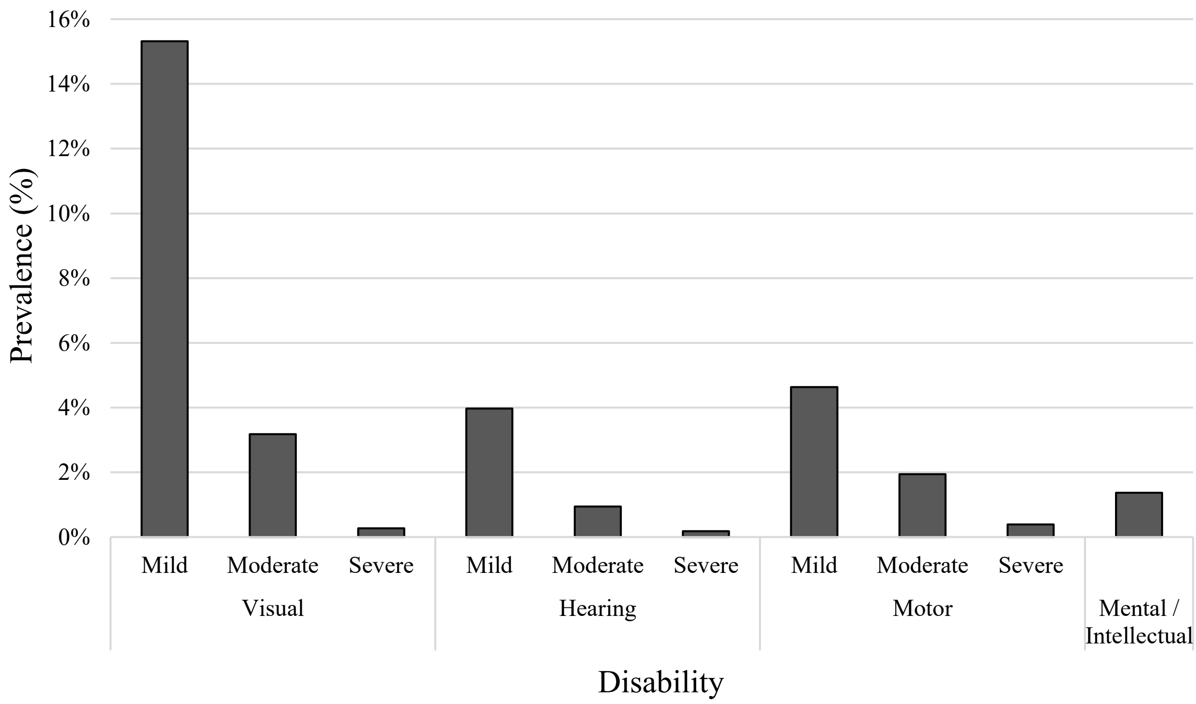

Figure 1. Percentage of Brazilian population with any type of visual, hearing, motor and mental/intellectual disability. The visual, hearing and motor disability are divided by its level of impairment (mild, moderate, or severe).

However, powered wheelchair control adaptations have been developed aiming to give these people more independence and quality of life. Some alternative control are head joysticks, chin joysticks, speech, and sip-n-puff [5]. An alternative method consists of monitoring specific bio-physiological signals related to user's body functions, such as brain or muscular activity [4].

Brain Computer Interfaces (BCIs) have been shown a promising technology. In BCIs, brain signals are recorded while reacting to specific stimuli (i.e. auditory or visual) or through a though or intention control (i.e. motor imagery), which are used as input commands to external device control [4]. The main goal of the BCI is to help people with motor impairment to restore the ability to move independently [6].

A BCI paradigm used in many BCI applications is the Steady-State Visual Evoked Potential (SSVEP) [7], which has been widely used for wheelchair control [8]. SSVEP is the brain activity generated in response to a visual flickering stimulus at a particular frequency, and the response signal is at or close to the same frequency of the stimulus [7]. SSVEP-based BCIs offer short response time, high Information Transfer Rate (ITR), ease of use with no or minimal training [6, 8-12]. However, there are still some specifications related to the interface design and signal processing that need to be discussed and improved for better system responses and increase of users' confidence while using the system, specially for BCIs applicable to wheelchair control.

1.2. Problem and Objectives

Interface design and signal processing steps of SSVEP-based BCI systems are not yet well-define in the literature. Interface design includes the characteristics of the visual stimuli and stimulator. SSVEP signal processing are related to signal pre-processing, feature extraction, and classification methods [13].

Overall, different authors have used different perspectives and parameters to develop SSVEP-based BCIs; some are complex, and others are straight-forward. In the review executed by Liu et al. (2014), these oscillations are confirmed, since different types of signal processing were exposed, and yet there is no strategy judged as the best one, as it is possible to get efficient results from different types of algorithms, which may be suitable for use in specific applications [13].

Besides this, online BCI applications are not yet clearly disclosed, since the classification accuracy may not be stable, which can compromise users' safety. In addition, most of these existing systems were not tested with people with disabilities. The goals of an efficient and practical SSVEP-based BCI systems should be lower preparation time, faster time responses, user-friendly interface, and user's comfort [13].

In this context, the aim objective of this study is to develop and investigate the offline and online performance of a SSVEP-based BCI applied to wheelchair control using Liquid-Crystal Display (LCD) monitor as visual stimulator.

The secondary objectives are the following:

1) Perform a literature review regarding SSVEP-based BCI using LCD screen to generate visual stimuli, and apply it to wheelchair control;
2) Develop and evaluate an offline interface to test different visual stimuli location emitted from an LCD screen, with different window length for the signal processing; and
3) Develop and evaluate an online interface with different modes for calibration, testing and online use.

1.3. Justification and Contributions

People with disability deserve new technology development and/or adaptations to help them socially interact, have easier access to information and education, facilitate activities of daily living, improve therapy/rehabilitation, and live with more independency.

For powered wheelchair users, SSVEP-based BCI systems can be an alternative to control them, which consists of brain activity interpretation while being stimulated by a visual cue (i.e.: light source or LCD). It is very important to prove the efficiency of this type of BCI system in order to satisfy users needs' and offer them autonomy.

However, to develop an efficient SSVEP-based BCI system, in order to provide faster responses, accurate classification results, and enhance the user's experience, all properties related to the interface design and signal processing should be better understood [13]. Essentially, the SSVEP-based BCI should be easy to use and minimize users' frustrations and/or fatigue. In addition, SSVEP-based BCI systems to control wheelchairs should improve quality of life and provide independency for those which disabilities but cognitively preserved.

In this study, we aim to contribute with relevant information about the current state of art of SSVEP-based BCIs using LCD screens and apply it to wheelchair control. In addition, this research provides new features and development strategies for this specific BCI system, since we develop and evaluate the performance of an offline and online approach. Besides it, this study details the development and test of an accessible and low-cost visual stimulator, which consists of an LCD screen associated with its hardware and software.

1.4. Outline of the Chapters

This master dissertation was organized in 5 Chapters. Chapter 2 reviews existing literature related to basic concepts of (1) assistive technologies (AT); (2) BCI anatomy, physiology, parameters, and applications; (3) SSVEP characteristics and applications. The Materials and Methods section is presented in Chapter 3, where offline and online experiments are described with the participants' information, experiment protocol, hardware and software details. Chapter 4 shows the results obtained from the experiments and discusses about them regarding what is presented in the literature. Finally, Chapter 5 discloses with final conclusions and future works.

Chapter 2

2. Literature Review

The literature review presented in this chapter is related to the development, applicability and use of assistive technologies and brain computer interfaces. Aspects related to the brain anatomy and physiology and signal recording are also discussed. An overview related to the SSVEP paradigm are introduced with details about the anatomy and physiology of the human eye where the stimuli are received, and, finally, the state of art of the SSVEP-based BCI systems using LCD screen as visual stimulator and applied to wheelchair control are presented.

2.1. Assistive Technologies

Physical and mental disabilities, such as spinal cord injuries and amyotrophic lateral sclerosis (ALS), can causes limitations of movements. Most of the people with this type of disability need help from others or from technology aids to communicate, move, learn, hear, and/or see. Technologies that assist people with disabilities allowed them to perform activities of daily living are known as Assistive Technologies (AT) devices [1]. An AT device can be defined as "any item, piece of equipment, or system, whether it is acquired commercially, modified, or customized, that is used to increase, maintain, or improve the functional capabilities of individuals with disabilities" [14]. Examples of AT devices include: crutches, orthoses, wheelchairs, hearing aids, cochlear implants, ocular devices, talking books, speech synthesizers. These devices have been shown as powerful tools to increase independence, improve learning and social interaction, and perform rehabilitation. In some countries, the national health care system includes the AT devices as an integral part of health care [1, 2].

AT devices need to be adjusted and adaptable to the user and the user's environment. It ranges from highly complex technologies to simple adjustments that can turn life more honorable and change lives; according to Able Data website [15], that consists of an information source related to products, solutions and resources of AT.

The AT products can be categorized into 20 groups, which are: (1) aids for daily living: products that assist activities of daily living; (2) blind and low vision: products developed for people with visual disabilities; (3) communication: products associated with communication skills, such as speech and writing aids; (4) computers: products that allow people with disabilities to use the computer and any type of information technology; (5) controls: products that provide people with disabilities control over devices, such as stop, start or adjust an electronic device; (6) deaf and hard of hearing: products developed for people with hearing disabilities; (7) deaf blind: products developed for people with both hearing and visual disabilities; (8) education: products that provide people with disabilities access to education and knowledge, such as materials and school instructions; (9) environmental adaptations: products that provide more accessibility to the environment; (10) housekeeping: products that assist in cooking, cleaning, and other activities as well as adapted appliances; (11) orthotics: products that support or supplement joints or limbs; (12) prosthetics: products developed for amputees; (13) recreation: products that assist people with disabilities while performing their athletic and leisure activities; (14) safety and security: products that protect health and home; (15) seating: products that turn seating more comfortable and safe; (16) therapeutic aids: products that assist health treatment, therapy, and training for certain disabilities; (17) transportation: products that allow people with disabilities to drive or ride in any type of vehicle; (18) walking: products that help people with disabilities to walk and/or stand; (19) wheeled mobility: products and accessories that enable people with mobility disabilities to move freely indoors and outdoors; (20) workplace: products that help people with disabilities at work.

This categorization helps health professionals, family members, caregivers, organizations and the user by himself/herself to learn and understand the AT options and programs available.

However, there are yet high abandonment rates related to AT devices because of the difficulties of interaction between users, their AT device and the environment [16]. According to Phillips and Zhao (1993), four factors that characterized the AT abandonment are highly related to the lack of consideration to the users' opinion, poor device performance, easy device acquisition, and change in users needs and/or priorities. For that reason, it is important to perform an evaluation regarding the appropriate match of user and AT device reducing the user's dissatisfaction and AT abandonment.

Through the Matching Person and Technology (MPT) process, it is possible to highlight and understand the user's expectations about the device and the benefits of the AT device for him/her.

The MPT Model (Figure 2) targets people with disabilities and consists of three primary rings that represent the levels of influences regarding user's personal factors, environments characteristics, and features and functions of the AT device itself [18].

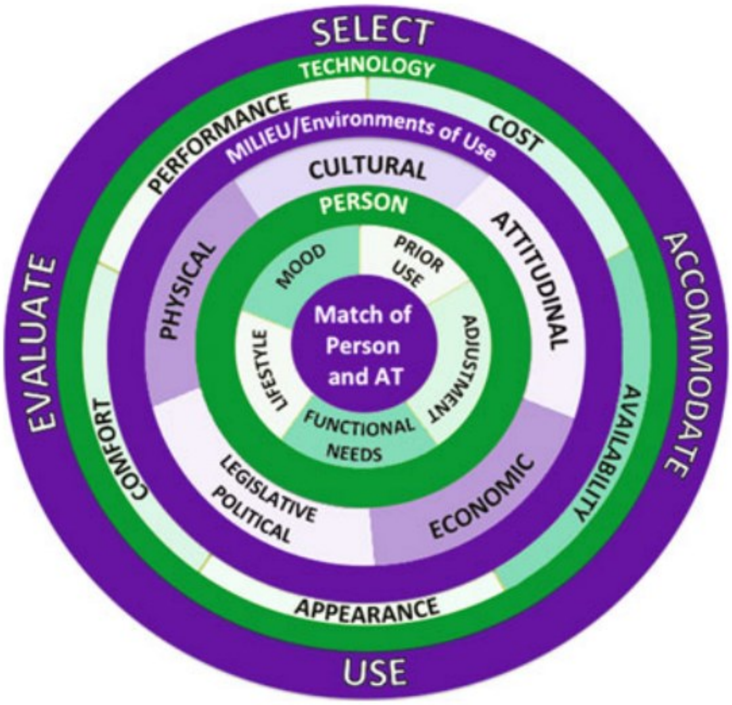

Figure 2. Example of The Matching Person and Technology conceptual model. *Source: Institute for Matching Person and Technology, Inc.*

The first ring of the MPT model is related to the user's individual characteristics and resources, and it consists of the five following items: (1) Functional needs question about the user's capability to performance and participation in desired area; (2) Adjustment item reports situations related to the benefit that the device or aid can provide to the user and questions about if this AT is really necessary to achieve the user's goal; (3) Prior use item lists the current and past AT devices the user used and question about why the actual devices are not sufficient and what is user's receptivity and predisposition to the use of the technology; (4) Mood arc represents the user's dreams, goals and biggest issues, it relates the current mood of the users if his/hers capacity to learn how to use the technology, and it analyses the reaction of the users when faced with life challenges; (5) Lifestyle item question about the importance and effectiveness of the technology in the user's life, and the interests and priorities of the user [18].

