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FABIANA SANTOS VIEIRA MACHADO

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Development of Serious Games for Neurorehabilitation of Children with Attention-Deficit/Hyperactivity Disorder through Neurofeedback

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MASTER DISSERTATION

Development of Serious Games for Neurorehabilitation of Children with Attention-Deficit/Hyperactivity Disorder through Neurofeedback

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Fabiana Santos Vieira Machado

Development of Serious Games for Neurorehabilitation of Children with Attention-Deficit/Hyperactivity Disorder through Neurofeedback

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Abstract

Attention Deficit Hyperactivity Disorder (ADHD) is a neuropsychiatric disorder, which is treated with the administration of psychostimulants, and cognitive behavioral approaches. The use of the medication may have side effects; thus, neurofeedback can be used to teach the user how to regulate their own brainwaves to help correct its dysfunctional patterns. NFB has a repetitive aspect and can be long lasting. Therefore, "serious games" can be integrated into training to maintain interest throughout the process. This research presents the development of a neurofeedback system based on serious games for neurorehabilitation of children with ADHD. For the brain data acquisition, a 20 dry-electrode wireless EEG headset. The *Neurofeedback Space* serious game, developed in Unity platform, was developed to be used throughout the NFB sessions and to provide immersion and engagement. In the preliminary validation and algorithm' selection, 5 volunteers were asked to watch a video with *attention* and *non-attention* tasks. Then, an SVM classifier was trained and tested with the collected data to choose between five brain regions and four algorithm versions with the best performance. The best results were achieved by (training accuracy of 98.12% and test accuracy of 93.88%) region 4 (F3, F7, C3 and T3) and version 2. Two experiments with 5 volunteers each, 5 sessions, and with an interval of 2 months between them were done to test the complete NFB system. The main difference between experiments was to fix game level 2 so that all metrics could be compared between volunteers. Three evaluation metrics were used to analyze the improvement in the performance: game's metric, brain signal's frequency bands power metric, and concentrated attention test metric. The analyzes show a divergence between the results obtained in both experiments. All volunteers improved in performance in the concentrated attention test. In Experiment 1, the Volunteers improved in the performance of the game metrics and reported feeling more concentrated throughout the week. In Experiment 2, the results of *attention*, *score* and *sustained attention* had large oscillations. Brain data results were inconclusive. Also, fixing level 2 showed no learning effect as perceived in experiment 1. Therefore, it is not possible to declare conclusive results for the developed NFB system, even with the improvement of some metrics presented. Factors that may have affected NFB training are number of sessions, duration of serious game, number of volunteers, game genre, and EEG dry electrodes headset. **Keywords:** Neurofeedback, EEG, ADHD, Serious Games, Signal Processing, SVM.

Acknowledgements

In this dissertation, this will be the only page written in Portuguese. It will be this way, because I would like everyone who helped me in this arduous journey to be able to read my acknowledgments.

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List of Abbreviations

NFB	**N**euro**f**eed**b**ack
ADHD	**A**ttention **D**eficit **H**yperactivity **D**isorder
FDA	**F**ood and **D**rug **A**dministration
EEG	**E**lectro**e**ncephalo**g**raphy
fMRI	**f**unctional **M**agnetic **R**esonance **I**maging
fNIRS	**f**unctional **N**ear-**I**nfra***R***ed **S**pectroscopy
MEG	**M**agneto**e**ncephalo**g**raphy
FASD	**F**etal **A**lcohol **S**pectrum **D**isorder
SMR	**S**ensori**m**otor **R**hythm
GUI	**G**raphic **U**ser **I**nterface
LDA	**L**inear **D**iscriminant **A**nalysis
K-NN	**K**-**N**earest **N**eighbor
ANN	**A**rtificial **N**eural **N**etwork
SVM	**S**upport **V**ector **M**achine
PTSD	**P**ost**t**raumatic **S**tress **D**isorder
BCI	**B**rain-**C**omputer **I**nterface
PCA	**P**rincipal **C**omponent **A**nalysis
ICA	**I**ndependent **C**omponent **A**nalysis
FFT	**F**ast **F**ourier **T**ransform
PSD	**P**ower **S**pectral **D**ensity
CWT	**C**ontinuous **W**avelet **T**ransform
DWT	**D**iscrete **W**avelet **T**ransform
IRA	**I**rish **R**epublican **A**rmy
NPC	**N**on **P**layer **C**haracter
PC	**P**layer **C**haracter
FIR	**F**inite **I**mpulsive **R**esponse
CAR	**C**ommon **A**verage **R**eferencing
TCP	**T**ransmission **C**ontrol **P**rotocol

IP **I**nternet **P**rotocol

Dedicated to my mother Claudia, my aunt Regina, my sister Raphaela, my late grandmother Dilcea and my Family…

Chapter 1

Introduction

1.1 Motivation

Attention Deficit Hyperactivity Disorder (ADHD) is a neuropsychiatric disorder that affects approximately 6 to 7% of the population of children and adolescents and 5% of the population of young adults [1]. ADHD is one of the most prevalent pediatric neuropsychiatric disorders and is characterized by hyperactivity, inattention and increased impulsivity [2]. Inattentive type is the most common subtype found in the population with the disorder, but individuals with the combined type are more likely to be diagnosed and referred to clinical services [1]. Children with ADHD can also characterize cognitive domain deficit such as working memory problems, inhibitory function deficits, delayed information processing, and so on [2].

Pharmacological treatment is the most used in both children and adults and is performed with the administration of psychostimulants. However, the use of the medication achieves 70 to 80% effectiveness and the individual may have side effects such as decreased appetite, dry mouth and irritability [3]. In addition, there are serious health risks related to the use of psychostimulants, and little is known about their long-term use. For example, according to the Food and Drug Administration (FDA), there is a warning about cardiovascular risk in the methylphenidate label, the most commonly used psychostimulant for the treatment of the disorder, although there is no support in the scientific literature [3].

Pharmacological treatment is usually given in conjunction with cognitive behavioral therapy (CBT) [4], which is a self-instructional training administered in a group or individual basis, to help the individual with ADHD to develop a more planned and reflective approach to thinking and behaving, including social interactions. However, the control of the manifestation of the symptoms of the disorder occurs only when the person is under medication, with no evidence for the reversibility of neurological dysfunctions, even under recommended treatments.

Due to these possible side effects' complications, there was a stimulus for the development of non-pharmacological treatments for ADHD, such as neurofeedback (NFB) [5]. In addition, there are studies that suggest the effects of neuroplasticity, that is, brain's ability to change in response to one's experiences [6], in patients with ADHD and with loss of sensorimotor functions. Making NFB an alternative to the currently used treatments [7–9].

Biofeedback is a health care approach that aims to help individuals take responsibility for their well-being, their cognitive, emotional and behavioral changes necessary to promote healthy physiological change. The approach involves monitoring and using physiological information such as respiratory rate, skin surface temperature, cardiovascular activity, and others to provide, through instruments such as computers, understandable feedback to the monitored patient [10]. NFB is a subspecialization of biofeedback that uses electroencephalography (EEG), functional magnetic resonance imaging (fMRI), functional near-infrared spectroscopy (fNIRS), and magnetoencephalography (MEG) to measure brain activity and aims to teach the user how to regulate their own brainwaves to help correct its dysfunctional or abnormal patterns [11–13].

The NFB technique is used for a variety of purposes, from improving cognitive activities such as multi-tasking [11], improving concentration and memory skills [14], helping children with FASD (fetal alcohol spectrum disorder), which are often diagnosed with ADHD [15], even helping to improve children with learning disabilities [16]. During NFB training, the goal of the technique is to increase or decrease brain activity over a certain frequency range of the EEG.

The characteristic pattern for ADHD, even though NFB efficacy aimed at reducing its symptoms has not been definitively established [5], are excess of theta (θ), related to sleep and decreased vigilance, and deficit in beta (β), related to concentration [17]. Therefore, protocols that increase β and decrease θ band power can positively affect the treatment of ADHD [13]. This is the most used protocol in clinics, and also in several studies [5, 15, 18], however, other characteristics of brain wave frequencies are also used, such as individual alpha (α) peak frequency, and individual α bandwidth [11], the energy values of the α, β, θ and delta (δ) frequency bands, as well as the α/β ratio [19], and entropy based features, since there is difference in complexity during EEG attention and inattention task [14].

NFB training has a repetitive aspect and can be long lasting for treatment to take effect [20]. Thus, especially for children, a tool is needed to increase engagement and maintain interest throughout the process. A widely used tool that can be integrated into training is the use of "serious games" [15, 18]. These, in addition to entertaining, have educational and/or health-related goals [21]. For training, the user must maintain the desired cognitive state in order to learn to regulate their own brainwaves, so, integration with serious game makes the player only advance in the game (receive power-ups, earn points ,among others) when the player maintain this state [11, 14, 18].

This research, aimed at improving the quality of life through technology, presents the development of a serious game, and a neurofeedback system for neurorehabilitation of children with attention deficit hyperactivity disorder (ADHD). In this way, children with the disorder may have a non-pharmacological alternative to regulate their brainwaves and lessen symptoms that disrupt or may disrupt them throughout their lives.

1.2 Research Objectives

The main objective of the research is the development of a neurofeedback system based on serious games for neurorehabilitation of children with ADHD. To achieve it, the following specific objectives are suggested:

1. To adapt and provide protocols and tests to measure the engagement of serious game, and its effect on the user's attention through NFB.
2. To check alterations in the brain signal's patterns throughout the sessions and their relationship with attention.
3. To analyze improvement in attention at the end of NFB training with the focused attention's psychological test.

1.3 Justification

There is no consensus in the literature on a specific game genre, total number of NFB sessions, a certain interval between sessions, and no single acquisition protocol to treat neuropsychiatric, neurological disorders or to improve cognitive activities in non-disordered persons. Different game genres attract players differently, some prefer simulators, others like adventure, so, different game genres can bring good engagement to different type of players. Also, there are several different protocols and EEG equipment for the acquisition of brain signals, and, because of that, also a different number of electrodes and regions of the brain for the NFB training. This results in a lack of standard in the protocols used.

NFB is a form of therapy that assesses brain activity and helps correct abnormal brain patterns or brain dysfunctions. It can be used with several techniques that detect brain rhythms [12], such as electroencephalograpy (EEG) [18], functional magnetic resonance imaging (fMRI) [22], magnetoencephalograpy (MEG) [23], and functional near-infrared spectroscopy (fNIRS) [24]. The most used technique is the EEG, as it is relatively inexpensive, portable and has an excellent temporal resolution [25]. NFB is done online and provides feedback to the patient in several ways. It can be tactile, visual or auditory, which enables the users to learn to modify certain aspects of their brain activity [26]. Users' motivation and mood can also affect their performance [26], and as the NFB has a repetitive character, serious games are used in order to positively influence the patient's motivation and engagement [18].

In [11], the authors developed a shooting game in which the player could shoot and hit enemies only when he reached the desired cognitive state. For that study, 3 individuals not affected by any neuropsychiatric disorder were selected, 6 sessions were held, the player used mouse and keyboard to play and the better the player's performance, the more difficult the game became. The proposed system allows different NFB methods to be chosen, such as fractal dimension, power of standard EEG bands, and β/θ power ratio.

Serious games are also used to improve concentration and memory skills. The authors in [14] developed a memory game in which the player could only guess which number was in the matrix gap (choose between two numbers, one on the right and another on the left, with the arrow keys) when it was in a attention state. The training was performed with 5 healthy individuals in a controlled environment (lighting, chair position, without sudden eye movement, among others). Entropy estimation was used as feature to calculate the attention score that is fed as the control input of the Graphic User Interface (GUI) of the proposed NFB game.

Unlike the articles already mentioned, a study was conducted for 12 weeks with 16 children with FASD, and there was no impediment in the game when the desired mental state, which was identified by the θ/β ratio, was not reached. In this study [15], the textures gradually obscured the graphics of the game chosen by the user, making it less enjoyable to play and, if the obfuscation was exaggerated, impossible to progress. Users stated the vision-impairing texture made the game less fun and this motivated them to pay attention while playing. Thus, when the user failed to perform the main task, the game mechanics did not change, but the game experience, since the texture in the screen prevented its full view.

The first two previously cited studies [11, 14] improved the results with few sessions and also few individuals, performing the tests with healthy patients in a controlled environment. However, depending on the subject's degree of hyperactivity and inattention, testing in a controlled environment, requesting them not to move, not to move their eyes sharply, and try to focus on the game can be challenging. In addition, the use of mouse and keyboard can make it difficult to measure the level of attention through the EEG signal, as voluntary body movement alters brainwaves. In fact, such signals, could be used, for example, to predict the intention of human movement [27], decode individual finger movements of a hand [28] and use motor imaging to control a NFB game [29].

In studies involving NFB there is a great variability of protocols with different aims and parameters being trained, such as different number of sessions, type of subject (age, education), duration of training and among others. This brings a limitation in the comparison and validation of the results, as there are people who do not have the ability to change their brain activity, and the lack of a general protocol makes it difficult to assess the effectiveness of training. In fact, the variability in the effectiveness of the treatment is high, but little mentioned, and many people do not benefit from the treatment. One solution to the inefficiency is to develop an individual protocol, but it does not solve the problem of comparing the results of different studies [26].

The game developed for this dissertation will not use a keyboard, mouse and joystick to avoid any artifact of motor intention or movement of fingers, since, as mentioned earlier, these can be measured in brain signals. All control will be performed only with the user's attention, changing the game's mechanics without needing any movement that may bias the data. The theme, gameplay, levels and characters of the game were designed with the aim of offering greater immersion, and a good/comfortable gaming experience for users to assist in the treatment of ADHD. The NFB method used will be the power of standard EEG bands, the ratios β/θ and α/β, and the classification will be done by the Support Vector Machine (SVM).

1.4 Organization of the Dissertation

This document is divided into six chapters introduced as follows:

The first Chapter presented the motivation, its main goals and the justification of this research.

Chapter 2 summarizes the theoretical background used to do this research. In this, the definition of EEG, NFB, Serious Games, and SVM as a viable solution for NFB are presented and explained.

Chapter 3 describes the methodology and methods used in this research. This will describe the choice of the serious game's theme, NPC's (Non Player Character), game mode, levels, database used, game operation, as well as algorithms to process the brain signal.

In Chapter 4, a protocol was developed to choose the best brain region, from predetermined regions, and the best algorithm's version that will be used in the NFB training of later chapters.

Chapter 5 describes two tests, with two different groups of volunteers, performed using the neurofeedback system and presents three types of results. One psychological result, another from the SVM classifier used in the test and a last one analyzing brain wave frequencies. In this, all the results are analyzed and discussed and the results of the two groups are compared.

In Chapter 6, the conclusions, contributions, and the publications of this dissertation are detailed. Finally, future works are suggested for the continuation and improvement of this research.

Chapter 2

Theoretical Background

2.1 Neurofeedback

Neurofeedback (NFB) is a subspecialization of biofeedback, also known as Neurotherapy, Neurobiofeedback and EEG Biofeedback, and is a treatment method in which patients are trained to perceive and control their physiology and improve their physical and psychological health. In NFB, brain electrical activity is measured, and possible dysfunctions and abnormal brain wave patterns can be corrected [12, 13]. This therapy offers a non-invasive tool, regardless of the method, to alter human brain function in a targeted manner, and may reach a potential to impact neuroscience and clinical treatment of neuropsychiatric disorders [30].

In the 1960s, the first indication that individuals could learn to consciously alter their brain waves were reported. However, the first experiments investigating the conditioning of brain activities is from the 1930s [31]. American neuroscientist M. Barry Sterman and biologist Wanda Wyrwicka initially monitored cats' EEGs that were conditioned to press a lever to receive a food reward after the end of a specific sound. In the second experiment, Sterman noticed that the cats that successfully received this reward went into a state of concentration while they heard the sound ending. Analyzing the EEG while the cats waited, Sterman observed a distinct rhythm in their brain waves, a pattern that became known as the SensoriMotor Rhythm (SMR). The experiments showed that it was possible for the animals to intentionally alter their concentration. Sterman also performed an experiment in which cats were exposed to a toxic substance that caused epileptic seizures, and cats that learned to control SMR were more resistant to the seizure effects of this substance, delaying the attacks or even avoiding them [12, 17, 32]. After a few years, studies were included in children with epilepsy and hyperkinesia and those who underwent NFB treatment showed significant improvement [17].

As previously presented in Section 1.3, the NFB can use several non-invasive techniques to detect brain electrical rhythms, such as functional magnetic resonance imaging (fMRI) [22], electroencephalograpy (EEG) [18], magnetoencephalograpy (MEG) [23], and functional near-infrared spectroscopy (fNIRS) [24]. The most used technique is EEG, but several studies also use fMRI in neuroimage. A disadvantage of this one is that real-time fMRI experiments are generally expensive, time consuming, and have low temporal resolution, as it is limited by hemodynamic response time, which has its peak response after at least 5 seconds, however, for offline simulations it is a powerful tool [30, 33]. EEG is a cheaper technology, is portable, unlike fMRI, and has a high temporal resolution.

Neurofeedback has been used to treat and assist in the treatment of various conditions and disorders such as ADHD, anxiety, depression, epilepsy, sleep disorders, Posttraumatic Stress Disorder (PTSD) and others. It is also used to improve creative performance and improve concentration in healthy people. However, whether the NFB is really effective is still unknown [12, 13].

The most used technique for ADHD treatment, which is the focus of this dissertation, is the EEG technique. In Figure 2.1, it is possible to observe the NFB process using a video game as visual feedback.

In an NFB session, which can last between 20-60 min, doctors connect sensors, known as electrodes, to the patient's scalp in a cortical region responsible for mental functions that require treatment. The brain's electrical activity is processed and returned to the user in form of a video or audio signals displayed in real time on the computer screen, this feedback informs the patient whether their brain wave patterns are desirable or not. There is no consensus on the number of sessions to have long-lasting results from the NFB, it depends on the type and severity of the disorder to be treated, the type of patient and among others [12, 13]. Feedback can be done in several ways, most of those mentioned in this dissertation were with video game feedback, but, feedback can also be done only by altering image and sound. For example, ADHD patients may be asked to make birds sing and flowers to bloom. When the brain is focused, the computer screen shows a field full of colorful flowers and birds singing. When the patient loses focus, the image turns gray and the flowers, once colored, wilt. The participants, in order to return to concentration and, consequently, restore the color of the image, perform mental exercises aided by a clinician. With repetition, the brain learns to associate these brainwave patterns with pleasant images or sounds [12].

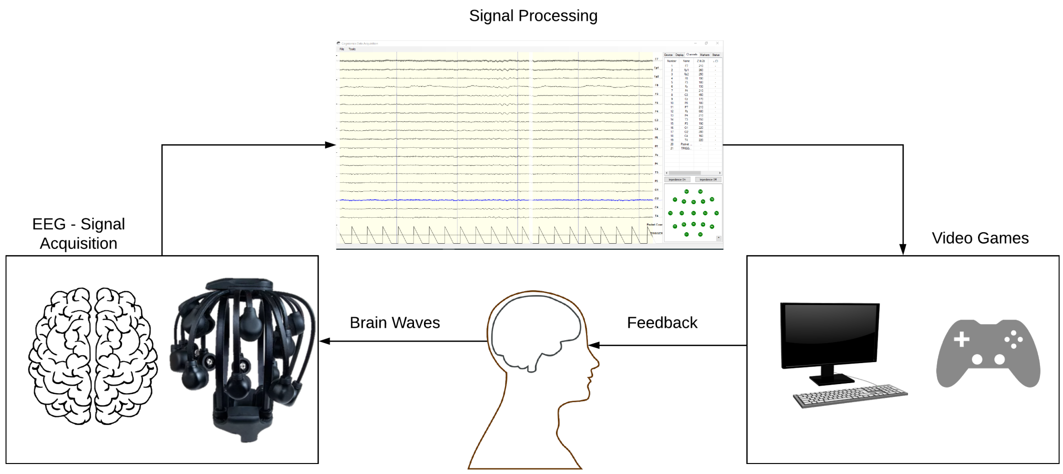

FIGURE 2.1: Neurofeedback process using Video games as feedback.

2.1.1 EEG

Electroencephalography (EEG) is a non-invasive method of measuring brain electrical fields. These fields are the result of electrochemical signals passing from one neuron to the another. After billions of these signals are passed simultaneously in spatially extended and geometrically aligned neural populations, the electrical fields sum and become powerful enough to be measured from outside the head [34]. Electrodes placed on the scalp record the voltage potentials resulting from the current flow around the neurons. EEG has several applications, the fundamentals of EEG in clinical diagnostics have more recently fit into neurorehabilitation treatments, it has been and is used in the experimental field of psychology, but it is also used as a neuroimaging method with more recent extensions in computational neuroscience. Its versatility and accessibility combined with advances in signal processing allows the renewal of this technology that has been going on for almost a century [35].

Figure 2.2 shows a series of analogies to contextualize and understand what would be the measurement of the results of neuronal activities on the scalp surface. Image *A* is analogous to recording action potentials of neurons individually, it would be a reporter recording an interview with a trainer, despite the noise of the stadium, it is possible to understand what she talks about. However, if you are in the press box, as shown in image *B*, it is not possible to record conversations between coach and players on the field, but it is possible to capture comments from other reporters, this is equivalent to recording local field potentials, where there are contradictions from both distal, near and relative events. In image *C*, after losing his press credentials, on the balcony of the hotel, it is possible to hear the cry of joy in unison of goal from the people inside the stadium. This is analogous to EEG recordings [35].

