

Design and Evaluation of a Musical Neurofeedback Software in Matlab

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Abstract

This work wants to draw together two different medical therapies which in the past have shown great potential for treating a wide range of emotional disorders: music therapy and neurofeedback. Numerous studies support music therapy as an effective means to help people with depression, with highly satisfactory results with regard to both elderly people and adolescents. On the other hand, neurofeedback has become a very popular non-invasive technique thanks, in great measure, to the emergence of low and mid cost electroencephalography (EEG) devices in the market. Despite a lack of double-blind randomized studies in the literature, neurofeedback is starting to show effective results dealing with a wide variety of different medical conditions such as depression, anxiety or attention deficit disorder. Musical neurofeedback is a new approach, born from the combination of these two disciplines, which by recent studies seems to have a high potential for helping elderly people with depression. This thesis presents an open musical neurofeedback system which is both easy to use and configurable for different disorder scenarios. We evaluate the system with a low-cost EEG device and assess experimentally which specific features extracted from the EEG activity contain more valuable information describing the emotional state of the users. Finally, we present the results of a pilot study consisting of seven 20-minutes musical neurofeedback sessions with an adolescent with depression.

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1. Introduction

1.1. State of the Art

Musical neurofeedback as a completely new concept, was born from the idea of combining the successful outcomes of music therapy with those of neurofeedback. So, we think it will be appropriate to start with a brief introduction of the state of the art of each of these fields. We will see how both therapies have a great potential to complement each other, especially when dealing with patients with emotional disorders.

1.1.1 Music Therapy

Most of us use to listen to music daily without being aware about all the potential benefits music could be providing us. Several studies have shown that music education at an early stage stimulates child brain in a way that helps them to improve communication skills, verbal skills and visual skills [58][59]. There is also ample literature reporting the relation between listening to music and the levels of dopamine in the brain (a feel good chemical)[60]. According to research music could provide us with similar dopamine levels to those achieved by sex or drugs. At the same time, among many other different benefits, music training can also help keep aging brain healthy [61].

The medical therapy field which tries to exploit all these potential benefits of music is called music therapy. This medical therapy, among many other contributions, has shown encouraging results improving the mood of people with depression[30], with particularly interesting results in elderly people with depression [62] [63] [64]. Some studies highlight the fact that passive music activities like listening to music or, active music activities like dancing or playing some instrument affect older adults perception of their quality of life [65][66]. Passive activities are rated as a very pleasant experience by older adults since it can distract them from unpleasant experiences and decreases anxiety [67] while active activities improves their perception about their physical, psychological and social aspects[65].



Figure 1.1 Music therapy has shown to be a very powerful tool improving the quality of life of elderly people [68].

There is also another particular group of patients who seem to be very receptive to music therapy which are depressed adolescents. Some studies describe how some adolescents use music as a mood regulator of their emotional states [69] and how music therapy can influence the self-confidence and self-esteem of adolescents who are sexually abused [70]. It has also been measured how music can shift frontal EEG in depressed adolescents which could be a good indicator of improvement of their mental condition [71]. Some recent randomized trials have revealed how music therapy can effectively treat depression in children and adolescents leading with emotional problems [72]. Other studies focused on how dance movement therapies can improve emotional responses and modulate neurohormones in adolescents with mild depression [72] and the importance of improvised music making to promote reduced isolation and increase expressive communication skills [73].

1.1.2 Neurofeedback

On the other hand we have neurofeedback, which is a relatively old technique (dating back to 1958) that just recently has begun to become popular thanks, in a big part, to the emergence of low and mid cost electroencephalography (EEG) devices in the market. Neurofeedback is a technique which consists mainly in what we can see in Figure 1.2.

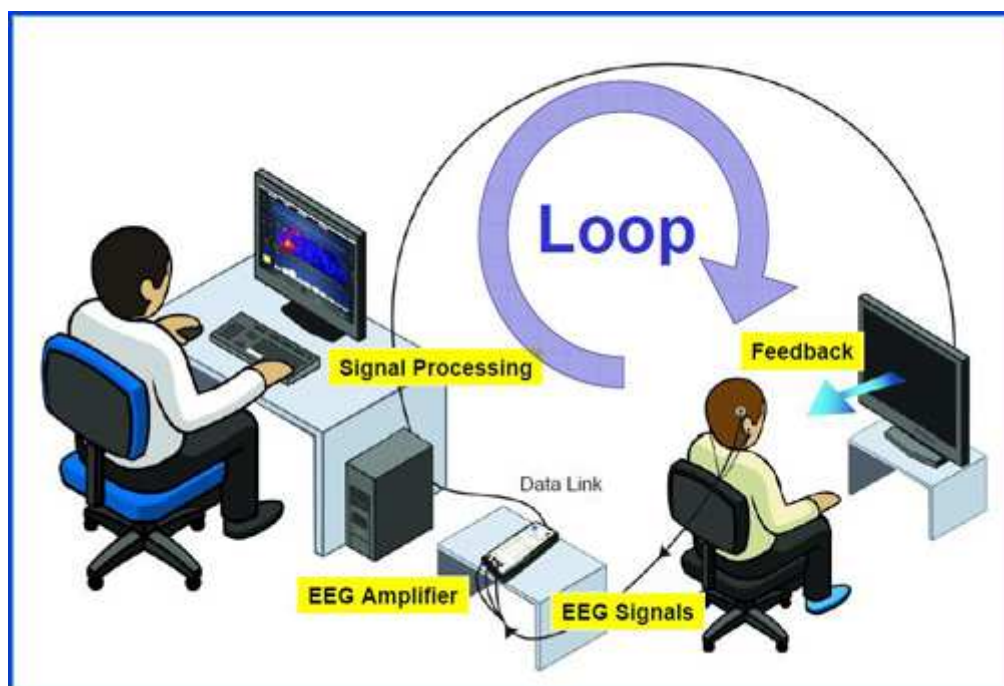


Figure 1.2 Schematic process of a neurofeedback session [89].

The patient needs to learn how to reach a concrete mental state (for example concentration in a patient with ADHD). Then, we measure the patient emotional waves using EEG and signal processing techniques. When the patient achieves the correct mental state then, the software provides an appropriate feedback which can be visual or auditory. Until the moment, there is ample literature about the benefits of neurofeedback in a wide variety of medical conditions

such as depression [75], anxiety [76], epilepsy [77], attention deficit disorder [78], among many others [79].

One of the main important criticisms rightly received neurofeedback therapy was the absence of double-blind and randomized trials [80]. Nevertheless, some studies point in the right direction claiming the effectiveness of neurofeedback for epilepsy compared to medication and placebo [81]. There is also some evidence about how neurofeedback is significantly more effective than ritalin in changing ADD/ADHD without having to remain on drugs [82]. Even more, other studies have found that neurofeedback has comparable improvements to those produced by ritalin even after only twenty 30 minutes session of neurofeedback [83]. Finally, with regard to depression, a recent study shows the results of a trial where depression patients were randomized into two groups: neurofeedback training group or treatment as usual [84]. Results found a significant reduction of depression symptoms of the patients of the first group and the effects were maintained the 2-month follow up.

1.2 Motivation

As we have seen, music therapy and passive music activities seem to be very effective when dealing with emotional disorders, like for example depression. On the other hand, neurofeedback is a technique which has recently started to show in double-blind and randomized trials his efficacy dealing with a wide variety of medical conditions, including also emotional disorders between them. Both therapies have shown encouraging results dealing with depression, anxiety, among many others. So, instead of trying to study which therapy is more effective than the other, an open perspective could make us see that they may not be exclusive therapies, but complementary.

The aim of this project is to create a neurofeedback system able to provide a musical feedback to the users. We want to preserve the emotional therapeutic effects of listening to music at the same time patients learn how to self-regulate their brain activity. Thanks to the development of new signal processing techniques applied to music, users could be allowed to manipulate expressive parameters in music performances using their own emotional state. These parameters could be used as an auditory feedback in a neurofeedback session. We can imagine two different approaches: to use specific songs chosen by the patient, allowing him to manipulate expressive parameters or, to synthesize music in real time through the EEG activity of the patient. In this work we will focus on the first option.

1.3 Proposed Goals

- To build an open and compact musical neurofeedback software, manageable, usable and easy to configure it for different therapies.
- Revise experimentally which specific features extracted from the EEG of the users contain more valuable information describing their emotional state.
- Do a pilot trial in patients with depression.
- Discuss our work and highlight what is needed for future work.

1.4 Organization of the thesis

We provide an extensive background in chapter two. There, we explain some of the most important concepts needed to understand the rest of the thesis along with a brief state of the art for each one of them. In the first part of the second chapter we explain what is EEG, what it exactly measures and how. We also provide a brief review of the research that links different brain waves with different mental states. In the second part, we present neurofeedback as a therapy and review some of the different neurofeedback protocols used to treat depression. The third part is a review of different studies which tried to classify emotions combining EEG with machine learning techniques, comparing different methodologies and finding out which are the most important features used in emotion recognition. In this part we also provide a brief review about some limitations the current emotion recognition algorithms have. Finally, we make a review of similar musical neurofeedback software made in the past, providing an explanation about their methodology and showing the results obtained.

In chapter three, we talk about all the materials used providing an explanation about the reason why we decided to use them and describing their strengths and weaknesses. Not only all the tools we have used to design the software but also those tools we used during the evaluation process.