The second ring represents the characteristics and requirements of the environment (physical objects and people) where the user uses the technology, and it consists of the five following items: (1) Cultural arc represents the support and encouragement the family, caregivers and others will express for the use of the technology; (2) Attitudinal item refers to the difference between the user's family and caregivers expectations and the own user's expectations, and it also analyses the interference the AT can cause to others life; (3) Physical item lists the necessary support and environmental adaptations the user should need to use the technology; (4) Legislative/Political arc represents the legislation related to the technology use and the resources the user can get from the community to legally use the device; (5) Economic item question about the possible funding, and available and affordable assistance the user can considerate in case he/she needs it [18].

The last and third ring report the technology features which must be adaptable to user's needs and preferences; it highlights five items which are: (1) Availability item expresses the time that will take for the technology be available to the user and the need for adjustments or setup; (2) Appearance arc questions about the technology physical aspect and the affect of it on social interactions; (3) Comfort arc is related to the security and comfort while using the technology, and it also questions about fatigue, strain, or pain that the technology can cause; (4) Performance item regards the technology functioning, setup, maintenance, durability, portability, and resistance; (5) Cost item refers to the cost of acquiring and maintain the technology as well as its cost-benefit in a long term period [18].

The cycle that covers all rings is represented by four integrating approaches that should be performed in order to evaluate and measure the technology outcomes. The first step is the *Technology Selection* that decides for the most empowering choice for the user based on the collected information. After, on the *Use* step, it is necessary to verify if the technology had been assembled and set up correctly and if there were any changes in user's needs or the environment. The *Evaluation* step performs an evaluation of the use of the technology. Lastly, the *Accommodations* step refers to possible adaptations or customizations that can be performed to the technology to better match user's needs and goals.

The MPT process can contribute to clarifying the influences the AT use can cause to the user in a positive or negative way. If there are many positive influences, the chance of technology abandonment can be increased. However, if only a few negative items appear, this technology can be successfully accepted and used.

A type of AT that has been shown as a promising technology is the BCIs. BCIs are assistive technologies that can help people with disabilities, specially those with motor impairments who may not be able to use devices and perform tasks autonomously. This technology was adopted in this study to be apply for wheelchair control and will be studied in the next sections.

2.2. Brain Computer Interface (BCI)

BCI is a technology that allows direct interaction between user's brain activity and specific devices which do not depend on the peripheral muscles and nerves [19]. BCIs translates intention, thought, and responses to external stimuli into input control commands, allowing the user to operate external devices or applications [20, 21].

A BCI is designed based on different stages which involves the user, the brain signal acquisition, the signal processing, and the final device (Figure 3) [22]. At the end of the signal processing stage, a output signal should be generated and it corresponds to a different intention or command of the user for the BCI control [23].

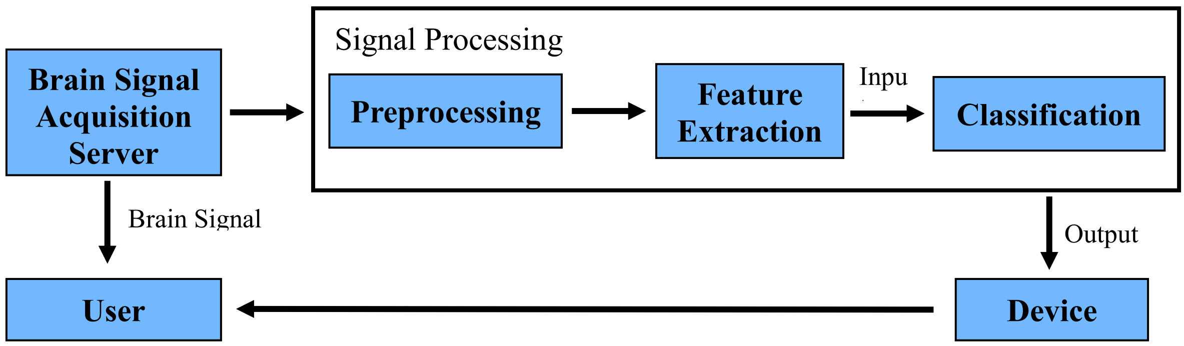

Figure 3. BCI system stages diagram.

The arrangement of the user and the acquisition server represents the first stage of the BCI system setup. More details related to the brain signal acquisition will be reported in the next section. After acquiring the signal, it should be processed, and the signal processing stage includes three main steps: preprocessing, feature extraction and classification.

The first one involves the signal preprocessing which filters the signal from artifacts and electrical noise. At this step the signal can also be divided into windows (epochs) that separate the signal in parts determined by amount of time or samples, improving the effectiveness of the next steps.

The second step refers to feature extraction, which is performed over a pre-define window signal. The chosen features should be able to best distinguish different classes and reduce signal dimensionality which increases the amplitude of the brain response and facilitates detection [24]. To perform an efficient feature extraction, it is crucial to transform the data to the appropriate domain [25]. Usually, features can be divided into two categories: features in time domain and features in frequency domain [26]. There are many types of feature extraction methods, such as Power Spectral Density (PSD) [10] and Fast Fourier Transform (FFT) [6], and its choice depends on the BCI application. Still, there is no feature extraction method applied to BCIs systems defined as an outstanding choice in the literature.

The last step of the signal processing is the classification. From this step, an output should be emitted and then control the final device. The classifier translates the input commands provided by the feature extraction step to perform a user's desired output [26]. There are many classification techniques, such as Support Vector Machines (SVM) [27], Canonical Correlation Analysis (CCA) [28], Linear Discriminant Analysis (LDA) [29], and Artificial Neural Network (ANN) [30]. There are both advantages and disadvantages for all classification methods. For example, SVMs are easier to configure in comparison to the ANNs, and it does not need a big amount of data for training [26].

2.2.1. Brain Signal

The nervous system consists of more than 100 billion neurons cells. It receives information from all the human organs and sensory nerves, processes them, and establishes responses to be executed by the body [31]. The brain functioning is manifested through electric activity. The neurons cells are specialized in reception, integration, and transmission of electrical impulses [32].

The main parts of a neurons cells are the cell body, dendrites and axon (Figure 4). Briefly, the cell body, also named soma, contains the cell nucleus, mitochondria, endoplasmic reticulum, microtubules, and neurofilaments. Dendrites conduct afferent impulses toward the cell body. Axon conducts efferent impulses away from the cell body to another neuron or organ [32].

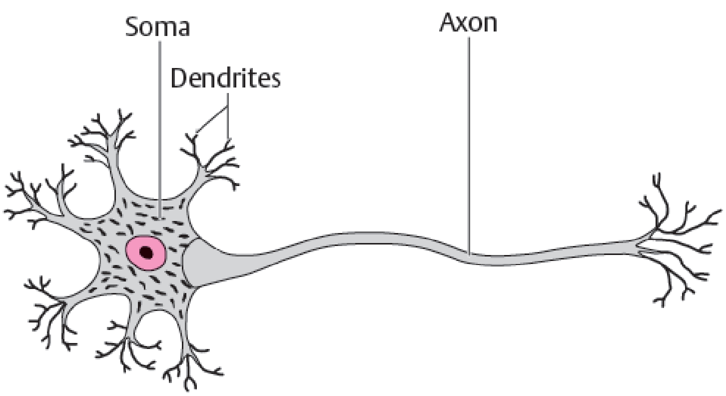

Figure 4. Neuron cell. *Source: Adapted from* [32].

Both dendrites and axon have terminals that work as information receiver and transmitter, respectively. Synapses are the gap between presynaptic (axon) and postsynaptic (dendrites, cell body or another axon) neuron where information is being transfer [32]. This information refers to nervous impulses that propagate by succession of neurons, one after another [31]. Dendrites can receive impulses from one or many axons; this input can be either excitatory or inhibitory. If the impulse is excitatory, the presynaptic neuron secretes a transmitting substance to stimulate the postsynaptic neuron; if inhibitory, the secreted substance provokes an inhibit action. These transmitting substances are called neurotransmitters; some examples of neurotransmitters are acetylcholine, dopamine, serotonin [32].

The neuron cell membrane is composed of proteins and lipids. The resting membrane potential is negatively polarized because there is ion difference, mostly sodium (Na^+) and potassium (K^+) ions, between the inside and outside of the cell, where the negative ion concentration is higher in the inner surface of the cell opposing to the higher positive ion concentration in the outer surface [33].

The electrical potential of the resting membrane ranges from -60 to -90 mV. However, this potential can be rapidly changed in response to an incoming impulse or stimulus. This change represents variations on the ion permeability across the cell membrane sustained by the selective permeability of the membrane and the active mechanisms of ion exchange, such as the sodium and potassium pump. When there is a stimulation, the membrane potential increases to +20 to +50 mV due to the opening of the sodium channels [32].

This phenomenon is known as cellular depolarization. After a brief delay, the potassium channels are activated and compensates the preceding sodium influx causing the repolarization of the membrane to its resting potentials [32]. Thus, this defines a complete cycle of the electrical transient called the action potential (Figure 5). The action potential propagates from the axon to the postsynaptic neuron [33] and it is responsible for the electrical brain signal generation.

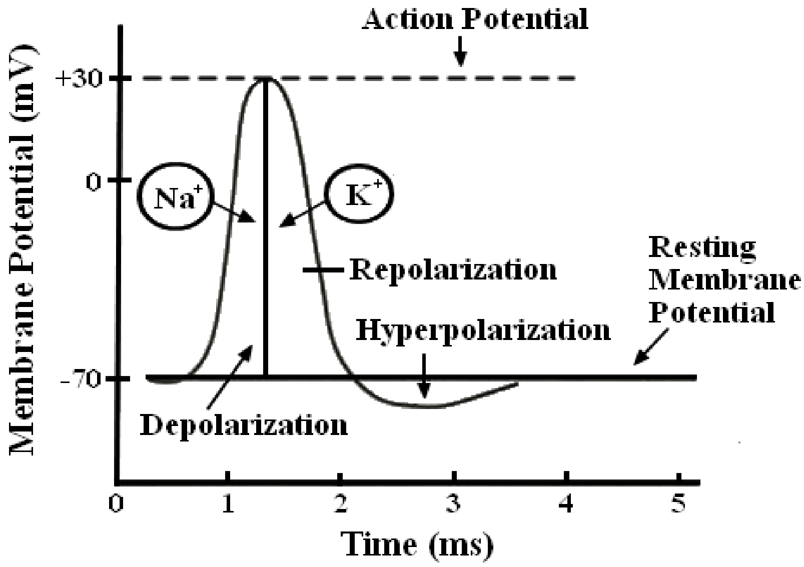

Figure 5. Action potential. *Source: Adapted from* [33].

2.2.1.1. Brain Regions

The human brain is divided into three main parts: (1) the cerebrum, (2) the cerebellum, and (3) the brain stem. The cerebrum is the largest part of the brain, and it is responsible for processing of the functions, such as memory and language. It is divided into two hemispheres, left and right, which are separated by a fissure and connected by the corpus callosum [34]. These hemispheres are divided into four lobes as shown in Figure 6: (1) frontal lobe, (2) parietal lobe, (3) occipital lobe, and (4) temporal lobe. The frontal lobe controls the higher brain functions related to motor control and planning. The parietal lobe is responsible for sensory perception, language and body orientation. The visual center is located in the occipital lobe. And, the temporal lobe controls the hearing, memory and feelings.

In addition, the cerebellum is an important part of the brain, it is responsible for the balance and coordination. On the other hand, the brain stem is connected to the spinal cord and controls important body functions, such as breathing, heart rate, body pressure and temperature. It is divided into three parts: (1) the midbrain, which is responsible for integrating and transmit signals to other parts of the brain, (2) the pons, which monitor the sleep and waking up functions, and it is the interconnection of neural tracts, and (3) the medulla oblongata (hidden brain), which contains the reflex centers, such ad the vasomotor and breathing center, and it is also immediately connected to the spinal cord.

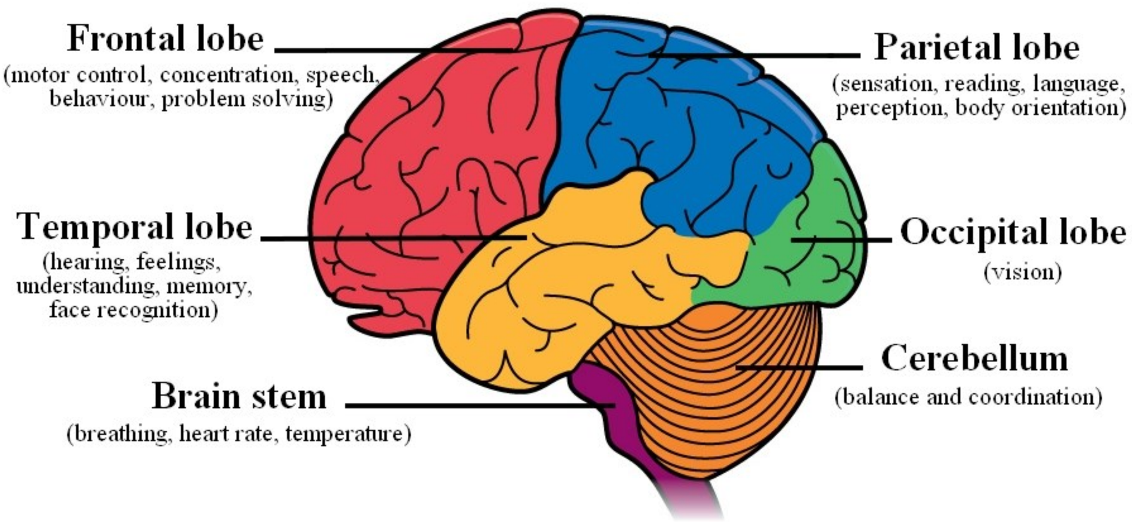

Figure 6. Brain regions. *Source: Adapted from https://www.macmillan.org.uk/information-and-support/brain-tumours/understanding-cancer/the-brain.html.*

2.2.2. Brain Recording: Electroencephalogram (EEG)

There are many techniques to record the physiological signal, which can be invasive (intracranial) or non-invasive. A non-invasive technique is the superficial electroencephalogram (EEG).