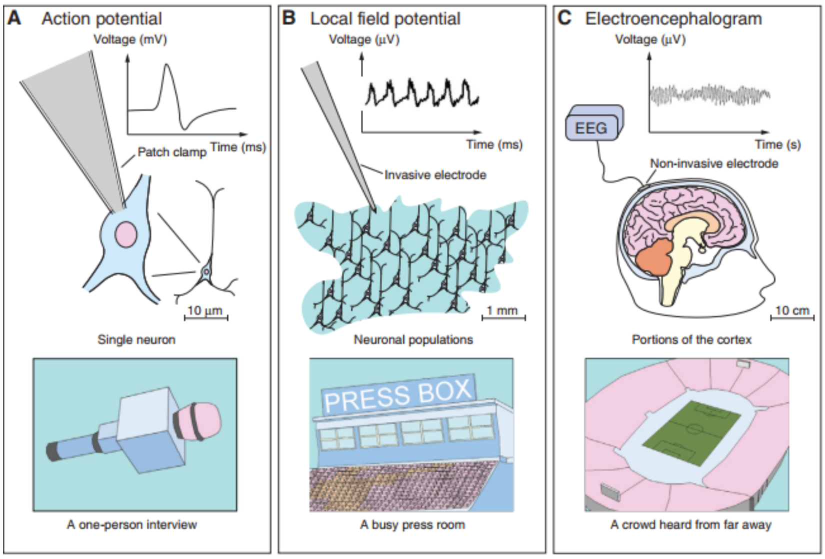

FIGURE 2.2: Recording the electrical activity of the brain [35].

The EEG technique was discovered by Hans Berger in the lates 1920s. He recorded signals that fluctuated rhythmically when the eyes were closed and that became less rhythmic and also decreased in amplitude when the eyes were opened, known today as "alpha blocking" [35]. Berger died in 1941, however, his legacy was left and this technology was quickly improved and is still today with advances in Brain-Computer Interfaces (BCI) and in the application of personalized medicine.

The time domain signal, seen in Figure 2.3, can be transformed into the frequency domain and decomposed into frequency bands already defined, however, depending on the study, they present little variation in the band limits. Many studies divide the bands as delta (δ: 0.2-3.5 Hz), theta (θ: 4-7.5 Hz), alpha (α: 8-13 Hz), beta (β: 14-30 Hz), gamma (γ: 30-90 Hz) and high frequencies (> 90Hz) [35]. In [19], delta values extend only up to 3 Hz and γ range has a range of 31-50 Hz.

Different activities cause different parts of the brain to increase its processing or decrease it, knowing where these signals originate, makes it simpler to know the type of activity that is being performed. Likewise, the amplification or attenuation of the signal and its frequency facilitates the categorization of the type of signal observed [36].

Each frequency band has a function analogous to the same. The delta band occurs when the person is in deep sleep, unconscious, anesthetized or when there is a lack of oxygen, the theta band is present when people experience emotional pressure, interruption of consciousness or deep physical relaxation, the alpha band is related to the state of consciousness, quiet, or at rest. The electromagnetic waves in the beta band originate when people are conscious and in alert states and, finally, gamma waves are related to perceptual activities.

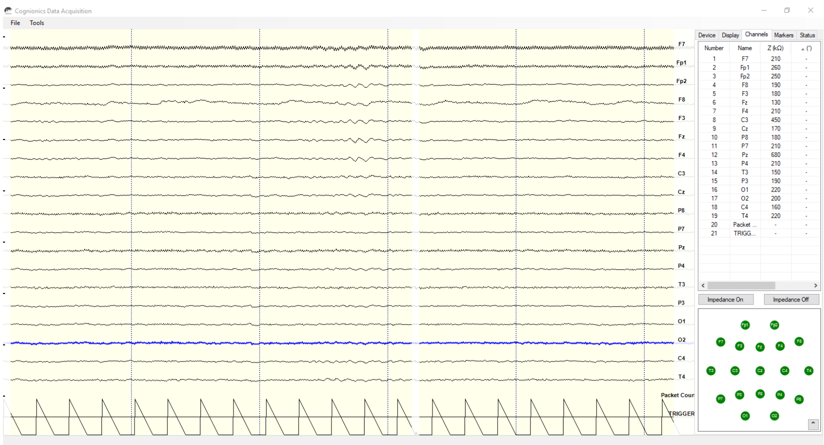

FIGURE 2.3: EEG signal for 20 electrodes from Cognionics software.

Brain activity occurs in the entire brain and these EEG signals are usually collected using the international 10-20 system, seen in Figure 2.4.

2.2 Brain signal processing using EEG technique

In the brain, it is possible to detect a variety of signals coming from electrical activity happening in the brain, and it does so despite the co-occurrence of other types of physiological electrical activity (such as cardiac, eye and other), muscle activity and environmental noise (such as computer screens) and other (electrical equipment, power lines) [35]. In this way, the signal needs to go through a pre-processing before the information contained in it can be extracted. Figure 2.5 shows the steps

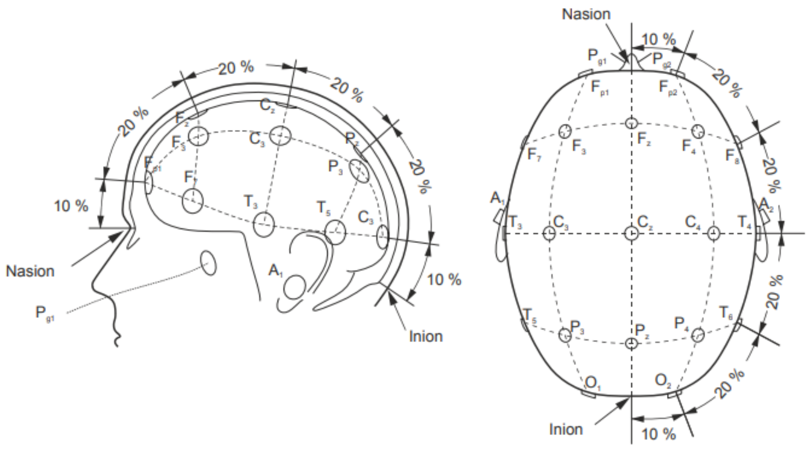

FIGURE 2.4: International 10–20 electrode placement system (10-20 System) [37].

for processing EEG signals and the operation of brain-computer interfaces (BCIs). After defining a protocol and acquiring data, the signal needs to be filtered, as the frequency range of interest is a low frequency band, therefore, a low-pass filter is applied to the signal. Artifacts referring to electrical, muscular, or environment noise are also removed so that they do not mask, hide or compromise the quality of the EEG signal. As the signal is inherently non-stationary, it needs to be separated into small segments, known as windowing, this segmented data within the windows is isolated and multiplied by the window function values, and the desired parameters can be extracted [37].

The information of interest for creating a set of features is hidden in a noisy environment, as the brain comprises several signals from various sources. These features are derived from properties of the signal that contain some discriminating information that distinguishes it from others. Also, the information may be in different regions of the brain, as different activities originate different patterns of brain activity. [19, 37].

The brain signal is inherently non-stationary. As a solution, some approaches divide the signal into small segments and the parameters are defined for each piece, however, being non-stationary, the size of this segment influences the result and the accuracy of the extracted features. There are several ways to extract information from the signal, for example, dimension reduction algorithms can be used to

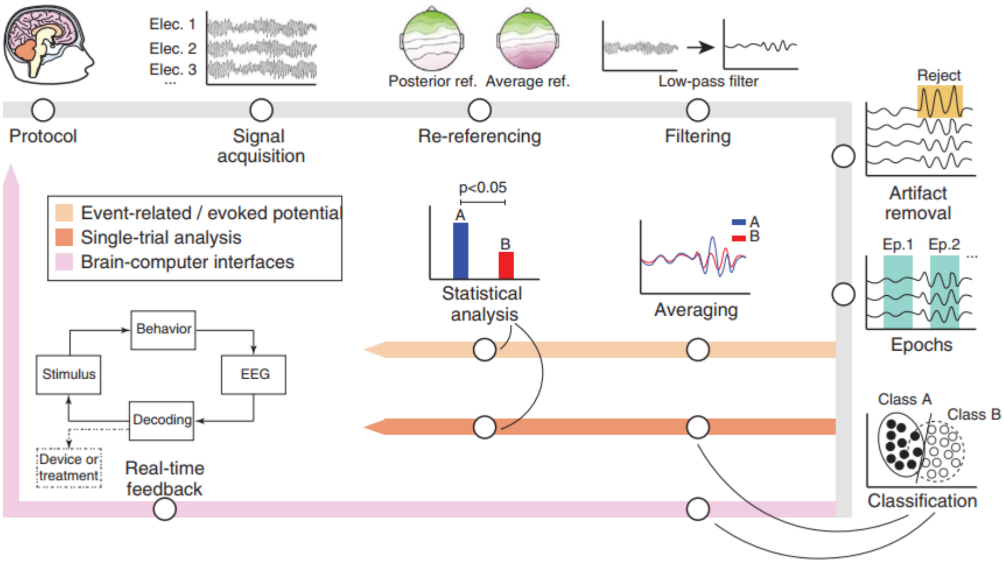

FIGURE 2.5: Process and Analysis of EEG signals [35].

remove signal features that are not relevant, they are Principal Component Analysis (PCA) and Independent Component Analysis (ICA), other approaches that work in the frequency domain, for example, Fast Fourier Transform (FFT) to extract the Power Spectral Density (PSD) of a given frequency band, and approaches that can provide both frequency and time information, such as Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT) [37].

As seen in Figure 2.5, these features are related to classes, that is, the activities that need to be differentiated, and the results can be analyzed, in a single-trial, in a statistical way to ascertain performance improvement or even change in electrical activity in a certain brain region. This information, after classification, can also be used to provide the user with real-time feedback on what is happening in their brain so that they can identify which class of activity they are in. For example, using a motor imagination task, a blue light can light up when the user imagines the movement of the right hand and a red light when he imagines the left hand, so the user will know if he has successfully accomplished the task.

A widely used feature in neurofeedback is the power or energy of a specific frequency band, since they have different characteristics for different activities. One approach to extracting the PSD is to transform the signal from the time domain, as seen in Figure 2.3, to the frequency domain. For this, FFT can be used, and the power is calculated by multiplying this signal by its conjugate and dividing by the number of sampling points of that segment, as shown in the Equation 2.1 [19]

$$P(n) = \frac{F(n)F*(n)}{N}. \tag{2.1}$$

One of the nonparametric methods used to find the estimated autocorrelation sequence, transformed by Fourier, in PSD is Welch's method. The data sequence is applied to data windowing, that selects a segment of the signal and multiplies it by a window function, excluding everything outside it, producing modified periodograms [38]. The information sequence $x_i(n)$ is

$$x_i(n) = x(n+iD), \qquad n = 0,1,2,...,M-1 \quad while \quad i = 0,1,2,...,L-1; \tag{2.2}$$

iD is the point of start of the ith sequence. Thus L of length $2M$ represents formed data segments. The resulting output periodograms give

$$P_{xx}^{\approx(i)}(f) = \frac{1}{MU}\left|\sum_{n=0}^{M-1} x_i(n)w(n)e^{-j2\pi fn}\right|^2. \tag{2.3}$$

In the window function, U gives normalization factor of the power and is chosen such that

$$U = \frac{1}{M}\sum_{n=0}^{M-1} w^2(n), \tag{2.4}$$

being $w(n)$ the window function. The average of the modified periodograms gives Welch's power spectrum [38]

$$P_{xx}^{W} = \frac{1}{L}\sum_{i=0}^{L-1} P_{xx}^{\approx(i)}(f). \tag{2.5}$$

To calculate the energy of a specific frequency, be it α, β, θ, or δ, which are the frequency bands most related to human mental states, the signal strength is added according to the waveband distribution of the EEG signals. With Equation 2.6, the energy of the theta band is obtained, for example [19],

$$E_\theta = \sum_{freq=4}^{7} P_{freq}. \tag{2.6}$$

2.3 SVM: a viable solution to classify EEG data

The brain signals' classification step aims to recognize the user's intention that is provided by the brain activity and translated into a vector of features formed in the stage of data processing. For this, regression or classification algorithms can be used. The classification algorithms, which have a more popular approach, use the extracted features to define limits between different targets and can be developed for offline processing, online processing or both [35, 37].

The offline method involves examining data and evaluating it statistically by estimating observations over sessions. However, despite its importance for calibrating the algorithm, they do not show real-time problems, since the data is collected and later processed. In the online method, the algorithm is tested in an environment in which the user may experience changes due to fatigue/motivation, and the signals are collected in real-time. The union of these two types of processing is of great importance for the design of an in-closed-loop algorithm, because while the offline simulation presents good methods to develop and test new algorithms, the online simulation presents evidence of the performance of the system [37].

There are several algorithms used for classification, from the simplest to the most complex, using linear approach, as well as Linear Discriminant Analysis (LDA), Support vector machine (SVM), as well as using non-linear approach, as k-nearest neighbor (k-NN) , artificial neural network (ANN) and even the SVM already mentioned. Simple algorithms have an advantage, as their adaptation to the characteristics of the brain signal is also simpler and more effective than for complex algorithms [37].

In order to choose the classifier, its properties must be analyzed and, whichever has the simplest implementation that can meet the proposed algorithm's objective, must be chosen. A classifier widely used for having a linear and non-linear classification modality, presenting a speed classification, and that is easy to implement, is the SVM [37].

SVM, first introduced by Vapnik [39], is a supervised classifier, that is, it uses information already categorized to train a model that represents this data and, later, having only new information, assigns it to a certain category according to the training [19]. SVM generates linear and non-linear models, uses a binary or multiclass classification method, has low computational cost, and is a simple classifier that performs well and is robust in relation to the "curse of dimensionality", which means that a large set of training is not necessary to obtain good results [37].

An SVM classifier separates a set of training vectors for two different classes, in the case of binary classification, (x_1, y_1), (x_2, y_2), ..., (x_m, y_m), where $x_i \,\epsilon\, R^d$ indicates vectors in a d-dimensional feature space and $y_i \,\epsilon\, \{-1, +1\}$ is a class label. This classifier builds a hyperplane or set of hyperplanes to separate these vectors into classes in order to maximize the distance between the closest training samples and the hyperplanes, seen in Fig 2.6. The SVM model is generated by mapping the input vectors to a new space with a higher dimensional feature space denoted as $\Phi : R^d \to H^f$ where $d < f$. Thus, an ideal separation hyperplane in the new feature space is constructed by kernel function $K(x_i, x_j)$, which is the product of the input vectors, x_i and x_j, and where $K(x_i, x_j) = \Phi(x_i) \cdot \Phi(x_j)$ [37, 40].

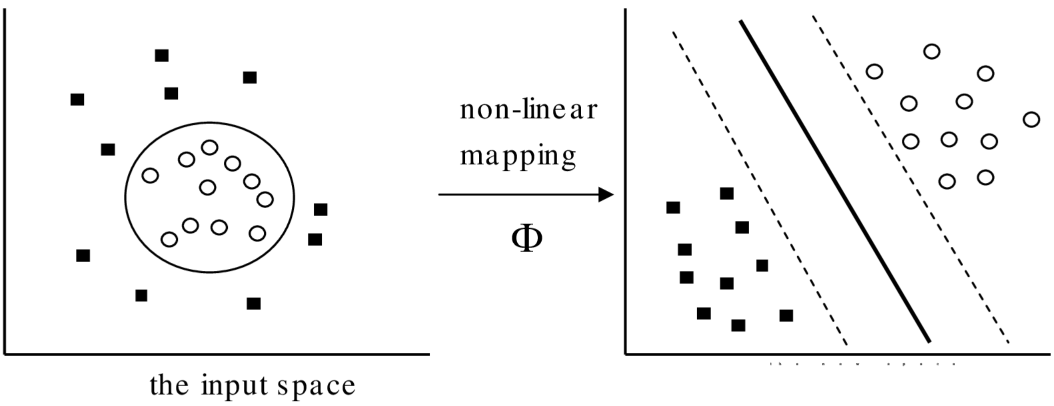

FIGURE 2.6: SVM Model Generation [40].

The solid black line in the Figure 2.6 represents the hyperplane that was calculated after mapping the input space to a new linearly separable space. On each side of this hyperplane, which divides the samples, parallel hyperplanes, represented by dashed lines, are located. All samples placed on one side of these parallel hyperplanes are labeled -1 and all samples located on the other side are labeled +1. The training samples that are closest to the parallel hyperplanes in the transformed space are called support vectors. The number of these support vectors is generally small compared to the size of the training set and they determine the decision surface [19, 40].

2.4 Serious Games

Educational approaches using video games have gained relevance by combining ludic aspects with specific content, stimulating the learning process. These games, that allow you to present new situations, discuss solutions, build knowledge and train specific activities, are known as serious games [41]. Serious games are games created with the intention of entertaining and achieving at least one additional goal, such as learning and/or health. To put it another way, serious games are not characterized by the developer's intention, but by the player's intention. For example, a digital game can become a serious game if used not only to entertain, but also to train motor skills and player's reaction time [42].

The definition of the term "serious games" follows the one described in Sawyer and Rajeski (2002) [43], however, this oxymoron, that is, when words of the opposite definition are combined, was used with a similar meaning before the publication of these authors. The use of games, more specifically video games, to deal with more serious matters is older than imagined. *America's Army* was the first well-executed and successful game that gained public knowledge that fit Sawyer's definition, however, even before *America's army* (2002) existed, games that fit that definition were already being played. In fact, it is assumed that the first games were created to serve serious purposes [44].

The first use of the term "serious game" as an oxymoron, with the definition close to the current one, was in a book written by Clark Abt (1970) [45]. He was a researcher who worked at the time of the cold war in a research laboratory in the United States. His goal was to use games for training and education. Clark points out in his book that games can be played seriously or casually, but serious games have a carefully planned educational purpose and are not primarily intended as an entertainment tool. Nowadays most games are made for entertainment purposes, but in the past, the first home video game console, the *Magnavox Odyssey*, had both entertainment and educational games. Therefore, it is plausible to say that entertaining video games only appeared after the first digital "serious game" [44].

Pioneering video games that even before Sawyer 's definition already supported a serious purpose, are diverse, for example, in the area of education in *The Oregon Trail* (Minnesota Educational Computing Consortium, 1971), Figure 2.7 the player was an American Pilgrim in 1848 that had to reach Oregon to settle down. The game contains a lot of information related to this period of American history and is still used by teachers today. Other areas like Health care, had games like Captain Novolin (Raya Systems, 1992) that was developed to teach children how to deal with diabetes, because the captain was a diabetic superhero who took care of the glucose level in his blood by fighting evil junk food aliens. Several other games, which also fit Sawyer's definition or are very similar to it, were developed in the fields of defense, art and culture, religion and corporate training and advertising [44].

FIGURE 2.7: Game The Oregon Trail.

If serious games have existed since the beginnings of video games, why did the term only start "to rule" after 2002 or to gain knowledge after 1970 with Clark Abt? Alvares [44] believes that U.S. designers had to invent this new label to convince people that games were not just for entertainment. However, why did video games had such a "negative" image that designers wanted to show how different serious games were from "entertaining video games"? In the early 2000s, marketing strategies for selling consoles and games were always targeting children, and there were also controversies, as some games were violent and the impact that this could have on children was not certain. This discussion worsened after the Columbine tragedy in 1999 when the two killers were regular *Doom*, seen in Figure 2.8, players (id Software, 1993). Criticism arose as to why this game was being used by Marine Corps for tactical training and the same game was being provided indiscriminately for children over the internet, only emphasizing this contradiction between fun for children and violent content. After these discussions in the 90s, video games were not very well seen in the United States, so when *America's Army* was launched, this serious game label was used to emphasize its serious purpose and that it was not for leisure for children. This oxymoron was so relevant that other video games, with the same serious purpose, started using this name, launching this "current wave" of serious games.

FIGURE 2.8: Game Doom (1993).

There are several motivations for creating serious games. One of them is to provide a fun experience for the user, because a game with good visuals and an involving soundtrack promotes a sensory pleasure that makes the use of software, for example, more pleasant. Another factor is to increase the user's motivation, since positive experiences with the game can generate interest and curiosity. Also, game creators aim to reach an emotional level of the user with good game plays, that are capable of evoking challenge, relief, thrill, and empathy with characters. Besides, serious games offer immediate user feedback, because players can assess their progress, and adaptability, since the game can be modified so that a user experience is not too difficult or too easy. Thus, by having this possibility of changing parameters, serious games tend to provide an emotional and/or physical experience that does not generate much stress or shame [42].

"Serious games" is not just a label, it has become an economic model. In the past, they were based on the same model as entertainment video games, people bought copies to play. Nowadays, the model is funded by "clients", who hire a studio to develop a game bespoke to their needs. The Studio is paid so that customers, mainly motivated by an event, can use the game any way they want. For example, in 1984, a bomb was planted by the Irish Republican Army (IRA) in order to assassinate Prime Minister Margaret Teacher. She was not hurt, but other guests who were at the hotel were hurt and even killed. A sentence spoken by the terrorist group marked the attack, "but remember we only have to be lucky once. You will have to be lucky always". From there, the need arose to create a strategy game that simulated a security agency and that helped to train and create strategies that could avoid this type of attack [44, 46].

For training purposes, serious games are used to simulate situations that offer some kind of risk, decision making, and/or to develop some skill. For teaching-learning purposes, it can simulate situations in which, to evolve in the game, the player need to learn something, as in *The Oregon Trail*. Games with teaching-learning purposes can be divided into 3 categories: awareness, knowledge building and training. Those aiming to raise awareness aim to highlight a new problem, making the player use reasoning to "overcome" the causes of the problem or seek to minimize them. Serious games for the purpose of building knowledge require prior knowledge, which will be integrated to generate new problem solving scenarios. As for the training category, the player performs tasks repeatedly to assess their accuracy and dexterity [41].