In chapter four, we describe in detail, all the design of the musical neurofeedback software. Showing an schematic process of the system, together with screenshots of the GUI. We also explain in detail the use we did of the different toolboxes along with some of the most important aspects of the code.

In chapter five, we talk about all the different evaluation processes. In this chapter we explain the methodology used for the experiments and for the clinical cases along with the results and its corresponding discussion.

Finally, in chapter six we summarize how we have achieved each one of our proposed goals and present suggestions for future work.

2. Background

2.1. Electricity in our brains: Electroencephalography (EEG) and brain waves

2.1.1- Introduction

The first human EEG was recorded by Hans Berger in 1924 [1]. Berger was a German psychiatrist and neurologist, with strong convictions about the existence of telepathy, who wanted to find evidence about the correlation between objective activity of the brain (what he called "psychic energy") and subjective psychic phenomena [2]. After failing into his attempts to find a correlation between temperature and psychic activity, Berger considered that the electrical activity of our brain should necessarily generate brain waves which could be detected with electrodes placed on the scalp of the patient.



Figure 2.3 Hans Berger. The father of the electroencephalogram (EEG) [3]

This is how Berger became a pioneer in the use of EEG and, even more, he was the first to describe a predominant emerging rhythm of our brain [4]. This rhythm oscillated between 7.812 and 13.28 Hz when subjects had their eyes closed and it was replaced by a faster one when subjects opened their eyes. He also ascertained how this phenomenon was reproduced in response to other sensory stimuli, which made him to conclude that those waves should be the fundamental activity of the cortex. Today, we call to these brain waves "alpha waves", also known as "Berger's waves". Since then, the scientific community has found a wider variety of different brain waves associated with different subjective phenomena.

2.1.2.- Classification of brain waves

Brain waves can be classified into different sub bands. Although there is no agreement in standard reference works on what these ranges should be, we can deal with these approximate values for practical purposes:

- **Delta waves:** First described in 1930 by William Grey Walter with oscillations up to 4Hz. They are associated with the N3 slow-wave sleep in adults [5] but also during some continuous-attention tasks [6]. They are also seen normally in babies as they have showed to spent a great deal of time in slow-wave sleep [7].
- **Theta waves:** Between 4 and 7 Hz, theta waves are associated with drowsiness and arousal in adults and teens, but also with meditation states [8]. They are also seen in situations when a person is trying to repress a response or action (inhibition of elicited responses) [6].
- **Alpha waves:** Between 7 and 14 Hz, alpha waves are reduced with open eyes, drowsiness and sleep and it is thought that could inhibit areas of the cortex not in use or play an active role in network coordination and communication [9]. Alpha waves became very popular with the creation of a biofeedback theory which connected alpha waves with relaxed mental states [9].
- **Sensory Motor Rhythm (SMR) waves:** Between 13 and 15Hz, SMR waves overlap with alpha waves. It has been observed that they are stronger during states of immobility and they decrease during motor tasks or even during motor imagery [13]. These waves became very important in neurofeedback, after the work of Barry Sterman, because supposed a new way for treating epilepsy [25].
- **Beta waves:** Between 15 and 30 Hz, beta waves are linked to motor behavior and are generally attenuated during active movements [11]. They are associated with normal waking consciousness and it is the dominant rhythm in patients who have their eyes open. Despite, it has also been associated with anxious thinking and active concentration [12].
- **Gamma waves:** Between 30 and 100 Hz, gamma waves are thought to be associated with the purpose of carrying out a certain cognitive or motor function [13].

In the next table there is a summary of the given contents related with the different EEG bands (Table 2.1).

	Location in the brain	Correlation with subjective phenomena	Important papers
Delta waves (up to 4Hz)	Either in the thalamus or in the cortex	N3 Slow-wave sleep in adults and during some continuous-attention task. Seen normally in babies	[5] [6] [7]
Theta waves (4-7Hz)	Cortex	Drowsiness and arousal in adults.	[6]

		Meditation states. Inhibition of elicited responses	[8]
Alpha waves (7-14Hz)	Posterior regions of head, both sides and in C3-C4 (10-20 system) at rest.	Relaxed mental states	[9] [10]
SMR Waves (13-15Hz)	Sensorimotor cortex	Stronger during states of immobility. They usually decrease in amplitude when sensory or motor areas are activated.	[13] [25]
Beta waves (15-30Hz)	Frontally and in both sides.	Normal waking consciousness. Anxious thinking and active concentration.	[11] [12]
Gamma waves (30-100Hz)	Somatosensory cortex	Carrying out a certain cognitive or motor function	[13]

Table 2.1 Summary of Brain waves

2.1.3- The 10-20 system

As we have seen, depending on the location of the scalp where electrodes are placed, a different kind of brain waves can be found. This is the reason why, a standardized method to describe and apply the location of scalp electrodes was needed in order to compare different studies and subjects over time; i.e. to allow studies to be duplicated correctly (reproducibility).

In Figure 2 we can see an example of "The 10-20 system" [15]. The reason for its name is because the actual distances between adjacent electrodes are either 10% or 20% of the total front-back or right-left distance of the skull. Each circle represents the location of the electrode on the scalp, which also has a letter to identify the lobe and a number to identify the hemisphere location. "F" stands for frontal, "T" for temporal, "C" central (used for identification purposes), "P" for parietal, and "O" for occipital lobe. Odd numbers refer to those electrodes on the left hemisphere, while even numbers for those on the right. "A" refers to the earlobes and "Fp" to the frontal polar.

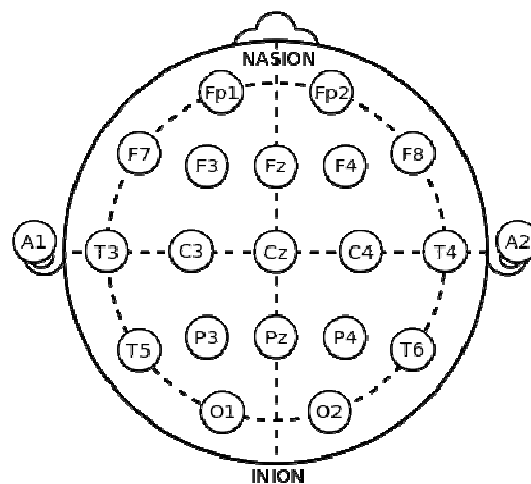


Figure 4.2 The 10-20 system [14]

"Nasion" and "inion" are two anatomical landmarks which are used for essential positioning of the EEG electrodes. The nasion is the depressed area between the eyes, just above the nose, while the inion is the lowest point of the skull from the back of the head.

In search of more resolution, others systems, like "The 10-5 system", have been also proposed [16].

2.1.4- Advantages and Disadvantages

The emergence of high-resolution anatomical imaging techniques like magnetic resonance imaging (MRI) and computed tomography (CT) have reduced the use of EEG for certain tasks. Nevertheless, EEG still continues to be a valuable tool with many advantages. In this section we are going to consider different advantages and disadvantages of the use of EEG.

Advantages

- Costs: EEG is cheaper than other techniques [17].
- Very high temporal resolution: Unlike other techniques, EEG has a temporal resolution of the order of milliseconds rather than seconds. This is the most important reason why EEG is the best option for neurofeedback purposes.
- It has tolerance to the movements of the subject: although movement artifacts are also a problem in EEG data, some methods exists for minimizing and even eliminating them [19].
- It is silent: this feature allows us to study better the responses of the auditory stimuli.

Disadvantages

- Low spatial resolution on the scalp: other techniques like fMRI allow us to recognize which areas of the brain are active, while EEG data requires intense interpretation [20].
- Poor measures of activity below the cortex.

- Long time to connect a subject to EEG: although the use of low-cost EEG devices can dramatically reduce this time [21].
- Poor signal-to-noise ratio: that is the most important reason why large numbers of subjects are needed in order to extract useful information from EEG [22].

2.3. Neurofeedback

2.3.1 History

In 1958, Joe Kamiya was the first person who began conducting experiments with EEG in order to investigate if subjects had the ability to distinguish, in a subjective way, which kind of waves were being generated by their brain [23]. The experiment was composed of two different parts. During the first part, subjects were asked to close their eyes in order to avoid interferences in EEG due to blinks, and to respond several times randomly if they thought they were in alpha state or not. After each response, subjects were told if they were right or wrong. What Kamiya noticed was that although subjects initially would get between fifty percent of correct answers, they were able to distinguish between the different states with training [24]. In the second part of the experiment, in order to test if subjects were able to achieve alpha state according to the desire, subjects were asked to go into alpha when a bell rang once, and not to go when a bell rang twice. Results proved that some subjects learned how to control their mental states.

Kamiya also designed a device which generated a sinusoidal tone when alpha state was reached by the user. The device worked as a reward system in order to motivate subjects to learn how to reach into alpha and the main interesting part of the device was his continuous (real time) feedback which allowed subjects to self-regulate. The reason why alpha waves were chosen for the experiment was because they were associated with relaxed mental states and it was thought that alpha training could alleviate anxiety, stress or other related conditions. So, the use of EEG signal as feedback to treat medical conditions received the name of neurotherapy or neurofeedback (as it was considered a type of biofeedback).



Figure 2.5 Joseph Kamiya. The father of neurofeedback. [28]

However, it was not until the 1970s when scientists like Barry Sterman and Joel Lubar showed to the world that the potential of neurofeedback was greater than imagined. Barry Sterman discovered that the training of SMR waves could reduce in humans the frequency of epileptic seizures [26], and Joel Lubar that the same training also conducted to great results in attention deficit disorder and hyperactive disorder in children [27]. The results in those last two areas were often better than those obtained with pharmacological treatments or classic psychotherapy [33]. That is the reason why actually, neurofeedback is especially applied in those cases.