EEG is a simple method which places electrodes on the surface of the human scalp that detects the spatially averaged electrical activity over a cortical area [19, 23]. It is a widely used approach due to its temporal resolution, portability, ease of use, and relative low cost [13]. Some challenges associated with EEG signal recording are related to the physiological, environmental, and electronic noise sources [35]. Physiological sources arise from motion artifact (for example, eye blinking, head movement) and muscle noise. The environmental interference is related to external noise (for example, people talking, noise devices). Electrical sources include 50-60 Hz power line noise, radio frequencies (RF), and other electrically or magnetically interference. To solve these problems, measuring techniques and efficient design projects should be applied.

EEG electrodes can be dry or wet. The wet electrode needs an electrolytic gel to decrease the skin-electrode impedance in order to record high quality signals [35]. These electrodes are positioned at the scalp following the International 10/20 system, which places electrodes based on measurements that are performed in relation to the size of the head and location of the external cranial landmarks [36].

This system is very comprehensive and helps, through the electrode location, to diagnostic features, such as seizures spikes [35]. Figure 7A and 7B represent the measurement that follows the 10% and 20% of the distance between the Nasion and Inion in order to position the electrodes in their correct location; this represents the configuration for 21 electrodes, where 19 are positioned in the scalp and 2 are in the hears lobes. And Figure 7C represent 64 electrodes positioning configuration where electrodes are placed 10% of distance from each other. The electrodes are numbered based on the side of the brain they are located, right hemisphere uses even numbers and left hemisphere are the odd numbers. They are also labeled by their location on the scalp which are F for frontal, C for central, T for temporal, P for parietal, and O for occipital.

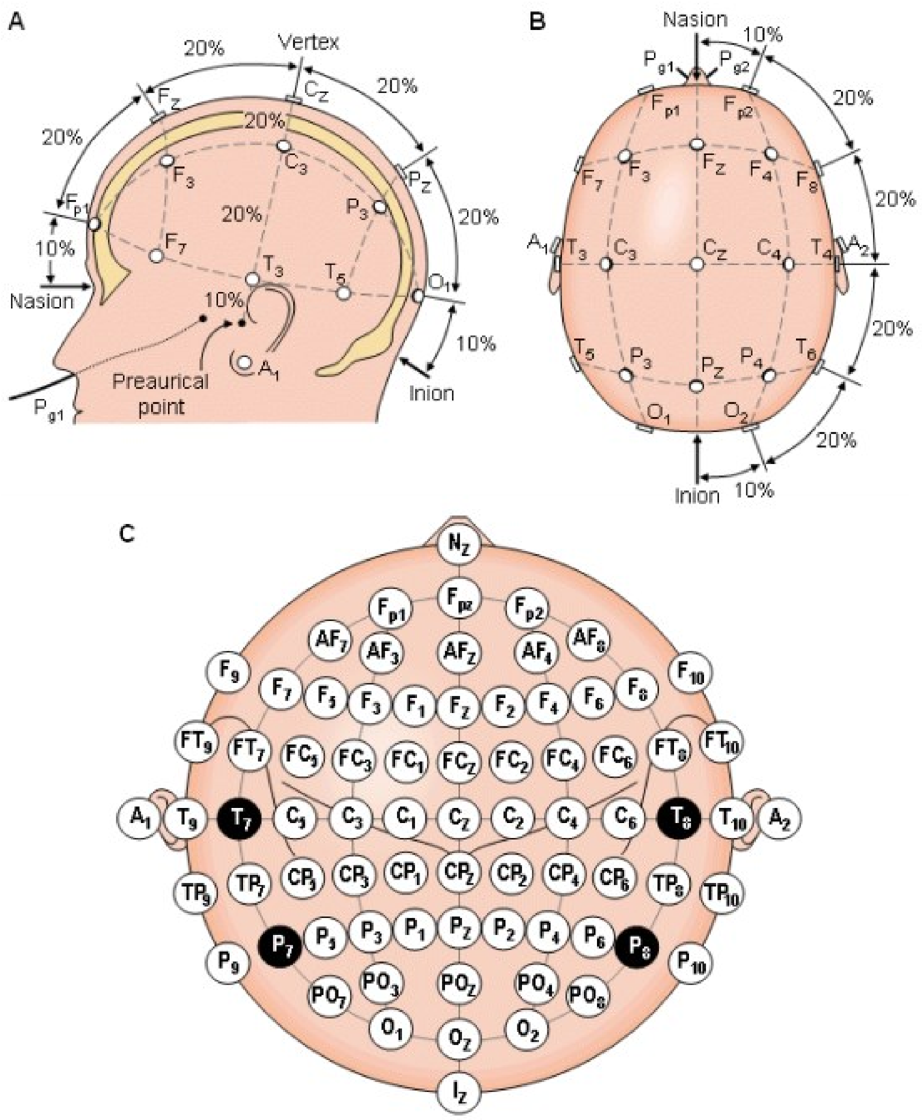

Figure 7. International 10/20 System represented by different perspectives. (A) Sagittal plane, (B) axial plane, and (C) location and nomenclature of 64 electrodes placement which where used in this study. *Source:* [34].

EEG signals have extremely small amplitudes (in the microvolt range) [35], around 20 to 100 μV and frequency bandwidth ranging from 0.5 to 70 Hz [33]. These frequency bandwidth range can be divided into different band frequencies named rhythms [33].

The most important rhythms are delta, theta, alpha, beta and gamma [33], and their characteristics are expressed in Table 1.

Table 1. Information referring to frequency, amplitude and period of different EEG rhythms. *Source:* [33].

Rhythm	Frequency (Hz)	Amplitude (μV)	Period (ms)
Delta (δ)	0.5 – 3.5	0 to 100 – 200	2000 – 286
Theta (θ)	4 – 7.5	30	250 – 133
Alpha (α)	8 – 13	30 – 50	125 – 77
Beta (β)	14 – 30	20	-
Gamma (γ)	> 30	10	-

Delta rhythm are associated with signal during the deep or slow wave sleep, and it is more predominate in newborns [37]. Theta waves are very difficult to detect, increasing in response to memory demands and during sleep at any age [33, 37]. Alpha activity is the most prominent in the EEG of a mature brain (older than three years). It is mostly located on the posterior-occipital region, and it is more accentuated in vigil with closed eyes and attenuates with eyes opening, attention increasing or mental exertion [33, 37]. Moreover, the amplitude of the alpha band is usually higher in the non-dominant hemisphere [33]. Beta waves are enhanced by states of increased alertness and focused attention and it is detected in the frontal-central regions depending on the performed task [33, 37]. Finally, the gamma band appears during active information processing, these are difficult to detect through superficial EEG [37].

2.2.3. EEG-based BCI Applications and Paradigms

EEG-based BCI systems can be used to various applications such as controlling a mouse cursor [38, 39] or a virtual keyboard [40], playing games [41, 42], control a robot [43, 44], browsing in the internet [45]. In the present study, we will be focusing on EEG-based BCI for wheelchair control.

EEG-based BCI systems can be categorized into two groups depending on the type of brain potential used, which are: endogenous and exogenous [46]. Endogenous signals are evoked by the own user's desires [21], such as Motor Imagery (MI) paradigm which represents signals elicited when the user imagines the movement ow action he/she wants to perform. By its turn, exogenous signals are evoked by external stimuli presentation [21], such as P300 evoked potentials, Sensory Motor Rhythm (SMR) and SSVEPs [9]. For the present study, the SSVEP paradigm is adopted and it is explained in the next section.

2.3. Steady-State Visual Evoked Potentials (SSVEP)

To understand the EEG signal recording during a visual stimulation, it is important to learn the anatomy and physiology of the eye and how the visual stimuli affects the brain signal.

The eye is an organ whose function is to detect and interpret the electromagnetic waves with wavelengths ranging from 400 (high energy, violet color) to 750 nm (low energy, red color), which consist of the visual light spectrum [47].

Basically, the eye can be divided into two segments: the anterior and the posterior (Figure 8) [48]. The anterior segment consists of cornea, aqueous humor, iris, pupil, ciliary body and crystalline lens. The posterior segment presents the sclera, choroid, retina, fovea, macula, optic nerve (or disc), and vitreous humor.

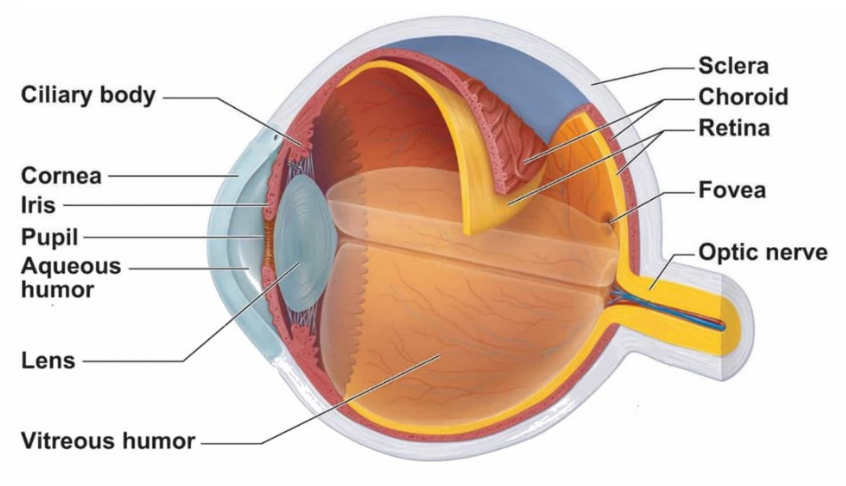

Figure 8. Eye anatomy. *Source: sites.google.com/a/bcssd.com.*

The eye globe consists of three layers: the external, medium and intern [47]. The external layer (or fibrous layer) is directly exposed to the external environment. It contains the cornea, which is transparent, with its epithelium (the conjunctive) and the sclera, which is opaque. The aqueous humor is an optically clear ocular fluid that maintains the cornea vitality by supplying glucose and oxygen [48].

The medium layer (or vascular layer) includes the iris and the choroid [47]. The iris contains muscular fibers that compose the pupil dilator muscles. The pupil is an opening in front of the lens that regulate the amount of light is admitted on the retina. Other important anatomic structure at this point is the ciliary body. It is responsible for secreting and draining the aqueous humor, and it contains muscular fibers that help to adjust the focus on the crystalline lens. The crystalline lens are transparent and biconvex, it is located behind the pupil and iris with the support of the ciliary body's fibers. It controls light entry and its refraction. The other part of the medium layer is the choroid which is highly vascularized and contribute to the vascularization of the retina. Other humor that fills the space between the lens and the retina is the vitreous humor which is a gel composed by extracellular fluid containing collagen and hyaluronic acid [47].

Finally, the most intern layer contains the retina. The fovea is the center of the macula, small region on the back of the eye in the retina, and it is an import region of visual acuity [48]. Photoreceptor cells are located in the fovea, and they consist of rods and cones that are capable to capture and convert the light photons into a nerve signal. Essentially, the light enters the eye and reaches the photoreceptors. The rods have high sensibility in detecting the low intensity light, but there do not contribute to the visual image or color vision. On the other hand, the cones are not sensitive to the light, which means they are more effective in day light. The cones are responsible for the visual acuity and color vision. Thus, the retina is responsible for transforming the received image or visual stimuli, by the photoreceptor cells, to electric signals which are transmitted through the nervous cells (axons) presented at the optic nerve to the visual cortex of the brain where it will be interpreted.

2.3.1. SSVEP Paradigm

One of the most used BCI paradigms is the SSVEP [7]. SSVEPs are generated by neuro activities in response of a repetitive or flickering at a particular frequency. Usually, these potentials are more prominent in the visual cortex (occipital lobe) since it is stimulating the vision [21, 49]. The brain signal obtained during the stimulation is synchronized with the stimuli. The amplitude of the recorded signal should increase at the same place or closer to the fundamental and harmonics frequencies of the visual stimulus [24, 27].

SSVEP-based BCIs have been used for many applications due to its short response time, high ITR, and ease of use with minimal or no training [9–11].

The visual stimulus can be generated by an LCD, Light-Emitting Diode (LED), Cathode Ray Tube (CRT) [50, 51]. Cecotti, Volosyak and Gräser (2010) reported no significant difference between the potentials provoked by the LCD and CRT. LEDs have been shown as reliable choice for visual stimulator, which can produce higher potentials as compared to the others [52].

However, to develop LEDs visual stimulators, it is necessary additional hardware and software which can demand time and increase cost of the system [52]. On the other hand, LCDs have been shown as promising visual stimulators due to its low cost and ease access, and it can achieve satisfactory performance for SSVEP-based BCI applications [51, 53]. However, the LCD screen has a restriction related to its limited refresh rate which results in a lack of frequency modulation, which should be considered by the developer while choosing the stimulating frequencies [53–55]. The present study uses LCD screen as visual stimulator.

Other characteristics that should be considerate are related to the interface design and signal processing. The interface design, besides the visual stimulator choice, involves the distance between the user and the stimulus, the distance inter-stimulus, the color of the stimulus as well as its size and shape, and the stimulation frequencies. The viewing distance can influence directly in the properties of the generated signal, such as time-locked and phase-locked to visual stimuli [56]. On the other hand, the distance inter-stimulus is important because a stimulus can influence another stimulus depending on the spacing between them [24]. When the distance increases, the classification accuracy improves [57].