The main elements for serious game development are: script, game design, gameplay and Interface. It is in the script that documents the game's differential in relation to others, and it should mention the elements of entertainment, challenges to users, types and forms of interaction (mouse, keyboard and among others), viewing mode, point of view, if the game is first or third person, gender classification, and all the elements that will be part of it. The game design is the artistic project, in which the characteristics of the scenario, the sketches of the characters, and the outline of the evolution of the story are developed. Sounds, soundtracks and sound responses for character interaction are also performed at this stage.

The next element is game play, it shows the rules of the game and its balance, that is, the different levels of difficulty to be played. These rules can be developed by the development team using strategies and techniques, originated from Artificial Intelligence (AI), to control the game. Finally, there is the interface element, which refers to the form of communication between the game and the player. The *outgame* interface represents the presentation of the game, such as introduction, instructions, settings and more. The *ingame* interface, which is made available during the game, is characterized by sending player data to the application and vice versa [41]. There are several other terminologies and definitions for the elements of serious games' development, such as game engines, lighting, multiplayer, physics and collision detection [42], that will not be mentioned in this dissertation. In Figure 2.9, the basic terms used in neurofeedback are shown.

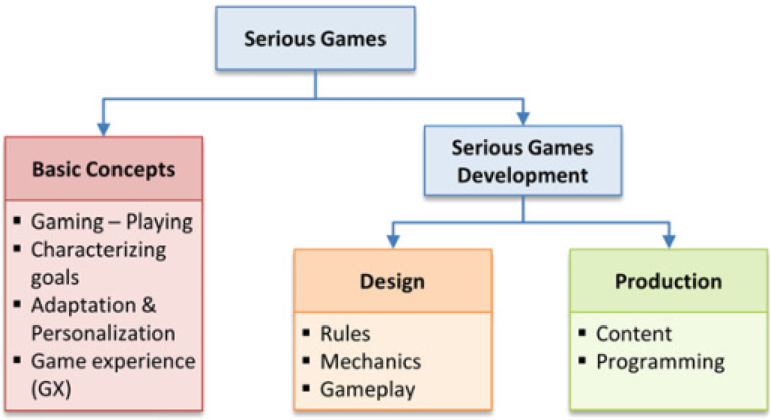

FIGURE 2.9: Basic serious games' terminology.

Two other important game components are the character types: characters controlled by the computer (Non Player Character or NPC) and the player's characters or PC. As it says in the acronym, the control of the PCs is performed by the player, the character has no autonomy, always translates the actions of the user by some element of interaction such as keyboard and mouse. The NPCs are controlled by the computer and have the autonomy to automatically respond to the situations in the scenario [41]. For a better gaming experience, a certain realism is expected, so, games that have characters and elements that reproduce real-life or similar movements are better accepted. Bringing artificial objects "to life" is the definition of animation, in this case, non-rigid objects, for example, can change their shape, such as water flows. In the animation, the animator changes the attributes of objects, such as shape, position, or color, and stops them from being static to becoming dynamic. Animating characters being PCs or NPCs can result in the character's personality change [42].

The creation and application of serious games with high-quality is a multidisciplinary task that unites the contribution of computer science, art and design, psychology, didactic and pedagogy, stories and storytelling. Thus, it is not enough for each area to do its part and then join the tasks. There needs to be cooperation from these disciplines so that, from the beginning, problems and challenges are treated as multidisciplinary [42].

Chapter 3

Methodology

3.1 Materials

For the acquisition of brain signals, a dry-electrode wireless EEG headset with 20 electrodes, Figure 3.1, called Quick-20 (Cognionics, United States) was adopted. This equipment was already owned by the research group. It was purchased to assist in outpatient problems and offer more practical solutions for system applicability, as it has wireless communication and dry electrodes. The equipment uses a combination of active electrodes and active shielding, and its amplifier has the following specifications: 24-bit ADC, low noise, high dynamic range inputs with flexible configuration of sample rates, bandwidth and channels.

FIGURE 3.1: Quick-20 Cognionics.

For data acquisition, and EEG signal processing, a desktop computer (i7-7700 processor, GeForce GTX 1070 6GB, HDD 1 TB, SSD 120 GB, 16 GB RAM) was used and the game was developed in a similar desktop (i7-7700 processor, a GeForce GTX 1080 6GB, HDD 1 TB, SSD 120 GB, 16 GB RAM). Data acquisition was performed with a Cognionics' proprietary software, and Matlab was used for data preprocessing and online processing of the EEG signal. For exchanging data between these two software a library called Lab Stream Layer was used.

Unity[1] was chosen as the game development platform, considering its low cost, prior knowledge of the software, ease to learn and with potential for 2D and 3D games. In addition, Unity allows the communication with other signal processing software, which is suitable to the application proposed.

3.2 Methods

3.2.1 Neurofeedback

The neurofeedback training method carried out in this dissertation uses EEG to collect the brain data and visual feedback, in the form of a serious game, to return to the users their mental state. *Neurofeedback Space* was developed with the purpose of increasing the user's engagement and comfort during the NFB sessions. The system developed to perform the NFB training is divided into steps that are shown in Figure 3.2.

In each session, the signal is acquired using a wireless EEG headset, and the data is sent via Bluetooth to the computer, which, through a library called Lab Stream Layer, sends it to Matlab software. This software processes the data and extracts features that are used as input to a supervised classifier, which will classify the user's mental state according to the mathematical model built during training. Then it send the classified data to the Unity software, where the serious game was developed. Finally, it sends visual feedback to the user who can either maintain their current mental state or change the stimulus so that their mental state changes as well.

3.2.2 Brain region's and electrodes' selection

The brain is divided into 4 main parts: the frontal, temporal, parietal and occipital lobes. There is in the literature a wide variety of number and combination of electrodes used in NFB. There are authors who use 1 electrode in the *frontal/occipital*

[1] https://unity.com/

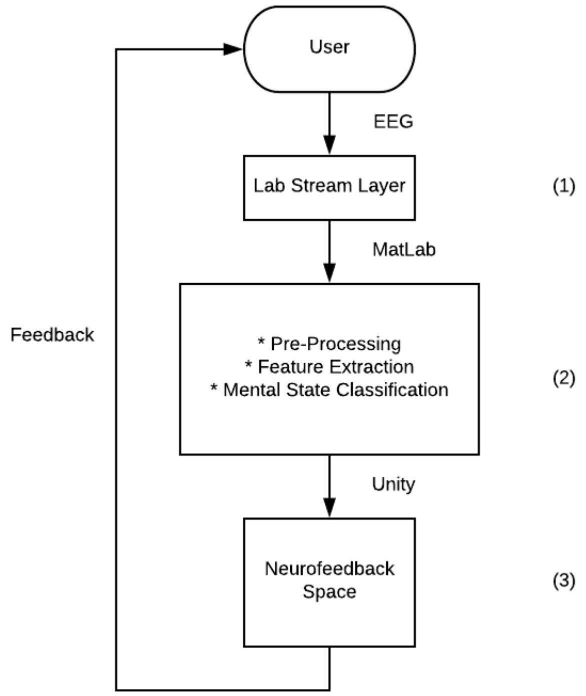

FIGURE 3.2: Neurofeedback System.

lobes, others who use EEG headsets with 10, 14 and up to 27 electrodes. The electrodes' combination is also diverse, but the most used regions are *frontal*, and *parietal* [5, 11, 14, 15, 18, 20, 29].

Thus, in order to choose only one local region of the brain, five regions, shown in Table 3.1, were chosen to perform an attention test and choose the one that obtained the best results. The letters in the second column represent the lobes and the electrodes position on the scalp. F represents Frontal, P Parietal, T Temporal and C represents the motor cortex that is situated in the frontal lobe. The even numbers are located on the right hemisphere, the odd numbers on the left and the higher the number the farther from the center of the scalp.

The 10-20 system was used and the regions shown in the previous Table, observed in the scalp in Figure 3.3, were agreed upon after meetings of the BRAEN research group (Brazilian Research Group on Brain and Cognitive Engineering).

TABLE 3.1: Brain Regions.

Regions	Electrodes
1	F3, Fz, F4
2	F3, C3, P3
3	F4, C4, P4
4	F3, F7, C3, T3
5	F4, F8, C4, T4

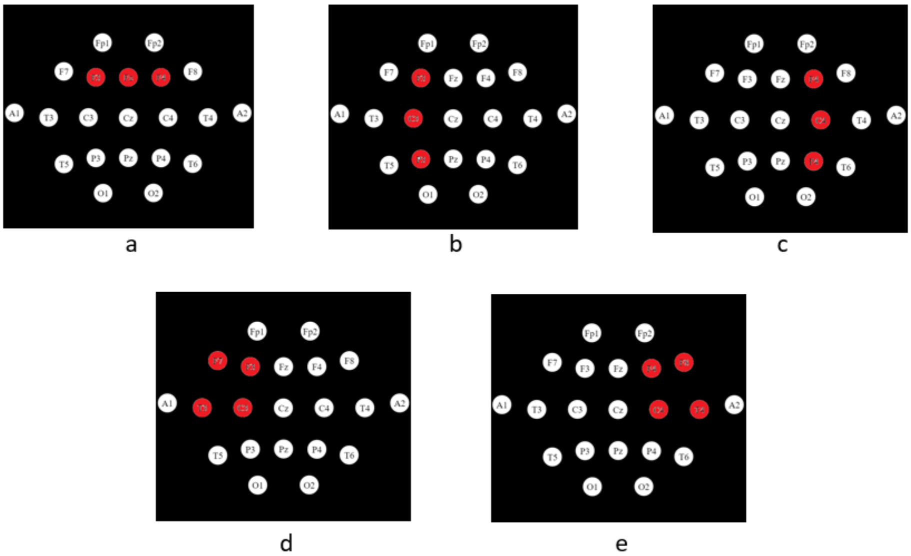

FIGURE 3.3: Scalp with Brain Regions: (a) First Region, (b) Second Region, (c) Third Region, (d) Fourth Region, and (e) Fifth Region.

3.2.3 Serious Game: Neurofeedback Space

The neurofeedback space game was developed to be used throughout the NFB sessions. The space theme was designed with the goal of transforming the NFB training into a pleasant, fun, challenging experience and, above all, thinking of providing immersion and engagement to the user. Also, the EEG headset can be presented as a helmet of a pilot and/or ship's commander, thus, avoiding negative feelings of strangeness or even fear of the device.

To create this environment, the game was divided in five scenes and all of them were set up to establish a connection between the user and the game.

3.2.3.1 Panels and Training Protocol Screens' description

As already mentioned, the game was divided in five scenes, of which two are panels. The first scene, and also the first interaction between user and interface, is the *menu panel*, as seen in Figure 3.4. In this screen, the user can choose between three buttons: Login, Games and Behavioral Observations. Also, there are two Non-Player Characters (NPCs) to integrate the ship's environment. They were created with the goal of being the ship's crew, so the user can be their commander. NPCs appear on all of the *menu panel*'s screens.

FIGURE 3.4: Menu Panel.

The login screen, showed in Figure 3.5 was built to be a logbook, where, in every session, the users had to enter their "name", "date of birth", "mission" and "mission's date". Mission was the session number, but, in order to create a "spaceship environment", and to increase engagement, this term was used.

To adapt the game into a more immersive environment and to make the user more comfortable with the NPCs, all instructions for performing the classifier training, which is the mathematical model that separate the mental states of attention and non-attention, are made by NPC animations. Figure 3.6 shows the training screen for the attention state, where the NPC is pointing and suggesting a location for the user to focus on. The game also has other training screen for the non-attention state, which is the same screen, but with only the space background, so that the user does not focus on any element. After training, the NPC requests the user to prepare for the game's start.

FIGURE 3.5: Login Screen.

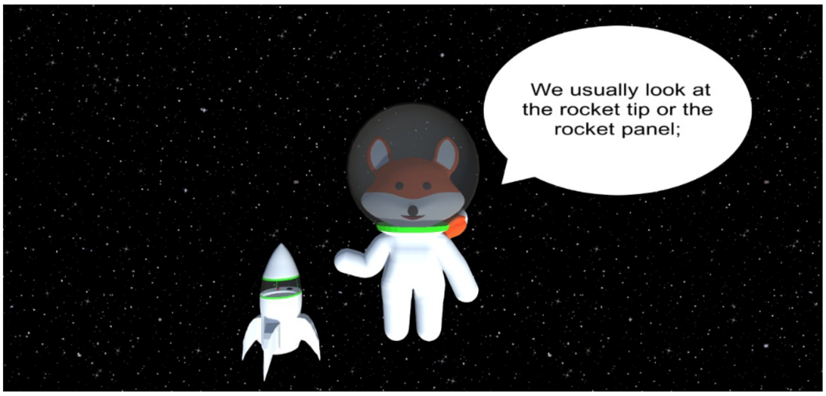

FIGURE 3.6: Training Protocol Screen - Animation.

The last screen in the *menu panel* is the level selection (3.7). Three levels were designed to keep the user interested, and to provide different difficulty experiences. A balance between anxiety and boredom, also called flow channel, as seen in Figure 3.8, is associated with an optimal experience during the game [47]. Thus, if the users experience greater challenges than they can handle, they can play an easier level to stay in the flow channel. Similarly, if the users have a tedious level experience, so, if they experience boredom, the game can be changed to make it harder. In this game, the adaptive concept of Figure 3.8 was not used, that is, over the same game level, changes in the difficulty occur so that the user remains in the flow channel during the session. The concept was used in a static way, so when the player's ability to focus his attention on some object of the game improves, the difficulty of the task can be increased by changing the levels of the game.

FIGURE 3.7: Level Selection Screen.

3.2.3.2 Game Levels

The first level was designed to be an introduction to the game. The level is composed by 7 elements that can be observed in Figure 3.9. The first one is the spaceship, it looks the same as the spaceship from the *menu panel*, but with an "outside" view. The second element is the star pickup, the yellow assets in the Figure 3.9. Both the ship's path and the pickup's path are created using perlin noise with a fixed seed, this makes the path always the same. The path needs to be generated automatically, because the user has no control over the direction the ship is moving, this will be explained in the next subsection. The third element is the speed feedback bar, which is located at the bottom-left of the image.

The fourth is the timer, based at the bottom-right and it was set to five minutes. This duration was chosen because the game cannot be long, since the EEG headset can cause discomfort being used for a long time, and the game becomes tiring due to not having joysticks and keyboard/mouse. Potential side effects for long or to intense training include nausea, dizziness, fatigue, agitation, cognitive interference, or destabilization [13]. Also, the game can't have a short duration, because it can cause frustration if the user fails to perform well at the beginning of the game. Thus, after testing, it was found, empirically, that five minutes was enough to keep the player entertained and not cause headaches.

The fifth element is the score text, situated at the top-right of the image and it shows the number of star pickup's collected. The sixth element is the "menu button" at the image's top-left and it can be used in two situations: at the end of the game, or at

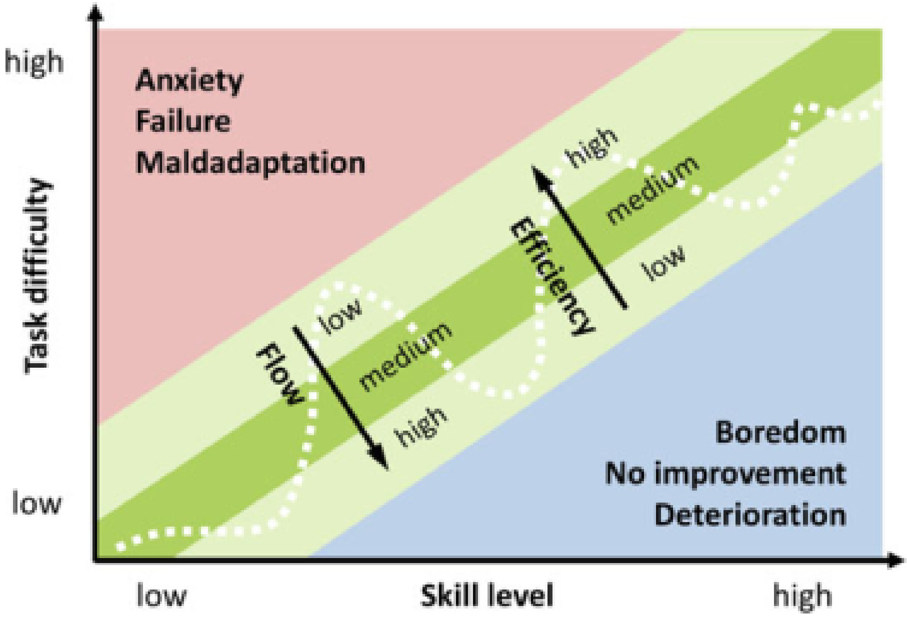

FIGURE 3.8: Flow Channel [42].

any time, if the user feels the need to give up the game, due to discomfort, sickness or any other situation.

FIGURE 3.9: Neurofeedback Space's first Level.

The last element of the game is the background, and to create it a technique called Parallax was used. This creates a depth optical illusion in the interfaces using image manipulation. Two equal images were created and positioned with a small offset in X Y axis, but in the same Z plane. Each image moves in the XY plane at a different speed, following the movement of the spaceship, and this difference in position and

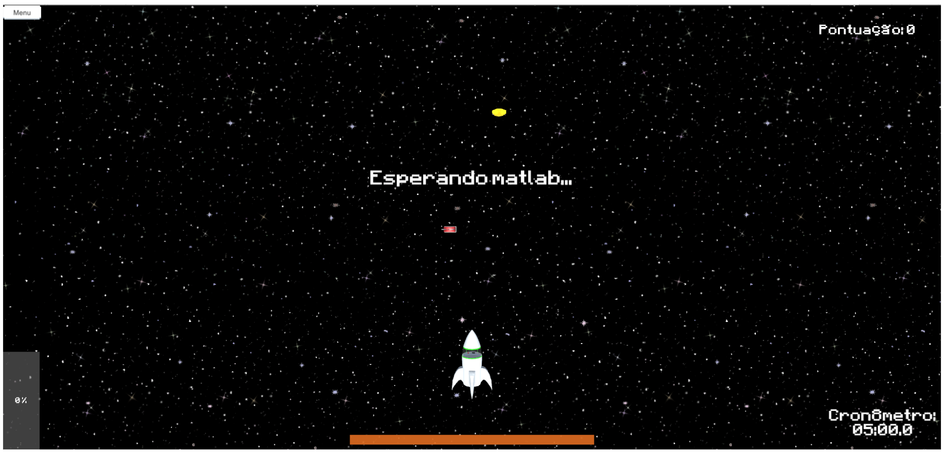

FIGURE 3.10: Neurofeedback Space's Second Level.

speed brings the illusion of depth, even without moving them in the Z plane. It makes look like that there is a distant image in the Z plane in the background, that moves slower, and a closer image, that moves faster.

The second level, seen in Figure 3.10, has the same elements as the first, but two assets have been added to offer a more challenging gameplay. The fuel element, illustrated by the red asset in Figure 3.11, and an orange bar, representing the spacecraft's fuel tank. During the game, the ship will consume fuel and the level of the orange bar will drop, if the player picks up the fuel asset, the bar fills again, if not, and the fuel tank empties, the player is prevented from picking up the star pickups until he finds a new fuel asset to fill the tank.

The last level has the same elements as the second, but a small modification has been made to make the gameplay even more challenging. If the fuel tank is empty and the user does not pick up the fuel asset, he loses one point per second until he reaches the fuel element and refills the tank. Fuel assets always appear after 3 star pickups and are at the same path, as already explained.

3.2.3.3 Neurofeedback Space Operation

The game's goal is to teach the users to self-regulate their brain waves, so they can understand how to focus and pay attention not only to the game, but also to their daily activities. Therefore, the game "punishes" the players when they aren't in an attention mental state and reinforce when they are.

FIGURE 3.11: Fuel asset - Red Element.

The neurofeedback training needs a feedback element to close the loop shown in Figure 3.2. The element chosen to show the user whether or not he is in a mental state of attention was the speed of the spaceship. For this, a TCP/IP (Transmission Control Protocol/Internet Protocol) communication protocol is established between Matlab, which is installed in a computer responsible for signal processing, and Unity, installed in a gamer computer. The signal received from the EEG headset is processed by Matlab and the classifier output is sent to Unity. If the classification output is the mental state of attention, then "1" is sent to Unity, otherwise "-1" is sent. After receiving this data, if the value is "1", the speed is added to 10 % of a standard value, otherwise, the speed decreases by 10 %. The minimum achievable speed of the spaceship is 0 % and the maximum is 100 %, thus, there are 10 speeds between 0 % in 100 %. Therefore, the player has always a visual feedback, and when the spaceship is getting slower, he can find another focus point (or another strategy) that works better for him, so that the velocity increases again.

Three items related to Unity and *Neurofeedback Space* were chosen to evaluate user's progress. The first item is the *score*, which is how many stars pickups the user can get within five minutes of the session. The second item is called *attention*, the number of times the classifier sent "1" to Unity via TCP/IP in a total of 300 seconds of the session. This is comparable because unity receives and modifies the speed 1 time per second. The third item is called *sustained attention*, which means the greatest "1"s sequence sent to Unity. So, it means, how much the user was able to sustain his mental state of attention over the 300 seconds of session.

FIGURE 3.12: Behavioral observations panel.

At the end of each game session, before the behavioral observations, questions regarding what did the users do to increase the spaceship's velocity were made. That is a strategy to encourage self-perception, because, if the users can identify what they are doing to have more focus, it can help them in real life in daily situations.

3.2.3.4 Behavioral Observations

The last panel, observed in Figure 3.12, is dedicated to evaluate the user's experience. Four questions, at the end of every game, were asked: "Were you feeling agitated or relaxed during the game?", "Were you feeling concentrated or distracted?", "How was your motivation today?" and "How much difficult was the game?". The last two were answered in a 5-point likert scale. Being the scale, in the third question: 1- not motivated, 2- less motivated, 3- neutral, 4- motivated and 5- very motivated. And in the last question: 1- very easy, 2- easy, 3- neutral, 4- difficult, and 5- very difficult. The other two questions were in a "binary format", and therefore there was only one answer for them.