Nonetheless, the use of neurofeedback used to have many barriers. Probably one of the most important was the cost. Neurofeedback required expensive and sophisticated systems which are no longer essential since the popularity of the PC during the 90s. Today, neurofeedback is starting to be very common in a wide range of activities. There are up to three organizations in the world dedicated to neurofeedback:

- ***The Association for Applied Psychophysiology and Biofeedback (AAPB)***: It was the first one founded in 1969. It is a non-profit organization that aims to promote biofeedback.
- ***The International Society for Neurofeedback and Research (ISNR)***: Founded in 1991, it was first called *The Society for the Study of Neural Regulation (SSNR)*. It is a non-profit organization for the promotion of self regulation of brain activity for healthier functioning and for professionals pursuing research.
- ***The Biofeedback Foundation of Europe (BFE)***: Established in 1996, it is a non-profit organization. It aims to promote a greater awareness of the field and to educate clinicians in the use of the latest biofeedback techniques.

2.3.2 Treating Depression with Neurofeedback

Davidson [34] summarized a robust body of research documenting that there is an association between depression and an activation difference between the right and left prefrontal cortex. A large number of other studies, summarized by Davidson [35] [36], demonstrate that the right hemisphere is associated with negative emotions and left frontal area with more positive affect and memories. A frontal asymmetry where the left area is less activated (which implies that there is more left frontal alpha activity) could mean that there is a biological predisposition to depression. Infants of depressed mothers have been found to display the same reduced left frontal activation [37].

The strongest tradition in the field of neurofeedback for depression is the protocol ALAY by Rosenfeld and collaborators [38] (standing for alpha asymmetry; F4-F3/F3+F4, with a reference electrode at Cz). The protocol uses a bipolar montage with active electrodes over F3 and F4 active sites (10-20 system). Still, if we take a look at the literature we can corroborate the existence of two clinical tendencies: rewarding inter-hemispheric alpha asymmetry [39][40][41] and rewarding the reduction of the Theta/Beta ratio in the left pre-frontal cortex [42][43].

The first trend focuses on the training of alpha predominance in the right prefrontal cortex and the decrease of alpha activity in the left pre-frontal cortex, in order to invert the commonly

observed Alpha predominance to the left in depression. On the other hand, the second trend aims to reduce Theta activity in relation to Beta in the left prefrontal cortex. Machado Dias and Van Deusen [44] found that both protocols are potentially complementary and offered a new protocol based on that new perspective.

2.4. Recognizing emotions with EEG

2.4.1 Introduction

One important area of research which has been in continuous growth during these last 10 years, and it is also a complementary tool for neurofeedback, is the use of EEG for emotion recognition. In [45] three real-time EEG-based emotion recognition systems are proposed for entertainment and medical applications such EEG-based music therapy software. There are different music therapies offered by the software such pain management and depression but the general music therapy can be described as follows: first, a music player starts reproducing music in order to evoke a target emotion in the patient. The emotion state of the patient is continuously analyzed by his real-time EEG signal, and if the software finds that the current song is not helping to evoke the targeted emotion it changes to another one. The process is maintained until it finds a song in accordance to the targeted emotional state. As we see, it is the reverse process from that given in neurofeedback. In this case, the patient is passive and it is the software who works actively using the EEG signal of the patient as feedback.

2.4.2 How to classify emotions.

When dealing with emotion recognition systems we can find in the literature two different perspectives that allow us to address the problem: discrete and dimensional models [46]. Using one model or another will determine the taxonomy used. Discrete models rely on the assumption that one emotional state is well defined and it can be fully differentiated from the rest, the objective of systems that use discrete models is to label and recognize different emotional states. For example, the work of Ekman et al [47] revealed a relationship between facial expression and emotions and found an association between facial expressions and six different emotions: anger, disgust, fear, happiness, sadness and surprise. Another approach is advocated by Plutchik [48] which defines eight basic emotions stages: anger, fear, sadness, disgust, surprise, anticipation, acceptance and joy. We can find then, other emotions like for example disappointment which can be formed by basic ones like surprise and sadness.

On the other hand, from the dimensional perspective, the bipolar model is the most widely used considering the arousal and valence dimensions. Thereby, we can represent emotions in a dimensional space called the Arousal and Valence Plane (Fig 4). This approach advocated by Russell [50] consists in a two-dimensional space. We have the arousal dimension, where the state of the patient changes from not aroused to excited, and the valence dimension where the state changes from positive emotions to negative emotions. As we can see in Figure 2.4, an excited state with positive emotions could lead to emotions like happiness, while a negative emotion with high arousal to a stressed state.

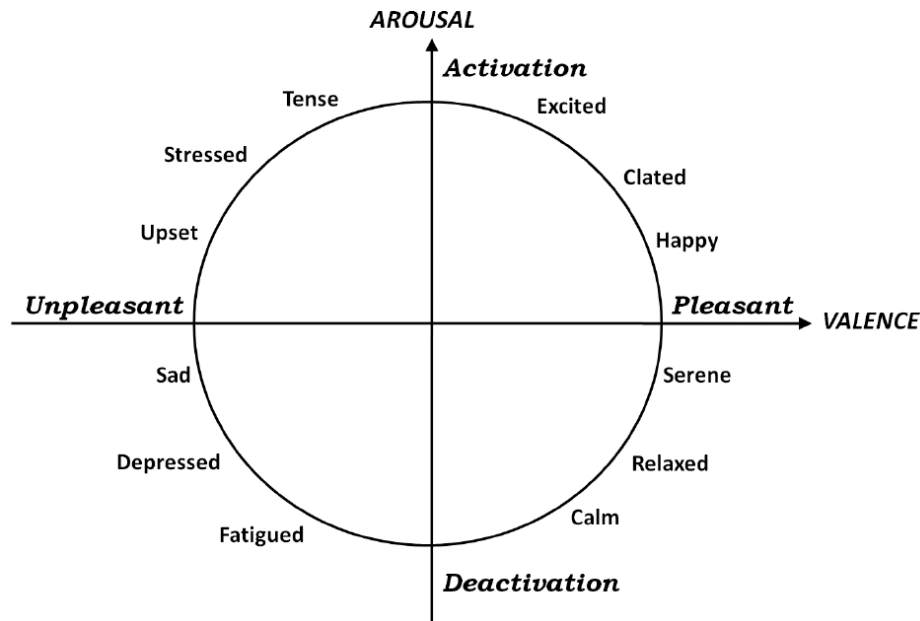


Figure 2.6 The Arousal and Valence plane. From the dimensional perspective, emotions can be represented in a dimensional space [49].

Until now, dimensional models seem to be the preferred one in emotion recognition systems due a very simple advantage: it can locate discrete emotions in its space even when no particular label seems to describe a certain feeling [51].

2.4.3 Induction Emotion Experiments

In order to obtain the data used to classify and recognize emotions, we need to induce those particular emotions in experiments carried out with different kind of stimuli as audio or visual. Lin, Y.P et al [52] used a collection of pre-assessed music pieces in order to induce emotion to 26 subjects and collect EEG-data. IADS database [53] is a labeled database of audio stimuli which has been used by Bos, D.O [54] in order to induce four kind of emotion states from the arousal and valence plane such as positive/aroused, negative/aroused, negative/calm and positive/calm.

For experiments with visual stimuli we have the IAPS database which uses pictures as stimuli [54]. For example, Savran, A. et al worked in the eINTERFACE project [55] and created a database using pictures selected from IAPS and three emotional stimuli like exciting/positive, exciting/negative and calm state. They published a database with the EEG data labeled which has been used by other studies like, for example, in Khalili, Z. et al [56]. In that study, they combined correlation dimension with statistical features which improved the results from 66.6% to 76.66%.

On the other hand, we have the work of Takashi, K. [57] where audio and video are combined and films are selected as stimuli.

2.4.4 Important EEG features used for emotion recognition

In 2000, Choppin [10] used neural networks to classify up to six emotions based on arousal and valence, with a 64% success rate. He also detected some influential EEG features during various emotional stimuli:

- **Valence:** Positive emotions are characterized by a higher frontal coherence in alpha, and a higher right parietal beta power, compared with negative emotions.
- **Arousal:** Excitation is characterized by a higher beta power and coherence in the parietal lobe, plus lower alpha activity.
- **Dominance:** The strength of an emotion is generally expressed in the EEG by an increase of the beta/alpha activity ratio in the frontal lobe, plus an increase in beta activity at the parietal lobe.

As we see, alpha and beta wave activity seem very important in order to detect arousal and valence states of mind in humans. Recognizing those states is something especially important because it could allow us to represent a specific emotion in the Arousal and Valence plane.

Those results are also consistent with techniques used for treating depression with neurofeedback by trying to increase positive emotions in patients [35].

Lin, Y., P. et al [52] used short-time Fourier Transform to calculate the power difference between 12 symmetric electrodes pairs with 6 different EEG waves for feature extraction and Support Vector Machines to classify 4 emotional states (joy, anger, sadness and pleasure). The result was 90.72% accuracy. They also found that most relevant features were primarily derived from electrodes placed near the frontal and the parietal lobes, consistent with the results of Choppin [10].