The shape and size of the visual stimulus can induce differences on the signal power at the fundamental and harmonics frequency [58]. It is known that higher contrast between the background color and the stimulus color as well as larger size as possible invokes higher potentials and increase visibility and brightness [9, 24, 59]. The most used background color is black; however, the color of the stimulus varies between studies. Some authors chose the white color as the most efficient one [60, 61], and other reported that the violet color generates the most accentuated brain responses as compared to green, blue and red [62].

Finally, the stimulation frequency is also a significant parameter to the system. SSVEPs can be evoked by frequencies in three different bands: (1) high-frequency (30 to 60 Hz); (2) middle-frequency (12 to 30 Hz); and (3) low- frequency (5 to 12 Hz) [54, 63]. In addition, the band between 10 to 30 Hz evokes stronger potentials and higher Signal-to-Noise Ratio (SNR) [9].

Regarding the signal processing, it involves three main steps as mentioned in *Section 2.2*: preprocessing, feature extraction and classification. For SSVEP-based BCI systems there is not yet defined a most effective feature extraction and classification method. In the review performed by Liu et al. (2014), the most used feature extraction were PSD, phase analysis, CCA, Last Absolute Shrinkage and Selection Operator (LASSO), Minimum Energy

Combination (MEC), and FFT. In addition, referring to the classification methods, they found that LDA and SVM have been mainly used.

2.3.2. Current State-of-Art of SSVEP-based BCIs using LCD visual stimulator applied for wheelchair control

Since this present study will be investigating the performance of a system designed with SSVEP-based BCI with visual stimuli generated by LCD screen and applied for wheelchair control, it is important to understand the current state-of-art of this topic.

In parallel to this master dissertation, a literature review was performed with bibliometric and systematic analysis on this specific topic which obtained 17 articles that were analyzed. In this section, the following information will be reported: (1) evolution over the years of this area; (2) visual stimulus location on the screen; (3) stimulating frequencies adopted by the authors; (4) used feature extraction with its respective accuracy result; (5) used classification method with its respective accuracy result.

The investigation through bibliometric review showed the evolution over the years of this area of study, in which most of the articles were published in 2014 (Figure 9). Through the systematic review, it was possible to understand about the visual stimuli location, where most of the found articles revealed 4 targets (top, right, bottom and left of the screen), resulting in an arrangement as intuitive as possible for wheelchair control, which indicates “forward”, “turn right”, “turn left”, and “stop” or “backward”. However, none of them adopted five stimulation frequencies at the same time as in this master dissertation. When adopting just 4 targets, the backward movement is, normally, not included, but we think it is relevant to have it, since we want to provide the user more independency and freedom to move around.

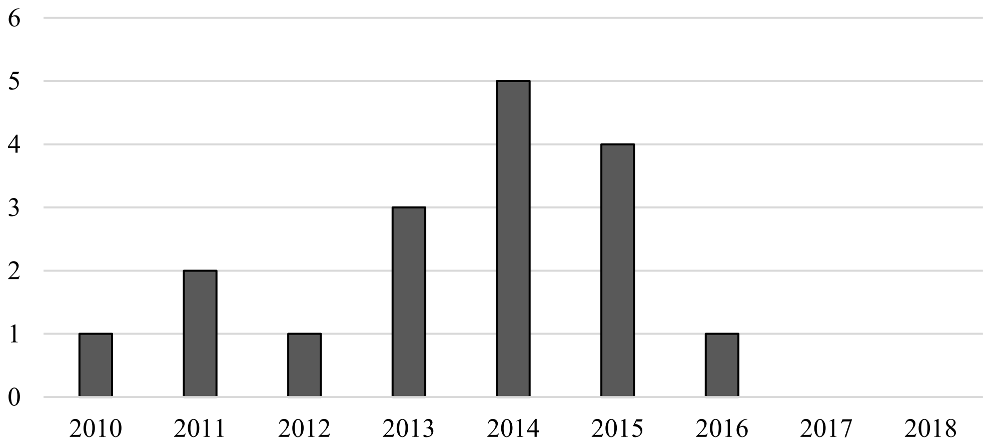

Figure 9. Evolution over the years of studies on SSVEP-based BCIs using LCD as visual stimulator applied for wheelchair control.

The systematic review also showed the most adopted stimulation frequencies for SSVEP-based BCI for wheelchair control (Figure 10). The most used one was 8 Hz followed by 11 and 13 Hz. However, authors normally do not discuss clearly how these frequencies are generated and if they are reliable. In this master dissertation, we provide the validation of the visual stimulation through a photodiode.

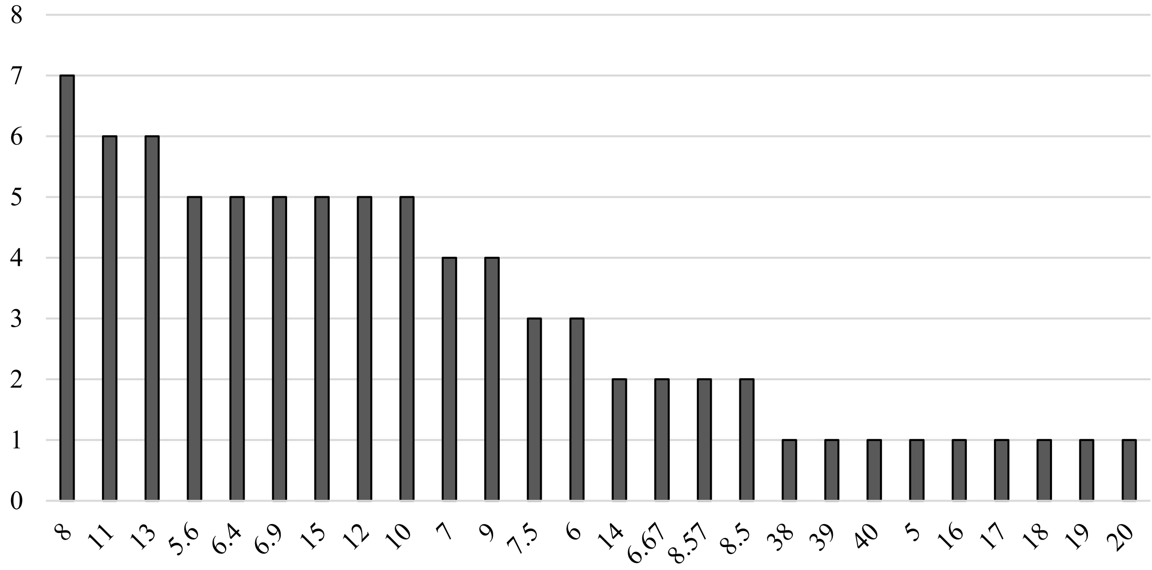

Figure 10. Most used stimulation frequencies in the researched articles related to SSVEP-based BCI using LCD as visual stimulator applied for wheelchair control.

Other important information regarding the development of this specific SSVEP-based BCI system is the feature extraction and classification method. Among the included studies, the feature extraction methods were heterogeneous (Table 2). The Spectra F-Test (SFT), PSD, FFT, and CCA were the highlighted methods used by the studies, where the study that used PSD [10] and other that used CCA [64] obtained the best classification accuracies.

Figure 11 shows the box plot of different feature extraction methods used in the experiments performed by the 17 selected articles. The methods involving PSD + SFT, PCA + PSD, and CSP + CCA represent hybrid systems, which used more than one BCI paradigm at the same system. The plots for these methods are represented for only a line because there were only one accuracy results for each one of them, making it difficult to analyze in this chart. On the other hand, the FFT shows as a promising choice, since its distribution is the smallest one, and it can produce satisfactory classification results. For that reason, this master dissertation adopted this method.

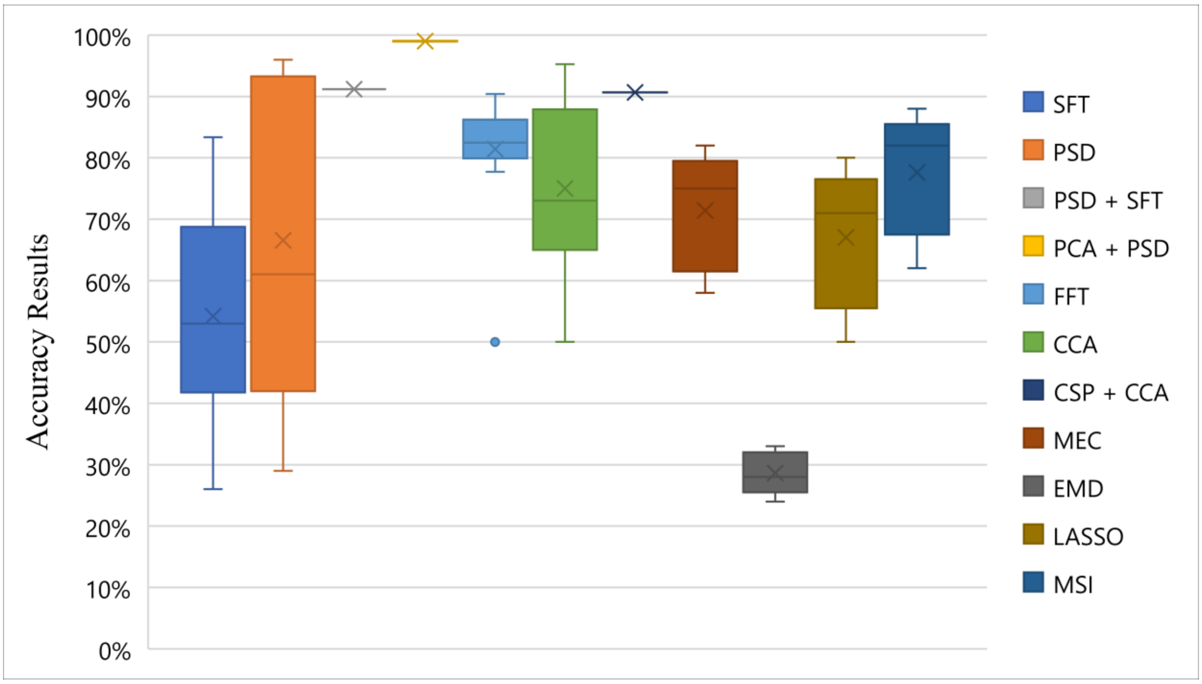

Figure 11. Box plot of the feature extraction methods and their respective accuracy results.

On the other hand, regarding the classification methods, the most used one among the studies was a decision tree method created by the own authors followed by SVM, threshold method, CCA coefficient analysis, statistical classifiers, LDA, and ANN, as shown in Table 3. The classification method that obtained the highest average of accuracy was the threshold method associated with statistics, followed by CCA.

Overall, the best classification result obtained among the 17 selected articles in the review was from Fan et al. (2015), that adopted a hybrid system using SSVEP and P300 paradigms. They obtained an accuracy of 99.07% in laboratory tests using PCA for P300 feature extraction, PSD for SSVEP feature extraction, and using LDA classifier.

Another important observation is that most of the studies performed an offline analysis, those that adopted online tests either did not expressed their results clearly [72] or they had low accuracy [66]. Clarity in exposing the process of experiments with an online approach is not seen in most articles. It is intended in this master dissertation to be clear about the details involved in the development of an offline and online SSVEP-based BCI system.

Table 2. Compiled papers with main characteristics referring to the feature extraction method and its respective accuracy rate.

Studies	Feature Extraction	Approximated Accuracy
[8]	peaks of SFT	73%
[65]	peaks of SFT	-
[66]	peaks of SFT	83.33%
[67]	peaks of SFT	54%
[43]	PSD (Welch)	-
[10]	PSD of fundamental, second, and third harmonics frequencies	2D: 93% Virtual environment: 96%
[8]	PSD and peaks of SFT	91.17%
[29]	PCA (P300) and PSD of fundamental and second harmonic frequencies (SSVEP)	P300: 90.68%[2] and 88.99%[3] SSVEP: 93.55%[2] and 90.48%[3] Both: 99.07%[2] and 98.93%[3]
[68]	statistical average (P300) and MEC and PSD (SSVEP)	Not clear
[62]	FFT coefficients of fundamental and second harmonic frequencies	ANN-FFBP: 77.71%, 79.27%, 79.69%, 83.76%[4] ANN-CFBP: 80.94%, 81.46%, 81.58%, 86.26%[4] SVM: 86.15%, 86.35%, 85.83%, 89.17%[4]
[69]	FFT	-
[6]	FFT	50%
[70]	FFT coefficients of fundamental and second harmonic frequencies	ANN-FFBP: 80.63% ANN-CFBP: 83.33% SVM: 90.42%
[71]	CCA (fundamental and second harmonic frequencies)	checkerboard target: 82% uniform target: 69%
[64]	CCA	95.25%
[72]	CSP (MI) and CCA (SSVEP)	MI: 98.77% SSVEP: 93.73% Both: 90.63%
[73]	PSD, SFT, MEC, EMD, CCA, LASSO e MSI (fundamental, second, and third harmonics frequencies)	PSD: 29%, 32%, 52%, 52%, 61%[1] SFT: 26%, 39%, 50%, 52%, 56%[1] MEC: 58%, 65%, 75%, 77%, 82%[1] EMD: 24%, 28%, 27%, 31%, 33%[1] CCA: 50%, 61%, 71%, 73%, 80%[1] LASSO: 50%, 61%, 71%, 73%, 80%[1] MSI: 62%, 73%, 82%, 83%, 88%*[1]

[1] Results for 1, 2, 4, 5, 10 seconds windows, respectively, using stimulation by LCD.
[2] Results for experiments performed in laboratory driving conditions.
[3] Results for experiments performed in real driving conditions.
[4] Results for blue, green, red, and violet colors, respectively.

Table 3. Compiled papers with main characteristics referring to the classification method and its respective accuracy rate.

