MONITORING ELECTROCORTICAL ACTIVITY DURING EEG BIOFEEDBACK

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Jury

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Abstract

The purpose of this work was to develop an EEG biofeedback platform. Additionally, it was studied how voluntary training of specific electro cortical activity, using the EEG biofeedback platform, produces any changes in the electroencephalogram along with the electroencephalographic correlates of memory.

The human brain was seen as an electrochemical machine capable of receiving stimuli and adapt accordingly. Relevant EEG activity was fed back to the trainee by a Brain Computer Interface in an intelligible way allowing the identification of phasic changes in the EEG and what cognitive state caused it, facilitating self-regulation.

The results from this study showed that it is possible to learn changing some rhythmical activity in the EEG after a few feedback sessions, in this case, the amplitude of the alpha activity. A positive relation between this frequency band and cognitive processes was also observed.

Keywords: EEG Biofeedback, Neurofeedback, Brain-Computer Interfaces, Signal Processing
Resumo

Este projecto teve como objectivo principal o desenvolvimento de uma plataforma de biofeedback através do EEG. Em seguida foi estudada a possibilidade do uso da plataforma permitir a alteração voluntária da própria actividade rítmica do EEG e, se esta alteração afecta de algum modo o desempenho cognitivo.

O cérebro humano é interpretado como um sistema que se adapta consoante os estímulos que recebe. Apenas a informação necessária do EEG é enviada de volta ao utilizador, através da plataforma desenvolvida, de modo a que este consiga identificar que estado cognitivo ou emocional foi responsável pela actividade registada.

Os resultados do estudo realizado neste projecto mostram que é possível, com poucas sessões de treino, aprender a alterar certos padrões do EEG, neste caso, a amplitude das oscilações alfa. Também se observou uma tendência positiva para o melhoramento de certos aspectos cognitivos com o treino desta banda de frequências.

Palavras Chave: EEG Biofeedback, Neurofeedback, Interface Cerebro-Computador, Processamento Sinal
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<td>Anterior Cingulate cognitive division</td>
</tr>
<tr>
<td>ADHD</td>
<td>Attention Deficit Hyperactivity Disorder</td>
</tr>
<tr>
<td>API</td>
<td>Application Programming Interface</td>
</tr>
<tr>
<td>BASC</td>
<td>Behavior Assessment System for Children</td>
</tr>
<tr>
<td>BCI</td>
<td>Brain Computer Interface</td>
</tr>
<tr>
<td>BOLD</td>
<td>Blood-oxygen-level dependent</td>
</tr>
<tr>
<td>CT</td>
<td>Computed Tomography</td>
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<tr>
<td>DFT</td>
<td>Discrete Fourier Transform</td>
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<td>DPSS</td>
<td>Discrete Prolate Spheroidal Sequences</td>
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<td>ECG</td>
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<td>EMG</td>
<td>Electromyogram</td>
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<tr>
<td>EOG</td>
<td>Electrooculogram</td>
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<tr>
<td>EPSP</td>
<td>Excitatory Postsynaptic potential</td>
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<td>ERD</td>
<td>Event related desynchronization</td>
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<td>ERP</td>
<td>Event related potential</td>
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<td>ERS</td>
<td>Event related synchronization</td>
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<td>FFT</td>
<td>Fast Fourier Transform</td>
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<tr>
<td>FIR</td>
<td>Finite Impulse Response</td>
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<tr>
<td>fMRI</td>
<td>Functional Magnetic Resonance Imaging</td>
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<tr>
<td>IIR</td>
<td>Infinite Impulse Response</td>
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<tr>
<td>IMF</td>
<td>Intrinsic mode function</td>
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<td>IPSP</td>
<td>Inhibitory Postsynaptic potential</td>
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<tr>
<td>LTM</td>
<td>Long term memory</td>
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<tr>
<td>LTP</td>
<td>Long term potentiation</td>
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<td>MEG</td>
<td>Magnetoencephalogram</td>
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<td>Peak alpha frequency</td>
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<td>Slow cortical potential</td>
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<td>SMR</td>
<td>Sensorimotor rhythm</td>
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<td>STM</td>
<td>Short term memory</td>
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<tr>
<td>UML</td>
<td>Unified modeling language</td>
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<tr>
<td>USB</td>
<td>Universal serial bus</td>
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<td>VR</td>
<td>Virtual Reality</td>
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Chapter 1

Introduction

1.1 Motivation

The motivation to develop an electroencephalographic (EEG) biofeedback system that can be easily used by any person comes from the fact that the brain is one of the most important and interesting biological structure in the human body but still, its processes and functioning are not available for everyone to acknowledge. When this possibility was offered, it was observed that people could modify certain aspects of their brain functioning for short periods of time and, when this was done in a methodological way, some changes could become permanent. The most interesting fact is that this type of biofeedback never showed undesirable effects and has been used to treat neurological conditions, sometimes with better results than with medication, or to improve some cognitive processes. However, more research in this area needs to be done to improve its visibility.

1.2 Objectives

The first objective of this work is the development of an EEG biofeedback platform providing most of the functionalities used in the experiments reviewed in the literature. When all the necessary requirements are met, a pilot study will be realized to contribute to the following validations:

1. Proper functioning of the platform.
2. Possibility of self-regulating the EEG.
3. Possibility of a training protocol to produce lasting changes in the EEG.
4. Possibility of a training protocol to produce improvements in certain cognitive aspects.
5. Relation between short term memory, peak alpha frequency (PAF) and age.
6. Experimenting additional EEG processing tools.

1.2.1 Proper functioning of the platform

The EEG biofeedback module consists in a series of connected plug-ins integrated in an already developed signal acquisition, viewing and manual scoring software platform – Somnium. This software receives signals captured by an external signal acquisition device and stores them in virtual channels for further processing. The quality of the developed plug-ins depends not only on its intrinsic quality
but also on the blending process which depends on the depth of knowledge about Somniums’ architecture. Having a proper functioning platform means having every developed plug-ins using every necessary resource from the main application without errors, delays or conflicts while doing exactly what it was supposed to do. This study will rely on volunteers so, to reduce their time spent on the lab, the platform must offer quick access, without many steps. Furthermore, because it is intended to be used by others than its programmer, it will have to be user friendly.

The following procedures must be present in the platform:

- Save and load data from each user.
- Calculate Individual Alpha Frequency.
- Evaluate a certain cognitive skill.
- Provide fully customizable training sessions.
- Feed back the signal in real time.
- Export results and to produce a written report.

1.2.2 Possibility of self-regulating the EEG

Empirical Evidence that cognitive or emotional states may produce different rhythmical activity

The pilot study only started after the platform is developed and functional tests performed,. The first expectation for this study is the observation of different rhythmical activities in the EEG between different cognitive or emotional states. This confirmation will ease the next steps because it provides strategies for the subject to change his/her EEG. For example, every time the subject starts doing some calculations mentally, like calculating the Fibonacci sequence, it’s observed a tonic (event related) increase in the beta1 band amplitude. If, later, a training session involves the production of beta1 activity, this particular subject will know what to do to produce it – calculate the Fibonacci sequence.

Empirical Evidence for the possibility of increasing or decreasing some rhythmical activity on demand

Even if the previous states are detected, the subject might not be able to reproduce them during the following training sessions. It’s expected that the subject learns gradually to control the desired rhythm. This learning is reflected by a gradual increase or decrease of this rhythm in the EEG along the sessions. The changes should happen only in the demanded frequency band, no parasitic changes are expected.

1.2.3 Possibility of a training protocol to produce lasting changes in the EEG

Comparing the quantitative EEG (QEEG) recorded in the beginning of the training with the last recordings to search for significant changes. The recording must be obtained during a reference period where hopefully the subject isn’t voluntarily changing any EEG rhythmical activity.
1.2.4 Possibility of a training protocol to produce improvements in certain cognitive aspects

If any of the two previous points are observed, it’s possible to expect improvements in certain cognitive aspects. So, ranked tests need to be done in the beginning and end of the study.

1.2.5 Experimenting additional EEG processing tools

Any additional EEG processing tool, like advanced spectrum analysis is helpful, not only for the present study, but to other future studies by anyone who uses Somnium software.

1.3 Project framework and contributions

In this work the necessary software for the proper use of EEG biofeedback is developed. It allows the tracking of different EEG characteristics such as relative band amplitude and power. Because one of the objectives is assessing any difference in cognitive performance before and after the training sessions. For this purpose several intelligence and response time tests are developed and presented here. Besides the traditional time to frequency Fast Fourier Transform, other signal advanced processing algorithms were also developed for future analysis purposes.

Due to time and logistic constrains of the project only a small sample of subjects were used to undergo a series of training sessions in order to validate minimally the functionality of the software and, in some cases, also the possibility to assess some aspects of cognitive improvement. Because the limited number of subjects, there was no real control population to exclude possible placebo effect and habituation to cognitive tests.

The contributions of this work to the EEG biofeedback area are the use of different approaches, from those used in the traditional studies, which are:

- Initial identification of the cognitive strategy that leads to a more successful training.
- Identification of individual frequency bands and how this improves the training results.
- Comparing different cognitive skills with certain EEG characteristics.
- Introduction of other EEG signal processing techniques for biofeedback besides the traditional Fast Fourier Transform.

1.4 Thesis organization

This thesis report presents the development of a software application for EEG biofeedback training and the results of its subsequent use. The basic principles needed to understand the electroencephalographic measures are present in the second chapter. A literary review of the applications of EEG biofeedback can be found in chapter three. Chapter four describes the several applications developed for this study and the biofeedback module. The methods used during the experiments are detailed in chapter five and its results in the following chapter. The conclusions drawn and future work are summarized in chapter seven. In Appendix A, a brief overview of the Somnium software is presented. Graphical interface can be seen in Appendix B.
Chapter 2

Background

Complexity in living beings doesn’t always mean evolutionary advantage but if it exists it’s because it has been proved useful. Good evidence is, probably, the existence of a nervous system in some animals, like the Human brain, responsible for the necessary capabilities and behaviors for survival or even self-awareness. However, there are simpler nervous systems in other animals, with reduced complexity and complication, where their main elements are more evident. One example can be found in the Cnidarians, whose simple nervous system is thought to be very similar to the one that higher animal nervous systems first evolved [1]. Here, instead of a central nervous system, there are decentralized nerve nets where sensory neurons communicate with motor neurons by electric signals. In an oversimplified view this communication can be seen as a logic circuit where some action is done if signals from a certain group of input sensory neurons are present. This kind of activity, known as bioelectromagnetism, already produces a measurable electromagnetic field.

In the human nervous system the electrical signal of a single neuron is too small to be measured by an electrode on the scalp therefore, the measured activity comes from the summation of the activity of hundreds of neurons on the vicinity of the electrode. If the electric field is measured, the signal is called electroencephalogram (EEG). Therefore, according to the measure location and the measured signal, it is possible to understand until a certain degree what kind of activity occurs. Sometimes, a group of neurons fire more synchronously reflecting immediately in the measured signal as it becomes stronger and more synchronous to the firing frequency. This is why these signals are seen as brainwaves and are categorized in different frequency bands. Each frequency band can correlate to a certain mental state for example; activity in the alpha frequency range (8-12Hz) is seen during relaxation whereas activity in the beta frequency range (15-20Hz) is present during high alertness and mental activity.

Besides the EEG clinical applications for diagnosis and monitoring, others exist like brain computer interfaces (BCI) and EEG Biofeedback. The last two rely on the fact that an individual can change certain EEG characteristics on demand. Brain computer interfaces allow its user to control a system using his EEG as an input. In EEG biofeedback a person’s EEG is used as an input as well but the target is the person himself. Certain characteristics of a person’s EEG are shown in a computer
screen in real time and this person tries to change them in the desired direction. It's not guaranteed that the closing of the loop provides a positive or negative feedback because it depends on several aspects of the implementation and on the user's motivation. Nevertheless, it has been proved that several successful sessions of EEG biofeedback produce tonic changes in the EEG and, along with this, changes in the cognitive capacity or behavior can be attained.

2.1 The neuron and the action potential

Neurons are excitable cells specialized in the reception and conduction of nerve impulses that can be seen in the brain and spinal cord and ganglia. Despite its shape and size variability, there are unique structural characteristics like a cell body with at least one projection. These projections are divided in two types: dendrites - conduct impulses to the cell body - and axons – a single projection that conducts impulses away from the cell body. The cell body is surrounded by a plasma membrane that, besides serving as an external boundary, is responsible for the initiation and conduction of the nerve impulse.

The plasma membrane is part of a semi permeable membrane that allows diffusion of certain ions through it and restricts others by specific ions voltage-gated channels. In particular, it is selectively permeable to the following ions in decreasing order: potassium (K⁺), chlorine (Cl⁻) and very few permeable to sodium (Na⁺). When unstimulated, the neuron is in its resting state. In this state, because of the selective permeability, there's a voltage difference between extracellular and intracellular spaces (across the plasma membrane into the cell) causing a steady potential of about -80mV known as the resting potential.

When the neuron is stimulated – by electrical, mechanical or chemical means – the opening of some Na⁺ channels increases the membrane permeability to Na⁺. These ions enter the cell because of the present electrostatic pressure and concentration gradient thus depolarizing the membrane (interior of the cell is more positive). If the depolarization doesn’t take the membrane potential to -50mV the electric current generated is small enough to be restricted to the area of the stimulation and the cell quickly returns to its resting state.

If the depolarization takes the membrane potential above the -50mV a sudden influx of Na⁺ occurs. This causes further depolarization of the membrane, opening more Na⁺ channels and creating a self-reinforcing cycle that only ceases when all the Na⁺ channels are opened. This is known as the Hodgkin-Huxley Cycle [2]. The membrane becomes completely permeable to the sodium ions (in rested state is only slightly permeable to these ions) leading to a concentration of these Na⁺ inside the cell responsible for a membrane potential of +50mV.
When this value is reached the refractory period starts. All Na⁺ channels close, no more depolarization can be done by Na⁺, and the potassium ions start to flow out of the cell polarizing it towards the -80mV until its channels close as well. This happens for a short time, the K⁺ and Na⁺ channels being both closed, but in this state the membrane is even more negative than the 80mV leading the cell to a hyperpolarized state. In this state, because the membrane potential is very negative, it takes more stimuli than normal to reach the -50mV threshold to create another self-reinforcing cycle. When this state ends the cell goes back to its resting state with a membrane potential of 80mV. These processes are the action potential. When generated it spreads over the plasma membrane, away from its point of origin, and it's conducted along the axon as the nerve impulse. Therefore, an action potential occurs when an excitatory stimulus depolarizes the plasma membrane to the threshold potential of -50mV. If several sub threshold stimuli are applied they can be summated and still initiate an action potential. The action potential is illustrated in Figure 1.

2.2 Synapses

The site where two neurons communicate is called a synapse. It usually occurs between the axon of the emitting neuron and the dendrite of the receiving one. Two types of synapses exist: chemical and electrical. The last ones are gap junctions connecting the cytoplasm of two neurons by bridging channels that allow ionic currents from one cell to another with minimal delay. They are usually used to ensure that a group of neurons are performing and identical function together. Chemical synapses are the most common type of synapses in the nervous system and their functioning relies on a chemical substance, one or more neurotransmitters, which connects to protein molecules in the receptor. The synaptic inputs to a neuron can produce excitatory postsynaptic potentials (EPSPs) or inhibitory postsynaptic potentials (IPSPs) on this target neurons membrane. The EPSPs raise the target neuron potential making it closer to the necessary threshold for producing an action potential. The inhibitory potentials work on the opposite way [4].
2.3 Neocortical Dynamics

The human brain can be divided into three primary divisions: the brainstem, cerebellum and cerebrum. The first one is where the efferent and afferent action potentials traverse between the spinal cord and higher brain centers. At its top is located the thalamus, the relay station for sensory (except olfactory) and motor signals as well as for the regulation of alertness, consciousness and sleep to the cortex. In the outer part of the cerebrum is the neocortex, a six layered, varying thickness and folded structure containing about $10^{10}$ strongly interconnected neurons responsible for most of the electrical potential measured on the scalp [4].