2.4.5 Limitations of Emotion Recognition Algorithms

Although this field has been in continuous growth as we have said in the introduction, EEG-based emotion recognition is still a new area of research. Liu, Y. et al [45] warn that the effectiveness and efficiency of those algorithms, however, are somewhat limited. In their work, they show a list with some unsolved issues in current algorithms:

- **Time constrains:** Authors emphasize that most of the algorithms were proposed for off-line recognition. The performance time consists from the feature extraction until the classification. The number of electrodes is another time constrain in the algorithm.
- **Accuracy:** Accuracy decreases when the number of emotions to recognize increases.
- **Number of electrodes:** The number of electrodes should be reduced in order to reduce not only the amount of features to process as commented before, but also to reduce the time to set up the EEG device, and to improve the comfort of the users.
- **Number of recognized emotions:** Only limited types of emotions can be recognized using EEG. The best performance was achieved by Petrantonakis, P.C. et al [60] using only 3 channels with a 83.33% of accuracy achieved for differentiating 6 emotions.
- **Benchmark EEG affective databases:** Very few benchmark EEG databases with labeled emotions are available. We need more EEG databases with visual or audio stimuli to be set up for future researches.

2.5. Musical Neurofeedback

2.5.1 Introduction

Until now, the most typical neurofeedback systems use visual feedback. In order to make it friendly (specially for children), the feedback could be, for example, a spacecraft travelling through a virtual world increasing speed (positive feedback) or decreasing speed (negative feedback). Even so, there are some projects who, taking advantage of the breakthrough of musical technologies, have tried to introduce music as feedback. The work of Ramirez et al in *Musical neurofeedback for treating depression in elderly people*[21] is not only unique in his area, but is also the match point of this work. In this chapter we are going to enter in detail about the different aspects of his work.

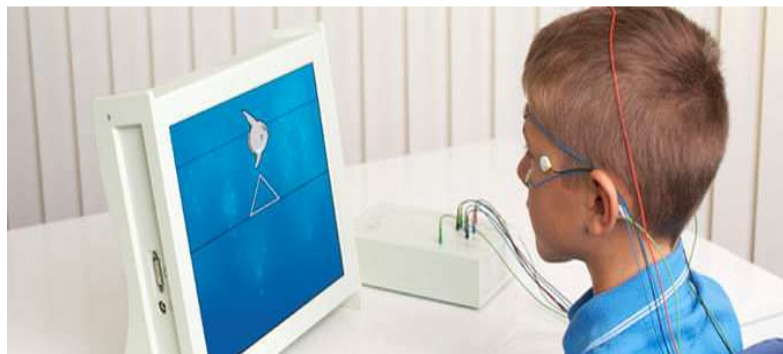


Figure 2.7 Neurofeedback with visual feedback [28]

Ramirez et al [21] proposed a neurofeedback approach based in music, in which users could manipulate expressive parameters in music performance using their emotional state. It presented positive results of a pilot clinical experiment designed to alleviating depression in elderly people.

There is ample literature about the benefits of music especially for older adults. Hays and Minichiello [31] for example, suggest that music promotes self-esteem, feeling of competence, independence and also diminishes the feeling of isolation in elderly people. On the other hand, Maratos et al. [30], highlight the potential benefits of music therapy for improving mood in people with depression. This is the reason why musical neurofeedback seems to be especially efficient in this specific case. Anyway, its potential benefits in other areas are yet to know but should not be slighted.

2.5.2. The Software

The user's instantaneous emotional state, decoded from their EEG activity, will be characterized by a coordinate in the arousal-valence plane (see Figure 2.6). During a musical neurofeedback session participants are encouraged to increase their arousal and valence in order to reach the top-right quadrant in the arousal-valence plane. One particular way of doing it, is tuning the system so that increased *arousal* corresponded to increased loudness, and increased *valence* corresponded to increased tempo

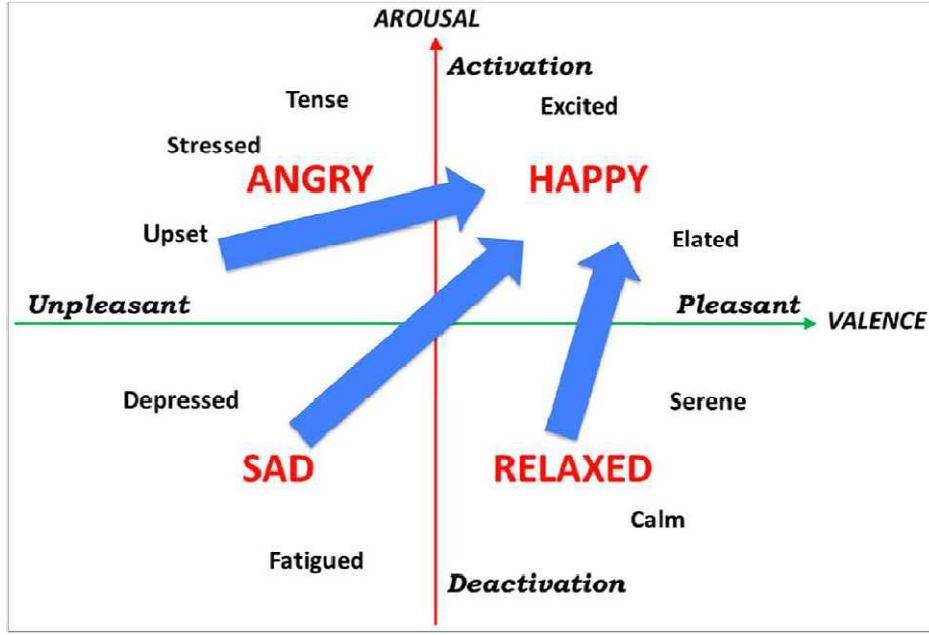


Figure 2.8 Participants are encouraged to increase their arousal and valence in order to reach the top-right quadrant in the arousal and valence plane. [21]

The EEG processing is going to be adapted from Ramirez and Vamvakousis [31] where the signal is measured with four electrodes in four different locations in the pre-frontal cortex and using the Beta/Alpha indicator, in order to map the arousal state of a person, while valence is computed by comparing the alpha power of two electrodes located also in the pre-frontal cortex.

$$Arousal = (\beta F3 + \beta F4 + \beta AF3 + \beta AF4) / (\alpha F3 + \alpha F4 + \alpha AF3 + \alpha AF4)$$

$$Valence = \alpha F4 - \alpha F3$$

Then, computed arousal and valence values will be fed into an expressive performance system based on a music performance model obtained by training four models (corresponding to happy, relaxed, sad and angry) using machine learning techniques [32]. The expressive performance system calculates appropriate expressive transformations, like could be on timing, loudness and harmonicity, in function of the emotional state registered by the EEG data of the participant. In order to obtain intermediate models between the four models commented before, the coefficients of those models are interpolated as we can see in Figure 2.7.

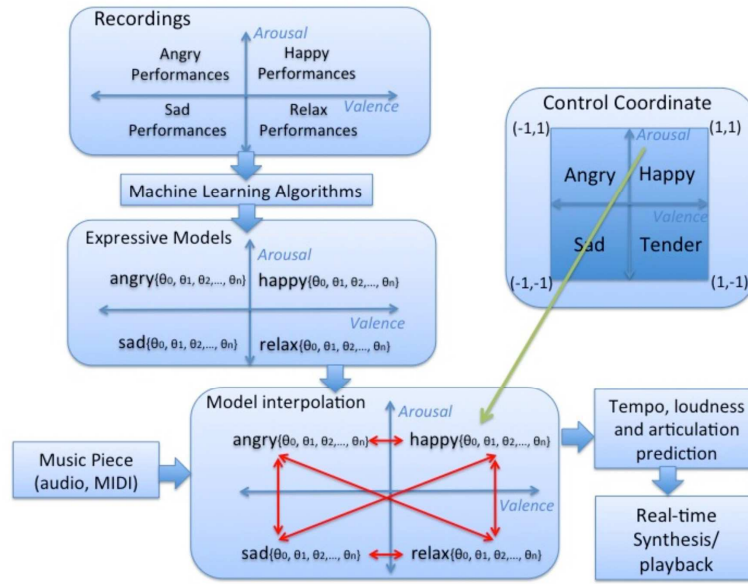


Figure 2.9 First the system is trained with four models corresponding to different emotional performances using machine learning algorithms. Then, the models are interpolated in order to obtain intermediate performance and different prediction parameters. [21]

2.5.3. Method

Participants were interviewed prior the first session in order to determine the music used during the session according to their musical preferences. Later, before starting the session participants were asked about which different game they would like to play, to sit in a comfortable chair in front of a pair of loudspeakers and, in order to minimize artifacts in the signal, to close their eyes and avoid movement. The session lasts 15 minutes and, during that time, participants were encouraged to increment a certain type of parameters (which depended on the game chosen) in function of the level of arousal and valence recollected from their EEG.

Participants could choose between two different modalities. Between the expressive performance system or, another different modality where the system reproduced songs in a way that, increased *arousal* corresponded to increased loudness, and increased *valence* corresponded to increased tempo. Most of the patients preferred that last modality because it allowed them to choose their favorite songs for the therapy.

2.5.4. Results

At the end, 7 participants completed the training requiring a total of ten 15 min session of neurofeedback, but only six were able to answer the BDI depression test. The BDI evaluation showed an average improvement of 17.2% (1.3) in BDI scores at the end of the study. The difference between valence of the participants before and after the experiment was statistically significant. As the authors said, there was no control group considered for this pilot study due to the limited number of participants.