The last item of the panel is the observation field. The purpose of this field is to note down extra comments from both the user and the professional who is applying the training. The user can report that the room was cold, that he was comfortable during the test, if any external elements bothered him, suggestions for new game assets, gameplay changes and so on. The professional, who is following the whole process, can note, after the user leaves the room, some inconsistencies observed during the game. For example, the user says that he was feeling calm, but was panting, moving his feet/fingers, and seemed restless. This tool is most useful for tests with children who have a hyperactivity disorder, and/or lack of self-perception.

One question always asked in all tests is whether the user thinks the system had a great feedback. This means that the user realized that when he was paying attention or not, the spaceship would respond with the correct feedback. Thus, in addition to working on self-perception, it is possible to verify the system's operation more reliably and completely.

All data from *login panel* to evaluation items such as *score*, chosen level and comments in the observation panel were saved in a database developed with SQLite, that is a C language library that implements an embedded SQL database. It was chosen for being free, easy to program, and it is also easy to use command to better visualize results. Since the idea is to develop NFB training to be done by non-engineering professionals, the idea is to make everything simpler or automated, so that, it is easy to implement and can be used by all types of qualified professionals.

3.2.4 Algorithm's Versions and Operation

Four algorithm versions with different types of filtering and normalization were tested to choose the one with the best performance, that is, the one that obtained the greatest SVM's accuracy result for the protocol's test samples. The purpose was to try to minimize the noise of the data collection, and reduce the processing time as much as possible, however, without losing the user feedback, that is, the feeling that the system is representing the user's mental state correctly.

All processing was performed offline, which means data acquisition was the first step performed and a matrix with all EEG raw data was saved for further processing. The data was recorded with a sampling frequency of 500 Hz and divided into training and testing, respectively, the first time and the second time the volunteer watched the video.

All versions follow the same structure, besides filtering and normalization. The first step is to separate the signal into windows. To process it, 500 samples are used, but a 90% overlap is applied to generate more samples for the classifier's input. Thus, if samples 1 to 500 are used for the first time, in the next step of the loop, samples 51 to 550 will be used, even if only 50 are new samples.

At each iteration, the signal is filtered, normalized, depending on the version, and Welch's Power Spectral Density (PSD) estimate is calculated for each frequency band used in this dissertation, in this case, $theta$, $alpha$ and $beta$. The $theta/beta$ and $alpha/beta$ ratios are posteriorly calculated, and with these features, throughout the iterations, the classifier input matrix is constructed.

The SVM classifier uses supervised learning to construct a hyperplane in order to separate the features vector, therefore it needs the predicted data for that specific input data. In the training step, or learning process, the classifier uses this data (input and predicted data) to build up a model to separate the classes. In the test step, the classifier only receives the inputs that are processed and classified. Thus, this class output can be compared with the desired output, that is already known, and the accuracy, which indicates how many classes were classified correctly, can be calculated. This classifier was chosen because it is a viable solution for classifying EEG data and because it has already been used in a dissertation with the same purpose in the BRAEN research group.

3.2.4.1 Version 1

The first version is the version that originated the tests, and the first one that got a good response in terms of feedback, that is, the user felt in control of a primordial serious game developed to test communication between the EEG headset, Matlab and Unity.

As already mentioned, this version, as all the others, follows a preprocessing, processing and classification pattern. After separating the window for processing, the polynomial trend is removed and a notch filter, which is a band reject type filter, is used to remove the frequency from the electrical power distribution, which is the 60 Hz noise. Then, a zero-phase digital filtering is applied by processing the input data, that is already filtered, in both the forward and reverse direction using a bandpass (0.5-100 Hz) 100th-order finite impulse response (FIR) filter.

The Welch's power spectral density estimate is calculated for each frequency band, summed, and the feature array is returned and stored for when processing is complete. The algorithm returns two matrices of 290 samples, and the number of features will depend on the amount of electrodes used for the analysis (since different regions use different number of electrodes). If there are 3 electrodes, 15 features, 5

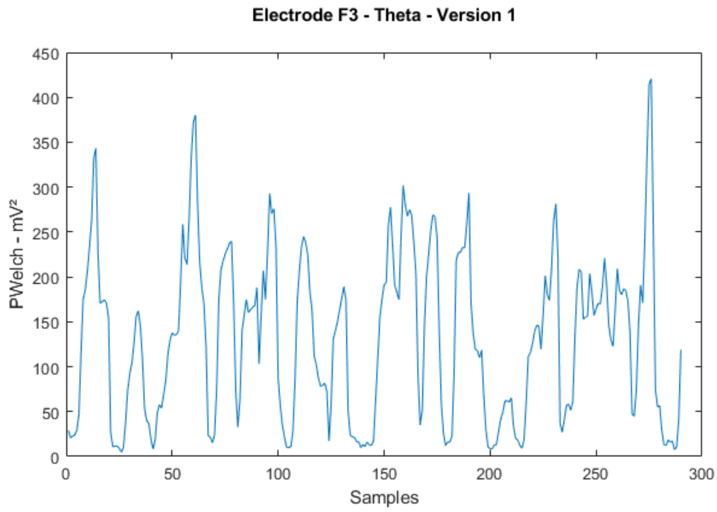

FIGURE 3.13: PWelch estimate for Theta frequency band for the algorithm's first version.

($theta$, $alfa$, $beta$, $theta/beta$ and $alfa/beta$) per electrode, if there are 4 electrodes, 20 characteristics and so on.

This matrix is used as input to the classifier that will train the mathematical model. Then, another matrix is built with new data, but to be used as a test. The motivation to program other algorithm versions was the magnitude of some features' peaks, as can be seen in Figure 3.13, which had a high chance of being noisy, and could be interpreted as some outstanding feature of some mental state and biasing the result.

3.2.4.2 Version 2

The goal of testing these algorithm versions was also to decrease process execution time, because, although this protocol had only the offline step, which does not depend so much on processing time, the next tests will also have an online step, where the faster the processing the better. Therefore, the algorithm has to have a combination between low processing time and good feedback.

In the second version, aiming in reaching the combination mentioned above, the only changes made were the changes in signal filtering and in the detrend of the signal. The 100th-Order filter and the notch filter are no longer used. Now, a technique called Common Average Referencing (CAR), which calculate the average of all EEG Headset electrodes and subtracts it from each signal from that sample from

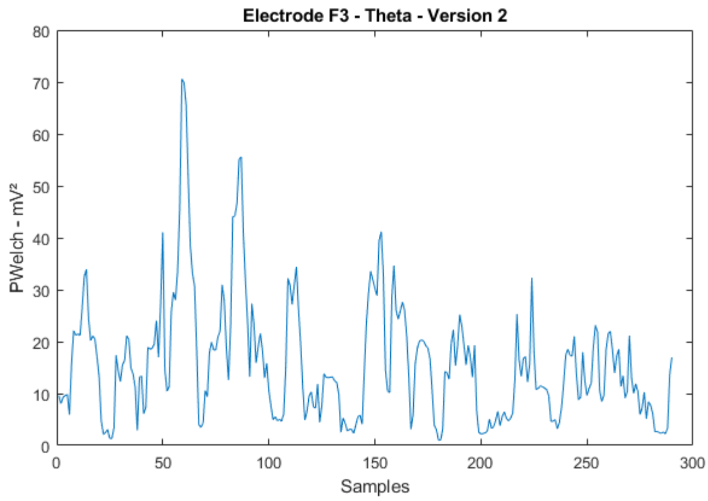

FIGURE 3.14: PWelch estimate for Theta frequency band for the algorithm's second version.

each electrode, is used. With this technique, the signal amplitude is reduced, but each channel contributes equally to the new reference.

A fast Fourier transform (FFT) filter is applied from 3 to 20 Hz, because from 0.5 to 3 Hz ($delta$ frequency) is not being used in this research. The signal is filtered in the frequency domain, and subsequently the signal is reconstructed. Then, the same steps for feature extraction and classification are repeated.

It is possible to analyze in Figure 3.14 that, although the amplitude of the feature has decreased, there are still peaks that can bias the classification.

3.2.4.3 Version 3

In the third version, the filters remain the same as in the previous version, but the changes made were regarding the features' normalization and in the way PSD is calculated. In previous versions, pwelch was calculated for each frequency band separately, and for this one, it is calculated for the entire signal to decrease the processing time, then, it is normalized with the Equation 3.1. The result in pxx, the PSD estimate of the input signal found using Welch's overlapped segment averaging estimator, is summed to obtain the average power in a specific frequency range for each electrode.

$$pxx = pxx./max(max(pxx)) \tag{3.1}$$

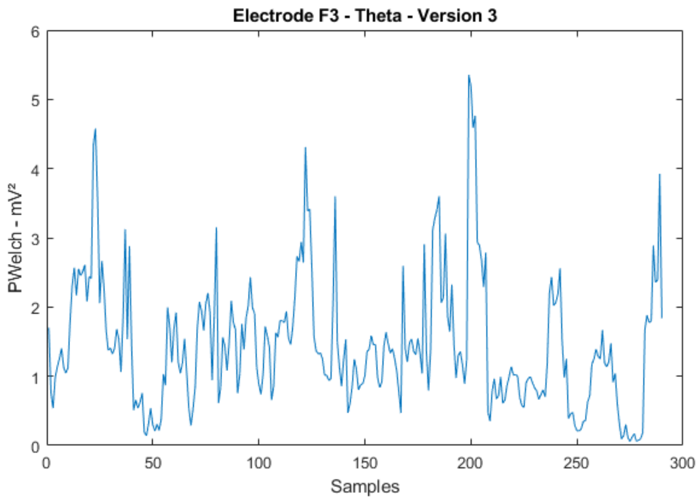

FIGURE 3.15: PWelch estimate for Theta frequency band for the algorithm's third version.

TABLE 3.2: Training step execution time.

Versions	Execution Time (Sec)
1	7.2073
2	3.9877
3	1.2103
4	1.2153

As can be seen in Figure 3.15, the feature's amplitude was much lower than in the other versions, and it has fewer peaks with high amplitudes due to data normalization.

3.2.4.4 Version 4

In the last version tested, the algorithm used was practically the same as version 3, the only change was in the normalization that used the base 10 log of pxx instead of just pxx. The result of this algorithm is shown in Figure 3.16. The peaks resemble the magnitude of the previous version, but are still smaller.

In the Table 3.2, it is possible to observe that the execution time decreases with the change of the versions. The last two versions, that are very similar, have very close results.

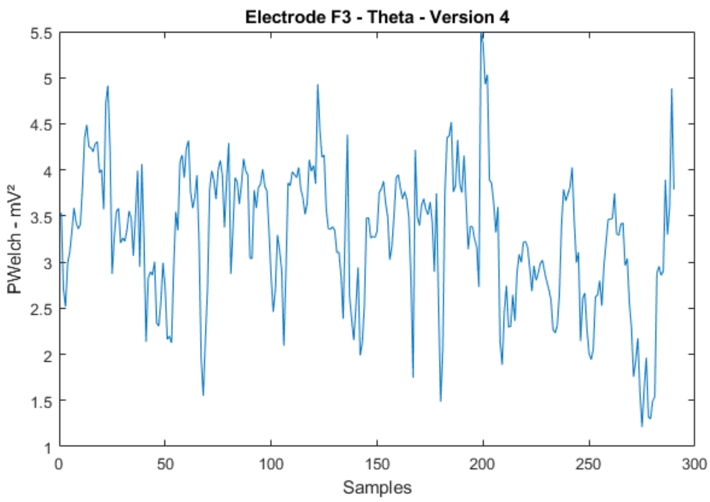

FIGURE 3.16: PWelch estimate for Theta frequency band for the algorithm's fourth version.

Chapter 4

Preliminary Validation and Selection of Algorithm

As mentioned in the previous chapter, 5 brain regions were selected and 4 versions of algorithms were developed so that the combination that obtained the best results, the shortest execution time and better feedback, was chosen to be used in the NFB training protocols.

4.1 Volunteers and Protocol

The protocol consisted of a two-step task performed with 5 college students, 1 man and 4 women between the ages of 19 and 25, in a single session. First, when the volunteers were ready for the protocol, they were asked to sit up straight in front of the computer, comfortable and looking at the screen, on which the tasks would be performed, observed in Figure 4.1. Secondly, the EEG headset was positioned on their heads, checking if all the electrodes were touching the scalp, and that the signal was apparently with low noise. If the signal was noisy, a fact that occurred mainly in people with bulky hair, the electrode was repositioned until the signal became clearer. Finally, the volunteers did a two-minute breathing exercise, accompanied by a psychologist, member of the research group, to calm down, and then, with the preparation done, proceeded to the two-step task.

In the first step, after the breathing exercise, a video, divided into 4 images, is shown to the user. The first image is a black background with an instruction asking the user to remain relaxed and calm. The second one is a light blue background. The third is again a black background with an instruction asking the user to focus on the red

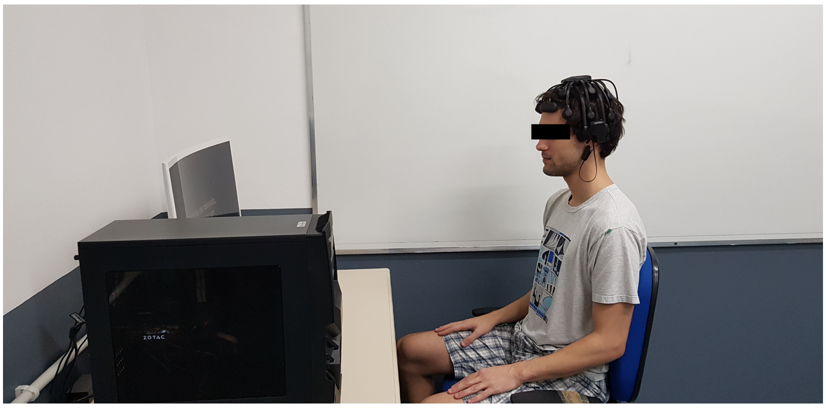

FIGURE 4.1: Volunteer in position to the data acquisition.

center circle to make the blue circle disappear. Finally, the fourth image has two concentric circles of different radius and colors, red being the smallest circle and blue being the largest circle. After the video ended, it was played again, and the volunteer's brain data, during the two times the video was shown, was recorded on the computer for further processing. Figure 4.2 shows the two screens used for data acquisition and processing. The left image is used for the non-attention mental state, and the right one is for the attention mental state, as explained earlier.

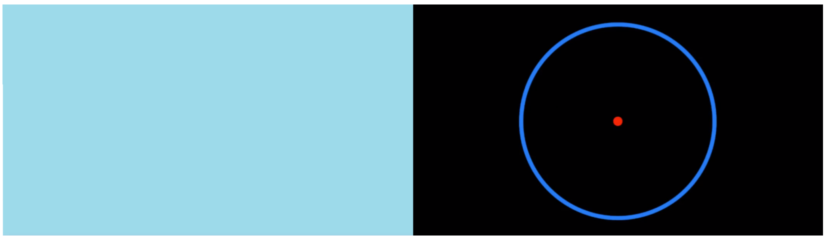

FIGURE 4.2: Protocol's images for data acquisition.

The desired output is already known, therefore, the only care that should be taken, is that instructional segments of the video should be discarded, as they do not present any of the attention or non-attention tasks used in this research. The attention and non-attention screens have a total duration of 31 seconds each, however, the first second is discarded to avoid any screen transition noise, totaling 60 seconds for both tasks.

4.1.1 Results and Discussions

The acquired brain signals were processed and, with the segmented and labeled data from the first video, SVM built the mathematical model that represents the mental states. The data in the second video were processed and used as Input to the trained model, generating outputs. Using the labels, called targets, and the generated outputs, the accuracy of each combination of region and version was calculated.

Table 4.1 shows the accuracy of the classifier used. Accuracy is the number of times the classifier has classified the input as the target output divided by the total samples, therefore, when multiplied by one hundred, the percentage of "correct answers". The Table shows the accuracy results for each region and version of the algorithm. An average was performed to obtain a single value for all 5 volunteers. So, the first value of 97.33%, for example, is the training accuracy of the classifier using region 1 and version 1 of the algorithm. Variance is the variance among volunteers. In the training step, the classifier uses part of the samples to calculate the mathematical model, as already mentioned in this chapter, and another part of the samples is used to measure the result. Generally, in the training step, the classifier presents better results than in the test step.

The last column of the Table represents the average of all versions for a given region. This metric was first analyzed to choose the best region, so the best region was the fourth one with training accuracy of 98.12%. The next step was to choose the version that got the best result from that region. Therefore, version 2 with 98.76% was chosen.

Table 4.2 shows the same result as above, but now for the test. The data from this step is the one acquired in the second time the volunteer watches the video, so, the second step of the protocol. The samples are placed in the SVM model created in the training step, and it then gives an output to each sample. As the target outputs are already defined, it is known the outputs that should be given by the model to each input. With the target output and the output given by the SVM, the test accuracy can be calculated.

The same previous method was used to choose the best region and the best version with the mean's accuracy of the volunteers. Thus, the chosen region was the fourth one with an accuracy of 93.88% and the best performing version was the second one

TABLE 4.1: SVM Training Accuracy Results.

Region 1	Version 1	Version 2	Version 3	Version 4	$\overline{Mean}/\overline{Variance}$
Mean	97.33%	95.69%	94.14%	95.46%	95.65%
Variance	0.00%	0.03%	0.02%	0.01%	0.01%

Region 2	Version 1	Version 2	Version 3	Version 4	$\overline{Mean}/\overline{Variance}$
Mean	96.78%	96.50%	94.31%	96.29%	95.97%
Variance	0.00%	0.02%	0.05%	0.01%	0.02%

Region 3	Version 1	Version 2	Version 3	Version 4	$\overline{Mean}/\overline{Variance}$
Mean	96.86%	95.72%	93.96%	94.83%	95.34%
Variance	0.03%	0.02%	0.01%	0.02%	0.02%

Region 4	Version 1	Version 2	Version 3	Version 4	$\overline{Mean}/\overline{Variance}$
Mean	97.79%	**98.76%**	97.50%	98.42%	**98.12%**
Variance	0.02%	0.01%	0.02%	0.02%	0.01%

Region 5	Version 1	Version 2	Version 3	Version 4	$\overline{Mean}/\overline{Variance}$
Mean	97.44%	97.96%	96.29%	97.41%	97.28%
Variance	0.02%	0.00%	0.01%	0.01%	0.01%

with an accuracy of 94.94%. Concluding then, that the best region for both training and testing was region 4, with the electrodes F3, F7, C3 and T3, and the best version of the algorithm was version 2.

In both Tables, the same regions and versions were chosen, however, by analyzing them, it is possible to observe that version 4 obtained the second best results and, according to Table 3.2, version 4 obtained a shorter processing time than version 2. Nevertheless, to choose between the two versions, an online test was conducted with a primordial game, already mentioned in this chapter, and the users' responses were that version 2 returned a more reliable feedback. This is probably because, as the signal is reduced to a smaller amplitude range, the separation of mental states by the classifier has become more difficult, so, the users do not feel in control of what is happening in the game. Therefore, version 2 was chosen. All tests performed after this were based on this result.

TABLE 4.2: SVM Testing Accuracy Results.

Region 1	Version 1	Version 2	Version 3	Version 4	$\overline{Mean}/\overline{Variance}$
Mean	88.68%	88.97%	83.45%	86.14%	86.81%
Variance	0.11%	0.11%	0.13%	0.05%	0.10%

Region 2	Version 1	Version 2	Version 3	Version 4	$\overline{Mean}/\overline{Variance}$
Mean	90.66%	88.79%	85.46%	87.70%	88.15%
Variance	0.07%	0.08%	0.12%	0.14%	0.10%

Region 3	Version 1	Version 2	Version 3	Version 4	$\overline{Mean}/\overline{Variance}$
Mean	89.59%	88.33%	84.63%	86.03%	87.15%
Variance	0.18%	0.13%	0.05%	0.06%	0.11%

Region 4	Version 1	Version 2	Version 3	Version 4	$\overline{Mean}/\overline{Variance}$
Mean	93.68%	**94.94%**	92.30%	94.62%	**93.88%**
Variance	0.07%	0.10%	0.18%	0.13%	0.12%

Region 5	Version 1	Version 2	Version 3	Version 4	$\overline{Mean}/\overline{Variance}$
Mean	92.67%	92.90%	91.66%	92.61%	92.46%
Variance	0.08%	0.03%	0.08%	0.01%	0.05%

Chapter 5

Neurofeedback Training

5.1 Experiment 1

5.1.1 Protocol and Volunteers

To test the complete NFB system, five new Volunteers, 3 men and 2 women between 22 and 28 years, were asked to integrate this Experiment. In order to take a more homogeneous sample, all volunteers are students in electrical engineering at the Federal University of Espírito Santo (UFES). Since the best version of the algorithm and brain region are already chosen, the scope of this Experiment is to carry out more sessions, considering that in the previous protocol there was only one session, to evaluate the self-regulation of brain waves, to evaluate other metrics used in the game and also the evolution of Volunteers throughout the Experiment.

Neurofeedback training was carried out in 5 consecutive sessions over a week. The Volunteers chosen were postgraduate students for two reasons, firstly, there is a high degree of difficulty in finding Volunteers who have 5 days on their agenda with 30 minutes free to take the test. That is why research environment makes it easier for Volunteers to join, as they already go to university to study and/or work. Secondly, in the literature, it is also possible to improve the focus of subjects not diagnosed with ADHD [11, 14]. In addition, postgraduate students need a lot of concentration to do their research, as well as attending classes and studying for exams.