Neuronal interactions in the neocortex form loops of two kinds: corticocortical loops (between cortical neurons) and thalamocortical loops (between cortical and thalamic neurons). The thalamus is seen by some authors [5] as a pacemaker for the cortex, modulating cortical rhythms with different firing patterns of its cells. This modulation is reciprocal as cortical activity can too modulate thalamic firing patterns [4]. Similarly, cortical loops can be seen as three different resonances. Local resonances, responsible for the very high frequency in the EEG around 30Hz, occur between adjacent clusters of synchronous neurons, macrocolumns. As the distance between communicating macrocolumns increases, the frequency decreases so, regional resonances produce firing patterns around 8 to 15 Hz and global resonances produce the slowest activity. So the difference in the frequency of the firing patterns in the cortex is related to the distance between the macrocolumns in the resonant loop.

The conditions for such resonant loops are dictated by the concentration of certain neuromodulators in the brain. Without being specific, increase in certain neuromodulators produce cortical-cortical coupling states [5]. These states, in turn, refer to the amount of a type of resonant loop. Hypercoupling is favored by large resonant loops like global resonances while hypocoupling is favored by the small regional and local resonant loops that produce higher frequencies. Usually, coherence measures are used to determine how functionally linked together two areas in the brain are by statistically measuring likelihood that two random signals arise from a common generator process for a certain frequency band. Very low coherence between two areas means that they are functionally disconnected while high values imply functional connection [5]. For example, low coherence measures between regions on the occipital cortex (visual cortex) is interpreted by Lubar by several local resonant loops due to the complex processing of several aspects present in an image [5].

2.4 Data acquisition in electroencephalography

Because of the extremely high density of neurons on the outermost layer of the human brain, the cortex [4], an EEG recording on the scalp cannot capture the activity of a single neuron, the action potential. One electrode on the scalp provides the average of synaptic activity over tissue masses containing 100 million to 1 billion neurons. This low spatial resolution can be, however, enough to study human cognition and behavior as these aspects can be seen in large scales, if the electrode
locations are well chosen. Furthermore, the easiest way of obtaining more spatial resolution with EEG recordings would be by means of intracranial measures and these are only done in extremely necessary clinical cases due to their technical and ethical limitations.

An important aspect to take into consideration when measuring the EEG is the location of the electrodes on the scalp. A single EEG measure consists in determining the potential difference between two locations, the same way it’s done in an electrical circuit, by means of a voltmeter. For example, if the desired value is the scalp potential referenced to the Earth’s ground then, one electrode should be placed on the scalp and the other on a grounding electrode. In this case, the amplifier would be fed with a very low amplitude, because of the high resistivity of the circuit, and noisy signal with the rest of the body’s potential added up to the measure. That’s why it’s necessary to reference the scalp’s potential to the potential of a nearby place with common interferences except, hopefully, those from the cortical sources. In this work, for example, the reference is always on the forehead, as an attempt to make all potentials from muscle activity, from the neck down, and external sources influence both electrodes the same way. To further guarantee this effect, both electrode cables are interlaced when going to the amplifier. Still, these measures are always problematic because many other variables influence the results. The exact location of cortical sources is unknown and some can influence the reference electrode without influencing the other one. In this project, it’s known that the muscle activity from the eyes, that produces the electrooculogram (EOG), has more influence in the reference electrode, on the forehead, than in other recording electrode on the scalp so, its effects will appear in the EEG signal.

The usage of the terms monopolar (or referential) montage and bipolar montage is frequent in some EEG literature although they are, in physical terms, the same type of measure. The first consists in the same recording process explained before: the potential difference between a scalp location and a previously chosen reference location. The term bipolar measure is used to define measures that involve potential differences between two scalp locations, allowing the identification of electrophysiological events like the spatial spreading of an EEG spike [6].

Although the specific location of the cortical sources which potential is trying to be measured is unknown, the fact that scalp readings have low spatial resolution relaxes the decision of where to place the electrode. Still, the electrode placement should be determined according to the “10-20 International System of Electrode Placement” since it’s based on the location of cortical regions and uses relative metric, given that head sizes vary [6]. The rules for placing the electrodes according to this system are represented in Figure 2.
2.5 EEG rhythms

Rhythmic patterns on the EEG reflect unique proprieties of thalamocortical circuits making them topographically dependant from the nervous system organization as well as from other sensory or cortical events [8]. So, the signal present in the EEG, despite possible contaminations, is the result of the more or less synchronous activity of large groups of neurons. Synchronism in the firing pattern of nerve cells leads to high amplitude and regularity in the EEG whereas asynchronism produces an irregular signal with smaller amplitude [9]. Because different resonant loops occur at one time, usually it’s easy to observe (if the signal is filtered above 40 Hz for example) that the signal is composed of different oscillations. Before spectral content analysis, these oscillations were detected counting zero crossings or extremis in a fixed window length of signal. Today, EEG analysis is greatly helped by spectral estimation using the Fast Fourier Transform (FFT) [10]. Here, the signal is divided into several frequency slots (quantitative EEG or QEEG) which can be grouped to form the typical frequency bands, called brain waves or brain rhythms, which usually correlate with different mental states.

In lowest frequency band lie the delta waves, also known as “slow waves”, whose frequency ranges from 0.5 to 4 Hz (Figure 3). These waves are common during deep sleep, associated with restorative process of repair, but can also be observed during waking state, although cautious measures need to be taken to distinguish them from muscle activity interference which occurs in the same frequencies [3]. Up to the age of 4, these rhythms are predominant in the EEG but, their predominance in later ages can be a sign of medical conditions [6].
Theta waves (Figure 4) have their frequency boundaries at 4 and 8 Hz. When observed in a healthy subject, theta activity might be an indicator of a deep creativity episode or inspiration [6]. Other studies connect theta rhythms with the encoding of information by long term potentiation (LTP), from thalamocortical and cortical systems, at the hippocampus [11].

Alpha activity (Figure 5) is supposed to be bound to the 8 to 12 Hz band and is detected in all parts of the posterior lobes with higher amplitudes over the occipital region. Most subjects show higher alpha activity when awake with closed eyes than with their eyes opened. This is understood as this rhythms being a waiting or scanning pattern produced in the visual areas of the brain when no visual information is available. When the eyes open, if visual information reaches the occipital cortex, the regular and synchronous neuronal decreases ceases giving place to an irregular activity due to the local resonant loops caused by visual image processing [4]. These rhythms have been related to relaxed awareness states [6], improved capacity to brainstorm solutions to problems and to cope with high workload. On the other hand, factors like anxiety, mental concentration, attention or unfamiliar stimuli reduce the activity responsible for these rhythms. Alpha rhythms can be further divided in three frequency bands, lower-1 alpha, lower-2 alpha and upper alpha each one with a different selective behavior [12;13].

The sensorimotor rhythm (SMR), also called Mu rhythm, is often detected with frequencies from 12 to 14 Hz (Figure 6) over the sensorimotor cortex. Its production is related to idleness in sensorimotor areas while its suppression happens when these areas are activated, by movement, sensation or motor imagery.
Beta activity (Figure 7) can be detected over frontal and central regions, vary within 14 to 26 Hz and is related to active thinking, attention, focus to the outside world or solving concrete problems. These oscillations are also usually divided in two rhythms, according to their nature, beta 1 and beta 2. The slower rhythms, beta 1, are associated with higher cognitive processes, problem solving and focused concentration while the fastest rhythms, beta 2, are more associated with physiological arousal and response to threat [6].

Although fixed frequency bands were present, variation still exists within individuals and a much better understanding of the brainwave phenomena can be achieved if individual rhythms are tracked.

2.6 EEG Biofeedback

Much like the measure of the pulse at the wrist with the index and middle finger, biofeedback is a technique that helps its users to control certain involuntary physiological processes by monitoring and displaying key characteristics of those processes. When applied to the EEG, the signal is measured at the scalp and some of its components are fed back to the user allowing self-regulation. Before displaying those components they need to be translated into some stimuli, auditory or visual, so that the user knows when and what changes occur. If the produced changes are the desired, the user is rewarded with a different stimulus. Usually, tracked EEG characteristics are changes in the signal frequency components or coherence measures between scalp locations.

Self-regulation of the EEG is rarely achieved in the first session. Several training sessions are needed for the user to understand what cognitive strategies lead to the desired changes in the EEG. More training will be necessary to produce lasting (tonic) changes. Because these sessions are based on operant conditioning, their protocol, according to M. Sterman and T. Egner, must follow certain rules in order to be effective [14]:

![Figure 6 - SMR filtered from the EEG](image)

![Figure 7 - Low and high Beta bands filtered from the EEG](image)
• Each training session should provide discrete trials separated by brief pauses.
• There must minimum delay between the reward situation and the reward stimulus for optimal learning to occur.
• The reward stimulus must have the highest reinforcement effect.
Chapter 3

State of the art

One of the first evidences of the possibility of using EEG biofeedback for treatment of clinical disorders dates to the mid 60’s when M. B. Sterman and his associates where applying operant conditioning in cats for the suppression of a previously rewarded response [14]. During the learned suppression of the response a particular EEG rhythm, ranging from 12 to 20 Hz, appeared over the sensorimotor cortex. The location dictated that rhythms name, the sensorimotor rhythm (SMR). The investigators decided to focus their study on the SMR production by applying operant condition to this EEG pattern to the cats. So, a food reward was given to these animals if SMR activity was produced. According to Sterman, cats easily accomplished this feat and it was possible to observe that SMR production is accompanied by behavioral aspects like body stillness preceded by reduction in muscle tone. Later, Sterman’s lab went on a different study with the objective to establish dose-response functions of a highly epileptogenic (starts epileptic seizures) fuel compound on a population of cats. Some of the cats in this test were also present on the previous SMR operant condition experience and showed significantly elevated thresholds to epileptic seizures compared to the others. This promoted the shift of these experiences to human epileptic subjects with positive results. In most cases significant reduction of seizures was achieved.

However, another researcher had already demonstrated that human subjects could control their EEG if provided with feedback [6]. In these studies subjects had feedback on the production of alpha rhythms that helped them to realize how to control these rhythms consciously and eventually identify alpha with the absence of feedback. With this training subjects increased the presence of alpha rhythms in the EEG from 10% to 70% [6]. Also, thanks to this studies alpha activity was related to a relaxed state.

3.1 Clinical applications of EEG biofeedback

Since the discovery of the self regulatory effects of EEG biofeedback in epilepsy that researchers and medical practitioners have been applying it to a wide span of clinical disorders. This can somehow give a bad idea about this technique since it is claimed that distinct clinical disorders like epilepsy [14-20] and alcoholism, for example, benefit from this treatment. This is, in fact, a fallacy because there’s
something in common between the disorders that have benefited from neurofeedback: they all correlate with specific types of abnormal brain activity. So, this treatment allows patients to regulate their brain function with the help of appropriate diagnosis of their QEEG abnormalities compared to normal values – QEEG guided neurofeedback. Another approach consists on the regulation of the connectivity between cortical modules. This is done comparing the patients’ coherence values with standard ones. Extensive studies between connectivity between cortical modules and cognitive aspects were performed by J. E. Walker and associates [21].

### 3.1.1 Epilepsy

Self-Regulation has been used since the 1970’s for the treatment of human epilepsy, especially on difficult cases of intractable epilepsies, by reducing seizure frequencies or attenuating their intensity [22]. There are two distinct protocols in this area, with the same goal of reducing cortical excitability, consisting in monitoring different brain activities – slow cortical potentials (SCP) and sensorimotor rhythm. Negative slow potentials are a reflex of lower excitation thresholds while positive slow potentials reflect higher excitation thresholds [23]. By learning how and when to produce positive cortical shifts (producing cortical inhibition), it is possible for epileptic patients to stop the seizure onset [8;14]. Usually the recording location is Cz and sessions consist on monitoring cortical positivity or negativity. Training sessions consist in two types of trials: feedback trials and transfer trials. On the first ones, patients are provided with feedback (visual or auditory) of their SCP. Transfer trials differed in that no feedback was provided and served to determine how well patients can control their cortical shifts in a normal situation (where no feedback exists) [24-26]. Training could last until 35 sessions. SMR feedback was considered by the American Academy of Child and Adolescent Psychiatry should always be considered by the clinician for the treatment of epileptic seizures [14]. A larger deviation exists between training protocols in this frequency band but, besides rewarding SMR production, usually theta production is suppressed. Recording varies between central locations except in studies with theta suppression where frontal and temporal sites are recorded. The number of sessions can reach 40 and don’t last longer than 60 minutes. In most of studies the EEG was recorded in the central region regardless of the seizure focus.

Sterman reviewed studies from 1972 to 1996 and concluded that 82% of the subjects studied (142 in 174) had their seizure rates reduced at least by 30% with an average value exceeding 50% [27]. Unfortunately control population or strategies were not applied in some studies. Later, Lantz and Sterman found positive results in a controlled study. After the treatment, 17 of the 23 patients in the training group achieved at least 61% of seizure reductions while no significant results seen in the control group [28]. More recently, QEEG guided neurofeedback was used by Jonathan Walker and colleges to normalize the abnormalities (according to reference databases) present in epileptics EEG amplitude and coherence [18]. All 10 patients became seizure free and two of them were able to stop taking anticonvulsant medication. In October 2008, Walker reported additional 25 patients with intractable epilepsies, all were having more than 1 seizure per month for 3 to 11 years, treated with QEEG and coherence guided neurofeedback [19]. Normalization of power and coherence took from
18 to 82 sessions and, after that, all 25 patients were seizure free and 19 of them no longer required anticonvulsant medication.

3.1.2 ADHD

During QEEG examinations most of the patients diagnosed with ADHD show an excess of slow cortical activity and a smaller percentage also show cortical 'hyperarousal'. In the past decades these patients were provided with treatments with the aim of enabling them to normalize the level of cortical activity. In these trainings based on operant conditioning the patients were reinforced, via tone or visual displaying, for producing a specific change in cortical activity (typically the patient had to maintain the desired change for 0.5 s to be rewarded). Monastra [29] reviewed some of the most significant controlled-group studies until 2005 and identified three mainly used protocols. In the first protocol, Protocol 1, patients are encouraged to learn to increase their production of the SMR (12 – 15Hz) over sites C3 and C4 while simultaneously suppressing theta activity (4-7Hz or 4-8Hz) in order to develop control over behaviors of hyperactivity and impulsivity. Feedback is given in visual (movement of puzzle pieces, animated figures, graphic designs) or auditory (tones) fashion based on the patients success in controlling theta or SMR amplitude or the accomplishment reward condition (above or below a certain amplitude threshold for a certain amount of time, typically 0.5 s).

Protocol 2 is based in the enhancement of the SMR (12 – 15Hz) activity and the simultaneous attenuation of beta-2 (22-30Hz) activity, both recorded over site C4. Activity feedback and reward is similar to Protocol 1.

Protocol 3 differs by encouraging the patients to increase beta-1 (16-20Hz) activity while suppressing theta activity (4-8Hz). Recordings are made on Cz, C3 or Cz-Pz.

In all the controlled-group studies reviewed by Monastra for the treatment of ADHD none of the patients were under 6 years old nor did show mental retardation or other medical or psychiatric condition known to adversely affect attention or behavioral control. Patients with history of neurological disease or substance abuse were also excluded and the family commitment in the training was also taken into account. From the review of several case studies the same author also states the importance of identifying "nonresponder" patients (patients that can’t regulate their cortical activity and therefore may not show reduction of ADHD symptoms) and evaluating and controlling other nonspecific factors like expectancy or maturation in efficacy studies of these treatments for ADHD.