3.Materials

3.1 Introduction

In order to reach our goals, the decision about which materials to use is something vitally important. In this chapter we are going to talk about the all the devices and open software we have used during the design of our musical neurofeedback system. We will start talking about the EEG device we decided to choose, which is a low-cost EEG called Emotiv Epoc [85]. The code will be made in Matlab R2013a [86] and we will talk about the Fieldtrip Toolbox [87], which is a Matlab software toolbox for EEG analysis which offers the possibility to analyze EEG in real-time and to create applications for Brain Computer Interface (BCI) thanks to the use of an external buffer. We will also talk about the TSM Toolbox[87], which contains Matlab implementations of various time-scale modification algorithms, and about the DSP System Toolbox[86], which in collaboration with the TSM Toolbox it will allow us to reproduce and alter musical parameters in real-time.

3.2 Emotiv Epoc

The Emotiv Epoc (Figure 3.1) is a low-cost EEG device, with prices between 500\$ and 600\$ (depending on the SDK), which validity has been proven by independent studies like *Detecting Emotions from EEG signals using the Emotiv Epoc device* [31] and many others you can find on the official website [85]. It is very easy to fit and it works with saline based wet sensors instead of needing sticky gels; making it a very attractive proposal for our work because that reduces dramatically the time needed to connect a subject to EEG.



Figure 3.10 The Emotiv Epoc device [85]

It consists of 14 electrodes and 2 references electrodes, located and labeled like according to the 10-20 system [15]. The available locations are: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4 as you can see in Figure 3.2. It has a sampling rate of 128 SPS and 14 bits resolution. The EEG signals are transmitted wirelessly to a laptop computer.

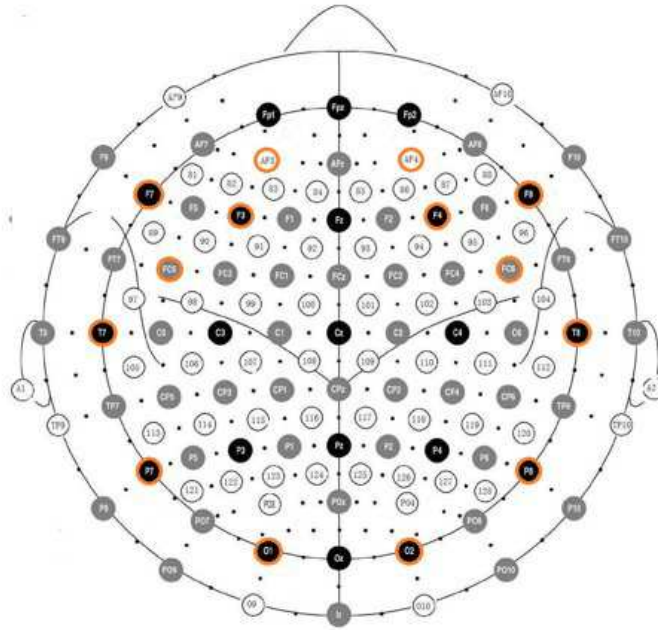


Figure 3.11 Emotiv Epoc Headset electrode positioning

3.3 Matlab Toolboxes

3.3.1 Fieldtrip Toolbox

FieldTrip Toolbox is an open source software for MEG and EEG analysis that is being developed at the Donders Institute for Brain, Cognition and Behaviour in Nijmegen, the Netherlands [87]. Although it is primarily developed for offline analysis, it can be used for real-time data analysis thanks to the use of an external buffer (the FieldTrip buffer) which is used to communicate between separate application programs. The acquisition program will write the data to the buffer while other programs can connect to read the data from the buffer. Matlab spends time when analyzing data in real time, and during that time, the new data coming would get lost. That is the reason why we need an external buffer to store the new coming data (more information about the communication protocols used by this buffer can be found at the official website [87]).

Still, one of the main important reasons why we decided to develop the neurofeedback system in Matlab, was because Fieldtrip offered an interface between the 14-channel Emotiv neuroheadset and the Fieldtrip Buffer. They provide a standalone tool called *emotiv2ft* to retrieve data from the headset and stream it to a Fieldtrip Buffer.

3.3.2 TSM Toolbox

The TSM Toolbox developed by Jonathan Driedger and Meinard Müller [87] contains Matlab implementations of various time-scale modification algorithms like OLA, WSOLA, HPSS and a phase vocoder. The wsola algorithm, will be the preferred algorithm to use for our application as it is able to time-scale the signal without affecting the pitch and without a considerable processing load.

As we will see, to control this algorithms in real time will make our musical neurofeedback system more interesting. Time-scale algorithms give the feeling that the tempo of the music is going up or down which is a more interesting musical feedback rather than just raise o lower the volume of the music.

3.3.3 DSP System Toolbox

The DSP System Toolbox offers algorithms for a wide range of algorithms for analyzing signal processing systems in Matlab [86]. With this toolbox we can also model real-time DSP systems and reproduce and alter wav files in real-time, making it an attractive proposal for our work.

3.4 IADS Database

The International Affective Database Sounds (IADS) is a large set of standardized, emotionally-evocative, internationally accessible sound stimuli [53]. IADS is being developed and distributed by the Center for Emotion and Attention (CSEA) at the University of Florida. They used a three dimensional model of emotions called the Self Assessment Manikin (SAM), which allows to assess the dimensions of pleasure, arousal and dominance. Each sound stimuli has a coordinate in this three dimensional space which is the averaged opinion of 100 users.

The use of this library is especially useful for the design of induction emotion experiments. Ramírez and Vamvakousis [31] used this library to detect emotions using the Emotiv Epoc device just as we will do in chapter 4.4. If we want to test which EEG feature is the most important one when trying to recognize a certain emotion in subjects, we need first to evoke those emotions in a wide variety of subjects. That is the main reason why more databases of this kind are needed.

3.5 Weka

The Waikato Environment for Knowledge Analysis is a free software machine learning tool (licensed under GNU General Public License) written in Java developed at the University of Waikato, New Zealand. We will use this tool in chapter 4.4 to create a classifier that will allow us to recognize emotions in users and to test between different machine learning techniques, which one is the most appropriate for our purposes.

4. Method

4.1. Introduction

In this chapter we are going to enter in detail about the design and operation of our musical neurofeedback software implemented in Matlab. First, we will explain the different processes occurring one after another while the system is working and we will show the appropriate flowcharts for its better comprehension. Secondly, we will show the General User Interface (GUI) explaining its operation and covering all its possibilities. And finally, we will go deep into the code explaining the most important functions and processes, but also explaining which has been the use given to some external libraries.

4.2. Workflow description

4.2.1 Previous steps

In Figure 4.1 we can see a basic flowchart of our system. There, we can see the flow of the different processes which take part before starting with the musical neurofeedback process.

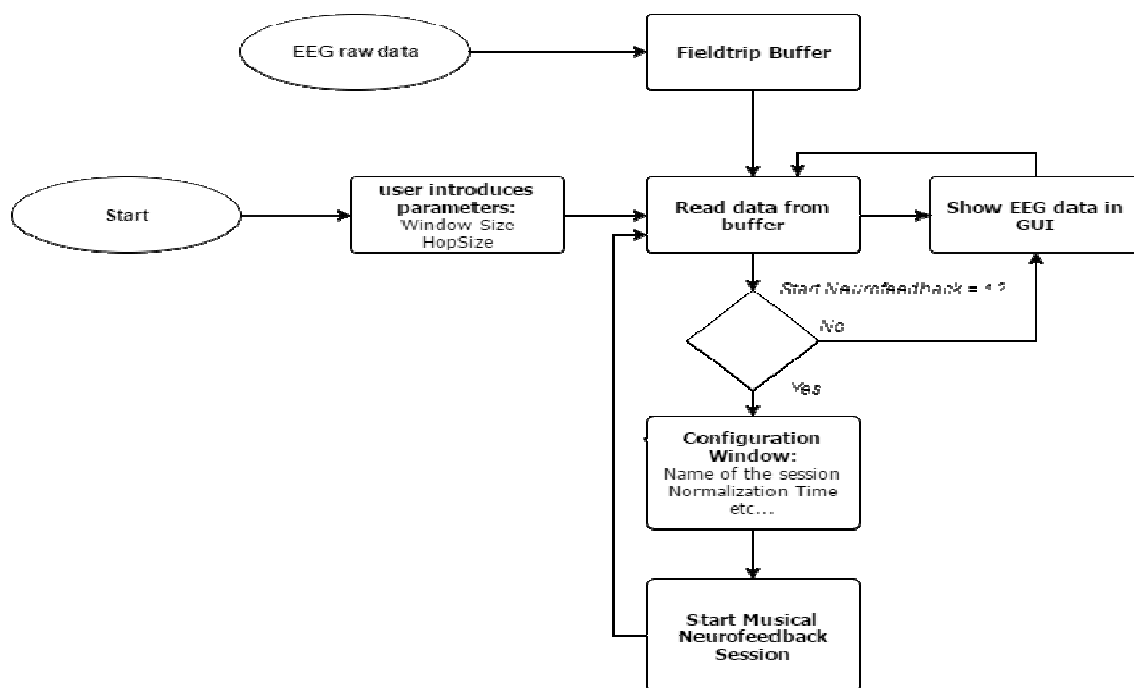


Figure 4.12 Flowchart of the previous steps of our musical neurofeedback system

First, when the user runs the software, he has to introduce some important parameters that will determine how the system analyzes and processes the new data that is continuously arriving from the EEG. This data is previously stored in the Fieldtrip Buffer in order to assure the correct real time operation of the system.