Studies	Classifier	Approximated Accuracy
[8]	decision tree method	73%
[65]	decision tree method	-
[66]	decision tree method	83.33%
[67]	decision tree method	54%
[43]	-	-
[10]	threshold method not specified and statistics	2D: 93% Virtual environment: 96%
[8]	threshold method and decision tree	91.17%
[29]	LDA	P300: 90.68%[2] and 88.99%[3] SSVEP: 93.55%[2] and 90.48%[3] Both: 99.07%[2] and 98.93%[3]
[68]	SVM and decision-making strategy	Not clear
[62]	ANN and SVM	ANN-FFBP: 77.71%, 79.27%, 79.69%, 83.76%[4] ANN-CFBP: 80.94%, 81.46%, 81.58%, 86.26%[4] SVM: 86.15%, 86.35%, 85.83%, 89.17%[4]
[69]	-	-
[6]	threshold method not specified	50%
[70]	ANN and SVM	ANN-FFBP: 80.63% ANN-CFBP: 83.33% SVM: 90.42%
[71]	statistics and LDA	checkerboard target: 82% uniform target: 69%
[64]	CCA coefficient	95.25%
[72]	SVM (MI) and CCA coefficient (SSVEP)	MI: 98.77% SSVEP: 93.73% Both: 90.63%
[73]	PSD: PSD value SFT: decision tree method MEC: MEC coefficient EMD: decision tree method CCA: CCA coefficient LASSO: LASSO coefficient MSI: MSI coefficient	PSD: 29%, 32%, 52%, 52%, 61%[1] SFT: 26%, 39%, 50%, 52%, 56%[1] MEC: 58%, 65%, 75%, 77%, 82%[1] EMD: 24%, 28%, 27%, 31%, 33%[1] CCA: 50%, 61%, 71%, 73%, 80%[1] LASSO: 50%, 61%, 71%, 73%, 80%[1] MSI: 62%, 73%, 82%, 83%, 88%*[1]

[1] Results for 1, 2, 4, 5, 10 seconds windows, respectively, using stimulation by LCD
[2] Results for experiments performed in laboratory driving conditions.
[3] Results for experiments performed in real driving conditions.
[4] Results for blue, green, red, and violet colors, respectively.

Chapter 3

3. Material and Methods

The objective of this section is to describe the materials and methods used in the experiments. These were performed during February to July 2018 at the Assistive Technology Centre (NTA) of the Federal University of Uberlândia (MG-Brazil), which was approved by the local ethics committee and by the National Commission of Ethics in Research of the National Council of Health (CAAE: 37756614.0.0000.5152).

Details related to the EEG acquiring equipment are described in first place. In sequence, the first experiment is presented, which involves offline evaluation related to the visual stimuli emitted from the LCD screen. Two different arrangements (cross and square) were tested in order to identify the most effective one that provokes less interference inter-stimulus on the brain signals. After, a second experiment was performed. The developed interface design in the second experiment was based on the results obtained from the first experiment. The aim of the second experiment was to execute online tests of the developed SSVEP-based BCI system. In other words, in this experiment the EEG signals were collected, and the signal processing was performed, resulting in an output control, was used to control a wheelchair.

3.1. EEG Acquiring Equipment

In this section, the hardware and software associated with the performed experiments will be presented.

3.1.1. Hardware

The amplifier device used to record the EEG signals was the EEGO™ rt, with a waveguard™ original cap of 64 electrodes from ANT Neuro corporation (NL) (Figure 12). This cap is based on the modified international 10/20 system electrode positioning (as shown previously in Figure 7). It is very light-weight with thin electrode wires, and it is reasonably flexible and comfortable for the user. The electrodes are made of sintered Ag/AgCl and a conductor gel is used to reduce the electrode-skin impedance. All electrode-skin impedances were maintained below 10 kΩ during the experiments to ensure less interference and accuracy of the acquired data. This device is also very small and portable. It assures high-quality data streams with resolution of 24 bit and a sampling rate of 2048 Hz.

Figure 12. ANT-Neuro EEG amplifier device and the waveguard cap. *Source: https://www.ant-neuro.com/products/eego_rt.*

3.1.2. Software

Through the Software Development Kit (SDK), it was possible to get direct access to the EEGO amplifier. The ANT-Neuro is compatible to all major open source BCI platforms. Thus, we connected to this device through the OpenViBE platform to acquire the signal. The OpenViBE is an open-source software platform for BCI and real time neurosciences. It is dedicated to acquiring, filtering, processing, classifying and saving or visualizing brain signals in real time.

For the first experiment, a four-poles Butterworth bandpass filter of 0.1 to 40 Hz was used, and then the EEG signal was saved in two different extension: .ov (OpenViBE extension) and .csv (Comma-Separated Values extension) for posterior analysis. For the second experiment, the same filter was used in addition to a channel selector that acquired the signal only from the optimal channels found in the first experiment analysis. After filtration and channel selection, the signal was transmitted online thought the Lab Streaming Layer (LSL) protocol to the developed python interface, which is described in the next sections. The LSL protocol is specialized in exchanging streaming data between applications.

3.2. Experiment 1: Target Location and Window Length Evaluation

This section describes the development and details of the offline experiment structures, which are related to the visual stimulation generation, involved participants, experimental proceedings and signal processing.

3.2.1. Visual Stimulator Development

To guarantee reliable visual stimuli, a visual interface was designed using a video editor and played on a 14-inches LCD monitor with resolution of 1366 by 768 pixels. Since the LCD screen used in this experiment has 60 Hz refresh rate, the stimulating frequencies chosen were 6.67, 8.57, 10, 12 and 15 Hz, which are usually used in the literature [74, 75]. In addition, when choosing the stimulation frequency it is important that a frequency is not harmonic of another chosen frequency [76]. The video was developed setting the information of time-period calculated by the Equation (1),

$$T = \frac{\frac{1}{f}}{2} * 1000\ (ms), \qquad (1)$$

where T represents the period of one flicker in milliseconds, and f is the value in Hz of the flickering frequency. Thus, each frequency has its specific time-period for the correct flickering to the white squares (Table 4).

Table 4. Stimulating frequencies and their respective flicker time-periods used in the interface.

Frequency (Hz)	Flicker On (ms)	Flicker Off (ms)
6.67	75	75
8.57	58	59
10	50	50
12	41	42
15	33	34

All the visual stimuli were verified by an oscilloscope and a circuit with photodiode. Figure 13 represents the photodiode circuit and the oscilloscope wave for the 6.67 Hz frequency. Table 5 presents the values obtained on the oscilloscope for each stimulation frequency.

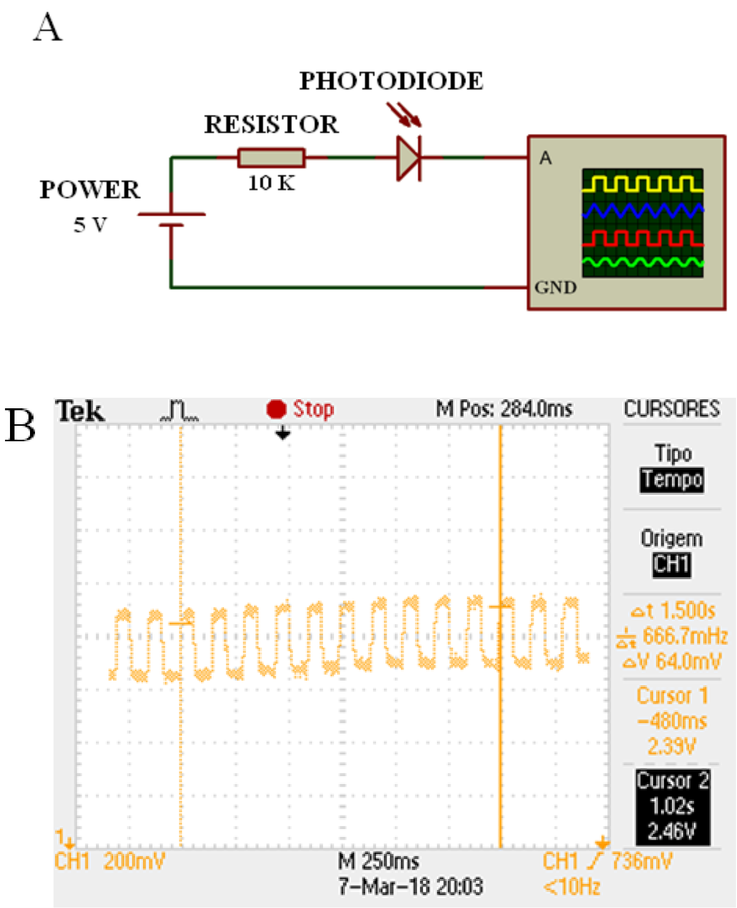

Figure 13. A) Photodiode circuit; B) Oscilloscope results for the frequency of 6.67 Hz.

Two different interfaces were developed with different visual stimuli arrangements using the five frequencies. These interfaces are referred to as “cross” and “square”, where the first interface reminds a cross image where the targets are located on the top, right, bottom, left and center of the screen, and the second interface creates a square shape due the location of the corner targets, which are located on the top-left, top-right, bottom-right, bottom-left and center (Figure 14). In all interfaces the stimulus had white color with black background and size of 155 x 155 pixels.

Table 5. Oscilloscope values for each stimulation frequency.

Frequency (Hz)	Oscilloscope Frequency (Hz)	
	Interface “cross”	**Interface “square”**
6.67	6.67	6.67
8.57	8.33	8.33
10	9.90	10.10
12	11.79	11.74
15	14.62	15.06

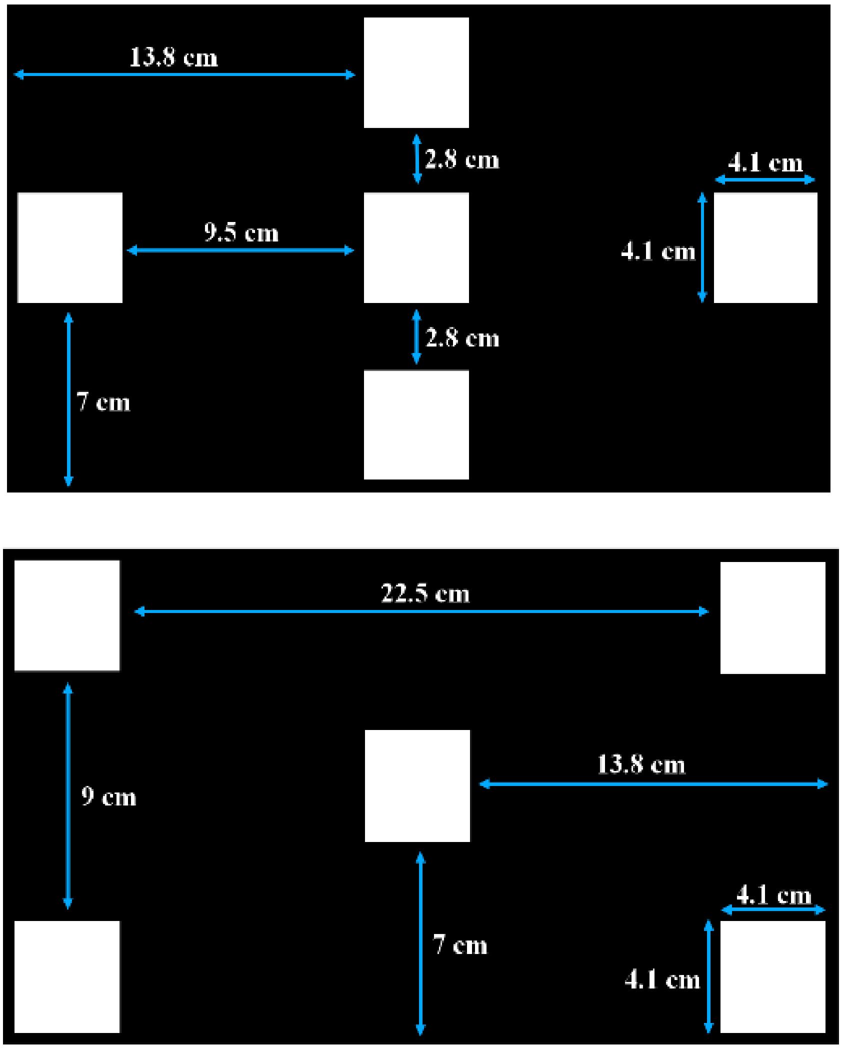

Figure 14. Interface "cross" and interface "square" are presented with their respective measurements (in cm) between targets and the target size.

3.2.2. Participants

Nine participants (2 males and 7 females, 24.11±3.07 years) were asked to participate in this study. All of them signed the informed consent form. To be included in the study, the participants had to:

- not present any type of cognitive or physical deficit;
- have normal or correct-to-normal vision;
- be over 18 years old;
- be able to arrive by themselves at the university' facility where the experiment took place;
- be available for two consecutive hours; and

• have their hair washed without conditioner and dried.

3.2.3. Experimental Procedure

The participants were positioned in a comfortable chair at 60 cm away of the LCD monitor where the visual stimulation was presented. The EEG cap was placed at the participant's head and a conductor gel was applied to reduce electrode-skin impedance. Figure 15 shows a participant performing the experiment.