Five controlled-group studies were reviewed with a total of 214 patients with ages between 6 and 21, number of sessions between 20 and 50 and number of sessions per week between 1 and 5. Protocol 3 was the most used but protocols 1 and 2 were also applied and all of them were able to produce positive statistically significant changes in the patients’ behavioral and cognitive aspects. In one of these studies published by Rossiter and LaVaque [30;31] the effects of Protocols 1 or 3 were compared with ADHD stimulant medication (methylphenidate or dextroamphetamine) in a population of 46 children (23 took EEG training). Sessions lasted 45 to 50 minutes and occurred three to five times a week (summing 20 sessions). Results were rated according to a continuous performance test
T.O.V.A. (Test of Variables of Attention) and a standardized behavioral rating scale for ADHD symptoms BASC (Behavior Assessment System for Children) and indicated significant improvement on both. There was no considerable difference between the percentage of patients who showed significant improvement with EEG training (83%) and stimulant medication (87%). In a similar study [32] 51 patients (aged 6-19) received Protocol 3 training and were compared to a population of 49 patients in a Ritalin treatment. One session (45 to 50min) per week was taken until certain QEEG activation was achieved. The average number of sessions was 43 and all patients concluded theirs. Post treatment evaluation was conducted one year after the initial evaluation in two ways: patients continued to take stimulant medication; patients stopped taking medication for a week and were evaluated after. Both groups showed significant improvement while testing was done in the first condition but only the QEEG-training group maintained these improvements when medication was dropped for a week.

The more recent controlled-study reviewed by Monastra also compared the effects of EEG training with ADHD stimulant medication (Ritalin) [33]. 12 children took Ritalin and other 22 trained their QEEG with Protocol 2 three times per week (30-60 min duration) for 12 weeks. Like previous studies, the attentional, behavioral and intelligence improvements with the EEG training were comparable with those achieved by the administration of Ritalin.

The effects of virtual reality environments in the attentional process of children with ADHD were also studied [33]. Five groups of 10 patients were examined. The patients were children from 14 to 18 years old who were in a reformatory for bad behavior. 30% of them estimated to have ADHD. One group trained the EEG frequencies from 15-18Hz over Cz with the help of the VR environment in a computer screen. Every time the training was going in the desired direction a certain animation was produced. Other group executed the regular tests of attention in the virtual reality environment. The other three groups were control. One of them was waiting list ant the others were receiving false VR trainings. There were 8 sessions of 20 minutes for two weeks and in the end the results showed similar improvements in both groups in the VR training and no improvement in the control groups.

There are also proofs that QEEG training besides improving attention is also responsible for the activation of certain cortical areas in patients with ADHD responsible for attentional tasks that aren’t activated by these kinds of patients [34]. In this controlled-group study, 15 children from 8 to 12 years old performed the EEG training while 5 other were part of the control group. Each training session consisted lasted for 60 minutes and consisted with several trials which went from 2 to 10 minutes. A total of 40 sessions were completed in two phases of 20 sessions each. The EEG was recorded at Cz and the frequencies to enhance were 12-15 and 15-18Hz while 4-7Hz and 22 to 33Hz were suppressed. During each trial, while trying to change their cortical activity, patients were told to relax, solve mathematical problems or read. The experimental group showed improvements while the control group didn’t in the Digit Span subtest of the Wechsler Intelligence Scale for Children-Revised, in the Integrated Visual and Auditory Continuous Performance Test, in Conners Parent Rating Scale-Revised. Significant Statistical improvements were also seen in the counting stroop task only in the experimental group. After the training only the control group showed activation (that wasn’t present
before the training) in the ACcd zone by BOLD fMRI. This area is involved in selective attention, the selection of an appropriate response, and the suppression of inappropriate responses which are useful in the Counting Stroop Task. Also, this area wasn't activated by the patients with ADHD in this study before the training.

Besides these training protocols which consist in enhancing or suppressing certain frequencies amplitudes there also exist another protocol with proven results based on the self regulation of the SPC (Slow Cortical Potentials). The patient learns how to control negative or positive potential shifts in the cortical activity aided with a display showing the current electric potential. Then the patient has to change it according to what is asked. The protocol has two main parts: the training trials and the transfer trials. In the first, the potential and its shift (correct or incorrect) are feed back to the patient in a form of animation or sound so that he knows how he’s performing. In the second, only the examiner knows the outcome and still, the patient has to try and produce the shifts that are asked. In the five studies analyzed the recordings were done above Cz in a total of 93 patients. Most of the patients who learned to produce positive and negative shifts experienced, at least, behavioral improvements. Four of the five studies had their results compared against control groups.

3.1.3 Mild Head Injury

Most cases of Mild Head Injury cannot be diagnosed with CT scan, MRI or raw EEG because there was no hemorrhage or brain edema. However, QEEG analysis with help with normative databases can detect the abnormalities caused by the injury. Patients with this condition experience unpleasant and limitative symptoms like poor short-term memory, attentional, concentration or vision difficulties among others. The first studies of EEG biofeedback on patients with this condition date from 1983. Random patients were assigned for the feedback sessions while the others stayed on psychotherapy [35]. Patients on the feedback sessions had their symptoms eliminated. The same didn’t happen for the psychotherapy population. More recent studies were performed by walker with QEEG and coherence guided neurofeedback where 88% of patients reported an average improvement in their symptoms of 73% [36].

EEG biofeedback has also been used to treat disorders like obsessive compulsive disorder, autism, depression and alcoholism. Subjects who had suffered from alcoholism for over 20 years experienced significant decrease in self-accessed depression after EEG feedback treatment. After 2 years 80% remained abstinent compared to the rehospitalization of 100% of subjects in the control group [37]. The treatment protocol included alpha band power increase and theta band power decrease. Executive control was also improved in children with autistic spectrum disorder with the help of EEG feedback [38]. Protocols were based on beta or SMR band power increase with theta band power decrease. Application of EEG feedback treatment for obsessive compulsive disorder is only documented by D. Corydon Hammond in a limited number of patients. Irregular activity is corrected with a QEEG guided neurofeedback protocol although treatment duration can depend on the level of deregulation. After normalization, symptoms have drastically decreased as did scores in two
diagnostic scales. Results have proven better than known placebos or medication without side effects or complications [39;40]. Unfortunately, there was no control population and the number of subjects submitted to the treatment was too small.

### 3.2 Cognitive self-improvement

EEG biofeedback is also applied to healthy subjects with the objective of studying how it improves certain cognitive capabilities that have been proved previously to produce changes in the QEEG. For example, Klimesch and associates have studied intensively the effects of short term memory (STM) and long term memory (LTM) access on the synchronization or desynchronization of certain frequency bands [13;41-43]. Synchronization in a frequency band means that there is an increase of activity with that frequency in the EEG during that period while desynchronization means the opposite. Also, tonic synchronization means an increase in some activity over time while phasic synchronization means an event-related and temporary increase in activity. It has been observed that phasic synchronization in the alpha frequency band is related to cognitive idleness or cortical inhibition [44]. On the other hand, phasic theta synchronization responds to STM tasks and it’s closely related to long term potentiation while upper alpha desynchronization to LTM tasks [41;42;45;46]. Other study by the same author found evidences that when STM demand is maximal, there’s synchronization in the upper alpha band, suggesting active inhibition of LTM access in order to “allocate” more resources for STM [43]. Recent findings show that in a task where the data retained in STM requires manipulation there’s a stronger synchronization in the alpha band at prefrontal areas and its frequency values equal those at occipital sites (in a simple STM task occipital alpha is faster than prefrontal alpha) [47]. These two findings are interpreted by the authors as an increase in functional coupling between prefrontal areas – prefrontal alpha synchronization – and control of the execution of processes in primary visual brain regions – occipital and prefrontal alpha coherence.

Because of the large interindividual differences in the alpha frequency band, W. Klimesch suggests that personalization of the alpha and theta band is the only way to observe and interpret any findings that involve these oscillations [48]. Therefore, the peak alpha frequency (PAF) is used as an anchor point for defining the individual bands. The PAF is the value of the predominant alpha oscillation which in the EEG spectrum is the peak value present in the alpha band [48]. With these individualized frequency bands Klimesch was able to further correlate cognitive processes with changes in certain frequency bands: PAF increases from childhood to adulthood but then decreases with age or neurological problems. PAF is an indicator of memory performance and speed of information processing (positively correlated) between age matched subjects.

The same thing happens with theta and alpha band power as the first decreases and the second increases from childhood to adulthood but then the process reverts as aging progresses. Attention demands and expectancy are reflected by a phasic desynchronization in the lower alpha band. Semantic memory tasks produce phasic desynchronization in the upper alpha band proportional to the difficulty of the task. The amount of desynchronization is also positively related to the success on those tasks. As for theta band, it was observed that when memorizing a series of words for later recall,
subjects showed more phasic theta synchronization in words that were recalled successfully. This suggested a positive relation between phasic theta synchronization and episodic memory encoding. Moreover, the amount of synchronization or desynchronization in a certain frequency band depends on that band absolute amplitude. It seems that higher amplitude values in the alpha frequency band allow for higher amounts of desynchronization and lower amplitude values in the theta band allow for higher levels of synchronization. So, higher values of alpha amplitude and low values of theta are positively related to good cognitive performance because, higher amounts of phasic desynchronization and synchronization are possible, in the alpha and theta band respectively. These associations are the basic rationale for the use of EEG feedback to improve certain cognitive processes.

3.2.1 Theta suppression

Theta suppression and stimulation feedback was used in 1974 two groups of subjects while performing a simulated radar monitoring task [49]. As unpractical as this experience may seem, curiously, subjects who were having feedback for the suppression of theta band power performed significantly better on the monitoring task and subjects with theta stimulation performed significantly worse, compared to their performance without any feedback which was similar in both groups. The theta band power measure was relative to the band power in frequencies from 3 to 30 Hz and it seems possible to some authors that relative theta decrease might not be due to an increase in its absolute value but to an increase in other frequency band, possibly alpha, between 3 and 30 Hz [50].

3.2.2 Alpha enhancement

Enhancement of alpha activity in the fixed frequency band (8.5-12.5 Hz) was also experimented in a small group of 13 participants to test its effects on STM [51]. The experience consisted in four sessions of one hour each. Testing for STM included a verbal free recall task and a digit span task while simultaneously asking subjects to produce alpha. Although a significant increase in the percentage of alpha activity was achieved by the end of the four sessions, no improvements were registered in the STM tests. Vernon states this failure can result from the use of a fixed frequency band instead of individual bands based on the PAF studied by Klimesch [50].

3.2.3 PAF value increase

Attempts to increase the PAF with the objective of cognitive improvement in a controlled study showed promising results [52]. A group of 6 elderly subjects was randomly divided into an experimental and control group and went on 35 sessions of feedback on the PAF. The protocol consisted in increasing this peak frequency while maintaining the alpha band power unchangeable. By the end of the 35 sessions the 3 experimental subjects PAF had increased about 0.8 Hz and had improved cognitive processing speed, some attention demands and word memory compared to the controls.

3.2.4 Alpha/Theta ratio

Sometimes, instead of stimulating the increase of relative alpha - the ratio between alpha frequency band and other large band like 0.5 to 30 Hz – the ratio between alpha and theta is used. In these case, this value increases whether if alpha increase or if theta decreases, not if both increase. In a
study Doppelmayr, Klimesch and associates this training was applied to test for cognitive improvements [53]. Here, test subjects were initially classified as responders or non-responders according to their ability to change their EEG. This way, in the final statistics, results were separated in these two groups thus removing the negative influence that non-responders sometimes introduce and to compare cognitive improvements in subjects that are able to modify their EEG. The frequency bands used for the ratio were individual theta and individual upper alpha and a mental rotation task was used to determine cognitive performance. Results showed a significant tendency for responders to have higher scores on the mental rotation task after the feedback training. In the non-responder group both improvements and regressions were observed in the rotation score after the training.

Beta training has also been used on healthy subjects, besides being used on the previously discussed cases of mental disorders, with the same objective of attention improvement. In a controlled study, Egner and Gruzelier tried the enhancement of SMR and beta1 separately [54]. SMR group showed less omission errors on an attention task while beta1 showed faster reaction times and an increase on the P300 (an event related potential due to decision making processes) amplitude.

3.3 Art, music and sports

A common field of study is the relation between certain EEG aspects in professional musicians, artist and athletes. For example: attempts to predict a pianist’s proficiency with certain EEG patterns (8.5-10.5 Hz activity on the sensorimotor cortex); increasing response time in athletes and non-athletes by previous visual stimulus of 10 Hz flicker [55]; alpha phasic synchronism during aiming period before shooting by expert marksmen or before putting in golfers is positively correlated with the shot accuracy [56-58]; HRV and alpha/theta biofeedback improving dancers capabilities [59]. These findings also suggest and reinforce the application of EEG feedback to study possible improvements.

3.4 Brain computer interfaces and neurofeedback applications

3.4.1 Brain Computer Interfaces

Brain-computer interfaces are systems that acquire and analyze brain signals in real time to provide an interface between the human brain and a computer. Brain activity expressed as electric or magnetically is recorded in real time in form of a signal to be processed by computer algorithms that will later be traduced in some action. Subjects suffering with neurological diseases that result in motor disability that lose their capabilities of communication and expressing justify these interfaces as it might be their only way of communicating. EEG based BCIs can track several different features of the EEG but the most used are slow cortical potentials (SCP) sensorimotor rhythm (SMR) and event related potentials like the P300 [60]. These applications are limited to binary choices as they’re based in high or low values of a specific frequency band or signal amplitude. SCP control has been proven to be possible by human subjects in several BCI [61] and neurofeedback studies [62]. A cursors vertical position can be determined by this potentials amplitude after it is calibrated to the users’ SCP amplitude range [63]. SMR rhythms are usually recorded over the sensorimotor cortex and its amplitude is related to sensory input, movement or motor imagery. Its control by human subjects is
also proved to be possible and the cursors movement vertical position is also dictated by the bands amplitude. Left to right movement with a constant rate can be introduced to give access to the extra dimension [60]. P300 is usually evoked 300ms after an infrequent stimulus over the parietal cortex [60]. The selection of a character, for example, can be done using a 6x6 matrix filled with characters. The rows and columns of this matrix flash with a certain constant rate and the user is instructed to count the number of times the flashing row and column crossing point coincides with the desired character. When this happens, because of the attentional demand similar to an oddball test, a P300 is evoked. At every flash, the EEG is recorded and associated with one character. After a certain amount of flashes, each EEG segment is averaged. The averaged signal with the highest amplitude is probably the one where more P300 were evoked leading to the conclusion that its corresponding character is the one desired by the user [60]. MEG scanning BCIs are also implemented with the same specifications for SMR activity with very good user accuracy after only 30 minutes of training [64]. However, in all strategies the maximum communication bit rate is low.

3.4.2 Neurofeedback systems

Every biofeedback treatment and training relies on hardware and software support starting in the signal acquisition to the feedback display and passing through analog to digital conversion, signal processing, decision making, database filling, animation rendering and user interface. Besides research confined applications, varied range EEG biofeedback solutions exist on the market for research, therapeutic and personal use. E. Tarasov presents a good example of a software system for EEG biofeedback [65]. The program provides adjustable variables for each training session with graphical interface, stores the patients records separately from the training records, exports training results to Microsoft Excel, allows integration of different libraries and applications developed by any user, provides a view of every recorded channel to the clinician an allows modification of the feedback display parameters. The software also allows feedback to be provided by visual animations, films and game scenarios.

Usually, EEG biofeedback systems depend on several levels of hardware and software. In another EEG biofeedback system developed recently [66] the EEG is collected at the scalp and is pre-processed in a device connected through an USB port to a computer. The EEG signals are sampled, digitalized and passed to the computer through an USB protocol. The received signal is used to estimate its frequency with FFT algorithms and each frequency bin power is calculated. The signal is also filtered into the typical frequency bands and the parameters for the feedback control are calculated. The feedback is given in a virtual reality game scenario with three spaceships traveling through space where one of them is controlled by the chosen parameter. If the parameter value reaches the defined threshold the spaceship speeds up. The authors of this study emphasize the importance given to virtual reality environments due to the level of immersion that it can provide. In fact, this kind of environments had similar relevance in other studies and seems to be a trend in recent neurofeedback applications.
Besides the traditional EEG parameters consisting in frequency band power or amplitude used in EEG biofeedback applications, other parameters that try to evaluate chaotic behavior of the EEG have also been used. Test subjects showed the ability to gain control of their EEG fractal and correlation dimension indicators and Lyapunov exponent the same way as in other experiences with frequency band power [67].
Chapter 4

Methods of analysis

In this work, each signal processing tool and application was developed as a library or plug-in to work with existing software named Somnium. Details about this software and the relevant classes can be seen in Appendix A.