Once the first coming data has been read, an user interface is opened where the real time flow of data acquired from each electrode is shown in a graph, so the user can confirm that the

system is actually capturing data correctly. In this same GUI there is a pushbutton called Star Neurofeedback Session. When pressed, the configuration window is opened, and the user can choose the desired configuration for the neurofeedback session (name of the session, the chosen song, normalization time, electrodes used, etc.). After all the needed parameters have been specified the musical neurofeedback session starts.

4.2.2 Musical Neurofeedback

In Figure 4.2 we can see the musical neurofeedback flowchart.

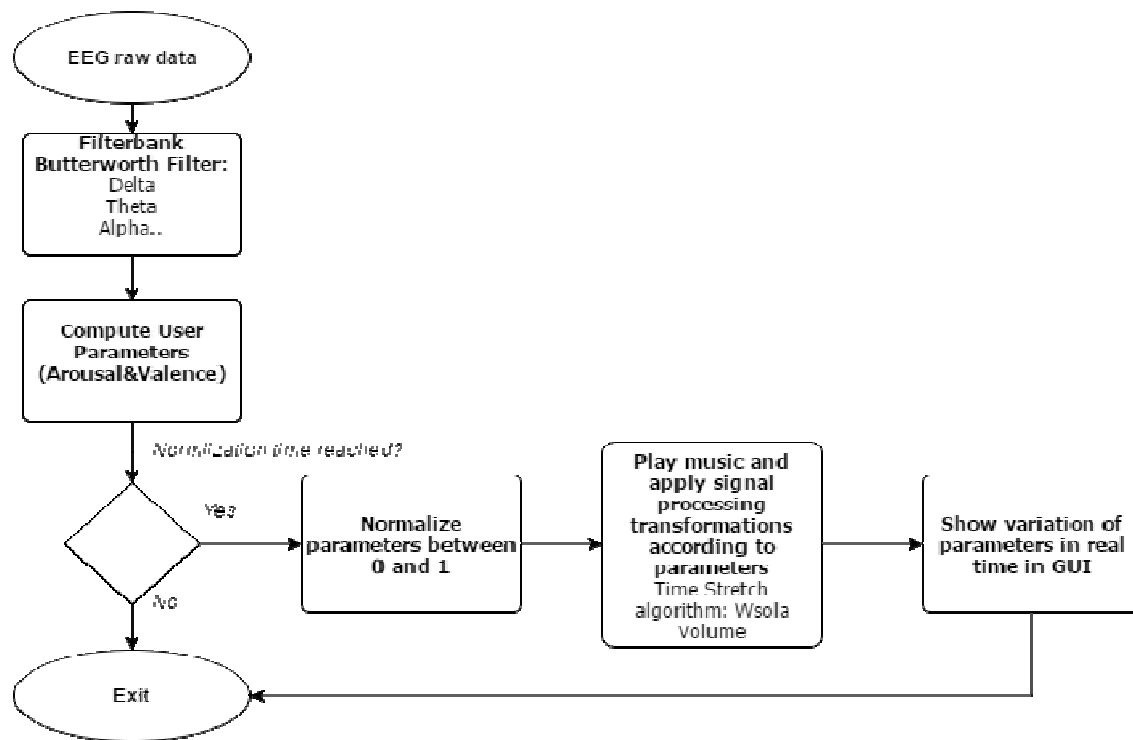


Figure 4.13 Musical neurofeedback flowchart.

Once all the configuration parameters are specified the musical neurofeedback session starts running. First, all the data goes through a filterbank butterworth filter where the energy related to the different frequency bands specified (alpha, beta, theta...) is computed. After this step, we use the energy values obtained to compute the chosen parameters (like Arousal or Valence) and we store them until the normalization time is reached.

After the normalization time is reached, we use all the captured values to normalize all the next coming values between 0 and 1. This normalized value will be to used apply signal processing transformations to the chosen songs. In this system we offer two possibilities: altering the volume of the music (minimum volume at 0, maximum volume at 1) or, using time stretch algorithms like Wsola in order to alter perceptually the bpm of the song (minimum bpm at 0, maximum bpm at 1). Finally, the variation of all the parameters is shown in a GUI which also offers the possibility to stop or restart the neurofeedback session.

4.3. General User Interface

The first thing that appears on screen when someone runs the software is a configuration window where the user has to select some initial parameters like the window size or the hopsize that is going to be used during the signal processing step. We can see in Figure 4.3 how it looks like.

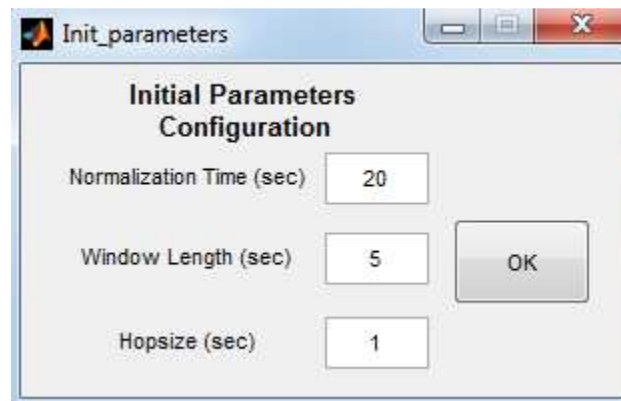


Figure 4.14 Initial parameters configuration window

If the chosen hopsize is not long enough, the delay obtained will be bigger since the processing time may be longer than the hopsize. On the other hand, a really long hopsize will give us problem maintaining the real time flow, since the processing time will be finished before the arrival of the next step. At the same time, we have to take into account that, when computing the parameters, we compute the energy of the whole window. So, when the difference between the length of the window and the length of the hopsize is considerable bigger, we will see smooth changes in the computation of our parameters, while if the window length and the hopsize is similar we will probably see more dramatic changes.

In Figure 4.4 we can see the Title Window. Here we can choose and see the received signal in each electrode and the amount of energy located in each frequency band.

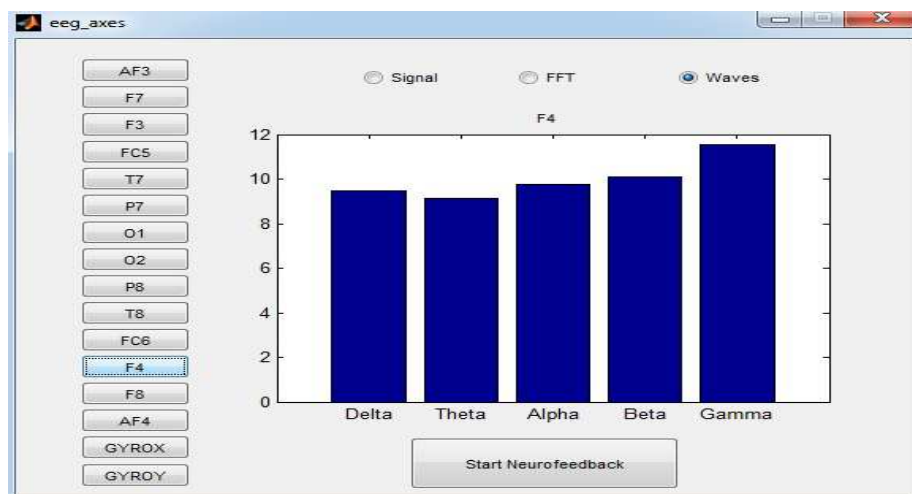


Figure 4.15 Title Window

When user pushes the Start Neurofeedback button a window appears asking the user to name the neurofeedback session. It is important to name the session because, after it, a folder with that name will be created, and all the data recorded during the session will be stored there for future purposes.

Once the user has chosen a name for the session, then the Configuration Window is opened. In Figure 4.5 we can see how it looks like.