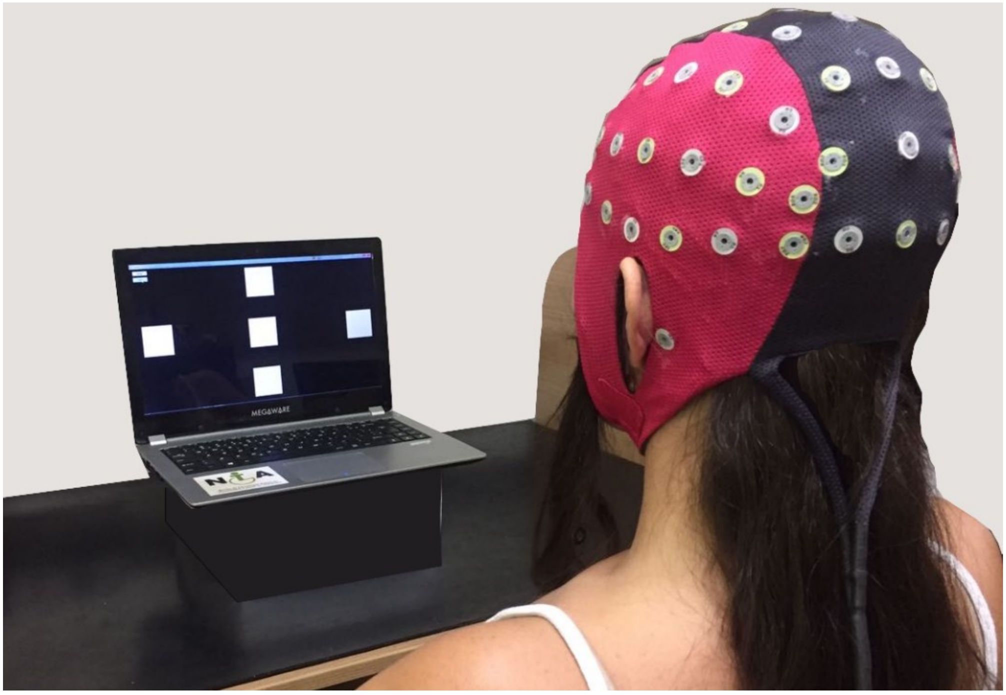

Figure 15. Participant positioned in front of the LCD screen while performing the experiment.

Each experiment was conducted for approximately two hours, from the placement of the electrode cap to the end of the entire protocol for each participant. All participants experienced both interfaces, and a random order for interface use was established between participants, which means some of them started the experiment using the interface "cross" and others the "square". Thus, the experiment was divided into two similar parts, where in each one of them a type of interface was used.

In each part, 10 trials of 110 seconds were performed, which consisted of 10 seconds at a resting state, 10 seconds performing the task (i.e. looking at a stimulus), and so on (Figure 16). All participants were instructed to avoid eye blinking and body movements while performing the task. At each 10 second, the participant should look to a different visual target on the screen. The sequence of targets was always clock-wise, where the first target in the interface "cross" was the top one and the last was the center, and for the interface "square", it started from the top-left to the center. The participant was oriented to change targets through a verbal command. The interval between trials was of one second, and the interval between different interfaces was of two seconds.

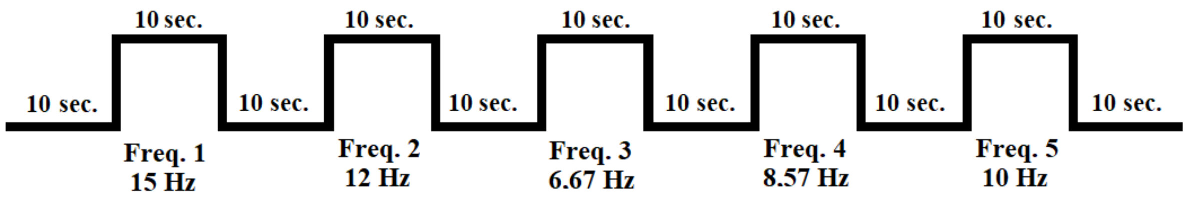

Figure 16. Representation of each trial setup with its respective frequency sequence.

3.2.4. Signal Processing

The EEG data was processed offline through MATLAB software from MathWorks® Incorporation (US). The signal processing consisted of three main parts that are described in this section: filtering and epoching, feature extraction and normalization, and classification. These are all important parts to identify the efficiency of each interface.

3.2.4.1. Filtering and Epoching

The signal was filtered using a bandpass Chebyshev Type II filter from 3 to 40 Hz with the order and cutoff frequencies provided by the `cheb2order` function. This filter was used because it showed better performance compared to the bandpass Butterworth filter. A common average reference (CAR) spatial filter was also used to remove common noise and improve the quality of the signal.

After filtering, it was necessary to divide the recorded signal in small time-window samples to be analyzed. Since ten seconds were recorded for each frequency during each trial, the first and last seconds were discarded to account for fatigue and possible head and/or eye movements, resulting in 8 seconds effectively analyzed. Then, the signal was divided into three different window length, which were: one, two and three seconds time-window (epochs) all with 250 ms of overlap. So, for the 1 second window, the number of epochs obtained was 290; for the 2 second window, this number was 250 epochs; and for 3 second window, 210 epochs.

3.2.4.2. Feature Extraction and Normalization

After filtering and epoching, the next step consisted of two different parts. The first one aims to identify the EEG optimal channels, and the second aims to obtain accurate results while differing the stimulation frequencies for the three different time-window used through signal processing.

For the first way, a signal averaging was performed over all time-window epochs for each participant. Afterwards, the Welch's PSD was performed over the averaged signal. To execute this step, the `pWelch` function available on MATLAB was used. The time-window signal was divided into 8 segments with a 50% of overlap, and these results were averaged to obtain the Welch's PSD estimate. Finally, a statistical analysis using Z-score was performed over the PSD data in order to obtain the optimal channels among all participants.

For the second way, an FFT from 3 to 20 Hz was used as feature extraction over each one of the epochs for each window length per participant. Only the signal from the optimal channels were used at this step. The FFT signal of each epoch was normalized from -1 to 1, and organized in a matrix, where the FFT signal for each channel where lined up in the same line of the matrix for each stimulation frequency. Moreover, an array was created with the respective frequency targets referred to each line of the signal matrix. Both matrix and array where used to train and test the classifier.

3.2.4.3. Classification

The classification method used to identify the performance of both interfaces for three different time-window was the SVM, which consisted of a One-Against-All (OAA) strategy for a multiclass SVM with a 4-fold cross validation method, using a Radial Basis Function (RBF) kernel, which had the parameter gamma set as default and C equals to 20. A confusion matrix for each interface and time-window was generated from the average from all participants.

3.3. Experiment 2: Online Application

This section describes the development and details of the online experiment, which are related to the interface development, participants, experimental proceedings and signal processing.

3.3.1. Interface Development

Results regarding target location, window length and optimal channels from the previous experiment helped to develop an interface for online performance. This interface was developed in Python language, which was connected to the OpenViBE through LSL protocol.

It has three different modes and three auxiliary buttons, as shown in Figure 17 and 18, which are:

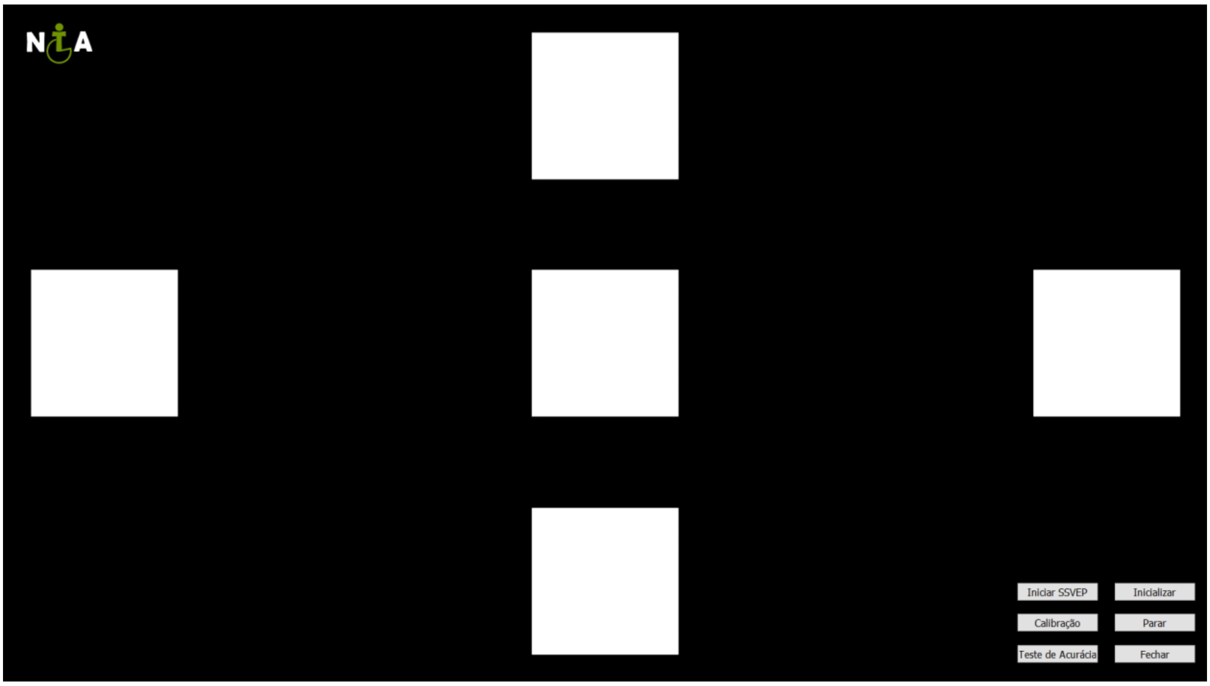

Figure 17. Online interface design.

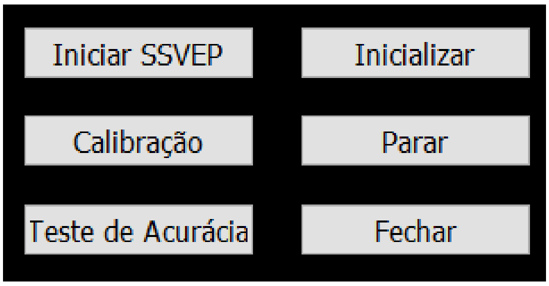

Figure 18. Buttons located on the bottom-right part of the online interface showed in Figure 17.

1) Button “Inicializar”: responsible for starting the video with the visual stimulation;
2) Button “Parar”: responsible for stopping the video, if needed, and also stopping the “Iniciar SSVEP” mode;
3) Button “Fechar” and “ESC” keyboard: exit from the entire interface;
4) Button “Calibração” (Mode 1): responsible to calibrate the system. It instructs the user to look at a specific target for 7 seconds, in a sequential order, generating a signal, which is processed and saved to be used as training data for the classifier. The calibration module consists of 6 rounds that goes through all the targets. To call attention of the user to the target, a white border is draw around the target for 3 seconds and after it turns red, indicating the recording period (Figure 19). The red border is maintained for 7 seconds. The recorded signal is filtered, and the 7 seconds

are divided into 3 seconds windows with 512 samples overlap. An FFT from 3 to 20 Hz is extracted from each window, normalized from -1 to 1 and saved.

5) Button "Iniciar SSVEP" (Mode 2): after the calibration, the SVM can be trained and used for classification. In this module, the classifier is trained, and then, at the click of the button, the signal collection already starts. At 3 seconds, a window of data is collected, filtered, processed (FFT is extracted, as in the calibration mode, and the signal is normalized) and sent to the classifier to online test, printing the result in the Python console. The signal is collected, and a result is emitted at each 250 ms because it works as an overlap window. It means the interface has a response time of 250 ms. For safety, 10 samples are collected in sequence and the classifier results are stored to a buffer array. The system only considers an output if 6 consecutive classification results in the buffer are equals, if not, the system preserves the last emitted command. This command is sent to the powered wheelchair through the COM port, which is connected to both Arduino Mega and a system board developed in a previously study [77] that sends the correct tension to the wheelchair motor.
6) Button "Teste de Acurácia" (Module 3): this button was created to test the system efficacy. At the click of the button, the signal collection already starts. This mode instructs the user to look at a particular frequency in the same way as in the calibration mode, but in a random order. In addition, the data goes through the same procedure as in the mode 2, which means the data is received, filtered, processed, sent to the classifier to test and then the result of the classifier is saved for posterior analysis. The white border appears for 4 seconds and the red border is shown for 1.25 milliseconds, as 5 samples windows of 3 seconds with 512 samples of overlap are collected. Through this mode, it is possible to identify the hit rate and, consequently, the accuracy of the system.

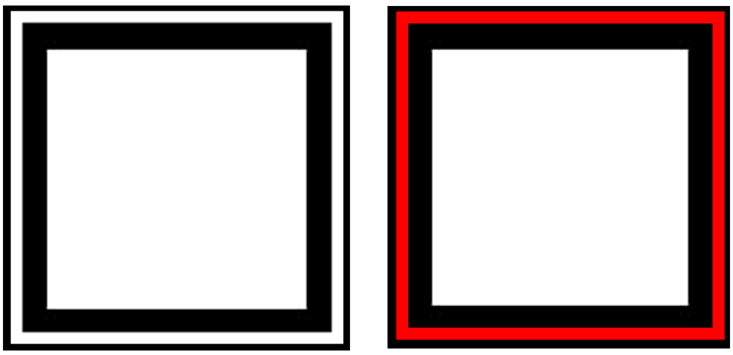

Figure 19. A white border (left) is drawn to alert the user which target he/she has to look at, and a red border (right) represents the EEG signal is been recorded.

3.3.2. Signal Processing

The online signal processing is performed in the same way as the offline processing. The signal is filtered using a Chebyshev Type II filter and a 51-point FFT (from 3 to 20 Hz) is performed in a 3 seconds window for each channel. Then, it is normalized from -1 to 1 and used either as training (calibration mode) or testing (online mode) data for the classifier. The classification method used was the OAA SVM with RBF kernel, which had the parameter gamma set as default and C equals to 20.

3.3.3. Participants

Four participants (4 females, 23.25±1.6 years) were asked to participate in this study. All of them had previously experience to BCI systems, since three of them participated in the offline experiment. These participants were chosen due to their availability. All of them signed the informed consent form. To be included in the study participants had to:

- not present any type of cognitive or physical deficit;
- have normal or correct-to-normal vision;
- be over 18 years old;
- be able to arrive by themselves at the university' facility where the experiment took place; and
- have their hair washed without conditioner and dried.