When the signal arrives at the application level, it's in its raw form. Except for amplification, no filtering or component separation was done so, it’s necessary to extract each frequency band or characteristic from the raw EEG. This separation can be done by filtering the signal with Fast Fourier Transform algorithms, FIR or IIR filters, wavelets, Matching pursuit algorithms [68] or empirical mode decomposition with instantaneous frequency [69].

Most of the applications that involve the EEG signal processing depend highly on its frequency domain representation. EEG biofeedback relies heavily on the analysis of specific frequency bands and most of the relationships between cognitive and clinical aspects couldn’t be done without the help of the quantitative analysis of the EEG. In this work this wasn’t an exception so, the necessary tools for signal processing had to be developed.

4.1 Discrete Fourier Transform

The Fourier transform can be used to transform a signal from time to frequency domain. When having a finite-duration discrete-time signal it’s possible to generate its corresponding periodic discrete-time signal that will have a discrete Fourier Transform (DFT) in form of a spectrum with discrete frequencies or spectral lines. Each spectral line is regarded as the k-th harmonic of the basic period in the signal and it’s expressed in Hz by the relationship in Equation 1.

\[ f_{\text{freq}(Hz)} = k \left( \frac{\text{sampleRate}}{N} \right) \]  

(1)
Where \( k \) is the \( k\)-th spectral line, \( \text{sampleRate} \) is the time series sample rate and \( N \) the total number of samples in \( T \) seconds. The frequency resolution is the width of a spectral line and can be given by the Raleigh frequency in Equation 2 [70]:

\[
\Delta f = \frac{\text{sampleRate}}{N} = \frac{1}{T}
\]  \hspace{1cm} (2)

The periodic signal is formed by basic functions generated from Equation 3 and Equation 4:

\[
c_k(i) = \cos \left( \frac{2\pi ki}{N} \right)
\]  \hspace{1cm} (3)

\[
s_k(i) = \sin \left( \frac{2\pi ki}{N} \right)
\]  \hspace{1cm} (4)

The first equation represents the sinusoids held in the real part of the frequency domain while the second represents the sinusoids held in the imaginary part. The amplitude from each \( k\)-th harmonic of the spectrum is associated to the proper sine or cosine wave resulting in a set of scaled sinusoids that added, form the periodic time-domain signal. Both real and imaginary parts of the spectrum are \( N/2 + 1 \) long where the first spectral line \((k = 0)\) gives the amplitude of the dc component and the next gives the amplitude of the amplitude for the oscillation of one cycle in \( N \) data points. The algebraic form of the DFT of a periodic signal \( x(n) \) is given by Equation 5:

\[
X(k) = \sum_{n=0}^{N-1} x(n)e^{-j\frac{2\pi kn}{N}}
\]  \hspace{1cm} (5)

The equations for calculating the real and imaginary part of the frequency domain are by Equation 6 and 7 respectively:

\[
ReX(f) = \sum_{n=0}^{N-1} x(n)\cos \left( \frac{2\pi kn}{N} \right)
\]  \hspace{1cm} (6)

\[
ImX(f) = -\sum_{n=0}^{N-1} x(n)\sin \left( \frac{2\pi kn}{N} \right)
\]  \hspace{1cm} (7)

One problem in this method is that the Fourier Transform assumes that the signal is periodic and will repeat itself forever. If a truncated signal is processed it will be seen as an infinite signal by periodic continuation – the signal repeats after the last sample. When the measured signal has a finite length, even if it is periodic, if the truncation doesn’t produce an integer number of cycles the transform will detect a discontinuity between the beginning and the end of the signal, that really doesn’t exist. Because sharp discontinuities require a wide range of sinusoids to be represented they have broad frequency spectra, causing additional energy to leak into other frequencies – spectral leakage. This
wouldn’t happen if the transformed signal was a sine wave sampled for an exact number of cycles: the signal would match when repeated and no discontinuities would be detected. If the signal falls smoothly to zero on its edges of the measurement interval, it won’t present discontinuities when made repetitive and so, spectral leakage is reduced. This is the main idea for the use of widow functions.

4.2 Window functions

Window functions are continuous-time functions that can be applied discrete-time samples in order to produce a continuous signal when the sample is subjected to periodic continuation. A window function needs to be zero-valued outside a chosen interval but, to ensure that the signal sample will produce minimal spectral leakage it needs to taper the sample. Therefore, a windowed signal is multiplied by a window defined with the same length as the signal. The spectrum of a window function is constituted by one main lobe and several side lobes. The frequency resolution of a windowed signal inversely related to the width of the main lobe width is defined as the bandwidth between the first negative and the first positive zero crossings in the windows spectrum. Interference of other frequency components also depends on window characteristics. To reduce interfering signals near the frequencies of interest a window with a low highest side lobe level is preferred. If the interference is far from the frequencies of interest a window with a high slope in the side lobes (side lobe fall-off) is preferred. Hamming and Hann window have a good tradeoff between frequency resolution and offer reduced spectral leakage. The Hamming window function is given by Equation 8 as:

$$w(n) = 0.54 - 0.46 \cos \left( \frac{2\pi n}{N - 1} \right)$$  \hspace{1cm} (8)

And the Hann window function:

$$w(n) = 0.5 - 0.5 \cos \left( \frac{2\pi n}{N - 1} \right)$$  \hspace{1cm} (9)

Other window functions exist like the Kaiser or Blackman windows but in this work, windowing is done with the Hamming window.

4.3 Fast Fourier Transform

The computational implementation of the DFT is most of the times done using the Fast Fourier Transform (FFT) algorithm, proposed in 1965 by James Cooley and John Tukey [71]. Without entering in details, and because the algorithm is present in the Somnium library, this algorithm takes advantage of forcing the signal length to be a power of two to break down a DFT into smaller length DFTs, most time to half the original size. It computes a DFT significantly faster, having a maximum of $O(N \log N)$ while, by its definition, the DFT would require $O(N^2)$ operations.

4.4 Welch method

The Welch’s method is used for estimating the spectrum by sectioning the signal with some overlapping points, using the FFT for each section and average all the resulting spectrum [72]. In a
non deterministic time series, the Fourier transform is an inconsistent estimator of the spectrum because, although frequency resolution increases with the number of samples, the variance of the estimation doesn’t alter. By shortening the length of the sample that is processed by the FFT algorithm this method sacrifices spectral resolution but, averaging segments guarantee a reduction in the noise of the estimated spectrum. If the segments contain overlapping values, the loss of information inherent to the windowing process is reduced. The computation time is also reduced. The steps for this method are the following:

1. The signal, of length $N$, is separated into $K$ possibly overlapping segments of length $L$ with the starting point of these segments $D$ points apart. The relationship between these points is:

   $N = (K - 1)D + L$ \hspace{1cm} (10)

   If there’s no overlap between the segments $D = L$ and the signal is divided into $K$ segments where:

   $N = KL$ \hspace{1cm} (11)

2. Each one of the $K$ segments is windowed and zero added until their length is a power of two.
3. Each new segment has its spectrum is estimated by the FFT.
4. The $K$ spectrums are averaged.

### 4.5 Event-related changes

Event-related changes are calculated as the percentage of a change in band power or amplitude during a certain interval, compared to a reference measure [Important implications for the calculation]. If the changes are measured as increases in band power this measure is named as event-related synchronization (ERS). The symmetric measures are event-related desynchronization (ERD) and, symmetrically to ERS, they measure the percentage in band power or amplitude decrease. These can be calculated as:

\[ ERS\% = \frac{BandPowerInterval[freqBand] - BandPowerReference[freqBand]}{BandPowerReference[freqBand]} \times 100 \] \hspace{1cm} (12)

\[ ERD\% = \frac{BandPowerReference[freqBand] - BandPowerInterval[freqBand]}{BandPowerReference[freqBand]} \times 100 \] \hspace{1cm} (13)

Where $BandPowerReference[freqBand]$ is the band power in a reference region and $BandPowerInterval[freqBand]$ is the band power in a selected interval.
4.5.1 Implementation

The developed application for the calculation of ERD and ERS allows the selection of one or more reference regions for the calculation of the reference band power. It’s also possible to select more than one interval for the measure of the event-related changes. After selecting the signal, reference regions and the interval the calculation is done in the steps illustrated in Figure 12.

![Diagram of calculation process](image)

**Figure 8 - Process of calculation the event related change parameter in one interval**

The event-related changes calculation follows two parameters. One is the length \( L \), in seconds, of the window that analyses the interval for spectrum estimation and the other is the sliding step for this window. The sliding step is how many points the window jumps between measures. If \( L = 2 \text{ seconds} \) and the iterative step is one point the application will calculate the spectrum for each point taking into consideration the previous two seconds for each point. This allows the analysis to be more flexible because it makes possible to define the ERS for a single location, with a constant value, or to have a sliding window of ERS, similarly to what’s done in a spectrogram\(^1\). Figure 13 shows this last possibility (spectrogram alike ERS) for a filtered portion of the EEG between 9 and 13 Hz and the respective ERS in this frequency band.

\(^1\) A spectrogram is a three-dimensional function of time, frequency and amplitude or power.
4.6 Multitaper method

The previously discussed Welch method offers a way to mitigate the problem of spectral leakage, due to finite data length, by multiplying these data by a windowing function (or taper) that apodizes the data segment at its extremities. The final estimation of the spectrum is the average of the spectrums of overlapping segments of the time series. This overlapping compensates the lack of information at the apodized extremities and the averaging offers a way to reduce the variance of the estimation, smoothing the spectrum. Still, the segmentation of the time series into shorter segments leads to a decrease in the frequency resolution of the final estimation.

The objective of the multitaper method is to provide the same benefits as the previous method but without losing resolution, making it a valuable tool for calculating the spectrogram. It consists on the average of several spectral estimates of the same time series with a set of orthogonal tapers [73]. In its simplest way, the multitaper spectral estimate is [70]:

\[
S_{MT}(f) = \frac{1}{K} \sum_{k=1}^{K} |\tilde{x}_k(f)|^2
\]  

(14)

Where \( K \) is the number of orthogonal tapers used and \( \tilde{x}_k(f) \) is the estimated spectrum using each different taper by the Fourier Transform. Instead of a simple average, sometimes a weighted average is done with a different weight for each taper. The tapering functions chosen for this method are the Discrete Prolate Spheroidal Sequences (DPSS) because of their optimal spectral concentration characteristics, having their energy concentrated in a bandwidth \( W \) [70;74]. For a bandwidth \( W \) and
sequence length of $N$ there are $K = 2NW$ sequences with energy effectively concentrated between $[-W, W]$. Having $X(f)$ as the Fourier transform of a sequence of length $N$ the sequences of interest are the ones where $X(f)$ is maximally concentrated in the interval $[-W, W]$. The DPSS $v_n^{(k)}$ are normalized eigenvectors of the symmetric matrix eigenvalue equation and represent the solution to this problem [74]:

$$
\sum_{m=0}^{N-1} \frac{\sin 2\pi W(n-m)}{\pi(n-m)} v_m^{(k)} = \lambda_k v_n^{(k)} \quad \text{for } n, k = 0, 1, ..., N-1
$$

(15)

where $\lambda_k$ is one of the $N$ eigenvalues. These, are limited between zero and one with the first $K$ of them being very close to one and the rest very close to zero. These eigenvalues are the result of Equation 16.

$$
\lambda_k(N, W) = \frac{\int_{-W}^{W} |X(f)|^2 \, df}{\int_{-W}^{W} |X(f)|^2 \, df}
$$

(16)

It’s understandable that the ones closest to one are those whose eigenvectors maximize the energy concentration. The eigenvectors of the symmetric matrix corresponding to the largest $K$ eigenvalues are the optimal windows. Because the eigenvalues of interest are very close to each other their computation might be problematic. This computation would rely on the power method which takes an initial guess for the eigenvector and iterates until it converges to the true eigenvector with maximum eigenvalue. If there is not a single highest eigenvalue the method might not converge and its convergence speed increases with the distance between the highest eigenvalues. To solve this problem, an alternative formulation was proposed [75]. This solution uses a difference equation which the DPSS satisfy during their finite interval. Since the equation is defined for the $N$ eigenvectors it can be written as a $N \times N$ system of equations and in the form of an eigenvalue equation:

$$
|\mathbf{A} - \lambda I| \mathbf{v} = 0
$$

(17)

Where the elements in the matrix $\mathbf{A}$ are defined as:

$$
a_{ij} = \begin{cases} 
\frac{1}{2} i(N-i), & j = i-1 \\
\left(\frac{N-1}{2} - i\right)^2 \cos 2\pi W, & j = i \\
\frac{1}{2} (i+1)(N-1-i), & j = i+1 \\
0, & |j-i| > 1
\end{cases} \quad \text{for } i, j = 0, 1, ..., N-1
$$

(18)

Matrix $\mathbf{A}$ has its eigenvectors with the same normalization as the matrix given by Equation 15 and are the new DPSS. Although the eigenvectors are similar, the eigenvalues are completely different, as the new do not correspond to the energy ratio represented before and are well spread. Again, the optimal windows are still the eigenvectors that correspond to the highest eigenvalues.
The parameters for the window length $N$ and frequency interval with maximum energy concentration $W$ are the two degrees of freedom possible in this method. The choice of the bandwidth parameter will affect the smoothing of the spectral estimate affecting the reduction of the estimate variance. The value for the parameter can be based on the amount of smoothing required and it is related with how wide the smoothing will be in terms of how many spectral lines it will influence:

$$2TW = 2W/\left(\frac{1}{T}\right)$$  \hspace{1cm} (19)

Previous applications of this method chose to fix the time bandwidth product $TW$ at a small number (3 or 4) and then varying the window length until sufficient spectral resolution is achieved [70]. Empirically derived formulas for the relation of these two parameters with more typical characteristics of the windowing technique like main lobe with (cycles per sample) and highest sidelobe level (dB) are also available [75]. In the relations equations, extracted from [75] the highest sidelobe level and the main lobe with are represented by $\alpha$ and $\beta$ respectively.

$$N\beta = -0.07401\alpha + 1.007$$  \hspace{1cm} (20) \hspace{1cm} for $\alpha \leq -13 \text{ dB and } 0 \leq \beta \leq 1 \text{ (cycles per sample)}$$

$$W = \begin{cases} 
-4.47 \times 10^{-3}\alpha^2 - 2.44 \times 10^{-1}\alpha - 2.25, & -13 \leq \alpha \leq -23 \\
-4.44 \times 10^{-2}\alpha + 1.04 \times 10^{-2}, & -23 \leq \alpha \leq -49 \\
-3.81 \times 10^{-2}\alpha + 3.16 \times 10^{-1}, & -49 \geq \alpha
\end{cases}$$  \hspace{1cm} (21)

The calculation of the higher eigenvalues is done with the help of the power method as it was previously said. The necessity of using this method comes from the fact that the matrix in question is, most probably, large enough so that calculating the roots of equation X is impracticable. The power method provides an iterative way of computing one of the eigenvalues $\lambda$, that is usually the highest, and its corresponding eigenvector $v$. To start the iteration process, an initial guess $x_k$ for the eigenvector must be provided, where $k$ represents the number of iterations (in first guess $k=0$). It must be an array of numbers with the same length as the desired window width where the maximum value is 1. As $k$ increases, $x_k$ will hopefully start converging to the dominant eigenvector. Knowing on which matrix the process is going to occur, like in this case, is beneficial because there is some knowledge about the dominant eigenvector and, the initial guess can be adjusted to reduce iterations.