The Experiment 1 consisted of 3 steps. The first step is to apply the Concentrated Attention Test [48], which aims to assess the subject's ability to keep his attention focused on the work he does, during a given period. The test consists of symbols, and the subject must locate, among all the symbols on the sheet, the 3 presented as models [49]. This test was performed twice with the participants, once on the first day and once on the last day, to assess whether there was an evolution during the NFB training. The test can only be carried out by psychologists, therefore, every time it was applied, all members of the laboratory had to withdraw to maintain the confidentiality of it.

The second stage is the same used in the previous protocol. The EEG headset is placed on the Volunteer's head, and the electrodes are positioned so that the signal is as free of noise and fluctuation as possible. The psychologist does a breathing exercise for 2 minutes so that the Volunteer can calm down to start collecting data. Then, a video, the same as the previous protocol, is showed to acquire the data of mental states of attention and non attention to train the classifier. The third stage is the neurofeedback training that was carried out in all sessions with all Volunteers.

5.1.2 NFB

For the NFB training, it is necessary to have a feedback so the users can perceive their current mental state. The new brain data is processed, and then returned as a new feedback, that will be perceived by the Volunteer, and so on until the session is over. In this dissertation, visual feedback was used, in the form of a serious game, as explained in previous chapters.

In all versions of the algorithm, the structure used for online processing, since processing takes place at the same time as the game is in progress, is the same. The algorithms' sampling frequency used was 500 Hz, and for data acquisition from the EEG Headset the *pull chunk* method was used. This "pulls" a chunk of samples and not one sample by one until it completes the 500 samples in one second. This method was used so that it was not necessary to wait for 500 samples to process the data, instead, a 500 sample buffer can be used to be updated and processed every time a chunk is "pulled", and this guarantees more samples to the classifier. As a result, instead of returning only one entry after processing with the 500 samples, it will return one entry each time Matlab requests the *pull chunk*. This amount is random and Matlab communication with the EEG headset is performed by a library called Lab Stream Layer(LSL).

The difference between online and offline is that the SVM classifier model is trained and only need to classify the new data based on it. The process is all exemplified in Figure 5.1. Every time the Matlab pulls a chunk (as the amount of samples per chunk is random, the number of chunks per second, to ensure the sample frequency, varies. Matlab makes this request about 140 times in one second) the buffer is update with the last received samples, all the 500 samples from the buffer are filtered and processed, creating a feature input matrix that will be given to the SVM classifier.

The mental state, classified by the SVM, is stored in the form of “1” and “-1” in an array until the sum of the samples of all the chunks add up to 500 samples, that is, after 1 second. If this condition is not met, the process begins again. As there are around 140 values per second, as already explained, the algorithm has to decide which mental state it will send to the Unity software. Hence, for that second, the content of the array is summed, and if the result is greater than 0, the mental state of attention prevailed and, otherwise, the state of non-attention prevailed. The result is sent via TCP/IP to Unity to increase or decrease the spaceship’s speed by 10% depending on the value sent.

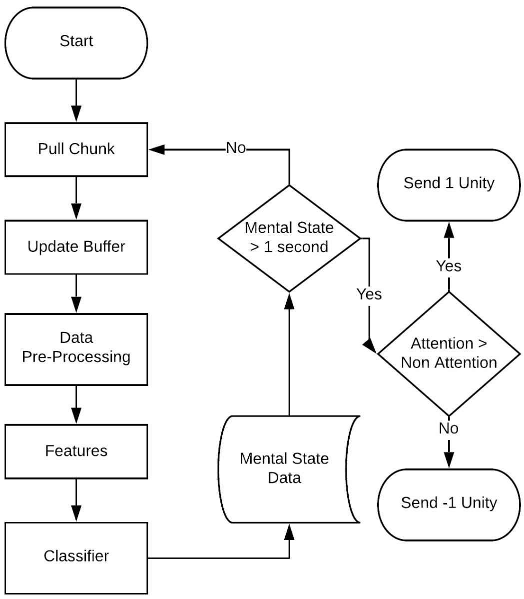

FIGURE 5.1: Flowchannel describing the decision-making in the NFB system to send the patient’s mental state to the serious game *Neurofeedback Space*.

The entire process is repeated until the 5 minutes in the game session are over. Then, TCP/IP communication is interrupted, and the processing ends, saving all the necessary data in the folder for further processing.

5.1.3 Results and Discussion

5.1.3.1 Game Metrics Analysis

Unity receives 1 sample, regarding the mental states, per second, therefore, as it takes 5 minutes to complete the session, 300 samples or 300 seconds. However, only 298 are used to compose the Tables from 5.1 to 5.5, as the first sample is discarded, because, as the processing and the game are synchronized, in the first second there are still no samples to compose the SVM entry, and unity places a random value to begin the game. The last sample is discarded, because in some sessions from different Volunteers, the value was not stored in the array, so it was chosen to eliminate the last sample from all participants.

There are 3 evaluation metrics used in the NFB sessions. The *attention* is how many samples, from the 298 total samples, were labeled as attention by the SVM classifier, the *score* is how many pickups the player picked up in the 5 minutes session, and the *sustained attention*, that is the greatest attention sample's sequence in the session. The last column, which has not yet been mentioned, of the Tables 5.1 to 5.5, is the *game level*. Right after training the classifier, it was asked the Volunteer how he was feeling and what level of the game he would like to play. The goal was to keep the player motivated/entertained to only change the levels when he was comfortable with it. It is possible to see in the Tables that players do not obey the same pattern of changing levels.

The results of Volunteer 1 are shown in Table 5.1. It is possible to observe that throughout the sessions there was an improvement in the *attention* metric and in the *score*. An interesting point is noticed when changing levels in the game. From session 1 to session 2, the level of attention and the score decreased, however, when repeating the level in the next session, there was an increase or permanence of these two metrics. Fact also observed from sessions 3 to 4, showing possible learning due to repeating the game level.

The metric of *sustained attention* did not follow the same results as the others mentioned, however, it is possible to notice an increase from the first to the last session. In this way, the Volunteer managed, even changing to the most difficult game level, to remain in the state of attention during the game for a longer time. An explanation for the fact that the last session had better results in *attention*, *score* and not *sustained attention* is that, probably, he was more attentive in this session, 268 of the 298 seconds, but, he couldn't maintain the attention.

In the second session, he stated that the fuel bar distracted him and he considered returning to the first level in the third session, but, for reasons of competitiveness, he thought it better to repeat the level and managed to improve his metrics. In all sessions, it was possible to observe an improvement in the middle towards the end of the game, the ship started slowly, but after finding the correct strategy to focus, he managed to maintain a good speed until the end of the game. In the last session, his pattern was a little different. The Volunteer started the game with great concentration, in the middle of the game he reduced a little, but soon after, he manage to concentrate himself and finished the game with a great score.

TABLE 5.1: Game Metrics - Volunteer 1.

Session	Attention	Score	Game Level	Sustained Attention
1	167	91	1	15
2	136	29	2	17
3	238	105	2	40
4	238	108	3	92
5	268	114	3	58

It is possible to observe in Table 5.2, that Volunteer 2 also had the same learning effect by analyzing the game levels' changes. Whenever the level was changed, so was the gameplay, there was a drop in *attention* and *score*, but then, repeating the level, either the metrics remained the same or improved. Some results seem inconsistent at first when comparing two different levels, for example, in session 3 she had 169 seconds of *attention* and a *score* of 70 and in the next session even with 168 in the *attention* metric, the Volunteer scored only 18 points. This is because the game modes are different. Each level punishes the player for not paying attention differently. For example, the third level takes point per second if the gas tank is empty. Concluding that, it is plausible that the score will decrease, however, evaluating at the same game level, she improved.

Sustained attention also worsened with the level changing and improved in their repetition. Her best session was the first one, but from the second onwards there is an improvement in the evaluated metrics.

TABLE 5.2: Game Metrics - Volunteer 2.

Session	Attention	Score	Game Level	Sustained Attention
1	280	146	1	83
2	118	23	2	9
3	169	70	2	18
4	168	18	3	11
5	164	49	3	15

Volunteer 3 behaved differently from the previous two. He got a low *score* and *attention* in the first session and even repeating the game level he was unable to improve these evaluation metrics, evident in Table 5.3. In the third session, he got a significant improvement, and when asked what he did differently this time, he reported that he was training to concentrate with a similar video showed in the sessions, before going to the NFB training. In the fourth session, he also did this pre-training and, even changing the game level, his *attention* did not decrease, despite his *score* having decreased, which probably happened due to the gameplay change, as already explained.

In the last session, he was asked not to do the pre-training, and he still got better results. Probably, this activity of watching a similar video before doing the NFB session, made him do a better training in the classifier step and the data became more reliable with what he was doing in the online stage of the NFB.

Sustained attention also behaved differently than for the other Volunteers. There was not strong changes in the values and they remained proximous between sessions. There was only a greater enhancement from session 2 to session 3.

TABLE 5.3: Game Metrics - Volunteer 3.

Session	Attention	Score	Game Level	Sustained Attention
1	80	13	1	5
2	64	6	1	4
3	201	123	1	23
4	229	105	2	32
5	262	115	3	32

Volunteer 4 was the only one to play three times the most difficult level of the game, level 3. It is possible to notice, looking at Table 5.4, that she obtained excellent results in all metrics, and remained with good results even with the change of game level.

Of the Volunteers analyzed so far, she was not the one who obtained the best results in *sustained attention*, however, analyzing it together with the metric of *attention*, it is possible to conclude that she had a good constancy. For example, in session 2, of the 298 seconds of the game, she was attentive in 262 seconds, so, 87.91% of the entire game session. Her longest attention span was 36 seconds, which indicates that, even though it is not such a high value of *sustained attention*, she always maintained her attention sequence very close to 36 seconds throughout the game.

TABLE 5.4: Game Metrics - Volunteer 4.

Session	Attention	Score	Game Level	Sustained Attention
1	226	135	1	26
2	262	112	2	36
3	203	106	3	10
4	236	112	3	34
5	215	108	3	12

Volunteer 5 was the one who presented the most discrepant result compared to the others. In the first session, he had a *score* of 1, and of a total of 298 seconds of the game, only 18 were classified as attentive. This fact probably occurred, because he did not follow the previously communicated instructions and went with hair cream to the NFB training. Participants were instructed not to go with wet hair or with any product in it, as it can change the conductivity of the scalp and bias the data. Therefore, this first session of Volunteer 5 can be discarded.

However, even analyzing the data by discarding the first session, it is possible to see with Table 5.5 that the learning effect with the game level, fact that happened to most of the other Volunteers, does not seem to happen for this one. He gets worse when the game level is changed, which is acceptable, but he also has a drop in all rating metrics when he stays at level 2 of the game. The player only played level 3 on the last day, as he was curious to know what it was like, since it was his last session.

A fact that may seem inconsistent is the last session held by this Volunteer. Despite the low *score* and low value obtained with the *attention* metric, its value for the *sustained attention* metric is relatively high for previous results. This is due to the gameplay of the third game level, as already explained. Although having managed

14 consecutive seconds of attention, the Volunteer failed to remain attentive and lost all the points he had achieved, remaining only with a total of 3 points.

The Volunteer felt frustrated and upset with the result of the first session, however, he reported being motivated in the second session to improve his *score*. He reported feeling well concentrated, but, in the third session his motivation dropped from 5 to 3 (likert scale), as he did not understand why the spaceship did not increase speed, since he was feeling concentrated. Another reason was the comparison with the other Volunteers, who had excellent *scores* and he did not.

TABLE 5.5: Game Metrics - Volunteer 5.

Session	Attention	Score	Game Level	Sustained Attention
1	18	1	1	2
2	166	81	1	9
3	135	30	2	13
4	116	20	2	8
5	125	3	3	14

By analyzing the data obtained with the SVM classification and game feedback, it is possible to conclude an improvement in the majority of participants throughout all sessions. The learning effect with the game level appears in most participants, and the result is entirely plausible as there is no anxiety and surprise about starting a new level.

All players reported good game feedback and only one managed to notice a delay in the game's response in the mental state change. For example, if the Volunteer was inattentive and started to pay attention, the game took about a second to increase the speed of the spaceship by 10%. Only the last Volunteer, who was feeling attentive, did not get good feedback, as his results were low in relation to the other participants.

All Volunteers felt comfortable during the sessions, did not experience headaches and reported improved attention during their academic tasks in the course of the week's Experiment.

5.1.3.2 Data Analysis

For the brain data's analysis, only two of the five characteristics used in the SVM were considered to make the analysis between sessions. The chosen ones were the two ratios $theta/beta$ and $alpha/beta$. Analyzing the others solo characteristics, such as $theta$, $beta$ and $alpha$, does not make much sense when considering that the patterns in the brain signal can change between sessions [37]. The conductivity of the scalp constantly changes, even on the same day of NFB training, it depends on the skin, sweating, cleaning of the scalp, and among others. So, comparing mathematical ratios make them dimensionless units that were "normalized" with the parameters of that day, making this comparison plausible to perform.

For each session, in the online step of the NFB training, several values of these characteristics were stored, since the processing was performed several times in a second. However, for comparison purposes, an average was calculated so that only one value represented the entire session. For this, it was necessary to clean the data to remove artifacts that could bias the average value. In this way, the characteristics were plotted on a graph and were divided into three types.

The first type, shown in Figure 5.2, is the easiest to identify and correct. Because the signal and the peak are quite contrasting. To calculate the average of this electrode's characteristic, for example, the peak was cut and equaled to zero.

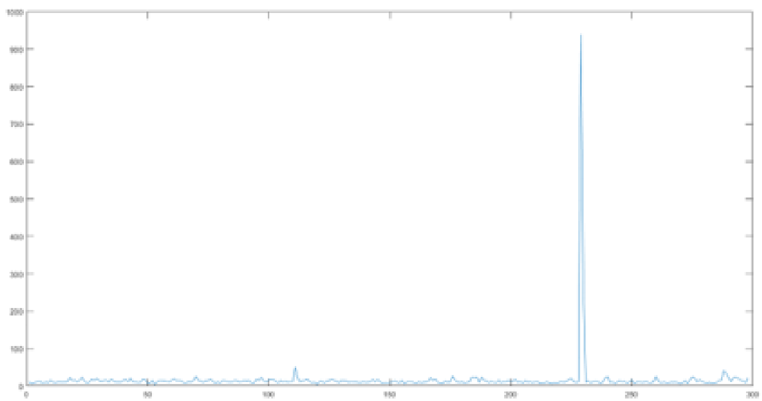

FIGURE 5.2: Feature that contains great magnitude's artifacts that can interfere in the signal average.

The second type is the one that presents the greatest challenge to be identified, since the peak does not differ so much from the rest of the signal. However, as observed in Figure 5.3, most of the signal has a lower average, visually interpreting, and there are not other artifacts of the same magnitude as the highest peak in the Figure. The lowest artifacts, even though the magnitude is slightly higher than the average signal, have neighboring artifacts with similar magnitude, which excludes the need to cut them. Thus, from this signal, only the largest peak is equaled to zero, and the new average is calculated.

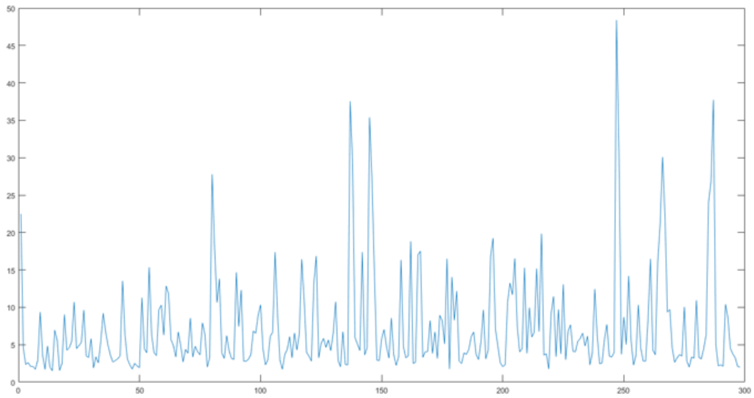

FIGURE 5.3: Feature that contains artifacts with moderate magnitude.

The last type is ideal for analysis, since the artifacts are close to the signal range, and there are neighboring artifacts with a similar magnitude, as can be seen in Figure 5.4. This signal does not need to go through any conditioning and the average is already calculated from these values.

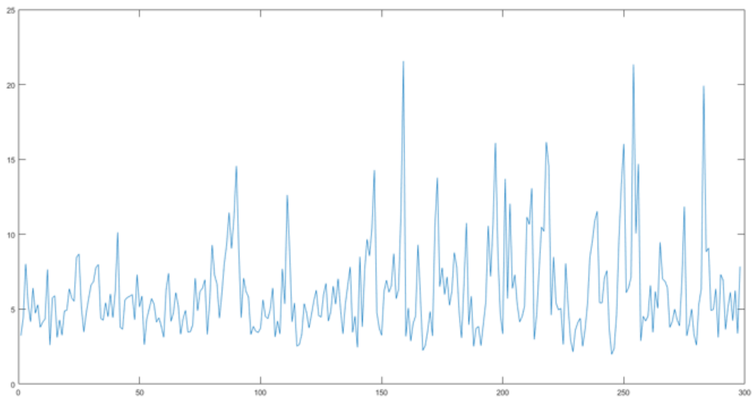

FIGURE 5.4: Signal that does not need any alteration.

After conditioning and recalculation of the averages, the data can be analyzed. In Figures 5.5 to 5.9, it is possible to analyze the data by Volunteer, and by electrode of all sessions. The abscissa axis contains the values of the $theta/beta$ and $alpha/beta$

ratios and the ordinate axis is represented by the *attention* metric. According to the literature, the greater the attention, the lower the $theta/beta$ and $alpha/beta$ ratio, as the magnitude of beta increases. In all Figures, the red line is the R-square (R^2), which is a statistical measure that represents the proportion of the variance of a dependent variable, which is explained by an independent variable or variables in a regression model.

Analyzing EEG data, low R-squared values are expected, because throughout the sessions the values are different and may have little correlation. Looking at Figure 5.5, which are the results for Volunteer 1, it is possible to notice that for the highest values of R^2, the expected does not occur. The two ratios ($theta/beta$ and $alpha/beta$) on the C3 electrode, have an increasing slope, which should not happen, since with higher values of attention the two ratios should decrease. Initially, the *score* value was used as an end of comparison between sessions, however, as the game levels changed and not in the same pattern for all users, the *attention* evaluation metric was chosen. The numbers next to the colored dots indicate the sessions in which the results occurred.

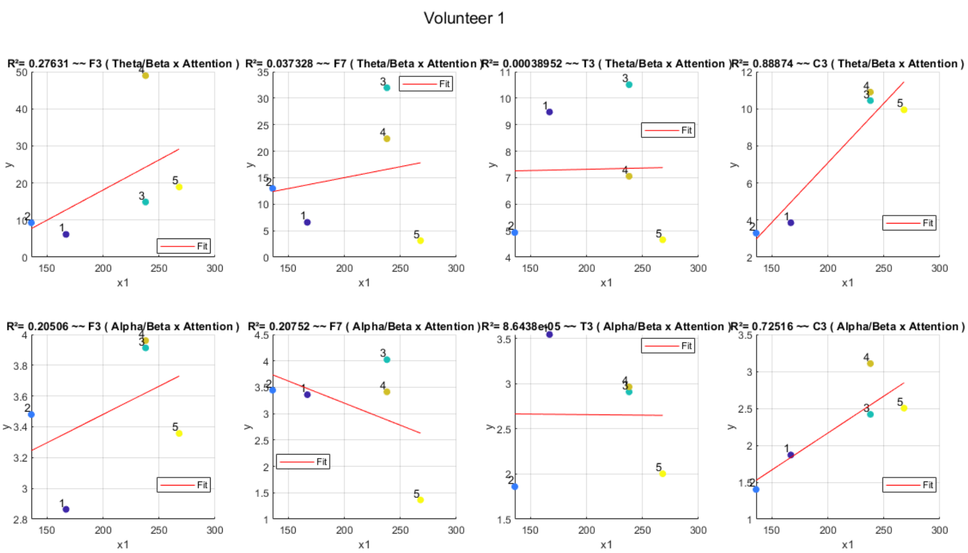

FIGURE 5.5: Data Analysis - Volunteer 1.

For Volunteer 2, evaluating only the line's slope, the observed behavior was as expected. Practically, all the electrodes obtained high values of R^2, only for the electrode C3, the opposite of the previous Volunteer, that the values were very low.

Nevertheless, analyzing the other electrodes, it is possible to verify that the inclination is negative, which means that high values of *attention*, have low values for both ratios. Yet, what is expected is that this drop occurs over the sessions, which is not what is seen in Figure 5.6. The first session has the lowest value of the ratios and then the values increase in magnitude.

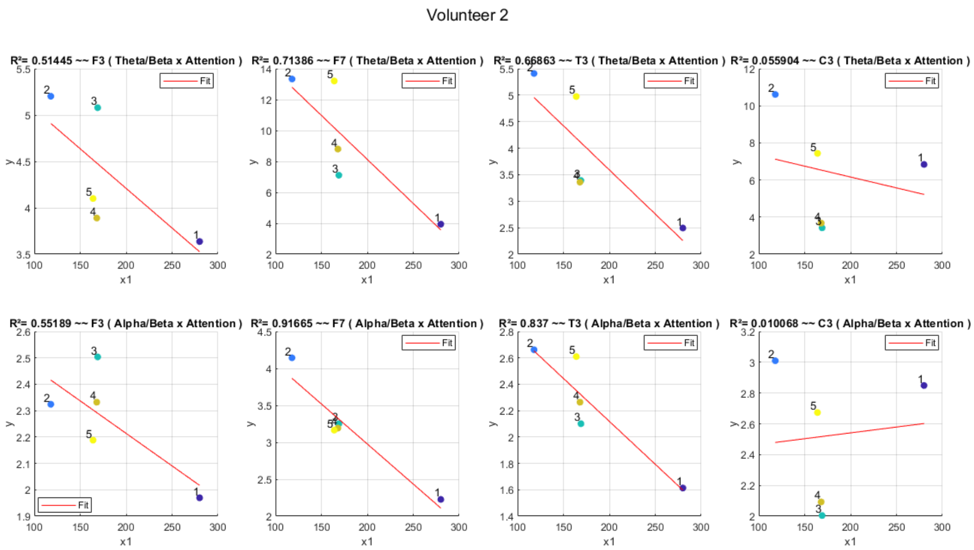

FIGURE 5.6: Data Analysis - Volunteer 2.