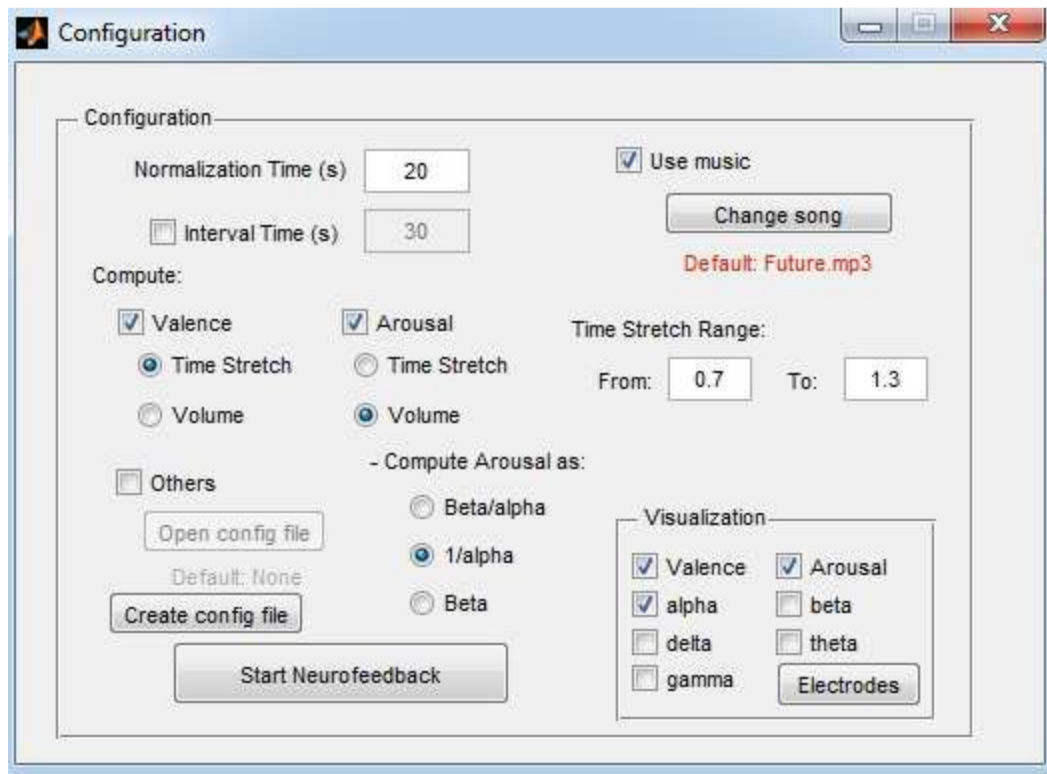


Figure 4.16 Configuration Window

As we can see, in the Configuration window we can select if we want to use music or not and, in the case we want, we can change the song by default and choose another one. We can also choose if we want any Interval Time or not. If we choose an Interval Time of 30 seconds, then we will receive a message every 30 seconds during the therapy. This option could be interesting for some kind of experiments where the experimenter want to realize more than one exercise during the same session and it is important to control time. We can change the Time Stretch Range, which means, that we can exaggerate more or less the change in bpm between both extremes of the normalization values.

In the lower right corner, we can choose which frequency bands want to visualize and store in the session folder at the end. If we click in the Electrodes button, we can choose also for each frequency band which electrodes want to visualize. In Figure 4.6 we can see the window that is opened when we click in Electrodes.

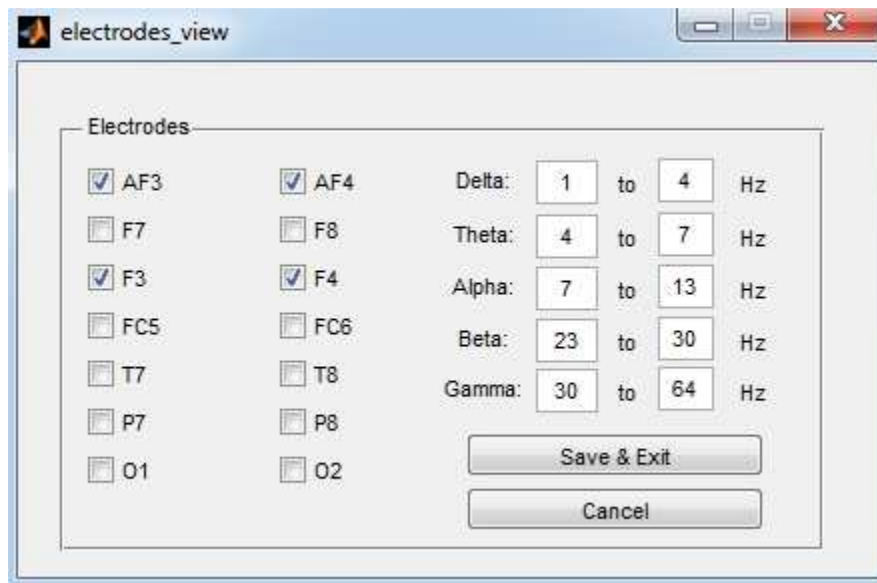


Figure 4.17 Electrodes Window

In this window, we can choose which electrodes we want to visualize but also, we can configure by ourselves the range to which each frequency band belongs. When the neurofeedback session is finished, a folder with the name of the session is created and we can see inside of it different graphs, each one for each frequency band, with the power evolution found in each electrode. In Figure 4.7 we can see an example.

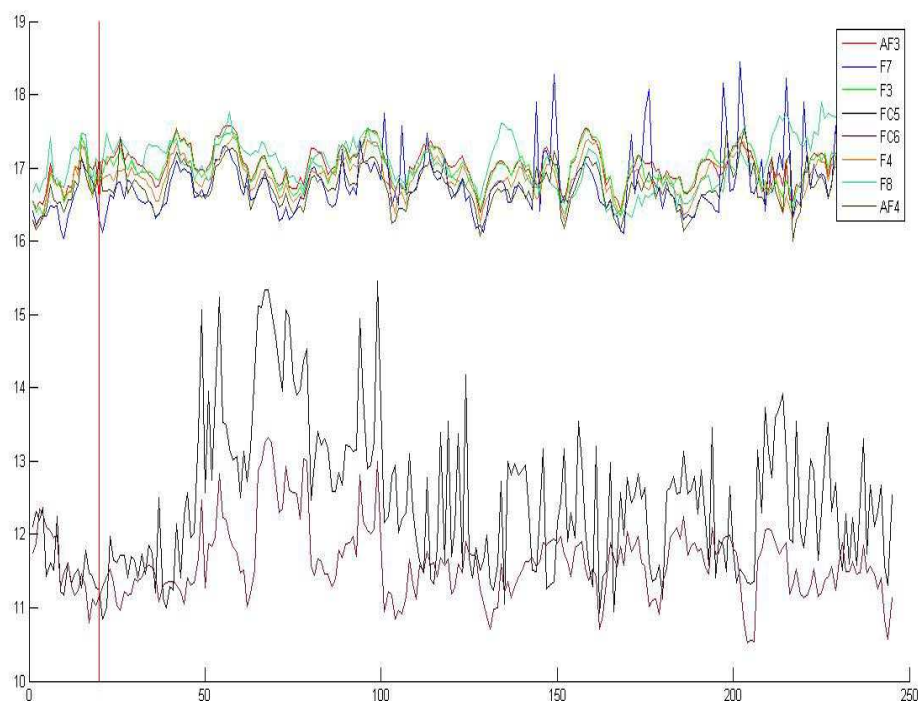


Figure 4.18 Neurofeedback session of 250 seconds

In this graph is represented, for each electrode, the alpha power obtained there. The red vertical line that appears on the left part of the graph corresponds with the normalization time, which in this case was 20 seconds. In the session folder, we will find a graph like this one, for each frequency band selected.

Returning to the configuration window, in Figure 5, we can choose which parameters we want to compute. By default, we can choose between Valence and Arousal, and for each one of them, we can select if we want to control Time Stretch or Volume. At the same time we can decide between different ways of computing Arousal.

Even so, one of our main goals of this project, was to build a musical neurofeedback software manageable, and easy to configure for different therapies. It is because of that reason, that we offer the possibility to the user, to configure his own parameters. If the user clicks on the *Create config file* button a new window as the one we can see in Figure 4.8 will appear.

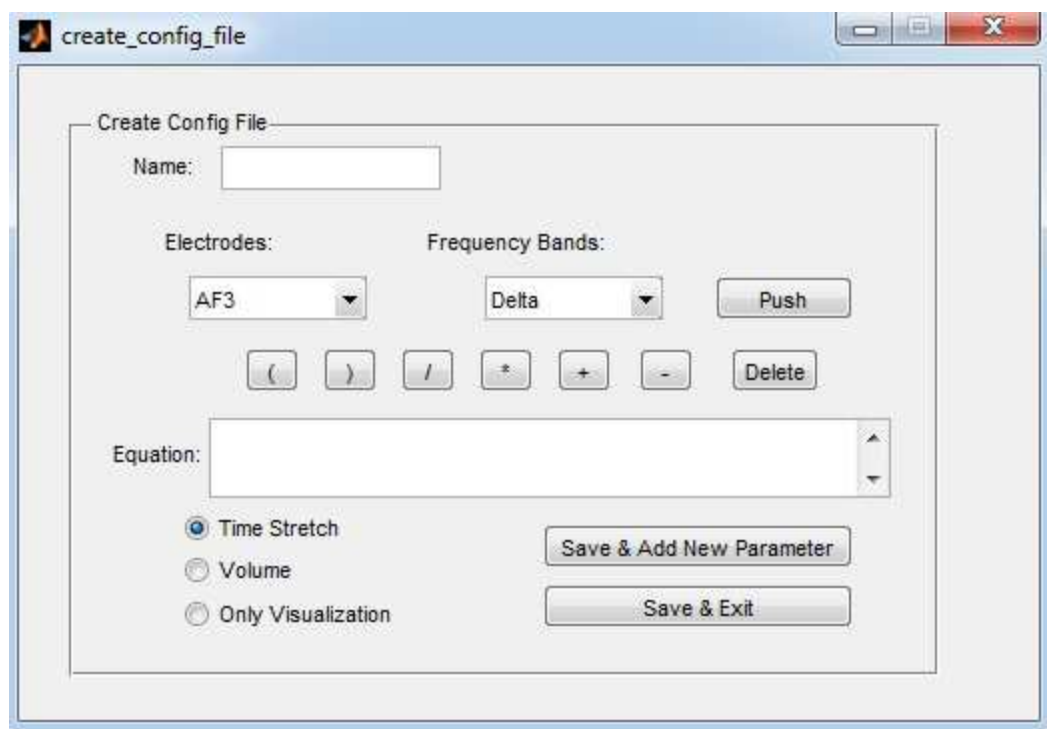


Figure 4.19 Create Config File Window

In this window, the user can configure different parameters for his purposes. He has to choose which name the parameter will have, and after that he has to write the equation for the different electrodes and frequency bands using the Push button. Then, the user has to decide if this parameter is going to control the Time Stretch process, the volume process or it is limited to be displayed. If the users wants to add a new parameter, he has to push the button *Save & Add New Parameter* or, if he wants to finish and create the config file he has to click on *Save & Exit*.