The iterative process is as follows:

1. Choice of the initial guess $x_0$.
2. $k = 1$
3. While the absolute difference between the estimated eigenvalues $\delta_k$ and $\delta_{k-1}$ is bigger than a certain tolerance value and the number of iterations is less than a specified maximum:
   - $y_k = \Lambda x_{k-1}$
   - $\delta_k$ = element with largest absolute value in $y_k$
   - $x_k = y_k / \delta_k$
   - absolute difference between $\delta_k$ and $\delta_{k-1}$ compared to tolerance.
   - $k$ is incremented.

4. $v_k = x_k$ and $\lambda_k = \delta_k$

Resulting in the highest eigenvalue $\lambda_1$ and its corresponding eigenvector $v_1$ which is the first DPSS. To find the next eigenvalue and vector the previously calculated eigenvalue must be removed. Spectral shift, Equation 22, could be used to accomplish this feat by subtracting matrix $\Lambda$ by an identity matrix with the previous eigenvalue in its diagonal.

$$\Lambda - \lambda_1 I$$

Now, applying the power method again it would converge to the largest absolute value of $\lambda - \lambda_1$. However, in this case, the value to which the method would converge may not be the second largest eigenvalue. So, the deflation method is used as it only shifts one eigenvalue to zero at a time, not changing the others. This method only works for symmetric matrices and matrix $\Lambda$ is symmetric. The calculation done to remove eigenvalue $\lambda_1$ from matrix $\Lambda$ is given by Equation 23.

$$\Lambda_1 = \Lambda - \lambda_1 \frac{v_1 v_1^T}{v_1^T v_1}$$

Applying the power method to $\Lambda_1$ will give the second largest eigenvalue and respective eigenvector. The process can be repeated until the $i$-th eigenvector's calculated as it's described in Equation 24.

$$\Lambda_i = \Lambda_{i-1} - \lambda_i \frac{v_i v_i^T}{v_i^T v_i}$$

4.6.1 Implementation

The developed application was designed to work directly in Somnium in order to provide the DPSS tapers to any other application or plug-in developed in this platform. The bandwidth parameter $W$ can be calculated from highest sidelobe height or mainlobe width using Equations 20 and 21 and, with that value set, the number of tapers with maximum energy concentration is presented, based on $K = 2NW$. The tolerance value for the stoppage criteria for the iteration is also configurable. Because of the probable high number of iterations, the iterative method runs on a separate, dedicated thread provided by the forms BackgroundWorker. While the iteration process is running its progress is displayed in the progress bar as how close the difference between two consecutive estimated eigenvalues is from the tolerance value. The iteration process can also be aborted if necessary.
The calculation of the DPSS follows exactly the previously discussed steps. When the form is created, the number of samples in the real time region of the main application is acquired. This value is going to be the length of the tapers \( N \). To change this value, the real time region length needs to be changed before calling the multitaper form. After choosing the \( W \) parameter, number of tapers and tolerance value the iterative process is initialized. The matrix \( A \) is defined with the values from equation \( x \) along with the initial guess that was left as an array of zeros except in the first slot where it is valued as one. When the DPSS are calculated they’re stored in a collection of double precision arrays that can be serialized and saved into a binary file. It’s also possible to load a set of previously calculated tapers.

### 4.7 Empirical Mode Decomposition

Empirical mode decomposition (EMD) is an iterative algorithm that removes the highest frequency oscillation from the analyzed data in each iteration. After each repetition, a lower frequency information residue remains that is further decomposed until only a trend remains. The resulting components of this adaptative decomposition are the intrinsic mode functions (IMFs) and represent the intrinsic oscillations of the signal so, when summed up, they should result in the original signal. These IMFs are defined as functions with equal number of extrema and zero crossings (at most differed by one) with zero average between their upper and lower envelopes. As they represent a simple oscillatory mode they can be seen as the equivalent to a spectral line in the Fourier estimated spectrum with the difference that IMFs may be frequency-modulated. The EMD is a fully data-driven mechanism and doesn’t require previous knowledge about the signal, contrary to filtering. It was developed by Norden Huang [76] for the analysis of nonlinear, nonstationary geophysical time series, which might have been the motivation for the data-driven character of this method, and has spread to different applications from biomedical to financial fields [77]. Despite the stated good results of this relatively new signal analysis tool, it is completely empirical and non-linear method without any mathematical basis until now [77]. Because of the IMFs restrictions (same number of zero crossings...
as extrema at most differed by one) these will have well behaved Hilbert transforms which will allow the calculation of the signals instantaneous frequencies in a time frequency distribution. Because the EEG is a non-stationary signal, with its frequency content quickly changing across time, the spectrogram calculated with the instantaneous frequencies tends to be more satisfying than the classical spectral analysis like Fourier or wavelet transform providing, at least, providing more frequency resolution [69;78]. The application of this method for the EEG data analysis is also promising as it allows the detection, and separation of a wide variety of EEG recording artifacts as power line and EMG interference while preserving important characteristics of the original signal [79]. Nevertheless, some limitations have been reported with this method. Patrick Flandrin and associates have applied the EMD to a specific type of noise and observed that it behaves like a dyadic filter [80]. However, as denoted by Sweeney-Reed, this can be due to the nature of the data applied and even if not, EMD would not suffer from certain limitations of band pass filtering like spurious harmonics or negative frequencies [81]. Other limitation demonstrated by Liang and associates is that EMD fails to decompose correctly a signal composed of two intersecting chirps\(^2\) [78]. Again, this poses no threat to the actual paradigm of EEG aided cognitive analysis that focuses on particular frequency ranges and its relates with cognition aspects [77].

![Figure 11 - Three consecutive sifting processes. The signal in blue represents the resulting IMF. The mean envelope is represented in red and it’s possible to see it lose its riding waves.](image)

### 4.7.1 Algorithm

The description of the EMD algorithm can be found in several articles and, due to its simplicity, it’s consistent among them. The algorithm is illustrated in Figure 16 and is as follows [79]:

The first step is taking the time series \(x(n)\) and, identifying all its maxima and minima. Secondly, the identified maxima are connected by a cubic spline curve forming the upper envelope \(x_u(n)\). The same process is repeated for all the identified minima originating the lower envelope \(x_l(n)\). The mean between these envelopes is then calculated as a new series \(m_1(n)\) where each point is valued after:

\[
m_1(n) = \frac{x_u(n) - x_l(n)}{2}
\]

This mean is subtracted from the original series resulting in the first attempt of an IMF:

\(^2\) A chirp is a signal with increasing or decreasing frequency in time
The above procedures constitute the sifting process which is used to remove riding waves from the series. Until an IMF is extracted, \( h_1(n) \) will have to undergo the sifting process, illustrated in Figure 15, again and again until certain stoppage criterion is met. So, now the new IMF approximation will be calculated by:

\[
h_{11}(n) = h_1 - m_{11}(n)
\]  

(27)

Where \( m_{11}(n) \) is the series with the mean values of the upper and lower envelopes of \( h_1(n) \). This process is repeated \( k \) times until the stopping criteria is met leading to:

\[
h_{ik}(n) = h_{i(k-1)} - m_{ik}(n)
\]  

(28)

The sifting process ends and \( h_{ik}(n) \) is the first IMF denoted as \( c_i(n) = h_{ik}(n) \) supposedly contains the finest scale component of the signal. This oscillations are then separated from the rest of the data forming the residue:

\[
r_i(n) = x(n) - c_i(n)
\]  

(29)

Because the residue might contain more oscillations (lower than the ones extracted in the previous IMFs), it is treated as a new signal to which all the above procedures are repeated \( M \) times, until the \( M \)-th residual is seen as constant. By now, \( M \) IMFs have been extracted. The first and last IMFs extracted correspond to the fine and coarse scales of the signal respectively. When all the IMFs and the \( M \)-th residue are added, the signal should be reconstructed almost identically:

\[
x(n) = \sum_{i=1}^{N} c_i(n) + r_M(n)
\]  

(30)

The stoppage criterion for the sifting iterations serves two purposes: Most importantly, as a way to guarantee that the resulting IMF has a well behaved Hilbert transform and secondly to guarantee that the extracted IMF corresponds exactly to the highest oscillation component of the processed signal by eliminating riding waves in the approximation to the IMF. The first is to guarantee that the IMF has a well behaved Hilbert transform the mean of its envelope should be zero at all points and the number of zero-crossings and extrema must differ at most by one. The second is achieved when the approximations start to saturate which can be expressed as a very low difference between two consecutive sifting results:

\[
SD = \sum_{n=0}^{N} \frac{|h_{k-1}(n)-h_k(n)|^2}{h_{k-1}^2(n)}
\]  

(31)

To guarantee that the IMF has a well behaved Hilbert transform the mean of its envelope should be zero at all points and the number of zero-crossings and extrema must differ at most by one.
After all the IMFs are determined, the instantaneous frequency (IF) of each IMF at each time point can be calculated. For a given time series $x(t)$ this calculation uses its analytical signal $z(t)$ defined as [78]:

$$z(t) = x(t) + iH[x(t)] = a(t)e^{i\theta(t)}$$  \hspace{1cm} (32)

Where $a(t)$ and $\theta(t)$ are the instantaneous amplitude and phase, respectively, of the analytical signal and $H[x(t)]$ is a signal orthogonal to $x(t)$, its Hilbert transform. Now, the instantaneous frequency can be obtained by differentiating the instantaneous phase:

$$IF(t) = \frac{1}{2\pi} \frac{d\theta(t)}{dt}$$  \hspace{1cm} (33)

For a discrete signal the instantaneous frequency can be calculated by:

$$IF(n) = 1/(4\pi) [\theta(n + 1) - \theta(n - 1)]$$  \hspace{1cm} (34)
4.7.3 Implementation

The developed algorithm and the functions used are illustrated in Figure 16.

![Figure 12 - EMD algorithm process](image)

4.7.4 Alternative implementation

One indispensable process for the calculation of the IMFs is the calculation of the upper and lower envelopes. As suggested in the literature, the cubic spline can be used, and is widely used, for this end as it calculates a smooth curve that fits to all the extrema. However, this method offers some limitations as it can only fit a curve to a limited, yet large, number of points and sometimes, the mean line produce between the upper and lower envelopes does not cross the oscillations right at their center. This last limitation produces the undesired riding waves in the first attempt to extract an IMF justifying the use of sifting iterations. One of the bad behaviors of the spline interpolation is due to the finite number of extrema present. The interpolation behaves badly at the beginning and end of the data because suddenly, it doesn’t have more information about it, and the curve between the two points at each extremity might assume undesirable uncanny shapes. These errors might propagate to
the rest of the interpolation leading to a misadjusted envelope in some places. Still, this problem is reduced in the original implementation by mirroring the data at the extremities or just account for an extra number of points and then ignoring the interpolation at these places. However, this does not alter the fact that errors occur at these new extremities that will propagate to the desired part of the interpolation. Despite this limitation, even a cubic spline cannot create a perfect envelope and sometimes the curve draws unexplainable trajectories just to fit all the points.

Some authors have tried to address this problem by calculating of the upper and lower envelopes with different other than the cubic spline. In a study employing the EMD algorithm for the analysis of bi-dimensional data (images) the authors used order statistics and smoothing filters for the calculation of the upper and lower envelopes (bi-dimensional in this case) [82]. Besides significantly shorter computation time, the authors also claimed a more accurate estimation of the IMFs using these techniques. So, in this work, an attempt to reproduce these results with one dimensional data from EEG recordings was taken. The algorithm is similar to the regular EMD method differing in the calculation of the envelopes. So, only the extra and alternative processes will be explained.

The first step consists in determining the window length \( l \) for the order statistic and smoothing filters consisting on the distances between the maxima and the distances between minima. This step has four variants that will affect this length:

- \( l \) is the lowest of one of this values: the lowest distance between maxima; lowest distance between minima.
- \( l \) is the highest of one of this values: the lowest distance between maxima; lowest distance between minima.
- \( l \) is the lowest of one of this values: the lowest distance between maxima; highest distance between minima.
- \( l \) is the highest of one of this values: the highest distance between maxima; highest distance between minima.

After this value is determined, if its value is even it is iterated so it becomes the next odd value. The calculation of the envelopes with the order statistic filter is done with a moving window of length \( l \) starting from the beginning where \( n = 0 \) until the end where \( n = M \). The value for the position \( n \) of the upper envelope \( x_u(n) \) will be the maximum value in the signal \( x(n) \) within the range of the window centered in \( n \). The same happens to the lower envelope \( x_l(n) \) except the value is the minimum instead of the maximum within the window. Finally, each envelope is smoothed by a moving average filter with the same window \( l \).

In the next iterative step of the algorithm, after the first IMF has been extracted, a forcing condition may be imposed to the window size, so that it’s bigger by a certain factor than in the previous iteration so that the algorithm extracts higher oscillations. Unfortunately, all these forcing and choice of the filters window size seem to limitative for an algorithm that is data driven.
4.8 Event related potentials

The ERP waveform is a time series that plots scalp voltage over time and consists in signal-averaged epochs of the EEG that are time-locked to the onset of a stimulus or motor event [83]. It’s constituted by a multitude of components which can be influenced by different factors. Because of their small amplitude, ERPs are usually masked by other EEG oscillations implying, averaging of several recordings. When using conventional averaging, the amplitude of the signal will remain constant as more trials are averaged but the noise will decrease because it’s randomly distributed. If $R$ is the noise of a single measure and $N$ the number of measures, the value of the noise in the average result is equal to:

$$R_{avg} = \frac{1}{\sqrt{N}}R$$

(35)

This implies an increase in the signal to noise ratio with the square root of N. In the referred literature, the author defines $N$ to be at least 30 for the visualization of a P300 wave. This wave is characterized as a large positive, 300 ms shifted, ERP component that can be visible in specific attentional tasks with the oddball paradigm because they’re elicited by rare stimuli. These tasks consist in the presenting different visual or auditory stimuli, spaced by unequivocal timing, where only a certain type of them requires response [84]. This stimulus needs to be infrequent compared to others and should only be present in about 10% of the trials in order to produce an attentional component of the ERP.

The amplitude and latency characteristics of specific ERP components, defined as positive and negative deflections in the ERP waveform, are quantified as a function of the specific experimental condition. If the latency of an ERP component varies from trial to trial, the amplitude of the component in the averaged result will be reduced and its shape distorted. This latency induced jitter is likely to affect endogenous components more than exogenous ones. The endogenous components are those elicited by cognitive processes that are less time locked to an event onset and more dependent on the demands of the task. Attentional tasks are more time-locked to an event onset leading to exogenous components.
4.8.1 Implementation

What lead to the implementation of a simple ERP extraction tool in the main application was the fact that in some EEG biofeedback studies, focusing on the enhancement of attention by SMR training, a post-training increase in the P300 component amplitude was observed [85]. This post-training increase was accompanied by cognitive improvements in attention.

The process is divided in two separate applications: an attention test and a method to sum and average signal chunks tagged by an event. The attention test is a simple application that runs on a separate window showing predefined geometrical forms at a specified rate. The geometrical forms consist on a circle, an octagon and a square and the user is instructed to only respond to the circle image by cliquing on the left mouse button. Besides choosing the rate at which the objects are displayed, it’s also possible to define the percentage of time the sphere will appear and the total number of trials. As the trials proceed, the corresponding EEG is labeled according to what happened. The labels are explained in Table 1.

<table>
<thead>
<tr>
<th>Event</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Interval</td>
<td>Interval between trials</td>
</tr>
<tr>
<td>Hit</td>
<td>Click in a circle</td>
</tr>
<tr>
<td>Wrong</td>
<td>Click in other geometric object</td>
</tr>
<tr>
<td>Timeout</td>
<td>A circle was not clicked</td>
</tr>
<tr>
<td>Square</td>
<td>An object besides the circle was correctly ignored</td>
</tr>
</tbody>
</table>
Chapter 5

The EEG biofeedback platform

The EEG biofeedback platform is constituted by a series of plug-ins built for Somnium. The set of applications delivered by these plug-ins allow a complete EEG biofeedback session. This includes individual EEG characteristics, like the PAF, extraction, cognitive assessment tests, biofeedback presented in a virtual environment and data storing and reporting. Detailed examples of this platform can be seen in Appendix B.