The Volunteer 3, as seen in in Figure 5.7, had the best R^2 value only for the T3 electrode and the $theta/beta$ ratio of the C3 electrode. However, only one of the three lines has a negative slope. The results do not show improvement according to the sessions, although, the results of sessions 4 and 5 were better than in the third session. For Volunteer 4(Figure 5.8), the analysis is the same, for those who obtained the best R^2 values, the line' slope behavior is not repeated and the improvement in results does not seem to follow a session pattern.

The last Volunteer had the data from the first session biased. However, removing the first session from the graphs in Figure 5.9, the result would not have major changes, because the lines that would have the greatest impact would have a positive slope without this sample, which is not what is described in the literature. An interesting outcome was the $alpha/beta$ ratio in electrode F3, which had the last sessions' results better than the first ones, since they were smaller.

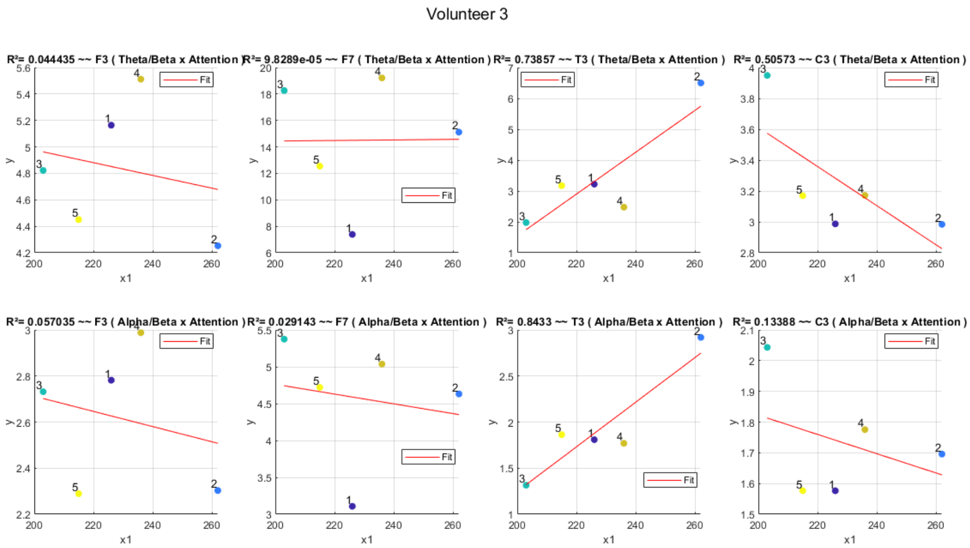

FIGURE 5.7: Data Analysis - Volunteer 3.

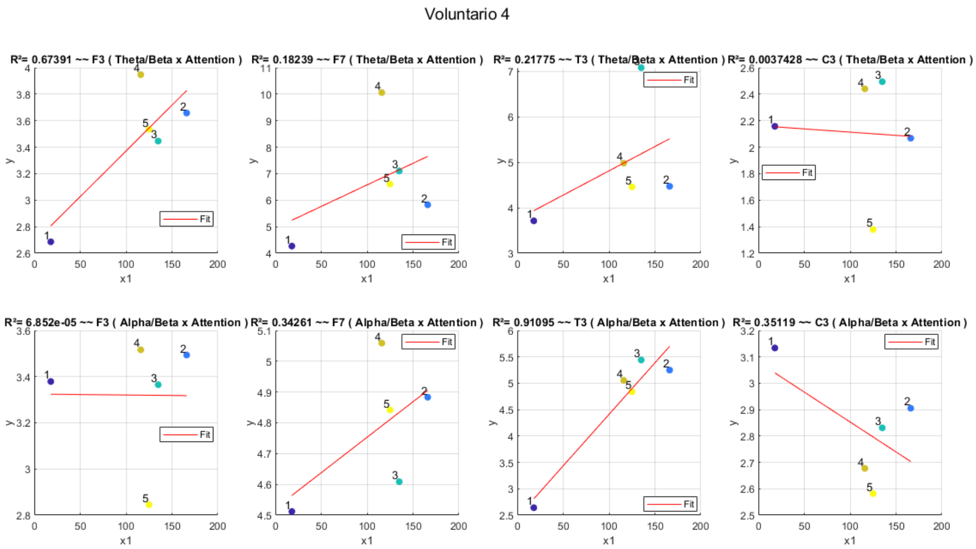

FIGURE 5.8: Data Analysis - Volunteer 4.

The results presented in this subsection, when compared with the Tables presented in the previous one, are contradictory. The Volunteer increases the *score* in the game, the *attention* metric and feels positive feedback from the game/system in relation to his current mental state at the time of the session. However, the results of the chosen features do not show the expected behavior. While most of the data shows no correlation, those with a significant R^2 have a straight line with a positive slope,

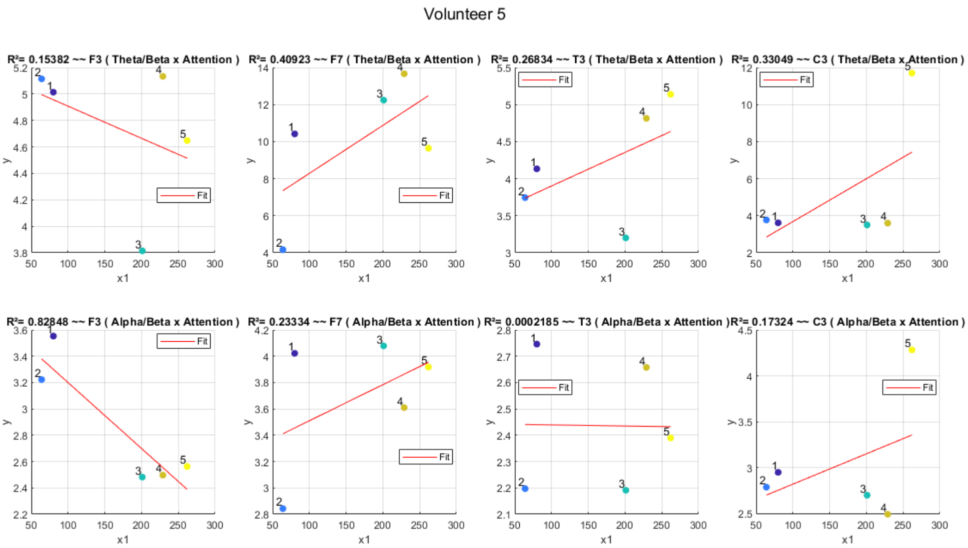

FIGURE 5.9: Data Analysis - Volunteer 5.

that is, the characteristics increase with the increase in *attention*, which should not happen.

One plausible explanation for this discrepancy is that the classifier, in order to build the model related to the two mental states of attention and non-attention, also uses the *alpha*, *beta* and *theta* data that were not used as comparisons between sessions for reasons already explained in this dissertation. Therefore, the model uses a greater complexity than that analyzed here so far.

5.1.3.3 Training Data Analysis

The training data of the first two Volunteers, for comparison purposes only, were shown in the two Figures below (5.10 and 5.11) so that this analysis corroborates with the conclusions made previously. In addition to the two features analyzed, the other three used in the training of the SVM model were included. The training data were separated into lables, therefore, the integer numbers (1, 2, 3, 4 and 5) are from the mental state of non-attention, data represented by the color blue, and the decimal numbers (1.5, 2.5, 3.5, 4.5 and 5.5) are from the mental state of attention, data represented by the color red. Thus, totaling 10 intervals on the abscissa axis, since 5 sessions were performed.

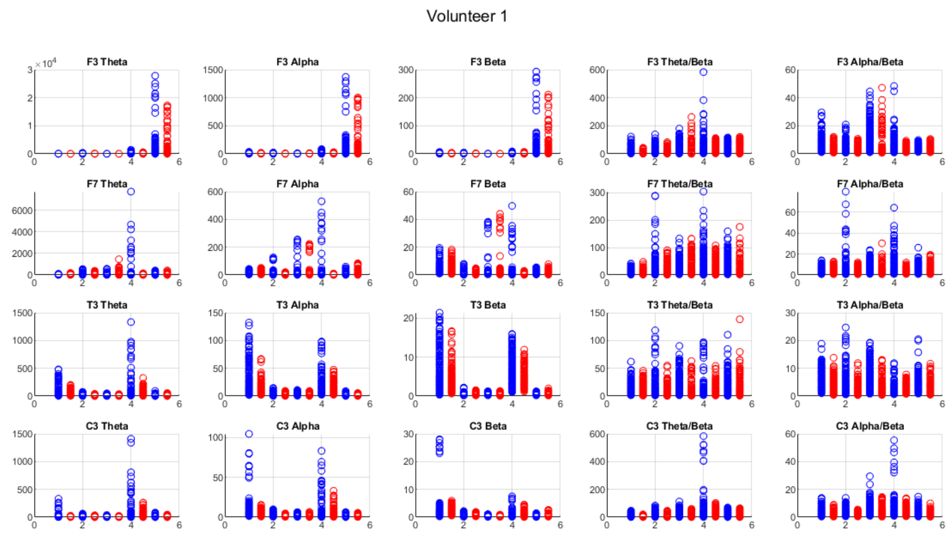

FIGURE 5.10: Features from the training data - Volunteer 1.

SVM receives the data from a session and separates them into labels, attention and non-attention, to build the mathematical model for that session. Therefore, looking at Figure 5.10, it is possible to notice that there is no simple pattern of separation between the labeled data. Some electrodes have a greater variance in the attention data, others in the non-attention data, some have a greater magnitude, thus, enhancing then, the complexity to obtain good separation results between the classes.

Examining Figure 5.11, and comparing it with the previous Figure, it is clear why the classifier has to be trained in every session and discriminated between Volunteers. The data are very different, and, if they were collected for the construction of a generalized model, probably the feedback offered by the system would be worse, and the Volunteers would find it difficult to perform the NFB training. Thus, emphasizing the importance of individualizing the classifier's training for a better use of the system.

5.1.3.4 Attention Test

In the first and last sessions, a concentrated attention test was applied by a BRAEN group's psychologist to assess the concentration levels of the Volunteers before and after the NFB training. The test is divided into 6 levels of attention, shown in Table 5.6. The test is confidential, it can only be administered by professionals in the

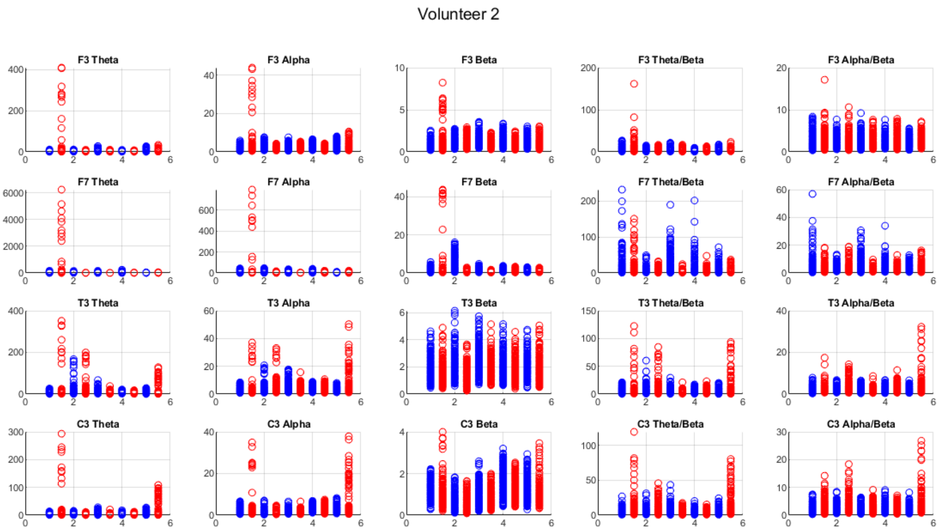

FIGURE 5.11: Features from the training data - Volunteer 2.

field of psychology, and was applied, in the first session, before starting the NFB training and, in the last session, after the last training.

TABLE 5.6: Attention Classification levels according to the psychological test. The Attention Classification within the parentheses is in Portuguese because it was the language in which the test was performed by the psychologist.

Levels	Attention Classification
1	Inferior (Inferior)
2	Lower Medium (Médio Inferior)
3	Medium (Médio)
4	Superior Medium (Médio Superior)
5	Superior (Superior)
6	Very Superior (Muito Superior)

Looking at Table 5.7, there is an improvement in the attention level of the Volunteers who obtained a classification equal to or less than “lower medium”. The Volunteers who had results already considered high (above “superior medium”), remained at the same classification. Observing the pre and post score, excluding Volunteer 3, everyone achieved improvement, even if they did not improve their attention level. The drop in the score of Volunteer 3 is not considered a concern, as she has already reached a very high level of attention in the first test, and this slight decrease is considered irrelevant.

TABLE 5.7: Psychological test's results applied at the beginning and at end of the NFB training.

Volunteer	Pre Classification	Post Classification	Pre Score	Post Score
1	2	4	74	113
2	3	4	86	128
3	5	5	141	139
4	4	4	112	131
5	3	4	110	115

5.1.3.5 Remarks and Preliminary Conclusions

The previous analysis shows a divergence between the results obtained with the SVM classifier, the attention test and the brain wave frequencies. While the first two showed improvements and good results throughout the sessions, the other did not obtain anything conclusive. At the end of the Experiment, some considerations were made in order to discuss in the research group a new Experiment that could be performed and compared to this one to provide a more reliable result.

The first consideration is that the participants were co-workers and commented on their *scores* and even competed and created leaderboards. As much as competition may be important for engaging in the game, it can also bias the data and bring some stress to the training. Secondly, the brain wave frequencies' results may not have been satisfactory, as the number of participants and/or the number of sessions was small. For this type of test, in the university environment, it is a challenge to get several different people, who are available for more extensive tests, to act as Volunteers.

Another fact to take into account was the "pre-training" that one of the Volunteers performed before two sessions, which may have biased his responses and evolution. Also, bulky hair can bring a certain level of bias to the data, as the EEG headset is dry and the electrodes can be pushed by the amount of hair, and that some more sudden movement can cause the electrodes to "slip" on the Volunteer's head and get a little out of position.

These conclusions led to the development of a new protocol, with new Volunteers, but with the same structure as this one. The results of the game metrics, the concentrated attention test and the brain signal analysis acquired with Experiment 2 will be presented in the next Section.

5.2 Experiment 2

5.2.1 Protocol and Volunteers

After the considerations of the previous Section, a new protocol was elaborated. 5 volunteers, 3 men and 2 women between 22 and 26 years old, were invited to participate in the Experiment 2. Of these, the 3 men had no contact with any stage of neurofeedback, either with the training video or with the serious game developed. Of the 2 women, one participated in the first protocol, having contact only with the training video and the other participated in Experiment 1. Apart from this Volunteer who is a graduate student in electrical engineering, all the other four participants are or graduate students in psychology at the Federal University of Espírito Santo (UFES) or psychologists.

The chosen Volunteer, who participated in the previous Experiment, was the Volunteer 2, who obtained the most consistent results when compared with the literature. The purpose of her participation was to analyze whether after 2 months without NFB training, but already having previous experience with it, if her results would be different from the others. In addition, collect more samples so that, instead of 5 sessions, 10 could be analyzed.

The Experiment 2 also consists of 3 steps. The first step is the Concentrated Attention Test [48], which was applied twice for each Volunteer, once before the first NFB session and again after the last NFB session.

The second step is the the SVM classifier's training. In all sessions, a 2-minute breathing exercise is performed by the psychologist, so that the Volunteer can relax and prepare for the brain data's acquisition. Then, the EEG headset is placed on the Volunteers' heads to check the brain signal's quality. Thereafter, all electrodes are adjusted until the signal is low in noise and fluctuations. The same video from the Experiment 1, which is divided into four images, is shown so that brain data related to the two mental states, attention and non-attention, are acquired and used for the SVM training.

After SVM training, the third step is the NFB. With the mathematical model of the classifier calculated, Matlab, which is receiving brain signals from the Volunteer and processing in real time, sends his mental state in the form of "1" and "-1" to Unity using a TCP/IP protocol. The serious game *Neurofeedback Space* receives the value, and change the spaceship's speed, giving the Volunteer a visual feedback.

The "pull chunk" method was also used with the strategy of processing the data more times per second, and acquiring more samples to compose the SVM input matrix. The process can be seen in Figure 5.1. The third Experiment's step is performed in 5 minutes, and at the end of it, the communication between Matlab and Unity is interrupted, saving all the necessary data that will be further processed and analyzed.

One of the alterations made for this Experiment was to fix one of the game levels for all sessions. It was fixed so that the *score* could also be compared between Volunteers and between all sessions, since the game mode and the punishment for when the Volunteer is not in the mental state of attention are the same. The second level was chosen because it has an intermediate difficulty. Thus, it would not be so easy, which could be tedious throughout the 5 sessions, and also not so difficult, which would bring a lack of motivation in the first sessions, if the performance was low.

For this Experiment, the same instructions for not going with wet hair or gel were given to avoid the sudden change in the conductivity of the scalp. In addition, they were asked to maintain confidentiality among themselves about NFB training and the psychological test, precisely to compare with the Experiment 1, in which the Volunteers had contact during the week that they held the sessions.

5.2.2 Discussion and Results

5.2.2.1 Game Metrics Analysis

Of the 300 samples/seconds, 298 were considered (the first and last seconds being discarded) to perform the analysis of the metrics used in the Experiment 1. There are two differences in the Tables in this Experiment when compared to the previous one, in addition to the metrics of *attention*, *score* and *sustained attention*, a metric of *sustained non-attention* is also being evaluated and the game's level was established.

Sustained non-attention is the greatest sequence of "-1", thus, non-attention label, in the session. This metric was added only to this Experiment to make comparisons with the *score* metric. Since at level 2 the penalty for when the player's fuel tank empties is the impediment of collecting stars, explained in Section 3.2.3.2. Thus, the longer the "-1's" sequence, the spaceship will move at low speed, the fuel tank will empty, because the fuel assets will not be collected, the player will not be able to collect stars, and, for that reason, greater the chances of the *score* being low.

Table 5.8 shows the results of Volunteer 1 for this Experiment. It is possible to observe that, even with a great variation in the *score*, there is an improvement over the sessions. However, the learning effect that occurred when the game's level was changed with the previous Experiment, does not seem to happen. In the *attention*, there is little variation in the value, and there is also a subtle improvement from the first to the last session. The fourth session was the one with the worst results and it is coherent, since it is the session in which the *sustained non-attention* obtained the highest value. Therefore, the game punished and prevented the *score* from increasing while the fuel tank was empty.

An inconsistency seems to occur in the second session, as the *attention* had little decrease and the *sustained attention* was the largest of all sessions. However, analyzing the game mode, it is possible to imagine a scenario for this result. The Volunteer managed only in one part of the game to keep the 44 seconds of attention in a row, after that, a great variation between attention and non-attention made the *attention* metric to have a good result, but, as the speed was not very high, the fuel tank was empty for a long time and the spaceship was prevented from catching the stars and increasing the *score*. When asked about her performance, she reported that she was using a smart band and it vibrated 3 time due to SMS (Short Message Service), which ended up disrupting her concentration.

The volunteer had an appointment after the collection and could not repeat it, so the sample was not discarded to maintain the session pattern of the other volunteers, and also, because the smart band only vibrated at the end of the session, as the volunteer stated. From this session, all the others were done without the accessory.

She reported good feedback from the system, just like two months ago when she conducted the training. Only in the fourth session, in which she stated that she was feeling attentive and motivated, but was not feeling in control of the spaceship, that it did not happen. Thus, this volunteer had the second session compromised, and the fourth session did not have good feedback from the system, unlike all other sessions.

TABLE 5.8: Game metrics from the Experiment 2 - Volunteer 1.

Session	Attention	Score	Game Level	Sustained Attention	Sust. non-Att.
1	158	53	2	11	8
2	*151*	*26*	*2*	*44*	*8*
3	164	64	2	7	6
4	114	6	2	5	11
5	189	98	2	14	5

Volunteer 2 obtained a very different result from the previous one, as seen in Table 5.9. His *attention* and *score* had considerable variation and a significant worsening throughout the sessions. The first session was his best, but he reported that he counted the amount of stars collected by the spaceship. The counting task can bias the result, since it was not the task he performed in the classifier training step, the idea is that the Volunteers focus on the visual feedback and only it. Mental tasks such as motor imagery, countdown, recitation of alphabet, word generation, concentration-only have their peculiarities, which are differentiated by classifiers, and are activated in different areas of the brain [50–53]. He was asked not to count in the next sessions. In addition, in the fourth session, he had personal problems and his motivation to participate in the last two training sessions was very low.

In most sessions, his *sustained non-attention* was superior to his *sustained attention*. He was the only Volunteer who reported a bad system's feedback during the sessions. He didn't feel in control of what he was doing most of the time and when asked what he did to speed up the spaceship, that is, which strategy he used to concentrate, he couldn't say. As it is possible to see in Table 5.9, despite the repetition of level, there was no learning and there was no improvement, by evaluating these metrics, at the end of the sessions.

Looking at Table 5.10, it is possible to notice an improvement of Volunteer 3 in all metrics throughout the training. Assessing the *attention*, all through the sessions,

TABLE 5.9: Game metrics from the Experiment 2 - Volunteer 2.