3.3.4. Experimental Procedure

The participants were positioned in a comfortable chair at 60 cm away of the LCD monitor where the developed interface was presented. The laptop used in this experiment was different from the offline experiment because, in order to run the interface, it was necessary a higher processor performance. Thus, the monitor of this experiment is a 13.3-inches with resolution of 1920 by 1080 pixels and refresh rate of 60 Hz.

The EEG cap was placed at the participant's head and a conductor gel was applied to the optimal channels and references to reduce the electrode-skin impedance. In addition, the participant was instructed about how the experiment would be performed (Figure 20).

Figure 20. Experimental protocol for the online experiment.

The first step performed consisted of the calibration mode, where the signal was recorded to train the classifier. The participant was oriented to avoid head and eye movements and eye blinking during this experiment, especially during the signal recording marked by a red border around the selected visual target.

After calibration, the participant used the “Teste de Acurácia” mode (Mode 3), two trials of 10 rounds were performed, and at each round the participant was oriented to look at a different visual target in a random order. Consequently, the participant had to look at each visual target for 20 times, and the classifier obtained 100 classification results (2 trials * 10 rounds * 5 frequencies).

Chapter 4

4. Results and Discussion

In this chapter, results regarding the first and second experiment are presented, and a discussion over them are performed to identify highlights of this dissertation regarding the target location, window length and efficiency of the developed SSVEP-based BCI.

4.1. Experiment 1: Target Location and Window Length Evaluation

This section presents the results and discussion of the first experiment, which is divided into participants opinion, identification of optimal EEG channels, ITR and classification results referent to the target location and processing window length.

4.1.1. Participants Opinion

After the experiment, the participants were asked about their feelings and opinion about the system. Unfortunately, it was not adopted any type of questionnaires; only informal questions were made.

Four participants reported feeling asleep while trying to concentrate on the visual stimulus in the first half of the experiment (approximately 15 minutes after starting the stimulation). Other three participants felt their eyes blazing also in the first half of the experiment. Most of them expressed mental confusion while looking at a stimulus in the first 15 minutes, and, again, after 42 minutes of the experiment. They reported seeing different shapes, colors, and changes in the size of the flickering target. This may be reflexes from the fatigue that may affect in the brain responses, because, according to Makri, Farmaki and Sakkalis (2015), during SSVEP stimulation the subject can get used to the stimuli, characterizing a habituation phenomenon, which can decrease the brain response of a repeated stimuli.

Regarding the differences among interfaces, three participants reported the interface "square" was easier to concentrate, since the flickering targets were farther apart from each other. In this case, the flickering stimulus located on the center of the screen elicits less interference to the competing stimuli [57] compared to the interface "cross". However, other two participant expressed preference to the interface "cross", claiming it was easier to remain alert.

The participants were also asked to guess the fastest and slowest flickering frequency (Figures 21 and 22). It is known that on the interface "cross" the fastest flickering frequency is the top, and the slowest is the bottom; and, on the interface "square", the fastest one is the top-left and the slowest, the bottom-right.

Regarding the interface "cross" and the fastest flickering frequency, the participants opinion was divided, which most of them selected the top target as the fastest one. For the slowest flickering frequency for the interface "cross", only one participant was confused about it, and the others selected the bottom.

On the other hand, all participants selected the bottom-right target as the slowest flickering frequency for the interface "square". Regarding the fastest flickering frequency on the interface "square", the participants were also confused about it; however, four of them chose the top-left frequency.

We noticed that people can perceive the slowest flickering frequency easier than the fastest one, which can be justified because, even if the highest frequency is more comfortable for the user, the human eye recognizes higher frequencies as a constant light and may not notice the flickering time, making it difficult to differentiate them [78].

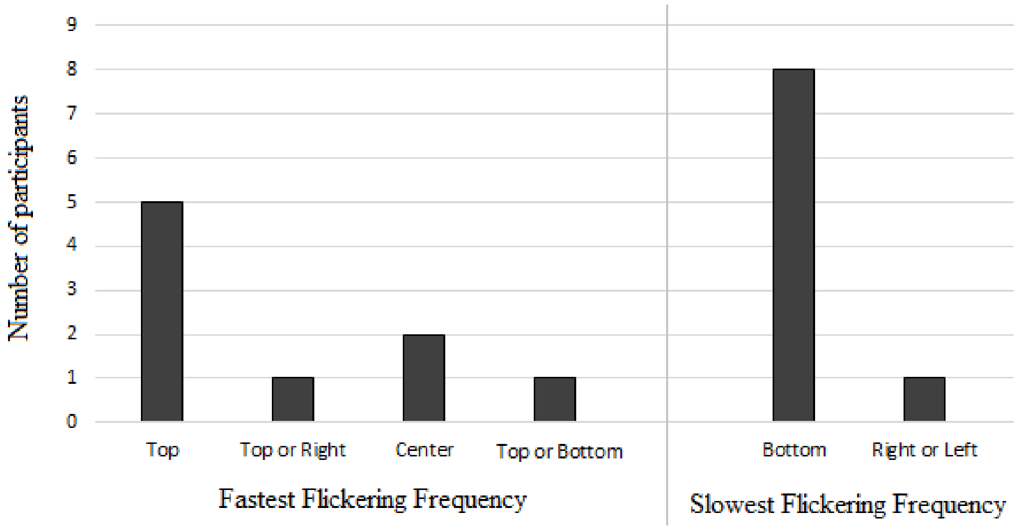

Figure 21. Participants opinion related to the fastest and slowest flickering frequency for interface "cross".

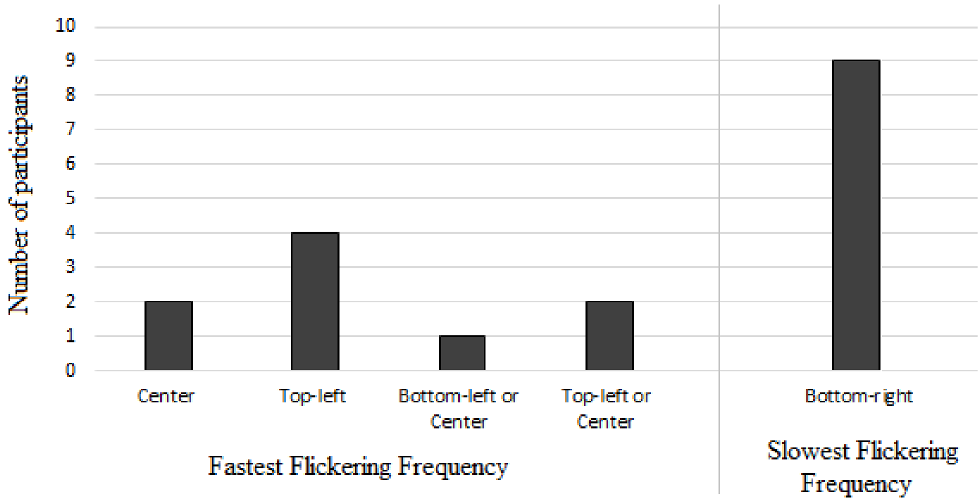

Figure 22. Participants opinion related to the fastest and slowest flickering frequency for the interface "square".

4.1.2. EEG Optimal Channels

After dividing the signal into 1, 2 and 3 seconds window length and executing the signal averaging for each participant, the Welch's PSD was performed over the averaged signal. Similarly, Müller et al. (2010) and Chatzilari et al. (2017) also applied the `pWelch` function to obtain the Welch's PSD to locate the optimal channels.

Posteriorly, a Z-Score test was applied over the PSD results, aiming to identify significant channels during the visual stimulation. The channels that showed significance were: O1, O2, Oz, PO5, PO6, PO4, PO3, PO7, and PO8 (Figure 23). These results can be confirmed by previous studies that have shown that SSVEPs are prominent on the occipital region (visual cortex) [32], in which other studies were also conducted [8, 79, 80].

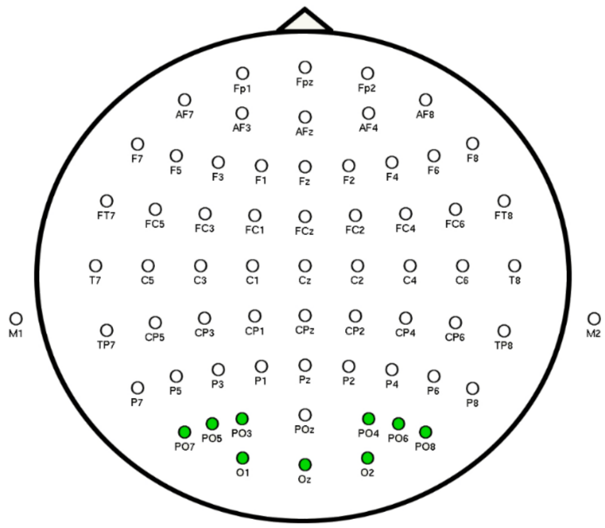

Figure 23. 10/20 electrode positioning system adapted for 64 channels. The significant channels are highlighted in green. *Source: adapted from https://www.ant-neuro.com.*

4.1.3. Information Transfer Rate (ITR)

The performance of a BCI can be evaluated using the accuracy in percentage and the ITR in bits per minute (bpm), according to Singla, Khosla and Jha (2014b). The ITR is calculated by Equation (2):

$$ITR = \frac{60}{S} * \left[\log_2 N + P * \log_2 P + (1 - P) * \log_2 \left(\frac{1-P}{N-1}\right) \right], \tag{2}$$

where S is the time taken for one command detection, which is the gaze duration in our experiment (8 seconds for offline experiment and 3 seconds for online experiment), P is the accuracy rate of the system, and N is the number of possible commands, which is 5 in our experiment (forward, right, left, backward and stop).

The results regarding ITR for both interfaces and the three different window lengths for the offline experiment are given in Table 6. Moreover, the results of ITR for the online experiment is shown in Table 7.

4.1.4. Classification Results

In our experiment, the white color was used for the stimulation targets, which resulted in a high performance and accurate classification. The reason for adopting it was because the white color has been presenting reasonable results as visual stimulator, as it induces higher brain activity, increasing classification accuracy and speed [60, 61]. However, some other colors have also been used in other studies and presented good results, such as the violet [62] and green [78]. Zhu et al. (2010) demonstrated that the most used colors in SSVEP based BCIs are green, black, gray, red and white.

Other details are related to the background color. Black was chosen for invoking higher SSVEP potentials and increasing visibility and brightness, since the contrast between black background and white stimulus is higher [9].

The classification results in Table 6 show the performance of both interface for three different window lengths. Both interfaces presented reasonable performance using a 2 and 3 second window, however, both had not satisfactory results for 1 second window. It is known that, while using a SSVEP-based BCI, as the time window of the capture input decreases, both detection accuracy and ITR decreases [7, 49, 82].

In fact, the window lengths characterize a trade-off between classification speed and accuracy [49, 83]. Since the results for 3 second window was higher than for 2 second, this length was chosen to be applied at the online experiment.

Table 6. Confusion matrices for both interfaces ("cross" on the right and "square" on the left) to the different window lengths of 1, 2, and 3 seconds with their accuracy average and ITR.

Interface "Square"

Window	Predict Target	Actual Target[1] 1	2	3	4	5
1 sec. window	1	0.60	0.08	0.07	0.11	0.14
	2	0.05	0.55	0.09	0.15	0.16
	3	0.05	0.12	0.42	0.19	0.22
	4	0.05	0.10	0.14	0.51	0.20
	5	0.03	0.05	0.09	0.10	0.73
				Accuracy Average	**56.20%**	
				ITR	**3.43 bpm**	
2 sec. window	1	0.78	0.02	0.13	0.05	0.02
	2	0.01	0.80	0.12	0.05	0.02
	3	0.01	0.02	0.87	0.06	0.04
	4	0.00	0.02	0.21	0.73	0.04
	5	0.00	0.01	0.09	0.03	0.87
				Accuracy Average	**81.00%**	
				ITR	**9.30 bpm**	
3 sec. window	1	0.90	0.02	0.05	0.01	0.02
	2	0.05	0.89	0.03	0.00	0.03
	3	0.06	0.04	0.82	0.02	0.06
	4	0.04	0.04	0.08	0.80	0.04
	5	0.05	0.01	0.03	0.01	0.90
				Accuracy Average	**86.20%**	
				ITR	**11.00 bpm**	

Interface "Cross"

Window	Predict Target	Actual Target[1] 1	2	3	4	5
1 sec. window	1	0.61	0.07	0.08	0.07	0.17
	2	0.17	0.48	0.10	0.06	0.19
	3	0.16	0.10	0.44	0.09	0.21
	4	0.17	0.10	0.14	0.40	0.19
	5	0.09	0.03	0.06	0.02	0.80
				Accuracy Average	**54.60%**	
				ITR	**3.15 bpm**	
2 sec. window	1	0.81	0.04	0.05	0.08	0.02
	2	0.03	0.85	0.04	0.06	0.02
	3	0.05	0.04	0.77	0.10	0.04
	4	0.02	0.04	0.07	0.84	0.03
	5	0.01	0.02	0.02	0.04	0.91
				Accuracy Average	**83.60%**	
				ITR	**10.13 bpm**	
3 sec. window	1	0.91	0.03	0.06	0.00	0.00
	2	0.06	0.90	0.04	0.00	0.00
	3	0.06	0.02	0.92	0.00	0.00
	4	0.03	0.02	0.05	0.90	0.00
	5	0.04	0.01	0.03	0.00	0.92
				Accuracy Average	**91.00%**	
				ITR	**12.79 bpm**	

[1] The numbers 1, 2, 3, 4, 5 represent the frequencies of 15, 12, 6.67, 8.57 and 10 Hz, respectively.