5.1 PAF extraction application

The peak alpha frequency (PAF) reflects the dominant oscillation in the alpha band and it’s a necessary value to adjust this frequency band between individuals. After reviewing previous studies relating PAF with specific abilities, Angelakis proposes this peak frequency value to be an indicator of cognitive preparedness [86]. Two aspects of this frequency have been studied: its event related (phasic) changes and the correlations between its average value and certain cognitive functions. As for phasic changes, PAF has been observed to increase during an auditory working memory task compared to other control task [87] or by the consuming of caffeine or nicotine [88]. The average value of the PAF has been positively related with reading performance between children with the same age, with age and with speed and performance in a series of cognitive tasks. PAF value relates positively with emotional states like joy and anger and negatively with fear or sorrow, compared to baseline values [86].

The PAF can be used as an anchor point to define the individual alpha band. The lower transition frequency (TF1) and the upper transition frequency (TF2) bound the alpha band which is further divided into three sub-bands: lower-1 alpha; lower-2 alpha; upper alpha. Only defining an individual alpha band for each subject it is possible to observe that each of these sub-bands correlate to different cognitive processes [13].

5.1.1 Extraction

Activity in the alpha and theta band respond in different and opposite ways, when one synchronizes usually the other desynchronizes [13]. With increasing task demands, theta synchronizes while alpha
desynchronizes the same way alpha synchronizes and theta desynchronizes when closing the eyes. This way, by plotting the EEG spectrum of a recording with opened eyes against a recording with closed eyes it's possible to identify the boundaries, transition frequencies, of the individual alpha band as well as the PAF. Figure 17 represents the scoring of the recording states with opened eyes and closed eyes for about one minute each. After having both EEG recordings labeled, the application is called.

![Figure 13 - Labels in EEG recorded with opened eyes and closed eyes](image)

### 5.1.2 Settings Interface

Its interface is present in Figure 18. The first two combo boxes allow the user to select the region of the recording to add to the estimation of the spectrum. At least one region for each state must be added. After the channel is chosen, the lower and upper boundaries for the individual alpha band searching must be defined. Because the final amplitude spectrum is calculated by the Welch’s method [72], the signal is divided into several overlapped segments. The values of the overlap and length of the segments are also defined in this window.

![Figure 14 - Settings for the PAF application](image)
5.1.3 Operations Sequence

Calculating the amplitude spectrum corresponding to both eyes open and eyes closed states and the transition frequency where these spectrums plot crosses is done in the following steps:

1. Starting and finishing dates from the selected eyes open and eyes closed states are retrieved and stored in a separate list of dates for each state.
2. For each date present in each list, the signal is extracted, notch filtered to remove the 50Hz and low pass filtered below 30Hz.
3. The amplitude spectrum is calculated for each signal using the Welch method and accumulated in separate buffers for each state.
4. Each buffer is averaged according to the number of recordings from each state.
5. The relative amplitude is calculated for both amplitude spectrums corresponding to the eyes open and eyes closed states.
6. PAF is extracted finding the maximum value in the eyes closed spectrum by finding the maximum value between Lower alpha and Upper alpha boundaries.
7. The intersection points between both spectrums, above and below the PAF value are also calculated corresponding to the new individual alpha band boundaries.
8. Both spectrums and calculated points are displayed, Figure 19, for the user approval.
9. If approved, the following values are saved:
   - Individual alpha band
   - Individual alpha band relative amplitude
   - Lower-1 alpha
   - Lower-2 alpha
   - Upper alpha
   - PAF
5.2 Cognitive function evaluation tests

5.2.1 Working memory

Working memory improvement is usually one of the results expected in EEG biofeedback experiments and one of the tests used to measure this type of memory is the digit span which is widely used in the IQ tests - Wechsler Adult Intelligence Scale. The test consists in a series of trials showing random digits with a specified rate and after, asking for the subject to write them with the same or inverse order they were displayed. The digit span is the maximum number of digits a person can recall in the correct order. The amount of digits displayed in each trial increases as the tests proceeds. Usually, the test starts with two digits, increasing until a certain number or until the subject misses. In the designed test, it's possible to choose with how many digits to start and to finish and in between trials, an increasing number of digits are shown. It's also possible to define the order the digits need to be remembered by the user: straightforward or inverse order. The amount of time the number is displayed and the time interval between trials can also be defined. If the subject inserts a wrong sequence of numbers, the test ignores the result and presents a new sequence of numbers with the same length but in a slower pace. If this happens, no more extra tries are given.

Implementation

The digit span application is called inside an *ActionBase execute()* method consisting on a Windows form where numbers are displayed, wrote down and where the parameters, described before, can be set up. It can run at the same time as the signal acquisition in order to label the signal with the
corresponding event that’s happening in the test. The application is rather trivial so it won’t be explained with detail. The form has a timer and inside its method the application decides the present trial, whether it shows a random digits or a blank image to appear in between and how many digits it has to show. When the session ends, the users score is calculated according to the digit span and to the ratio between numbers remembered in the correct order and total numbers showed. The score is then displayed and saved. Meanwhile, the signal had already been labeled. The events and their corresponding meaning are present in Table 2.

<table>
<thead>
<tr>
<th>Event</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Recalled</td>
<td>A remembered digit was displayed</td>
</tr>
<tr>
<td>NotRecalled</td>
<td>A not remembered digit was displayed</td>
</tr>
<tr>
<td>Recalling</td>
<td>The application asked for the sequence of numbers as they were displayed</td>
</tr>
<tr>
<td>Backwards</td>
<td>The application asked for the sequence of numbers in the inverse order</td>
</tr>
<tr>
<td>Waiting</td>
<td>Interval between trials</td>
</tr>
</tbody>
</table>

5.2.2 Rotation test

Other way of measuring cognitive performance is by testing the mental rotation skill [53]. In this test, two tridimensional objects are displayed side by side. The second can be the first object rotated in a certain axis or it can be a mirror image of the first object also rotated. This force the user to produce a mental image of the object and rotate it until it’s possible to determine if it’s the same as the reference image or not.

Implementation

The rotation test application is called inside an ActionBase execute() method consisting on a Windows form with two picture boxes where both images are displayed. The number of images displayed, time for each test and interval can be set up and images for this test are stored as application resources. Still, the application doesn’t rotate nor mirrors any image. It only displays images according to certain parameters in their names which are used to decide what images belong to the same object and if it is mirrored. The score is calculated based in the number of correct responses and the total number of tests. In the end, the application labels the recorded signal with the corresponding events, present in Table 3.

<table>
<thead>
<tr>
<th>Event</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rotated</td>
<td>Image was correctly rotated</td>
</tr>
<tr>
<td>NotRotated</td>
<td>Image was not rotated correctly</td>
</tr>
<tr>
<td>Interval</td>
<td>Time interval between image sets</td>
</tr>
</tbody>
</table>

Table 2 - Description of the labels used in the digit span test.

Table 3 - Labels used in the metal rotation test.
5.3 Feedback application

According to the reviewed studies about neurofeedback, the training programme must follow a set of rules. One training programme consists in a certain number of sessions that are divided into trials and intervals (Figure 20). During a trial the tracked signal characteristic is fed back to help the user self-regulating his/hers cortical activity. Intervals provide a resting period and no signal feedback is displayed. If intervals have the same length as trials the users EEG can be compared between these two states to see if the user is successfully changing his/hers EEG activity during trials.

Changes in the EEG activity must reach a certain threshold and be sustained for some time for the trial to be successful. For example, the user can be asked to increase the alpha band amplitude for 1.5 times the amplitude value from the 0.5 to 30 Hz band and sustain this activity for two seconds. Only if this happens the user is rewarded with some notification event. In all reviewed protocols, trials have a fixed length but, in some, the trial ends when the user is rewarded. The relative amplitude is always used to measure the activity within each band as it measures how much a certain band is above or below the rest of the EEG. Equation 36 shows how this is calculated.

\[
r_{\text{Amplitude}}(f_{\text{Initial}}, f_{\text{Final}}) = \frac{\sum_{k=f_{\text{Initial}}/\text{delta}}^{f_{\text{Final}}/\text{delta}} X(k)}{f_{\text{Final}} - f_{\text{Initial}}} \frac{\sum_{k=0.5/\text{delta}}^{50/\text{delta}} X(k)}{29.5}
\]

Here, \(f_{\text{Initial}}\) and \(f_{\text{Final}}\) are the boundaries of the frequency band expressed in Hz, \(X(k)\) is the frequency amplitude spectrum where \(k\) is a frequency bin and \(\text{delta}\) is the relation between frequency bins and frequency measured in Hz. In this case, the EEG frequency of interest is considered to be between 0.5 and 30 Hz. Using the amplitude spectrum instead of the power spectrum prevents excessive skewing that results from squaring the amplitude values which increases statistical validity [14].

5.3.1 Settings

This training application allows the setting of all the previous values and some more options in the window presented in the Appendix A, Figure 52 and explained in Table 4. The session will run according to the chosen options.
## Table 4: Settings for the EEG biofeedback application

<table>
<thead>
<tr>
<th>Option</th>
<th>Influence on the session</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Session number</strong></td>
<td>Number of current session</td>
</tr>
<tr>
<td><strong>User control</strong></td>
<td>Defines whether the user controls when the trials start and end</td>
</tr>
<tr>
<td><strong>Number of trials</strong></td>
<td>Number of trials in the current session</td>
</tr>
<tr>
<td><strong>Trial duration</strong></td>
<td>Duration of each trial</td>
</tr>
<tr>
<td><strong>Interval duration</strong></td>
<td>Duration of each interval between trials</td>
</tr>
<tr>
<td><strong>Threshold level</strong></td>
<td>Threshold level for the trained amplitude band</td>
</tr>
<tr>
<td><strong>Time above threshold</strong></td>
<td>Time to be above or below the threshold necessary for reward</td>
</tr>
<tr>
<td><strong>Region to enhance</strong></td>
<td>Region of scalp for band increase feedback</td>
</tr>
<tr>
<td><strong>Band to enhance</strong></td>
<td>Frequency band to increase</td>
</tr>
<tr>
<td><strong>Region to decrease</strong></td>
<td>Region of scalp for band decrease feedback</td>
</tr>
<tr>
<td><strong>Band to decrease</strong></td>
<td>Frequency band to decrease</td>
</tr>
<tr>
<td><strong>End trials after reward</strong></td>
<td>Defines if trials end when reward is achieved or not</td>
</tr>
<tr>
<td><strong>Record involuntary activity</strong></td>
<td>Introduces trials where the user doesn’t need to control his EEG</td>
</tr>
</tbody>
</table>

Feedback type divides in two categories: band increase or decrease. If both types are selected the application creates a ratio between the amplitude from the band to enhance and the band to decrease. Band amplitudes are always relative to the amplitude of the signal from 0.5 to 30 Hz but in this last case only the two selected bands are taken into account. If alpha/theta training was desired, the alpha band would be chose in *Region to enhance* and the theta band in *Region to decrease* and the ratio would increase with alpha and decrease with theta. For band increase feedback, the feedback parameter is the relative amplitude of the selected band. For band decrease the difference is that both the feedback parameter and the threshold value are inverted. This way, the inequality between feedback parameter and threshold remains unchangeable:

\[
\text{feedback parameter} < \text{threshold}
\]  

(37)

According to the selected option in *User control* the session can run following the selected values of *Number of trials*, *Trial duration* and *interval duration* or can be controlled by the user. In this last case, during an interval the user can save a message describing his/hers cognitive or emotional state during the previous trial. The sessions flow, according to trials and intervals, is illustrated in Figure 20.
The decision whether trials end after reward or not and its influence on the feedback displaying is explained in Figure 21. During each trial the selected band amplitude is being displayed. In the case of a band increase training, the way the band value is displayed differs whether it’s below or above the threshold. If it remains above the threshold for more than a certain amount of time, the user is rewarded.

The Record involuntary activity option introduces trials where the user must not try to regulate his EEG. These sessions can be used to check if the effort in controlling EEG rhythms is actually
producing any relevant changes, by comparing both trials, and to measure the user’s ability to produce changes only when asked.

In these settings there’s also the possibility to use the band values determined with the PAF application and to set the threshold with some value between the relative amplitude of certain signal regions and the relative amplitude of the region measured with closed eyes. This is usually useful because it gives a threshold level coherent with the users EEG. It’s also given the possibility to define the colors of the objects present in the display.

5.3.2 Feedback parameter calculation

Feedback consists in the relative amplitude value of a certain frequency band so, its calculation is done inside the method `Calculate()` of a `SpectrumFunctionBase` object because this method receives the amplitude spectrum from a region that can capture the signal immediately after its arrival at the main application. This method is called each time a new sample from the real time region is captured and it has to calculate the feedback parameter before a new sample arrives. Besides that, it also decides when the feedback parameter reaches the defined threshold, when the reward condition is present and whether the session is at a trial or at an interval. The calculation of the feedback parameter and the remaining decision is done in the following steps:

1. The spectrum from the chosen channel is copied into a buffer
2. The relative amplitude is calculated for the chosen frequency. If two frequency bands were chose the ratio between them is calculated instead.
3. This value is compared to the threshold and according to the current state, the application decides what action to take (Figure 22).
The recorded signal is labeled with each corresponding event (Table 5).

<table>
<thead>
<tr>
<th>Event</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Session</td>
<td>Goes from the beginning to the end of the session</td>
</tr>
<tr>
<td>Trial</td>
<td>When a trial occurred</td>
</tr>
<tr>
<td>Interval</td>
<td>When and interval occurred</td>
</tr>
<tr>
<td>Above</td>
<td>Feedback parameter &gt; threshold</td>
</tr>
<tr>
<td>Achieved</td>
<td>Feedback parameter &gt; threshold for more than x seconds</td>
</tr>
</tbody>
</table>

5.3.3 Display

The display was created with the aim of producing a simple visual feedback but at the same time immersive. For this effect, the Microsoft DirectX library was used to draw tridimensional objects that would respond to the values received from the `Calculate()` method. The display is called inside the `Execute()` method from an `ActionBase` object. Here, the method `Calculate()` is called and it will remain idle until the session starts. Meanwhile, a new thread is created to run the display form. This implies that the feedback parameter calculation and the display run in different threads. Their dynamic is represented in Figure 23.
The display contains two objects, a sphere and a cube (Figure 24). The sphere is where the feedback parameter is reflected. Its value is directly reflected into the sphere's radius and if it reaches the threshold the sphere color changes. This sphere is constituted by several slices and the more slices it has, more smooth it looks. Initially, the sphere is only constituted by four slices, which is the minimum number possible, and while the feedback parameter is above the threshold slices are added to the sphere. When the feedback parameter is below the threshold, the sphere loses slices until it only has four of them. This gives the user an idea of how well he/she has been performing. The cube's height is where the reward is reflected, making it rise. If the reward ends, the cube starts falling slowly until it reaches the bottom or the reward is present again. So, the best outcome would be having the cube as high as possible.
Display classes and methods

In order to create a simple graphical interface the DirectX API and Direct3D were chose because they provide several classes focused in the creation of virtual environments. The necessary aspects to take into account when creating a virtual environment with this API are the connection between the application and the hardware, the location of the vertices used to draw the objects, textures, camera perspective and scene illumination. Despite the temptation to create a complex scenario, in this case, the camera perspective, textures and illumination were kept within modest levels. The classes used and their utility is explained in Table 6.

Table 6 - Description of Direct3D classes used.