Session	Attention	Score	Game Level	Sustained Attention	Sust. non-Att.
1	258	112	2	55	8
2	45	0	2	4	37
3	166	74	2	12	9
4	78	13	2	9	26
5	100	3	2	12	18

there was an increase in the seconds that the SVM classified as attention, and an increase of more than 100 seconds from the first to the last session. His best session was the second one, in which he was attentive in approximately 77.52% of the game and achieved a *sustained attention* of 46 seconds. His session with the worst values was the first in which he had low scores, high *sustained non-attention* and low *sustained attention*. Despite the great decrease from the second to the third session, the Volunteer managed to progress in all metrics from all sessions .

His strategy for most sessions was to focus on breathing. He reported that the more he controlled his breathing, the faster the spacecraft moved. In addition, he is a gamer, and that was exactly what hindered him in the first session. He reported that even focusing on the spaceship, his gaze moved almost involuntarily to the other elements in the screen's corner, such as speed bar, stopwatch and score text, where elements such as life bar, mana bar, skills and others are usually found in role-playing games (RPG). In addition, the fixed elements were more attractive to him, focusing on the spaceship or the stars made him lose focus, so he chose elements such as the stopwatch, speed bar and even the "menu" button of the game and it worked for him.

For players with this type of profile, used to playing games that need their attention on several screen elements simultaneously, a simpler interface with fewer feedback items and more concentrated in the center of the screen is needed to avoid possible distractions. Since the attention evaluated in this dissertation is concentrated attention.

The Volunteer felt a good system's feedback, only in the third session, he reported that he was unable to find the correct strategy for the spaceship to increase its speed, so he did not get a high *score*. This may have been due to frustration, since in the second session he performed very well and, probably, at the beginning of the third session, he did not, therefore, questioning his strategy, getting a little frustrated and trying to change it to have a similiar performance to the previous session. However, evaluating the system as a whole throughout the NFB training, he found that the game translated his mental state well.

TABLE 5.10: Game metrics from the Experiment 2 - Volunteer 3.

Session	Attention	Score	Game Level	Sustained Attention	Sust. non-Att.
1	81	3	2	4	17
2	231	99	2	46	5
3	114	16	2	6	15
4	147	36	2	9	6
5	184	86	2	18	7

Volunteer 4 had a good development during the sessions, with only a subtle drop from the third to the fourth session and then a more abrupt decrease in the values of the metrics used from the fourth to the last session. Her best performance was in the third session in which of the 298 seconds evaluated, 278 were classified as *attention* and achieved a *sustained attention* of 92 seconds. Table 5.11 also shows that in the third session, her *sustained non-attention* was only of 2 seconds, indicating great concentration and a permanence in attention during the session.

At first, the Volunteer found the game difficult and tried to change the stimulus for the spaceship to accelerate, but was unsuccessful, reaching a *score* of only 3 stars collected. From then on, her results improved and she reported that the strategy that made her have a good progress was to focus on something fixed, as focusing on space or on the stars deconcentrated her. Regarding feedback, she said she felt in control of what she did, but sometimes her self-perception indicated that she was staring at some game element, but thinking about other tasks and appointments that she would have on that day or week. Her best strategy was to focus on the stopwatch, but in the fourth session, she said she was mentally counting along with the timer, a problem that was explained previously with Volunteer 2. In the last session, she was asked to focus on the stopwatch, but not to count, just fix her eyes. She found it difficult for the spaceship's speed to increase, but at the end of the session she also reported that she was not feeling motivated to participate in the last session. From a 1-5 Likert scale, she chose 3, neutral.

TABLE 5.11: Game metrics from the Experiment 2 - Volunteer 4.

Session	Attention	Score	Game Level	Sustained Attention	Sust. non-Att.
1	68	1	2	4	16
2	158	64	2	12	8
3	278	116	2	92	2
4	251	112	2	42	5
5	118	11	2	7	10

Volunteer 5 was the one with the best self-perception of the group, every session he came with new observations, ideas and relevant comments from the system. He was very competitive and was always motivated to play the game. His results, however, are not gradually improving, despite having achieved good results. His best session was the fourth in which he got a surprising *attention* of 290 seconds, seen in Table 5.12, of the 298 seconds of the game, in addition, he got 259 consecutive seconds of attention. It is a result that seems to be a system error, however, the Volunteer said he felt totally focused and when asked about what strategy he used to speed up the spaceship, he controlled his breath, like he did in the SVM training video, and focused on the stars and pretended he "pulled" them to the spaceship.

In this same session, he noticed two mechanics of the game that were imperceptible to all Volunteers who have already played the *Neurofeedback Space* game. He asked if the background, the outer space, moved and the ship was fixed in the same place. It's not really what happens, because the background moves with the ship, but the parallax effect, gives this depth illusion and when you pay attention, it seems that the ship is stationary, and the stars come to the spaceship. Demonstrating how attentive he was in the game.

This last Volunteer is also a gamer and plays often. In his first session, he had to change constantly the adopted strategy to focus, because he realized that he was bored with it, and the spaceship's speed was falling. In the third session, despite achieving 184 seconds of *attention*, his *score* was low in relation to the previous session, even with an improvement in the *attention* metric. This was due to the game mode and *sustained attention*, since in session 2 he got 44 seconds of attention sequence and in the third only 9 seconds, which caused him to be punished in the game and prevented from catching stars to increase his *score*. The last session was the only one in which he did not feel in control of the spaceship, he did not feel a good feedback, and even though he was focused, he reported that the ship did not increase its speed, bringing some frustration since it was the last session.

TABLE 5.12: Game metrics from the Experiment 2 - Volunteer 5.

Session	Attention	Score	Game Level	Sustained Attention	Sust. non-Att.
1	172	64	2	13	12
2	165	59	2	44	7
3	184	14	2	9	8
4	290	117	2	259	3
5	74	1	2	3	10

5.2.2.2 Data Analysis

To perform the analysis of brain data, the same precautions were taken as in the previous chapter. Graphs were generated with the two analyzed features ($theta/beta$ and $alpha/beta$) and an average was calculated for each session. The theta, alpha and beta features were not analyzed individually, because, as already explained, from one session to the next, these features can change a lot in magnitude, since the scalp's conductivity can change with its physical characteristics. To calculate the average, the artifacts that could bias the averages were removed, thus, the data was cleaned as in the previous chapter, identifying the type of peak, as in the Figures from 5.2 to 5.4, and equaling it to zero to calculate the average.

According to the literature, with increased attention, there is an increase in the $beta$ frequency activity and a decrease in $theta$. Therefore, it is to be expected that with increased attention, the $theta/beta$ and $alpha/beta$ ratios will decrease. In Figures 5.12 to 5.16, the expected is a descending line, since the abscissa axis represents the *attention* metric and the ordinate axis is the average value of one of the characteristics for a specific electrode.

Analyzing Figure 5.12, it is possible to conclude that Volunteer 1's result did not occur as expected. All lines of both features and for all electrodes have a positive slope. As for Volunteer 2, observed in Figure 5.13, all lines have a downward slope, and the graphs with higher R^2 belong to the $theta/beta$ feature of electrodes F7, T3 and C3. Volunteer 2, in the previous analysis, was the one who did not feel in control of the spaceship, and did not have a good self-perception, as he did not understand which strategy the spaceship increased its speed. However, his brain wave frequency results followed what was expected in the literature.

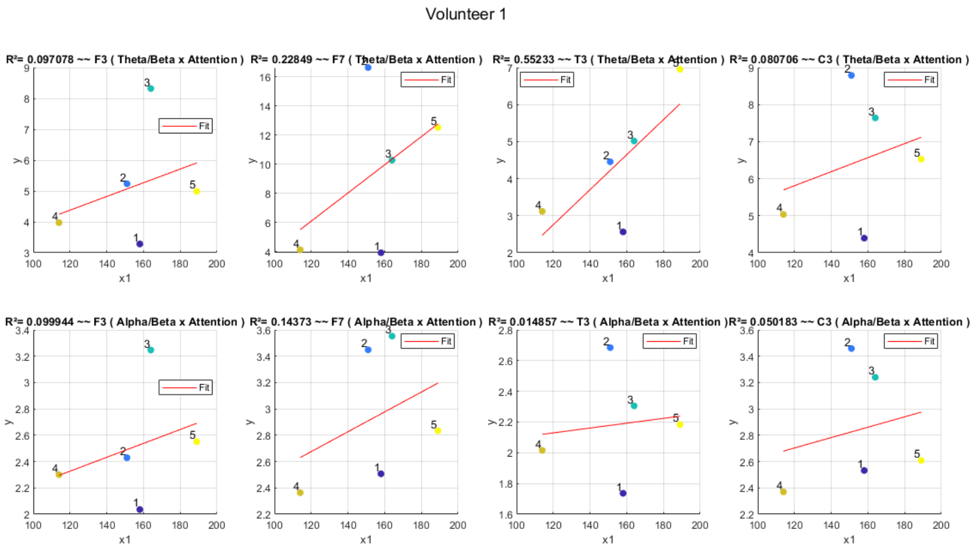

FIGURE 5.12: Data Analysis - Volunteer 1.

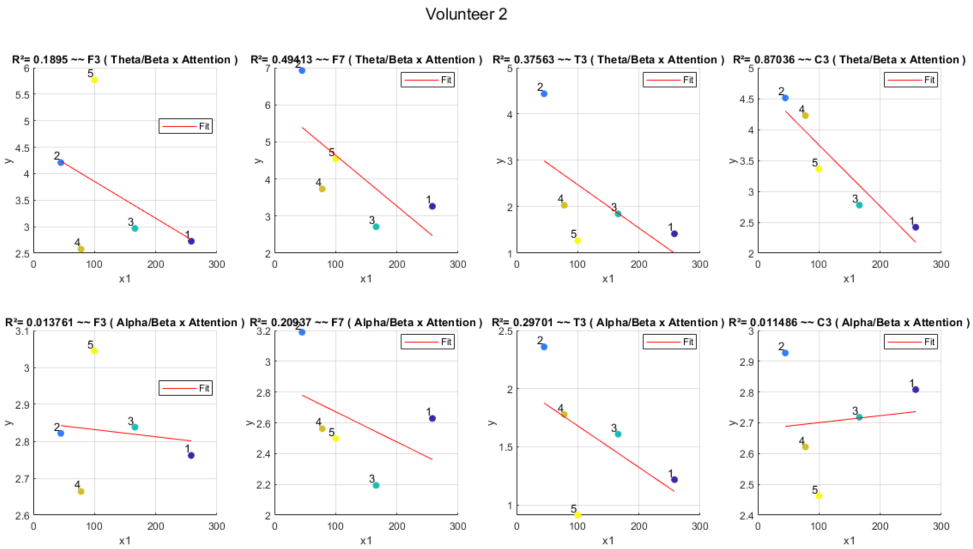

FIGURE 5.13: Data Analysis - Volunteer 2.

Volunteer 3 also showed a positive slope for the features with higher R^2, that is, for higher values of the $theta/beta$ ratio, the greater is the *attention* metric, seen in Figure 5.14, contrary to what should occur. For Volunteer 4, from the graphs in Figure 5.15, the two with the highest R^2 are from the $alpha/beta$ feature of electrodes T3 and C3. In addition, sessions 3 and 4 present the lowest values of these features for the C3 electrode, what is practically expected in the literature. The first session has the lowest attention value and the highest $alpha/beta$ value and throughout the sessions, excluding the last session, this decreases.

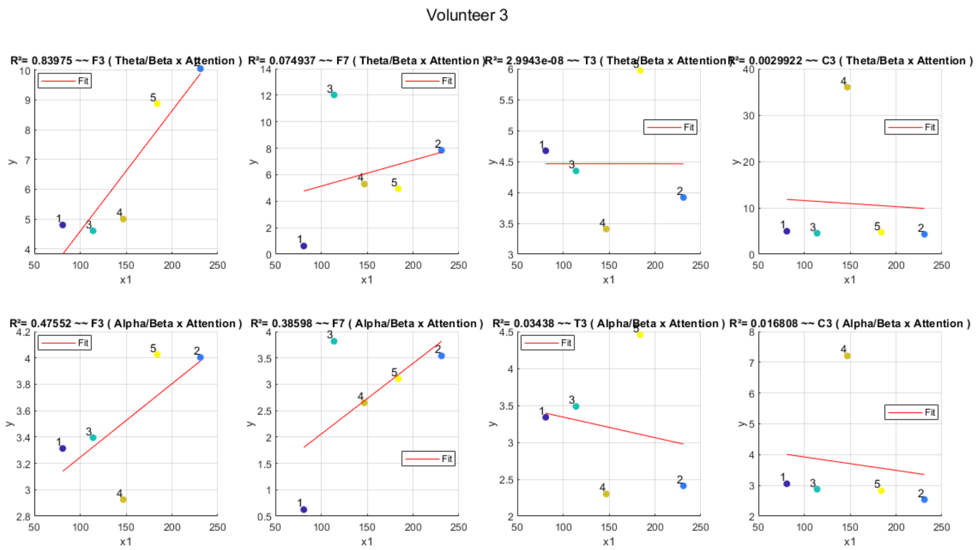

FIGURE 5.14: Data Analysis - Volunteer 3.

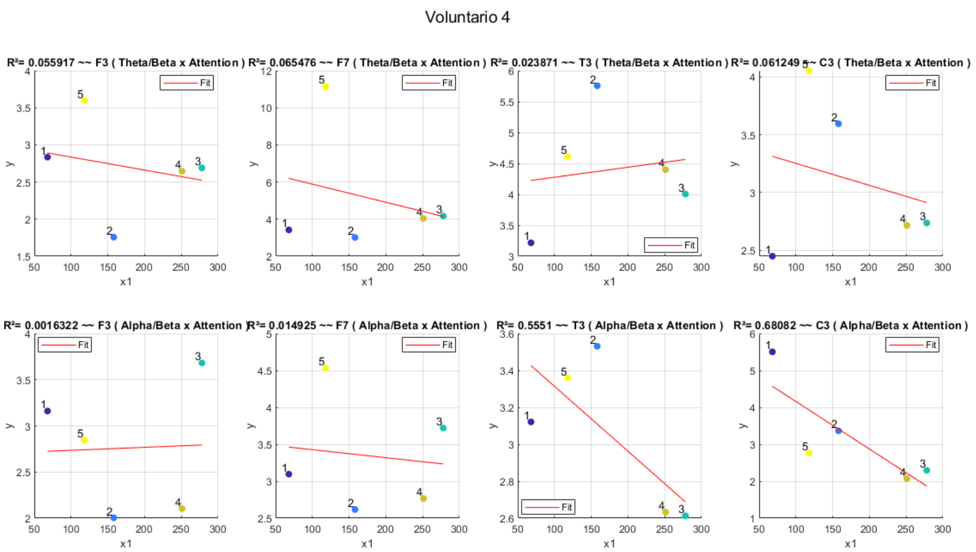

FIGURE 5.15: Data Analysis - Volunteer 4.

The last Volunteer did not obtain R^2 values close to 1, however, the highest value belong to the $alpha/beta$ ratio of the C3 electrode, which was also the best value for Volunteer 4. Unlike the previous Volunteer, the graph does not show a decrease in

$alpha/beta$ values throughout the sessions, since the values of the first and third sessions are very close, however, the expected was a downward line, which occurred. Observing the other graphs, the result of session 2 seems to differ from the results of the other sessions, and it is notable that if it was excluded from the analysis, most graphs would have lines with greater negative slopes.

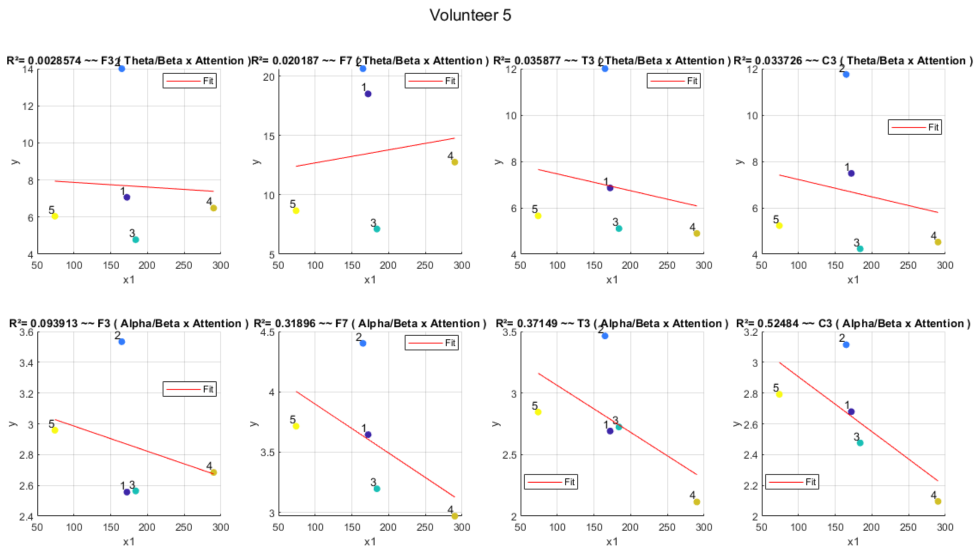

FIGURE 5.16: Data Analysis - Volunteer 5

With this analysis it is not possible to find a pattern of which feature and which electrode, in general, represents the best combination for the NFB training, since some Volunteers obtained only straight lines with positive inclination, others with negative inclination, but with low values of R^2, others with high values of R^2 and with negative slope. This is due to the complexity in the training phase of the classifier, which does not choose only these characteristics to extract information about the mental states of *attention* and *non-attention* for a session.

5.2.2.3 Training Data Analysis

Only $theta/beta$ and $alfa/beta$ were chosen to analyze and compare what happens to the brain signal when the attention, which was classified by the SVM, increases. However, the classifier trains the model with all the features of all electrodes, making the analysis much more complex than the one performed so far.

Figures 5.17 and 5.18 show all the characteristics used in the SVM training of the first two Volunteers. In each session, the classifier was trained to build the mathematical model regarding the two mental states, for this, two types of data were collected per session. The integer numbers correspond to that session's *non-attention* mental state, data represented by the color blue, and the decimal numbers, that session's *attention* mental state, data represented by the color red.

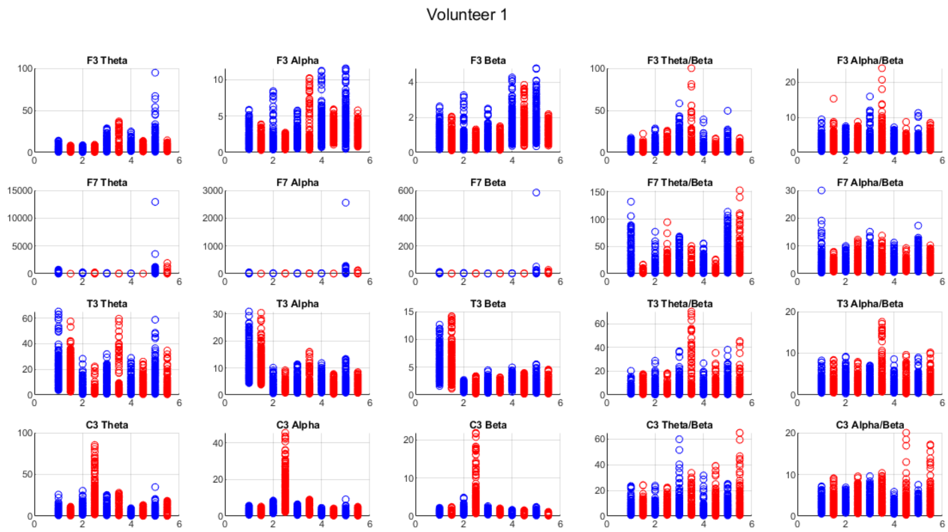

FIGURE 5.17: Features from the training data - Volunteer 1.

Analyzing the images it is possible to perceive the change in the variance of the data of different characteristics for the same session, and of the same characteristic for different sessions. That is why the SVM is trained in every session and for each Volunteer, since, if the model were used for the other sessions, it probably would not give a good feedback, since the changes, notable in the Figures mentioned, are significant.

5.2.2.4 Analysis of the Volunteer 1

The Volunteer 1, which also performed Experiment 1, was asked to participate in this Experiment for two reasons: first, analyzing the data from all Volunteers so far, five sessions may be few samples to analyze the improvement in the Volunteers' performance. Therefore, she was chosen so that, with these five sessions, she would have an analysis of ten samples. Second, the objective was to analyze the Volunteer's

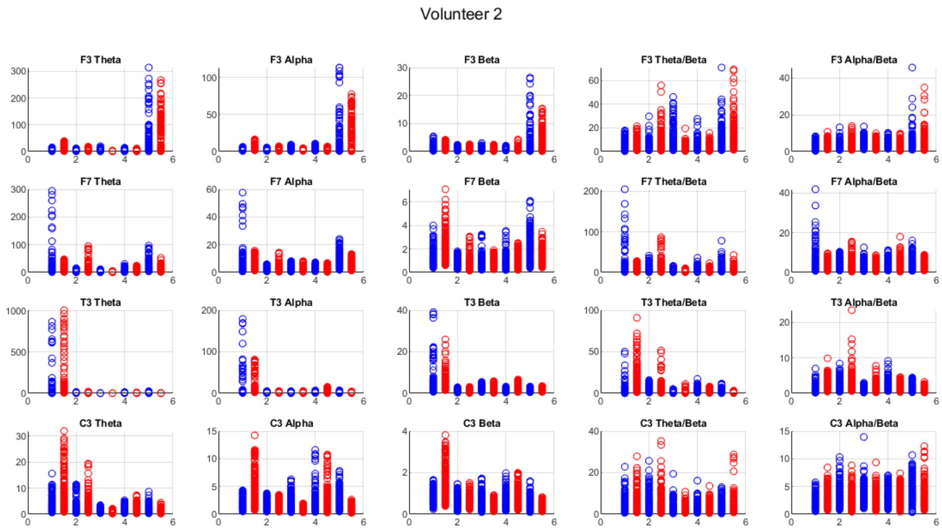

FIGURE 5.18: Features from the training data - Volunteer 2.

performance after a 2-month break, since she had already participated in the NFB training, if and how it would make a difference in her performance.