The obtained results contradicts the studies of Ng, Bradley and Cunnington (2011) and Wei, Feng and Lu (2016) that identify a potential gain of evoked potentials as the distance between stimuli increases, facilitating the classification of stimuli frequencies, which was not perceived in our results since the amplitude of the signal for the interfaces "cross" and "square" were not different from each other. On the other hand, Duszyk et al. (2014) expresses that the inter-stimulus distance provokes no significant effect on the SSVEP magnitude. Based on the results, we decided to use the interface "cross" for the online experiment, since it represents a more intuitive and straight-forward target location for wheelchair control, and it obtained the highest ITR and accuracy rate. The commands to control the wheelchair were defined as forward, turn right, turn left, backwards and stop.

Regarding the stimulation frequencies, the highest accuracy rates were evoked by 15, 12, and 10 Hz (frequencies number 1, 2 and 5, respectively) in both interfaces. Anindya, Rachmat and Sutjiredjeki (2016) found that SSVEP-based BCI systems work better when the stimulation frequency used is in the low and medium range frequency (around 10 to 15 Hz [27]), which highlight these results. In addition, Cecotti, Volosyak and Gräser (2010) also obtained good accuracy results for 10 Hz while testing among frequencies of 6.66, 7.5, 8.57 and 10 Hz.

The FFT showed as an efficient and simple feature extraction method to be used. Figure 24 illustrates an FFT spectrum for one participant when he/she is stimulated a specific frequency using a three seconds time-window for the interface "cross"; this chart highlights a peak of the signal at the same frequency as the stimulation frequency.

In addition, the SVM classifier also presented to be a satisfactory method to be used for SSVEP-based BCIs. A similar experiment of Singla, Khosla and Jha (2014b) also expressed higher classification results using the combination of FFT and SVM.

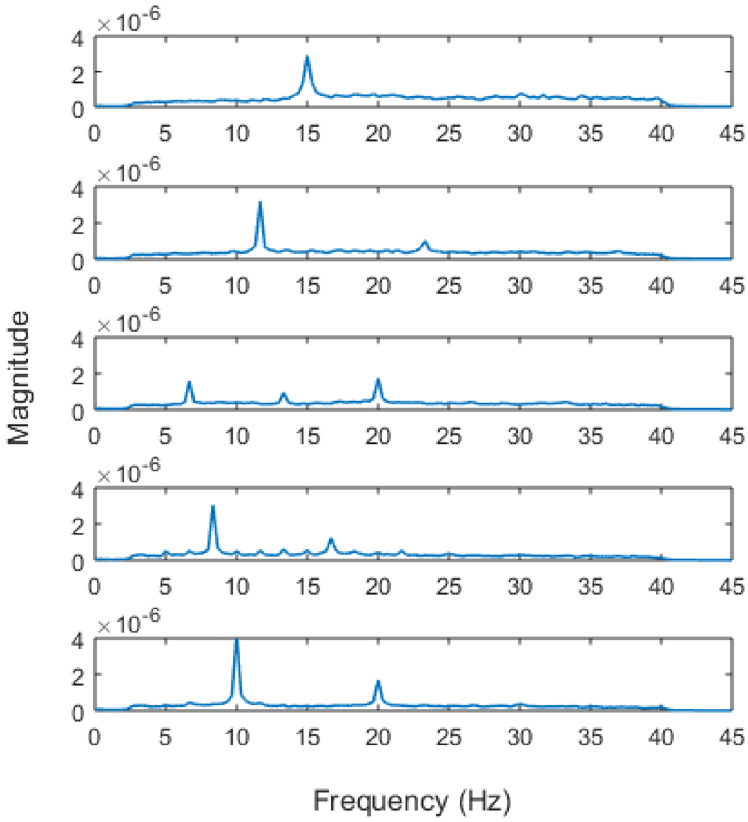

Figure 24. FFT spectrum for interface "cross" for one participant. The charts represent, from top to bottom, the stimulation by frequencies of 15, 12, 6.67, 8.57 and 10 Hz.

4.2. Experiment 2: Online Evaluation

This section presents the results and discussion for the second experiment (online).

4.2.1. Classification and ITR Results

Through the online experiment, the developed SSVEP-based BCI system was evaluated and the results proved that this is a promising system to used for wheelchair control. However, the online experiments were not yet performed with people with deficiency because we believe that are some adjustments that may be done in order to guarantee safety and highest performance, reducing frustration for the real users. The classification results and ITRs for four participants are shown in Table 7, which represents the performance of each participant while operating the system.

Online experiments are yet few cited in the literature, and, sometimes, it is not clear. Müller, Bastos and Sarcinelli-Filho (2013) proposed a SSVEP-based BCI system to command a robotic wheelchair, and tested it online with three participants, which obtained hit rate of 96%, 47% and 49%. Through these results, they reported that the motivation and concentration of the user can influence the hit rate, as happened with two participants. However, they also reported a successful performance of their system which allowed one participant to navigate and explore the environment.

In our study, the results were satisfactory for all participants. One participant obtained 98.2% of accuracy with ITR of 43.12 bpm (Table 7), proving that the SSVEP paradigm can be a good option for BCI systems. All participants could use the system without any difficult, confusion and/or fatigue. The best classification results are related to the stimulation frequencies of 15 and 10 Hz (frequencies number 1 and 5, respectively, on Table 7), confirming the results of the offline experiment. Participants reported satisfied with the interface and its fast response time.

Studies from Widyotriatmo, Suprijanto and Andronicus (2015) also reported online testing for operating a robotic wheelchair and obtained good results. However, their system had only one flickering frequency as target, so, the wheelchair movement was limited to one command (forward). Different form them, our study presents five different commands for the wheelchair control and obtained good results. Some authors reported that depending of the distance inter-stimulus, a stimulus can influence and be affected by a competing stimulus [25, 57]. For this reason, the number of targets used simultaneously should be chosen carefully, since increasing the number of targets may decrease the accuracy rate. However, even with 5 targets performing the stimulation simultaneously, the classification responses were effective in the online experiment using the developed system. On the other hand, when adopting 5 commands some concerns about security should be taken into consideration; anti-collision sensors may be installed, specially for the backwards movement.

Table 7. Confusion matrices for all participants of the online experiment with their accuracy average and ITR.

Participant 1

Predict Target \ Actual Target[1]	1	2	3	4	5
1	0.97	0.03	0.00	0.00	0.00
2	0.00	1.00	0.00	0.00	0.00
3	0.00	0.05	0.95	0.00	0.00
4	0.00	0.05	0.00	0.95	0.00
5	0.00	0.01	0.00	0.00	0.99
			Accuracy Average	**97.20%**	
			ITR	**41.63 bpm**	

Participant 2

Predict Target \ Actual Target[1]	1	2	3	4	5
1	0.90	0.00	0.08	0.02	0.00
2	0.01	0.65	0.34	0.00	0.00
3	0.01	0.00	0.65	0.00	0.34
4	0.00	0.00	0.22	0.78	0.00
5	0.00	0.00	0.04	0.00	0.96
			Accuracy Average	**78.80%**	
			ITR	**23.05 bpm**	

Participant 3

Predict Target	1	2	3	4	5
1	1.00	0.00	0.00	0.00	0.00
2	0.07	0.89	0.04	0.00	0.00
3	0.00	0.00	1.00	0.00	0.00
4	0.04	0.00	0.02	0.94	0.00
5	0.00	0.00	0.07	0.01	0.92
			Accuracy Average	**95.00%**	
			ITR	**38.71 bpm**	

Participant 4

	1	2	3	4	5
1	1.00	0.00	0.00	0.00	0.00
2	0.00	1.00	0.00	0.00	0.00
3	0.03	0.00	0.97	0.00	0.00
4	0.01	0.00	0.05	0.94	0.00
5	0.00	0.00	0.00	0.00	1.00
			Accuracy Average	**98.20%**	
			ITR	**43.12 bpm**	

[1] The numbers 1, 2, 3, 4, 5 represent the frequencies of 15, 12, 6.67, 8.57 and 10 Hz, respectively.

After obtaining satisfactory results with the online experiment through the "Teste de Acurácia" mode, a primarily experiment was performed using this developed system to control a real powered wheelchair (Figure 25). At this point, the "Iniciar SSVEP" mode was used for online classification and to send commands to the Seat Mobile do Brasil (SMB) SM2 wheelchair motor through the COM port. In this experiment, the user was oriented to move freely in an open room at a recovery facility in Uberlândia-MG, which was a crowded place where people would walk around the experiment. The system was able to perform the signal classification in real time and execute the wheelchair movement according to the user's desires, where he/she was able to stop the wheelchair and avoid collision with people and chairs.

Even with good performance and fast responses time of the developed system, SSVEP-based BCIs have their disadvantages related to the fatigue, EEG electrode and usability that should be worked around while developing it. The constant visual stimulation after a long time can cause fatigue, which can influence on the EEG signals, decreasing the responses reliability [71]. In the study of Castillo (2014), a hybrid SSVEP-based BCI was developed to activate and disactivate the visual stimuli when they are not being used, which the user could command it by opening and closing his/hers eyes, reducing the visual fatigue and contributing to the user's comfort. Regarding EEG electrode placement, the conductive gel used may get dry, which increases the impedance electrode-skin and decreases the SSVEP amplitude reducing the system's accuracy rate. Besides that, the usability of a SSVEP-based BCI are not very favorable, since the user has to wear an EEG cap during the entire time, which can cause discomfort, and the conductive gel may be insert again after some time (approximately 1 hour).

Figure 25. Participant controlling a powered wheelchair using the developed SSVEP based BCI system.

Chapter 5

5. Conclusion

In this chapter, the conclusions about the results are described and future works are presented.

5.1. Conclusion

This study presented an offline and online investigation and development of a SSVEP-based BCI using LCD monitor as visual stimulator applied for wheelchair control. A literature review was performed, which helped to understand the current state-of-art of SSVEP-based BCIs for wheelchair control.

Both literature review and offline experiments contributed for the development of the whole final system. In particular, during the offline experiments, it was possible to noticed that the LCD properties are important to guarantee reliable stimulus, since the refresh rate of the screen can influence on it. Those experiments were also important to define the best location of the targets on the screen, allowing them to be set more intuitively to the user for wheelchair control. In addition, it was noticed that the window length influences directly on the quality of the acquired information.

Feature extraction and classification methods were studied to be used on developed system. The aim was to develop a straight-forward system, which could contribute for less processing time, but still resulting in high classification accuracy and ITR compared to previously studies, as studies of Müller; Bastos; Sarcinelli-Filho (2013) and Widyotriatmo; Suprijanto; Andronicus (2015). Regarding the feature extraction, FFT proved to be an easy to use method. The SVM as classification method also improved the system with its faster response time. So, the developed algorithm showed efficient and reliable for application control, especially for wheelchair control. It was proved by online experiments, where a user was able to drive a wheelchair through brain responses to visual stimuli.

SSVEP-based BCIs have, once again, shown to be a great choice, offering great results with high accuracy rates for classification. However, despite all efforts of the global scientific community, there is still a long way to go to establish this technology as reliable enough to become available to its final users.

To the best of our knowledge, there are only few authors that describe online application for SSVEP-based BCIs, which gives some questioning about the reliability and efficiency of all reported online experiments. It is hope that this master dissertation contributes to other authors of this research area, and to development of SSVEP-based BCIs that can be used safely by people with disability and provide them more independency.

5.2. Future Work

Future works involves performing adaptations over the developed SSVEP-based BCIs to increase classification accuracy while online use and guarantee safety to the user. This system should be efficient and comfort aiming to offer wheelchair users the ability to control this aid by themselves through brain activity. Besides it, tests with real users (people with deficiency) should be performed, and questionnaires should be adopted to acquire participants' opinion regarding the system use.

5.3. Publications

P. ZAMBALDE, E. ; JABLONSKI, G. ; ALMEIRA, M. B. ; NAVES, E. L. M. . Evaluation of the Target Positioning in a SSVEP-BCI. In: XXVI Congresso Brasileiro de Engenharia Biomédica (CBEB), 2018.

R. BORGES, L. ; M. ALVES, C. ; R. REZENDE, A ; **P. ZAMBALDE, E**. . Analysis of Complementary Colors through Brain Response and Human Perception. In: XXVI Congresso Brasileiro de Engenharia Biomédica (CBEB), 2018.

R. BORGES, L. ; **P. ZAMBALDE, E.** ; B. SOARES, A. . Influência do Padrão de Cor em Potenciais Evocados Visuais. Anais do V Congresso Brasileiro de Eletromiografia e Cinesiologia e X Simpósio de Engenharia Biomédica. Uberlândia, 2017.

G. RABELO, A. ; R. BORGES, L. ; **P. ZAMBALDE, E.** ; A. M. VALENTINI, C. ; L. M. NAVES, E. . Acionamento Remoto de uma Televisão por meio do Bracelete MYO. Anais do V Congresso Brasileiro de Eletromiografia e Cinesiologia e X Simpósio de Engenharia Biomédica. Uberlândia, 2017.

P. ZAMBALDE, E.; H. C. SOUZA, R. ; E. S. RODRIGUES, M. ; G. CARDOSO, R. ; L. M. NAVES, E. Avaliação das Forças Flexo-extensoras do Joelho antes e após Reconstrução do LCA com ou sem Preservação do Remanescente Lesionado. Anais do V Congresso Brasileiro de Eletromiografia e Cinesiologia e X Simpósio de Engenharia Biomédica. Uberlândia, 2017.

A. MARQUES, I. ; **P. ZAMBALDE, E.** ; M. SANTANA, E. ; L. M. NAVES, E. Influência da Propriocepção Plantar no Equilíbrio de Adultos Jovens. Anais do V Congresso Brasileiro de Eletromiografia e Cinesiologia e X Simpósio de Engenharia Biomédica. Uberlândia, 2017. (Honorable Mention).

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