<table>
<thead>
<tr>
<th>Direct3D Class</th>
<th>Used for</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Device</strong></td>
<td>Communicate with hardware, set illumination points and define objects material. Every object in the scene is associated to the device.</td>
</tr>
<tr>
<td><strong>Mesh</strong></td>
<td>Group several vertices to form an object, draw the object through a Device object.</td>
</tr>
<tr>
<td><strong>Material</strong></td>
<td>Define how the material reacts with different illumination stiles.</td>
</tr>
<tr>
<td><strong>Texture</strong></td>
<td>Integration with external textures.</td>
</tr>
<tr>
<td><strong>LightType</strong></td>
<td>Defines how the light from an illumination point reacts when reflected.</td>
</tr>
<tr>
<td><strong>Color</strong></td>
<td>Provides a set of predefined colors.</td>
</tr>
<tr>
<td><strong>Vector3</strong></td>
<td>Coordinates of a point.</td>
</tr>
<tr>
<td><strong>Matrix</strong></td>
<td>Allows rotation and translation of an object or camera.</td>
</tr>
</tbody>
</table>
5.3.4 Scene rendering

Because the signal capture device sends data chunks to the application at discrete times (spaced, for example, by 125ms) it’s necessary to do some smoothing to improve the scenes frame rate. Smoothing is done to the sphere and cube movement and consists in a linear interpolation between two separate sets of values. So, when the first set of values arrives at the display, it will have to wait until the second set arrives to start rendering the interpolated values. This introduces an initial delay corresponding to the refresh rate of the capture device (in the previous example, 125 ms) but the advantage of high frame rate makes it worth (Figure 25).

![Figure 21 - Illustrative example of the necessary delay for the artificial increase of frame rates.](image)

When the scene starts the method `InitializeGraphics()` is called to initialize the `Device` object. The initialization consists on deciding, according to the hardware available in the machine where the application is running, if the scene is hardware or software accelerated. The device is then associated to a picture box, lightning and specular effects are enabled for this device. After having the device set up, the scene is constructed. The method `CreateVertexBuffer()` creates the objects present in the scene using two `Mesh` objects, one to create a cube and other to create a sphere. Then, the scene illumination is set up in the method `SetupLights()` and the camera is positioned in `SetupMatrices()`. Now, for each interpolated value, the `Render()` method is called to draw the objects on the screen (Figure 26).
5.3.5 Storing results

Each session’s information is saved in an Amplitude object that will serve as a guide while building the session and for future queries. At the end of a session the object is added to a collection in a Singleton object SessionVars. Here, collections of objects from other applications, like individual frequencies, can also be found. When saving the session values, the Singleton object is serialized and saved in a binary file. In the next session, the file is loaded and deserialized allowing new values to be added to previous ones. The UML diagram of how the session data is stored can be seen in Figure 27.
Figure 23 - UML diagram for the stored objects.
Chapter 6

Experimental Study

6.1 Participants

Twenty people volunteered to participate in this study. All of them had at least their peak alpha frequency (PAF) measured and eighteen also participated on the short term memory test and at least in one EEG biofeedback session. Two of them were available to participate in a considerable number of sessions (14 and 20) while the rest participated only in one to three sessions. Due to time limitations it wasn’t possible to obtain more sessions from the majority of people.

6.2 Procedures

All the recording and experiments were realized at the Evolutionary Systems and Biomedical Engineering Lab. The time of the day when the experiments where done vary from person to person but, in the subjects that participated in more sessions, almost all occurred around 5 p.m. For all subjects, four electrodes were placed. The recording location was always at Cz as it’s captures activity from left and right hemisphere and is widely used in EEG biofeedback studies, referenced to a location in the middle of the forehead. The remaining two electrodes where placed in the left and right mastoids to enable common mode rejection in the amplifier. The scalp-electrode impedance was carefully kept under 10 kΩ for all recordings at all time with the help of a saline conductive paste. This was done without any abrasion to the skin and the hygiene of the process was high at all time. Electrodes were disinfected with alcohol after every use and left in a saline solution until the next experiment. The electrode cables were kept interlaced and far from any interference source like computer keyboard or monitor. In all processes, the signal is being observed by the practitioner in order to detect any eventual problem in the signal acquisition.

After stabilization of skin-electrode impedance the recording starts and the following steps are taken:

- The subjects EEG is recorded under two conditions, eyes opened and eyes closed.
- PAF is determined along with the individual alpha frequency band.
- The subject does a diagnostic test to measure his/hers working memory.
- Feedback session
• If the subject asks, the results of the session are displayed objectively.

The recordings with eyes opened and closed are only done when the individual frequencies need to be calculated. This only happens in the first session for most cases. When the subject participates in a more elevated number of sessions, these parameters can be calculated at more times, especially in the last session. The working memory test is only done when the individual frequencies are measured. Because the calculation of the individual frequencies and the short memory test add more time to the session, and volunteers not always had much time to offer, they were only done when necessary. Some subjects also participated in the attention test but there were no participants for the mental rotation test because the image library was only finished when the experimental trials had already began.

6.3 PAF extraction

For the extraction of the PAF value subjects had to previously record their EEG under two conditions. One with their eyes opened and other with eyes closed. When the recordings where taking place, subjects were asked to reduce their head and limbs movements. If necessary and if time was not scarce, both recordings were repeated. In the PAF application, after choosing the signal recordings and the channel where they’re present, the parameters for the Welch method were defined. Most times the overlap value was set to 50% and the length of the segments for the average of the spectrum estimation were set to five seconds leading to a spectral resolution of 0.2 Hz*. If the transition frequencies were hard to detect*, the spectrum resolution could be drop by decreasing the window length making the spectrum more smooth. However, if this is done, the PAF value should be extracted after, with higher resolution, because its value will be more inaccurate with a drop in resolution. The transition frequencies accuracy can be detected with low resolution because they are detected as the crossing point between two spectrums. After the boundaries of the individual alpha band and its peak are defined, they are saved and the application is closed. If no significant difference exists between the spectrum from the recordings with eyes open and eyes closed, if there’s time, new recordings under either conditions (or just eyes closed) are done. Else, a typical alpha frequency band is defined (8 - 12 Hz).

6.4 Working memory test

The working memory test consists in two digit span tasks to determine the subjects’ digit span and the percentage of correct numbers. These values are determined in two different conditions: remembering the numbers in the same order as they were presented and in the inverse order. When each test ends, the results are presented on screen and saved. The test is set up to start with two digit trails and end with ten digit trails regardless of how correct the answers are. The subject encouraged no to give up answering even if the number of digits is too high. If the subject fails, the test reduces the digit rate on screen by 0.2 seconds.
6.5 EEG biofeedback protocol

The EEG biofeedback protocol is focused on the increase of the individual alpha band amplitude defined previously. Besides setting up the training with the individual alpha band values, a threshold is also defined. This is a value between two boundaries: the average relative amplitude of the alpha band in a reference region (usually the recording of the eyes open) and the average relative amplitude in the same band in the region with the eyes closed. In the first sessions this value is kept closer to the lower boundary to decrease difficulty. As sessions proceed this value is increased approaching the upper boundary. Other parameter to set up is the time required above threshold for a reward to be given. This is usually set to two seconds for all sessions.

The training can take two variants. In the first sessions, the training is done under the user control. The user is advised to do as many trials as possible and to try a different cognitive or emotional state at each trial instead of mixing various states into one. Here the user decides how many trials he/she does and the length of each trial. However, the recommendation is that each trial lasts about one minute so that the user doesn’t lose focus. In the first session, some suggestions for cognitive and emotional states are made based on the knowledge of their relationship with the alpha activity. So, the user is recommended to relax or to keep his mind locked in simple tasks and do the session with opened eyes. Nevertheless, other strategies are encouraged. After each trial, the user saves a record informing what cognitive or emotional process was tried. In later sessions, when the user already knows what to do to produce alpha activity, the user control option is deactivated and the session follows certain defined values for the number of trials and the duration, in seconds, of each trial and the intervals in between. The standard values are ten trials of twenty seconds separated by intervals of five seconds for each session. These values were chose to provide short length sessions to avoid saturating the subject.

Having all the variables set up, the session starts. Here, besides displaying the feedback of the signal to the subject, information concerning the signals time and frequency domain also needs to be displayed to the practitioner to detect any problem in the EEG recording. Because the feedback window is maximized, these signals features are displayed in a second screen, connected to the computer. In the end of a session, after presenting the results, the subject is asked to do one more session with the same or different parameters.
Chapter 7

Results

This section comprises the evaluation of the proposed objectives for this study:

1. Proper functioning of the platform.
2. Possibility of self-regulating the EEG.
3. Possibility of a training protocol to produce lasting changes in the EEG.
4. Possibility of a training protocol to produce improvements in certain cognitive aspects.
5. Relation between short term memory, PAF and age.
6. Testing additional EEG processing tools.

7.1 Proper functioning of the platform

The platforms functioning proved to be consistent as all sessions went without critical errors and in relatively short time. Sessions that included PAF extraction and digit span tests lasted about forty five minutes while regular feedback sessions lasted about thirty. All the steps required are displayed in the Annex X with the graphical user interface.

7.2 Possibility of self-regulating the EEG

7.2.1 Evidence for cognitive or emotional states that produce different rhythmical activity

This evidence can be confirmed with results from the first sessions where subjects write what cognitive or emotional state corresponds to each trial. Because the EEG is a non-stationary process results from just one session might not be enough. However, if the same state produces higher alpha band amplitude in more than one session, compared to other states, this possibility is more probable. So, as the number of sessions increases, more strength these consecutive relations will have. The results of two subjects that repeated some of the cognitive states in consecutive sessions are presented.

Subject A

This subject participated in six sessions where the first three were user controlled. Despite the variability, it’s possible to assume which states are more recommended for the production of alpha rhythms. Figure 28 shows the ratio between total alpha activity above the stipulated threshold and the
time of each trial for each cognitive state along the three initial sessions. Because the length of these trials were controlled by the subject resulting in different lengths, this normalization was required. The threshold level is the same for the three sessions.

Figure 24 - Normalized total alpha activity over threshold in the first three sessions for Subject A.

Figure 29 shows what states produce more alpha activity for more than two seconds. From these results, there is no concrete evidence that there's a distinction between different cognitive and emotional states in the production of alpha activity because of the high variability of the results. However, it's possible to determine that some states have always better results than others.
Figure 25 - Normalized number of rewards for each different condition for Subject A.

Subject B

The same analysis is done for Subject B. By the observation of figure 30 it's possible to assume that when the subject is imagining visual scenes, the production of alpha activity is higher. Still, it does not occur in a sustained way from what's represented in Figure 31 for the third trial, at least for more than two seconds.
Figure 26 - Normalized total alpha activity over threshold in the first three sessions for Subject B.

Figure 27 - Normalized number of rewards for each different condition for Subject B.
7.2.2 Evidence for the possibility of increase or decrease some rhythmical activity on demand

If the average value of the relative alpha band in a session increases, two things can be expected: or there is more production of alpha oscillations per trial, thus the subject can produce them more often or, the alpha oscillation amplitude has increased. This second possibility can be excluded if there was no necessity to increase the threshold level as the training progress. The results of the subject who underwent more than ten sessions will be analyzed.

Subject C

The evolution along sessions of the relative amplitude for the alpha band and three other neighbor frequency bands is plotted in Figure 32. It’s evident that the amplitude in the alpha band has increased significantly more than in other frequency bands along sessions.

Figure 28 - Evolution of relative amplitude for different frequency bands for Subject C.

The increasing tendency of the amplitude is confirmed applying a linear regression to the data (Figure 33). The statistically significant regression (p<0.05) has an R squared value of 0.494 and is expressed as a line with a positive slope of 0.038.
The slopes for the lines fitted to the values of the four frequency bands are present in Table 7. It’s clear that the line fitted to the alpha values has a considerably higher slope than the other lines, suggesting that the subject selectively increased the individual alpha band activity and improved its control over time.

Table 7 - Slopes for each frequency band evolution with time regression line.

<table>
<thead>
<tr>
<th>Frequency band</th>
<th>Slope</th>
</tr>
</thead>
<tbody>
<tr>
<td>Theta</td>
<td>0.0008</td>
</tr>
<tr>
<td>Alpha</td>
<td>0.038</td>
</tr>
<tr>
<td>Beta 1</td>
<td>0.0083</td>
</tr>
<tr>
<td>Beta 2</td>
<td>0.0075</td>
</tr>
</tbody>
</table>

As the training progressed, the threshold level was consecutively altered to fit keep a certain trial difficulty. The decision of altering the threshold level was based on the subjects’ improvements. In Figure 34, the number of rewards given (number of times above threshold for more than two seconds) in each session is plotted with the information of when the threshold was altered.
Because each session consisted of ten trials, when the subject was receiving an average of one reward per trial (or more) the threshold is increased. It’s possible to see that in the following sessions to that, the activity adapts to the new threshold as the number of rewards suddenly drops when the threshold is raised but then, it starts increasing again.

Table 8 shows the percentage of how many times alpha activity went above the threshold during the first and last session with the threshold applied in the last and in the fourth session. The fourth session was chose because the three initial sessions were controlled by the user, so no fixed trial lengths were used. In the fourth session, and following, the number of trials and their length are constant and plus, by this time the subject already knows what cognitive state triggers alpha production.

Table 8 - Percentage of time relative alpha band was above the thresholds.

<table>
<thead>
<tr>
<th>Session</th>
<th>First threshold</th>
<th>Last threshold</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>30,37%</td>
<td>8,01%</td>
</tr>
<tr>
<td>20</td>
<td>74,84%</td>
<td>47,43%</td>
</tr>
</tbody>
</table>

Until now, the evidence points to the possibility of an increase in the amplitude of the alpha oscillations (compared to other oscillations in the signal) which is influencing the higher values of this band in the relative amplitude spectrum along the training. However, this may not be the only reason because the
average of this amplitude in each session can be also influenced by the amount of alpha activity. So, there're two possibilities. The first is that the oscillations have higher amplitudes and the other is that there are more oscillations, which will have more weight on the average. Table 8 indicates the possibility that more alpha bursts were produced in the last session but this would only be true if this threshold had the same proportion to the amplitude of alpha waves as the first threshold had in the fourth session. In Table 9 it's possible to see how much alpha oscillations exceeded the threshold in both sessions. Alpha waves amplitude exceeded the threshold value for a slightly higher margin than in the fourth session.

<table>
<thead>
<tr>
<th></th>
<th>Fourth session</th>
<th>Last session</th>
</tr>
</thead>
<tbody>
<tr>
<td>% maximum peak amplitude above threshold</td>
<td>12.66%</td>
<td>19.93%</td>
</tr>
</tbody>
</table>

Interestingly, if the threshold was increased so that the values in Table 9 were similar, Table 8 would have the following values (Table 10, only the values of interest are displayed)

<table>
<thead>
<tr>
<th>Session</th>
<th>First threshold</th>
<th>Modified threshold</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>30.37%</td>
<td>-</td>
</tr>
<tr>
<td>20</td>
<td>-</td>
<td>33.19%</td>
</tr>
</tbody>
</table>

This means that with the thresholds adjusted equally to the highest amplitude in the alpha oscillations, there would be the same amount of detected alpha activity in the fourth and in the last sessions.

**7.3 Possibility of a training protocol to produce lasting changes in the EEG.**

The test subjects that successfully controlled and increased their alpha activity are expected to have higher relative amplitude values in these frequency bands at the end of the experiments. The differences between initial and final PAF are also going to be checked. These values have to be measured in a period where no feedback is being provided and the subject is not making any effort to alter his/her EEG. The reference region during eyes opened can be a good place to compare these values. Because Subject C was the only test subject that participated in a considerable number of sessions, this analysis will only focus on him/her.

The average relative amplitude in the individual alpha band, measured in a reference location of one minute length, increased 17%, from the first session to the last session. However, the variance between the intermediate measures was considerably high. Figures 35 shows the line fitted to this measures, separated by days. The linear model, despite its positive incline, weakly explains this distribution (low R squared) and has a very low significance due to the high variance in the measures (p>>0.05).
The PAF values did not suffer any significant changes during this training as can be seen in Table 11.

### Table 11 - PAF value along the experiment.

<table>
<thead>
<tr>
<th></th>
<th>Session 1</th>
<th>Session 9</th>
<th>Session 20</th>
</tr>
</thead>
<tbody>
<tr>
<td>PAF (Hz)</td>
<td>10.3</td>
<td>10.1</td>
<td>10.4</td>
</tr>
</tbody>
</table>

#### 7.4 Possibility of a training protocol to produce improvements in certain cognitive aspects.

In this section, the digit span score progress from both subjects that participated in more sessions are compared with their success in controlling the EEG and with their differences between the initial and final relative amplitude of the alpha band and PAF.