In Figure 5.6, in Experiment 1, the Volunteer obtained results comparable to those in the literature. Excluding the C3 electrode, all others achieved straight lines with R^2 values above 0.5 and had a negative slope, that is, the higher the *attention* metric, the lower the $alpha/beta$ and $theta/beta$ ratio. Although, this decrease in the values of these features does not occur during the sessions, the first session is the one with the lowest value, but, in any case, the negative slope already suggests a correct correlation of the two metrics of the graphs.

In this Experiment, as already shown in Figure 5.12, the result of this Volunteer was the opposite of what happened in the Experiment 1, along with very low R^2 values, the straight lines have a positive slope, the opposite of what the literature suggests.

Joining the results of the two Experiments, it is possible to see in Figure 5.19 the sessions held by the Volunteer. The only difference from the previous graphics is that now, next to the colored dots, the numbering goes up to 10, symbolizing the 10 performed sessions. As this Experiment did not obtain good results, it was expected that the combination of the two Experiments, even with the results of the first, would result in something inconclusive. The values of R^2 are very close to zero, showing little or no correlation of the variables, however, the two that had the

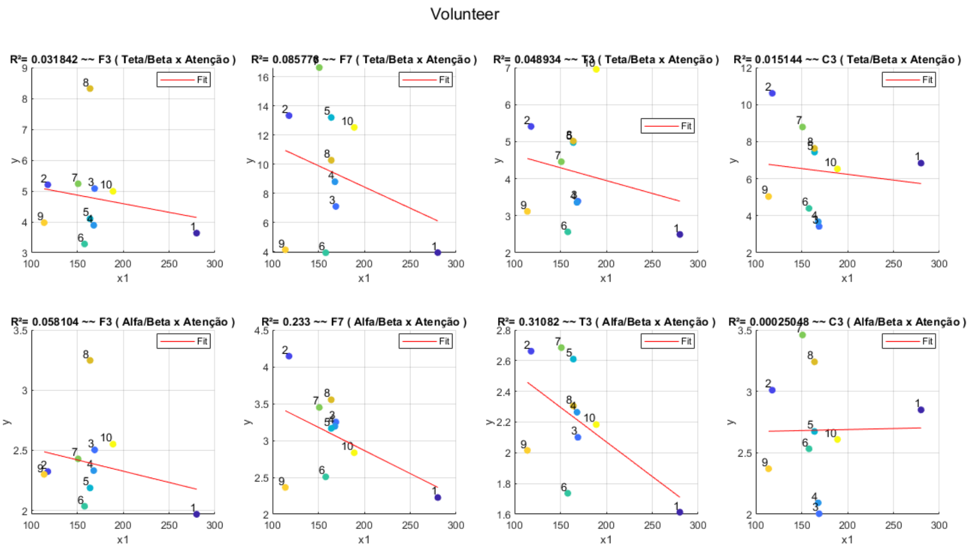

FIGURE 5.19: Features from the training data.

best values, electrodes F7 and T3 for the $alpha/beta$ ratio, obtained a straight line with negative slope.

Analyzing the data, it is possible to conclude that the number of sessions made no difference in the performance of the Volunteer. There are many variables to be evaluated and questions to be asked, such as, for example, the 2-month pause, usually in the literature there is no pause, was it a long period to be without the NFB training? Only one Volunteer repeated the Experiment and she had already obtained good results, what if a Volunteer with a worse performance had repeated it, there would be a greater chance of improvement? In this Experiment, the Volunteers were forbidden to communicate about the NFB training, was there a decrease in motivation because of that? because when asked, the Volunteer reported being competitive and feeling more challenged in the Experiment 1. When dealing with tests that involve emotions, well-being, comfort, motivation and other variables, it is difficult to reach just one conclusion without taking into account the person's routine and other variables that can cause a spurious relationship.

5.2.2.5 Attention Test

The Volunteers took the concentrated attention test to assess their attention before and after the NFB training. The results are shown in Table 5.13.

Of the 5 Volunteers, only Volunteer 1 and Volunteer 4 did not level up. The first was at level 4, already considered a high level of concentration and remained there, while the Volunteer 4, remained at medium level 3. All the other 3 progressed from 1 to 2 levels when compared from the beginning of training to the end of training NFB. The best result was achieved by the Volunteer 3 who achieved level 5. Even Volunteer 2, who did not feel good feedback from the system, progressed from level 3, medium level, to 4, upper middle.

Analyzing the Volunteer 1, who participated in the Experiment 1, on the first day of the NFB training, she started at level 3 and, at the end of the Experiment, she went to level 4. In Experiment 2, in her first psychological test, she has already achieved a sufficient score to be on the same level as she finished the first one, and continued with this score at the end of the NFB training.

TABLE 5.13: Psychological test's results applied at the beginning and at end of the NFB training.

Volunteer	Pre Classification	Post Classification	Pre Score	Post Score
1	4	4	123	122
2	3	4	93	124
3	4	5	117	141
4	3	3	84	85
5	3	4	101	130

Then, the psychological test showed an evolution of the majority of participants during the NFB training, as it also happened in the Experiment 1. The biggest difference between them is that in the Experiment 1, a Volunteer managed to reach level 5 and one of the Volunteers achieved a score that placed him in level 2, facts that did not occur in the Experiment 2, at the end of the last Experiment no Volunteer remained at the level 3.

5.2.2.6 Remarks and Preliminary Conclusions

As in the Experiment 1, there were divergences between the metrics used to assess the Volunteers' performance. It is possible to observe that by the attention test there was an improvement during the NFB sessions, by the brain data, as well as in the Experiment 1, the result was inconclusive and does not follow what the literature affirms.

In the game metrics, according to the SVM classification, most users reported good system feedback and had no headaches and/or discomfort during sessions. It is possible to observe that even with the repetition of game level 2 during all sessions of the week, there was no noticeable learning by the Volunteers. Analyzing also the other metrics of evaluation, it is not possible to see an improvement of some participants from the beginning of the NFB training to the end. There was improvement in some sessions, but there was a huge oscillation in the results. Only Volunteers 1 and 3 showed improvement from the first to the last session, with the first one having expressive improvements and worsens in consecutive sessions.

The first consideration to be made is that the participants in this Experiment belonged to the area of humanities and social sciences, while those in the Experiment 1 belonged to the area of technology. This discussion was raised in the meetings of the BRAEN research group to ascertain the result in volunteers with different profiles.

The difference in the results between Experiments was in the way of describing what made the volunteers maintain their state of attention or the strategy used. Those in this Experiment were very detailed and had many arguments about their routine and the reasons for dispersing during the NFB. The second difference was in the motivation to play the game, the competition between the participants of the Experiment 1 made them seem more willing to play and more willing to surpass their previous score and the score of the co-workers. But in Experiment 2, with the confidentiality of results between them, Volunteers were not always motivated to participate, especially one of the Volunteers who had personal problems in the middle of the week. However, the sample is limited, and despite the different profiles, it is not possible to make any conclusions taking this into account.

Participants who were gamers, that is, who played games frequently, had a greater perception of the strategy used to keep their attention focused, and also knew, in most cases, what deconcentrated them in the sessions. Comparing them with the other Volunteers, it is not possible to see any advantage caused by being a gamer, the results were similar to the other participants.

Chapter 6

Conclusion

6.1 Conclusions, Final Remarks and Limitations of this Work

Neurofeedback can be used as an alternative treatment for ADHD and it is also used for improving concentration, memory skills, and cognitive activities. This research is the development of a serious game and a neurofeedback system for neurorehabilitation of children with ADHD. For this, three protocols were developed and conducted to verify the improvement in the performance of concentrated attention of people not diagnosed with the disorder.

In the preliminary validation and algorithm' selection, from five predetermined regions to perform the neurofeedback, the one with the best results (training accuracy of 98.12% and test accuracy of 93.88%) was region 4. Composed of the electrodes F3, F7, C3 and T3, thus being a frontal region on the left side of the scalp. Of the 4 versions of the algorithm developed, the one that obtained the best result, combined with a shorter execution time and also good feedback for the user, was version 2.

The Experiment 1, used 3 evaluation metrics to analyze the improvement in the performance of the 5 volunteers throughout the NFB training. One of the metrics related to the game and the classifier, one related to the frequency bands' power of the brain signal, and finally, one that evaluates the performance in the concentrated attention test. The analyzes show a divergence between the results obtained by all metrics. The volunteers obtained an improvement in performance in the concentrated attention test, it was also possible to observe an improvement in performance in the game's metrics, however, when analyzed the brain frequencies, the result is inconclusive. Since for some volunteers the result follows what is described in the literature, but for others it does not, having a random characteristic.

In the Experiment 2, of the five participants, 3 men had no contact with any stage of neurofeedback, and of the 2 women, one participated in the first protocol, having contact only with the training video, and the other participated in Experiment 1. The same analysis as the previous Experiment was performed and, practically, they reached the same conclusion. There was an improvement in performance in the concentrated attention test, and for the analysis of brain signals, the result was also inconclusive, as it did not follow any pattern and there was not a group of electrodes or features that obtained a better result. For the game's metrics, only 2 volunteers improved from the first to the last session, for the others there was a big oscillation between sessions of all game metrics such as *score*, *attention*, *sustained attention* and *sustained non-attention*.

One of the volunteers participated in both Experiments. She was Volunteer 2 in Experiment 1 and Volunteer 1 in Experiment 2. She was the one that obtained a more similar response to that described in the literature when analyzing the frequencies power of the brain signal, and, for this reason, she was chosen to repeat the Experiment and compose the new group after a 2-month pause. However, in Experiment 2, differently from what was expected, the volunteer had no decrease in the values of $theta/beta$ and $alpha/beta$ with the increase of attention. What suggests an inconclusive result, because in Experiment 1, she got good results. However, this outcome brings relevant questions that must be considered, for example, duration of break time, change in motivation due to lack of competitiveness, start a Experiment 2 already having a great result in the first, and among others. Nevertheless, she managed to maintain her classification, despite the pause, in the attention test, because in the Experiment 1 she improved to level 4 and, in Experimet 2, she already started from the level 4.

The two Experiments were developed with some changes between them to analyze whether they would have any effect on the result of the NFB training. The volunteers in the Experiment 2 belonged to the area of humanities and social sciences, while those in Experiment 1 belonged to the area of technology. The biggest difference between them was the strategy used to focus and the way they analyzed their perception. While the volunteers in the Experiment 1 were more succinct in explaining what strategy was used to focus on an object, those in the second had a broader explanation and always tried to change the stimulus in the sessions, while those in the Experiment 1 tried to maintain one. However, the sample is limited, and despite the different profiles, it is not possible to make any conclusions taking this into account.

Another change was in the confidentiality of the results among the participants. This alteration caused a direct change in the motivation to play and to attend the sessions, but it also took the stress out of competition and the negative feeling of being "worse" than others volunteers.

The last alteration was to fix game level 2 in the Experiment 2. It was observed that the learning effect of the Experiment 1, when there was a level repetition, was not observed in the second one. That is, even with repetition of level 2, there was no continuous improvement justifying learning by repetition, a fact that occurred in the Experiment 1. It is concluded that the change in level generates a drop in expectation and, soon after, with the repetition of the same, the volunteer is able to learn and improve his game metrics.

With the analysis made in this research, it is not possible to declare conclusive results for the developed NFB system. Although the volunteers had an improvement or remained in the same classification in the concentrated attention test, the metrics of the classifier and the brain signal behaved at random and not as expected. Several factors may have contributed to the results obtained. The EEG headset used for data collection is wireless and has dry electrodes, despite being a new technology and presenting facilities for its preparation, the electrodes move easily in the head, being able to get out of position and cause noise, in addition, by not using the conductive gel, the brain signal is less reliable, as conductivity is reduced.

Other factors to be taken into account are number of sessions, duration of serious game, number of volunteers, game genre, as a genre may be attractive to some volunteers, but it may not be for others, which hinders motivation and engagement . Therefore, for the NFB system to be validated also for the metric that evaluates the power of the frequencies of brain signals, and tested with children with the disorder, it is necessary to do the tests with the EEG that uses conductive gel, or using another technology that can return more reliable data whether they are brain waves or brain imaging.

6.2 Contributions

The work contributions of this Master Dissertation is the development of a serious game and a neurofeedback system for neurorehabilitation of children with ADHD. The most important technical and scientific contributions of this research are listed below.

1. Development of a serious game to be used by the research group BRAEN for future tests and publications.
2. Development of four algorithms with different types of pre-processing and processing for NFB training.
3. Design of an interface to facilitate and make accessible all the NFB training steps.
4. Proposal and validation of metrics related to serious game and classifiers.
5. Study of the progress of the θ/β and α/β features of the brain signal of 9 volunteers over 5 sessions and 1 volunteer over 10 sessions.
6. Analyze of the development in attention levels, due to NFB training, according to the concentrated attention test used in this dissertation.

6.3 Publications

The research developed in this Master Dissertation allowed the publication of the following work:

1. (**Conference Proceedings**) F. Machado, W. Casagrande, A. Frizera and F. da Rocha, "Development of Serious Games for Neurorehabilitation of Children with Attention-Deficit/Hyperactivity Disorder through Neurofeedback," 2019 18th Brazilian Symposium on Computer Games and Digital Entertainment (SBGames), Rio de Janeiro, Brazil, 2019, pp. 91-97.

   DOI: 10.1109/SBGames.2019.00022

Other works were published as a consequence of the interaction with other researchers in BRAEN:

1. (**Conference Proceedings**) W. Casagrande, F. Machado, H. Oliveira-Junio, A. Ferreira, E. Palacios, A. Frizera, "Identificação de estado mental de atenção através do EEG para aplicação em treinamento Neurofeedback". 2nd International Workshop on Assistive Technology (IWAT 2019), Vitória, Brazil, 2019. Proceedings of IWAT 2019, 2019.

2. (**Conference Proceedings**) H. Oliveira-Junior, W. Casagrande, F. Machado, D. Delisle Rodriguez, M. Souza,T. Bastos-Filho, and A. Frizera, “Towards an eeg based bci system for neurofeedback assisted rehabilitation of attention deficit hyperactivity disorder”, X Congreso Iberoamericano de Tecnologías de Apoyo a la Discapacidad (IBERDISCAP 2019), Buenos Aires, Argentina, 2019.

6.4 Future Work

In this dissertation, the mental states of attention and non-attention were classified exclusively by the SVM classifier. Therefore, if the training data was not reliable or if there was some data with a lot of noise, this could damage the classification and make the NFB training less reliable. In this way, a future work could be the development of a tool, which, together with the classifier, works as a logical ’and’ gate. An example would be the development of a gaze tracking, to assess whether the volunteer is focusing at any part of the screen. With this tool, it would also be possible to build a heat map to assess "preferred" areas and even strategic locations where volunteers can achieve greater focus on the game.

In addition, for the training of the classifier, a video with 4 images was used. For future work, training can take place in an environment more similar to that used in NFB training. Besides, other classifiers could be used to compare with the results obtained in this dissertation. Also, to facilitate the editing of tables created to store data such as name, score, and other information already mentioned in this dissertation, an algorithm can be developed using JSON instead of SQLite.

The protocols had a duration of 5 uninterrupted days and for one volunteer 10 days with a 2 months pause between protocols. Future work may increase the number of sessions or change the break’s duration between sessions to assess the effects of these alterations. Further, a control group can be used to evaluate whether the result of improvement in attention is a placebo effect, that is, the volunteer has no control over the game, but at the end of the training, there is an improvement in the metrics evaluated.

Game changes are also required after receiving user's feedback and analyzing the obtained results. Firstly, for visual feedback, a change can be made in the spaceship's physics engine, transforming it into a dynamic rigid body. A dynamic object is affected by forces and gravity, so it presents a more real simulation and has a more pleasant speed transition for users.

After carrying out the experiments, a distraction was noticed due to certain items on the screen, such as the speed bar, stopwatch and fuel bar. A change that could be made in future works is to reduce the information shown to the user based on the game interfaces, there are 4 types of them: Diegetic, Non-Diegetic, Spatial, and Meta. One of the suggested changes would be to transform the game scene to a representation closer to the meta interface, that is, representations may exist in the world of the game, but these are not necessarily observed spatially for the player, they are often used for effects such as to indicate a characters speed and taking damage. For example, the fuel bar, which is theoretically visualized on the spaceship control panel, could be substituted for a meta component, so, when the fuel is running low, the spaceship can change its color to alert users and prevent them from diverting focused attention from the spaceship.

Appendix A

Human-Computer Interface for NFB system

A.1 Graphical User Interface

A graphical user interface (GUI) was created aiming to making the developed algorithm's access not restricted only to people who have minimal Matlab software knowledge. The BRAEN research group is multidisciplinary and, although it is extremely important to have people who have expertise with EEG and with the developed system, it is also essential that, even with the exit of members and the entry of new ones, everything is well documented and easily accessible for research to continue. Thus, in figure A.1, there is the interface created in the Matlab software to facilitate the use of the algorithm in NFB training.

The panel is divided into 4 parts: protocol data recording, feature extraction, classifier training and NFB. The first instruction is to press the *start* button, that is used to clear the variables if any are recorded in the MatLab and to close all windows that may be open. When the text *start the app!* changes to *ready*, the user can move on to the next section. Then, the user has to fill in the fields that will start recording the protocol. The next instruction is to record the data acquired with the video protocol, this specific part needs to be modified so that it works for any application, so far, it only serves for the 82 second video of this dissertation. The first field is the duration of the protocol to be recorded and the second field is the total electrodes of the system, BRAEN has 2 EEG headsets from Cognionics, one of 20 and the other of 30 electrodes. After filling in the fields, the user can press the *record* button and the text

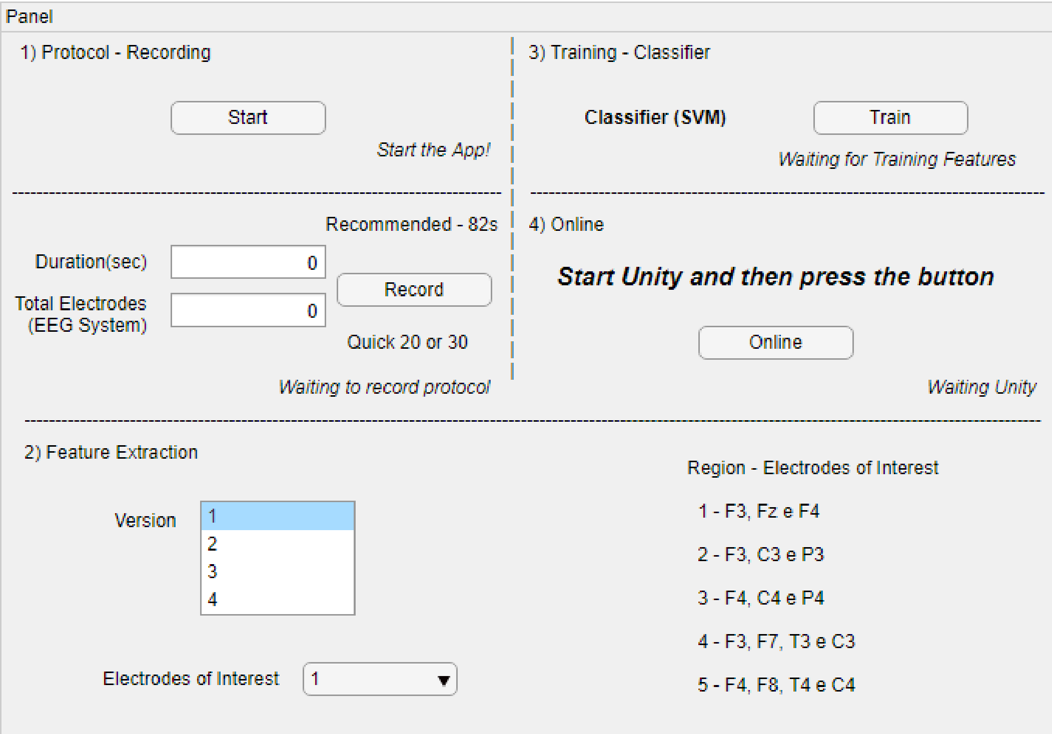

FIGURE A.1: Interface developed for NFB application

waiting to record protocol will change to *recording protocol! Wait* and at the end of the 82 seconds, the text will change to *protocol recorded*.

The second step is to extract features, the user chooses the version of the algorithm, all versions are explained in a file *README.txt* in the same folder of the interface, and the region of interest of the brain to process the data previously acquired. This step is very quick and does not require a warning text for the user to wait. The third step is the classifier training, because in the previous step, the features matrix was already calculated to be used as input of the classifier. After pressing the *train* button, the text *waiting for training features* changes to *training the classifier* and as soon as the classifier finishes training, the text changes to the accuracy rate achieved in it.

The last step is NFB training, the online part of the algorithm. As unity needs to be initialized before MatLab, so that there are no problems with TCP/IP communication, a bold text *start unity and then press the button* was created just to avoid this type of error. When everything is ready, the user presses the *online* button and the text *waiting Unity* changes to *processing*, when the 5 minutes of the game is over, or when the game is "closed", the TCP/IP communication protocol is interrupted and an exception in the algorithm is generated. When this occurs, the text changes to *the process is over* and some predetermined variables are saved in the same folder of the interface for further processing.

The entire panel was created using the Matlab tool *appdesigner*. The interface still needs improvement and the creation of a tab for processing and displaying graphics is of great value for the research group.

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