The improvement in the digit span test can be seen in Table 12 for subjects C and D.

### Table 12 - Digit span scores for Subjects C and D.

<table>
<thead>
<tr>
<th>Measure 1</th>
<th>Measure2</th>
<th>Measure 3</th>
</tr>
</thead>
</table>

<table>
<thead>
<tr>
<th>Subjects</th>
<th>C</th>
<th>D</th>
<th>C</th>
<th>D</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal order</td>
<td>7</td>
<td>7</td>
<td>8</td>
<td>7</td>
<td>10</td>
<td>-</td>
</tr>
<tr>
<td>Reverse order</td>
<td>6</td>
<td>6</td>
<td>7</td>
<td>5</td>
<td>9</td>
<td>-</td>
</tr>
</tbody>
</table>

Despite the average number of feedback sessions of Subject D, the results did not improve and this is also happens to the digit span scores. Subject C, similarly to the successful results in the feedback experiment, showed improving results in the memory test. However, the possibility of habituation to this type of tests cannot be excluded even with a small number of measures. The relationship between the digit span results and the alpha band relative amplitude in the days of the memory tests are sketched in Figure 36.

![Figure 32 - Digit span plotted against Relative alpha for Subject C.](image)

### 7.5 Relation between short term memory, PAF and age.

The PAF has been related in some studies as an indicator of cognitive performance. To evaluate this relationship, its value is compared against the results in the digit span test (Figure 37).
Results were not significant enough and the linear model doesn’t fit well. However, a positive tendency can be observed between both.

### 7.6 Testing additional EEG processing tools.

The multitaper method is applied to regions of the signal where the standard spectrum estimation detects elevated levels of alpha amplitude to check if the decision was the same when using this method. No significant changes were seen but the spectrum seems smoother, like it was expected. The relative amplitude spectrum estimated using the MTM with four weighted tapers compared to the estimation with a Hamming window is illustrated in Figure 38. These measures were from a two seconds segment of the EEG. The weight for each estimation using a different prolate were: the first had a weight of 3, the second of 0.5 and the others 0.25 each. The results seem to improve with the calibration of the weights. However, more detailed testing conditions, with previously known time series, would be necessary as this section is just a demonstration of the functioning of the plug-in.

The EMD algorithm is applied to a portion of the signal. Figure 39 shows the resulting IMFs without IMF0 because that was only composed of the 50 Hz from the power line. In the figure, the signal
displayed from the Cz recording is also notch filtered around 50Hz and low pass filtered below 30 Hz but the EMD algorithm was applied to the raw signal, the filtering is only applied to Cz for visualization purposes. The algorithm decomposed the raw signal in eight IMFs plus the residual and in all the IMFs, the number of extrema does not differ for more than one from the number of zero crossings.

When the IMFs and the residual are summed, Equation 30, the resulting signal is very similar to the original one in both time and frequency domain Figures 40 and 41.

---

**Figure 35** - EMD of a EEG signal. IMF0 was the first mode to be extracted but it corresponded to the mains hum so it was not displayed.

**Figure 36** - Original signal, Cz and signal resulting from Equation 30, sum. Both signals are filtered to the frequencies of interest.
The alternative implementation for the EMD method proposed by Bhuiyan for bi-dimensional data [82], which was here modified for one-dimensional data, produced more than twenty IMFs. The initial suspicion that this process, for calculating the signal envelope, would remove the data driven character from the algorithm is confirmed.

The results from the attention test are also used to calculate the ERP associated with decision making. The test was done to Subject E where 200 images were shown during one second on screen and were separated by an interval of one second also. Measuring was done at Cz. The probability of an image to appear was 5%, which require the subject’s response. The total number of responses was 12 and their average signal is showed in Figure 42.

The remaining 188 images yielded the potential present in Figure 43.
The same test was done to Subject F with the same settings but was repeated after an interval of thirty minutes (so the subject doesn’t saturate from looking at the screen) resulting in 400 trials. This gave 24 responses which their average is present in Figure 44 in the same scale as Figures 42 and 43.

![Figure 40 - Average of 24 segments of EEG after a rare stimulus in Subject F.](image)

The remaining 368 (eight recordings had to be removed due to artifacts) resulted in the potential displayed in Figure 45.

![Figure 41 - Average of 368 segments of EEG after a common stimulus in Subject F.](image)

By visual inspection of the four figures it’s possible to distinguish some differences and similarities. Both Subject E and F showed a large positive component shifted by about 0.1 seconds after the rare stimuli. For the other measures this doesn’t verifies, however they are a result of a larger average. So, it’s possible that the attention test successfully elicited a P300 potential.
Chapter 8

Conclusions and future work

The length of this work was dependent on the number of volunteers and the number of sessions each one could participate in. With the data from the subjects that participated in at least one session it was possible to test the relationship between the peak alpha frequency and working memory. Subjects that participated in a more elevated number of sessions opened the possibility for testing the EEG biofeedback protocol for training the individual alpha frequency and see how it affects cognitive aspects like working memory.

The results of this work are in pair with the results from other similar studies in several ways. First, they showed that peak alpha frequency and individual alpha band are parameters that vary between subjects. Therefore, any future study which involves the use QEEG measures should be based on the individual frequency bands instead of the typical bands as these last can be misleading.

Despite its low significance, a positive relationship was also verified between the peak alpha frequency and cognitive processes performance as working memory and mental inversion of a string of numbers. Still, these results show no evidence for using the PAF value as a predictor of these cognitive skills.

The results from the EEG biofeedback sessions, for most subjects, showed that there are some cognitive and emotional states related with the production of alpha activity. Although this relation is not stable between sessions, some states always facilitate more alpha activity than others. It was not possible to draw any conclusion about which type of cognitive or emotional strategies are more indicated for alpha production because these varied within subjects.

For Subject C, who participated in more training sessions, a promising result was observed. Not only was this subject able to improve his/hers results in the feedback training, he/she also showed a significant improvement in the cognitive test. Unfortunately, the unitary size of the sample limits any statistical significant conclusion relating EEG biofeedback training and cognitive improvement. Nevertheless, this result validates the proper functioning of the developed feedback platform and gives a reason, along with other studies, for future studies with larger populations to be performed. This pilot
study also opened the possibility for the use of this platform with other objectives like peak performance training, clinical cases or communication.

The developed algorithms for the Somnium software application, although not thoroughly tested, also produced interesting results. Future testing, with known time series, is needed to evaluate these applications and allow their integration in other studies. The use of instantaneous frequency as the feedback parameter would also be interesting.

In this work the signal was measured only in the central location of the head, Cz, to mimic other that had successful results, reduce the time spent placing the electrodes and because there was no clue for other location to be preferable. In future studies, other locations can be recorded to see if different relations are obtained. Other demands in future work would be a follow up study for subject C to see if the achieved improvements are maintained. Experiments with larger population, control group and an increased number of sessions are also required for any statistical validity.

The use of EEG biofeedback for the treatment of epilepsies and ADHD is nowadays so well documented that its use has been taken into consideration by several physicians, instead of medication. Hopefully, this will also happen in other areas if the same increase in studies occurs.
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"Negative potential shifts and the prediction of the outcome of neurofeedback therapy in


Appendix A

A.1 The Somnium Platform

Somnium is a signal processing software mainly used for polysomnographic analysis. Biological electrical signals like, electrooculogram (EOG), electromyogram (EMG), electrocardiogram (ECG) can be stored in virtual channels and displayed, as well as oximetry measures, snoring recording and respiratory pressure. Channels can be viewed in the time or frequency domain or both, along with other functionalities.

When the desired functionalities aren’t present in the software application, they can be added through the development and integration of an external plug-in because Somnium uses plug-in architecture. So, the plug-in developer doesn’t need to know all the details about the main application. To be executed, every plug-in need to have a class that inherits from some other class or interface provided by the main application. These work like entrance points for the plug-ins and there are several. In this work four classes are used: IDetectorProcess, IReportProcess, SpectrumFunctionBase and ActionBase. In this work, all plug-ins were developed in C# language.

A.1.1 Offline Processing

For offline processing on a signal already stored in a virtual channel, the IDetectorProcess interface can be implemented. This class constructor creates an array of objects, of the type Parameter, which will have the requests for the input values. When the plug-in is called, the main application creates an object of this interface, and asks the user for input values. After that, the main application runs three methods, which must have been implemented, from the object: ValidateParameters(), Init() and Run(). The first method validates the input values, present in the array of Parameter objects. If Boolean false is returned, the application asks again for input values else, it proceeds to running Init() and then Run(). The main application passes an object with some of the values from the analysis to the function Init() through its arguments for the initialization of some attributes. For example, if a plug-in needs the signal from a certain channel, its values can be obtained and stored in one of the objects variables during Init() to be used, later, in the method Run(). In the method Run(), calculations are done with the variables stored during Init(). The result can be displayed as a new channel or stored in any existing outer variable. Figure 8 illustrates the explained steps.
A.1.2 Real Time Processing

*SpectrumFunctionBase* and *ActionBase* can be inherited when real time processing of the recording is necessary. When the class inherits from *SpectrumFunctionBase* the method *Calculate()* must be overridden. As this object is created by calling the plug-in, the main application calls the method *Calculate()* with a certain rate, defined in the programs' settings. Usually it's set for 4 to 8 times per second. The main application passes an object containing the amplitude spectrum of a certain part of the signal as an argument to this function. It also expects the method to return an array of double precision values to display in the screen. For example, if the relative amplitude spectrum is required: inside *Calculate()* the amplitude spectrum is extracted and an average of the values between the 0.5 and 30 Hz is calculated. Then, each value of the amplitude spectrum is divided by the average and stored in a double precision array which is finally returned. The main application receives this returned array and displays it on the screen. This keeps happening with the defined rate while the plug-in is still active. Figure 9 illustrates the explained steps.
A.1.3 Any purpose plug-in

For the plug-in to be available as a toolbar button the class must inherit from the *ActionBase* class. The following steps are illustrated in Figure 10. When the button corresponding to the plug-in is pressed the main application calls the method *Execute()* from the object. The fact that this method is only called once and, the application doesn't wait until it finishes, makes it the best place to call other forms or dialog boxes to display additional content.

A.1.4 Exporting report to document

An object implementing the method *Run()* from the interface *IReportProcess* is able to export values to a variable assigned in a external document. As Figure 11 shows, report process is similar to the offline process except no data input is asked.
Figure 45 - Report process
Appendix B

Graphical user interface.

The graphical interface of all the applications developed is shown. Figure 46 shows how the *Somnium* application looks like when it’s recording. Time and frequency views are available at the same time and the recorded signal can be labeled by the user or any application.

![Figure 46 - Somnium interface during an EEG biofeedback session.](image)

**B.1 PAF application**

When the PAF calculation plug-in is called it allows choosing any of the previously labeled EEG segments in its settings. As a label is selected in the combo box, the window shifts to the region where the signal was labeled (Figure 47). If the region is the desired the user adds it to the memory for future calculation.
If the individual alpha band and the PAF haven’t been automatically detected, the user can set their values if they are possible to distinguish by visual inspection. In Figure 48 the application was able to detect the boundaries so the user only needed to accept the values.

**B.2 Digit span application**

The digit span application shows an increasing number of digits at a time. In this case, it started with showing two digits, the three digits, until a trial of 10 digits. The interface is present in Figure 48.
B.3 Attention test

The display of the attention test can be seen in Figure 50. The three objects in the test are present. Usually, the circle is the rare stimulus.

B.4 Mental rotation test

Although it was not used in this study, this test was eventually finished and proved to work well. The objective is to determine if the two images are the same but rotated or if they are the same but mirrored (and rotated as well). Its display is present in Figure 51. In the present case, both images are the same but rotated. The user needs to answer before the progress bar reaches its end.
B.5 EEG biofeedback application

The settings to start a new session are present in Figure 52. The variables introduced in Table 4 are present in these settings.
B.6 Feedback Interface

Two examples of the feedback interface are present in Figures 53 and 54. Figure 53 corresponds to a part of the trial where the relative amplitude of a certain frequency band is above the threshold. Figure 54 on the right shows a situation where the relative amplitude is below the threshold.

Figure 53 - Relative amplitude > threshold

Figure 54 - Relative amplitude < threshold
### B.7 Reports

An example of a typical report is present in the following tables.

<table>
<thead>
<tr>
<th>Session number</th>
<th>Number of Trials</th>
<th>Trial duration (seconds)</th>
<th>Trial Start date</th>
<th>Interval Duration (seconds)</th>
<th>Region Enhanced</th>
<th>From (Hz)</th>
<th>To (Hz)</th>
<th>Region Attenuated</th>
<th>From (Hz)</th>
<th>To (Hz)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>16-06-2009</td>
<td>2:53:25</td>
<td>Cz</td>
<td>6,7</td>
<td>12</td>
<td>--</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>0</td>
<td>18-06-2009</td>
<td>22:55:47</td>
<td>Cz</td>
<td>6,7</td>
<td>12</td>
<td>--</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Session number</th>
<th>Time above threshold</th>
<th>User control</th>
<th>Threshold level</th>
<th>Nº achieved attempts</th>
<th>Without intention</th>
<th>% achieved attempts</th>
<th>Without intention</th>
<th>% time above threshold</th>
<th>Without intention</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
<td>Yes</td>
<td>1,59</td>
<td>15</td>
<td>300%</td>
<td>%</td>
<td>19,72%</td>
<td>%</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>Yes</td>
<td>1,59</td>
<td>11</td>
<td>91,67%</td>
<td>%</td>
<td>15,98%</td>
<td>%</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>195,83</td>
<td>%</td>
<td>17,85%</td>
<td>%</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Session number</th>
<th>Higher than threshold (%)</th>
<th>Without intention</th>
<th>Lower than threshold (%)</th>
<th>Without intention</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>16,09%</td>
<td>0%</td>
<td>25,15%</td>
<td>0%</td>
</tr>
<tr>
<td>2</td>
<td>14,83%</td>
<td>0%</td>
<td>26,39%</td>
<td>0%</td>
</tr>
<tr>
<td>Session number</td>
<td>Trial number</td>
<td>Trial duration (seconds)</td>
<td>Stimulus</td>
<td>Times above threshold</td>
</tr>
<tr>
<td>----------------</td>
<td>--------------</td>
<td>--------------------------</td>
<td>-------------------</td>
<td>-----------------------</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>173.88 sec</td>
<td>meditação</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>124.74 sec</td>
<td>respiração</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>3</td>
<td>437.98 sec</td>
<td></td>
<td>8</td>
</tr>
<tr>
<td>1</td>
<td>4</td>
<td>225.04 sec</td>
<td>Corrida</td>
<td>3</td>
</tr>
<tr>
<td>1</td>
<td>5</td>
<td>299.63 sec</td>
<td>desenhos</td>
<td>3</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>88.7 sec</td>
<td>controlar o objecto</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>87.95 sec</td>
<td>Mar</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>95.76 sec</td>
<td>controlar a respiração</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>4</td>
<td>94.75 sec</td>
<td>respiração sem feedback</td>
<td>6</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
<td>180.94 sec</td>
<td>relaxar</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>6</td>
<td>177.66 sec</td>
<td>lembrar o caminho de casa ao xt</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>7</td>
<td>215.96 sec</td>
<td>caminho do x ao y</td>
<td>2</td>
</tr>
<tr>
<td>2</td>
<td>8</td>
<td>167.33 sec</td>
<td>lembrar caminho</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>9</td>
<td>128.27 sec</td>
<td>lembrar caminho</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>10</td>
<td>100.55 sec</td>
<td>Nadar</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>11</td>
<td>139.36 sec</td>
<td>contar</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>12</td>
<td>69.55 sec</td>
<td>contar</td>
<td>0</td>
</tr>
</tbody>
</table>