Finally, a .txt file will be created in the same folder with a name chosen by the user. The file will have the next structure:

```
Concentration          %Name of the parameter
(AF3(Delta)*F3(Theta))-F4(Beta) %Equation
V                      %V for Volume, TS for Time Stretch
----- %OV for only Visualization
Valence
F4(Beta)-F3(Beta)
TS
-----
```

If we want to load a certain configuration file, we have to click on *Others* in the Configuration window (Figure 5) and push the button *Open Config File*, then we choose the desired configuration file and the musical neurofeedback software will work according to our specifications.

Once we are ready and we have configured everything we needed, then we push the button *Start Neurofeedback* and the session will start. We will see the next window shown in Figure 4.9.

In this window we have all the most important information used during the therapy displayed for the experimenter. In each column, we have the information relative to those parameters used by the user, like could be in this case Arousal and Valence, but also information about how the normalization value has been computed. Each slider is actualized after the new information has arrived with its corresponding value normalized between 0 and 1. As we can see, the user is able to mute the Time Stretch transformation by clicking in the checkbox called Tempo and also to mute the Volume transformation. If the experimenter suspects that there was noise during the normalization process, this GUI offers the opportunity to renormalize and start the song again. In case the experimenter wants to finish the session before the end of the song, he has to push the *Stop and see the record* button, and the session will finished and the resulting data will be displayed and saved in its corresponding folder.

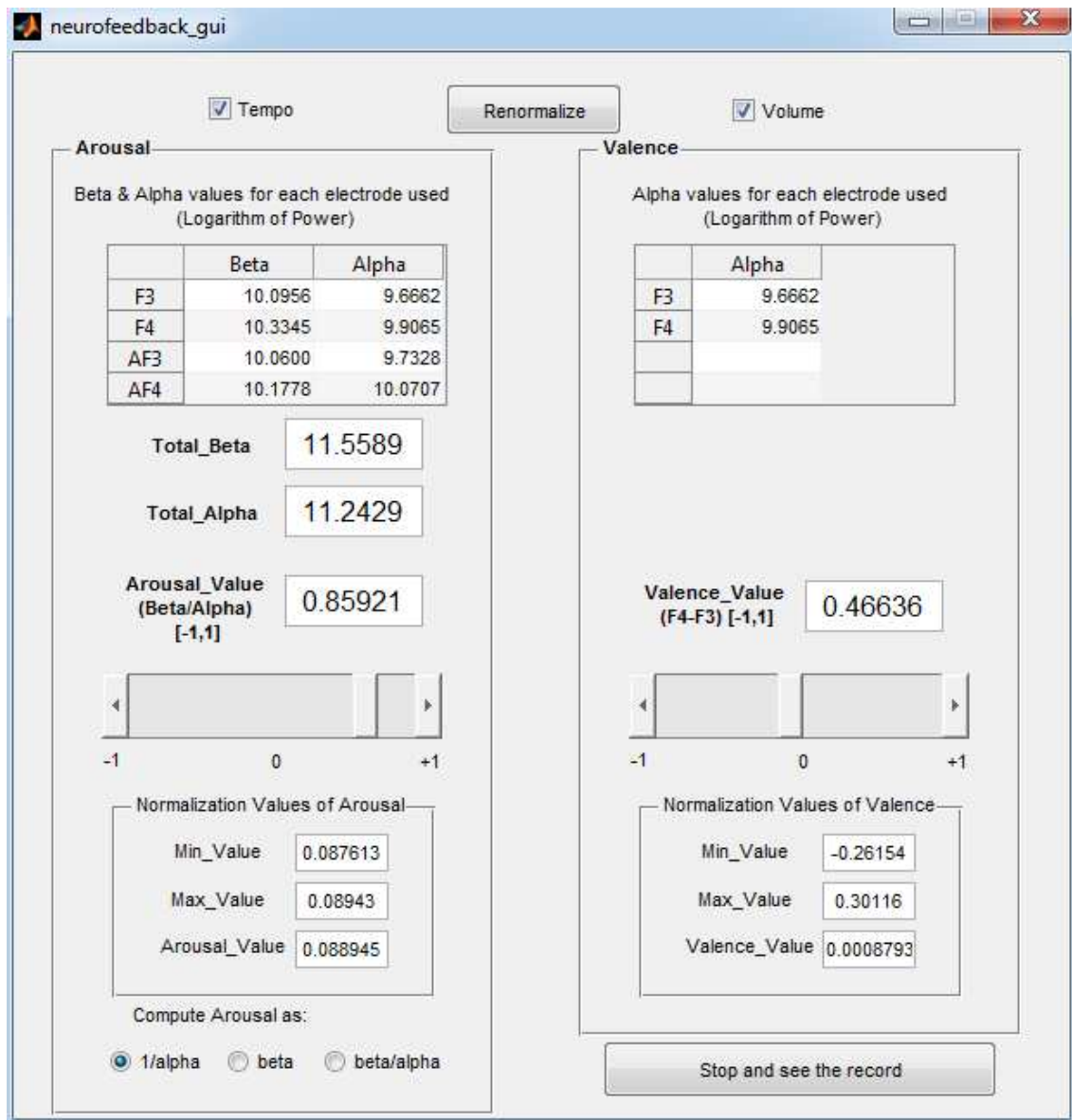


Figure 4.20 Musical Neurofeedback GUI

4. 4 Software design

4.4.1 The Fieldtrip Buffer and the *emotiv2ft* tool

With respect to code, we needed to allow Matlab to receive the raw EEG data captured by the Emotiv Epoc device. This was achieved by using the Fieldtrip Buffer Toolbox. In the *initialization.m* script from Matlab we can find the next lines of code.

```
addpath ../Neurofeedback\fieldtrip-20160111
addpath TSMtoolbox
ft_defaults
```



```
cd fieldtrip-20160111\realtime\bin\win32\
!buffer.exe &
!emotiv2ft emotiv_config.txt &
cd ..\..\..\..\
```

This is the initialization step of our code. Here we add the Fieldtrip Toolbox path but also the TSM toolbox path. The script *ft_defaults.m* has to be always executed before using any tool offered by the Fieldtrip Toolbox. In this case, we are working in Windows so, if we want to configure the Fieldtrip Toolbox in order to enable communication between the Emotiv Epoc device and Matlab we need to go to the *win32* folder inside *realtime* and execute first *buffer.exe*. This will allow the storing and retrieving of data in the buffer by means of fieldtrip functions and procedures available in the Fieldtrip Toolbox. Fieldtrip also offers a standalone tool called *emotiv2ft* which captures the data from the headset and stream it to the fieldtrip buffer. Data is always streamed out at the full sampling rate (128Hz). We call this tool in this way:

```
emotiv2ft <config-file> [hostname=localhost [port=1972 [ctrlPort=8000]]]
```

We can find the default config file in the same directory called *emotiv_config.txt*. When called only with the config-file argument, *emotiv2ft* will use the default settings shown.

Then, in the *read_data_eeg.m* script we capture data stored in the buffer by using the fieldtrip function called *ft_read_data*. We can see its reference documentation by typing *help ft_read_data* in Matlab.

FT_READ_DATA reads electrophysiological data from a variety of EEG, MEG and LFP files and represents it in a common data-independent format. The supported formats are listed in the accompanying **FT_READ_HEADER** function.

Use as

```
dat = ft_read_data(filename, ...)
```

Additional options should be specified in key-value pairs and can be

```
'header'          header structure, see FT_READ_HEADER
```

'begsample'	first sample to read
'endsample'	last sample to read
'begtrial'	first trial to read, mutually exclusive with begsample+endsample
'endtrial'	last trial to read, mutually exclusive with begsample+endsample
'chanindx'	list with channel indices to read
'chanunit'	cell-array with strings, the desired unit of each channel
'checkboundary'	boolean, whether to check for reading segments over a trial boundary
'checkmaxfilter'	boolean, whether to check that maxfilter has been correctly applied (default = true)
'cache'	boolean, whether to use caching for multiple reads
'dataformat'	string
'headerformat'	string
'fallback'	can be empty or 'biosig' (default = [])
'blocking'	wait for the selected number of events (default = 'no')
'timeout'	amount of time in seconds to wait when blocking (default = 5)

This function returns a 2-D matrix of size Nchans*Nsamples for continuous data when beevent and endevent are specified, or a 3-D matrix of size Nchans*Nsamples*Ntrials for epoched or trial-based data when begtrial and endtrial are specified.

The list of supported file formats can be found in [FT_READ_HEADER](#).

See also [FT_READ_HEADER](#), [FT_READ_EVENT](#), [FT_WRITE_DATA](#), [FT_WRITE_EVENT](#)

After reading data, we will want to extract only the size of the last window. So the code in Matlab for the script *read_data_eeg.m* will be:

```
%We read data from buffer
```

```
dat = ft_read_data('buffer://localhost:1972', 'begsample', begsample,
'endsample', inf);
```

```
%We take only the the size of the last window

actual_length = length(dat(1,:));

index_data = actual_length - Window_length_samples;
```

Where *Window_length_samples* is equal to $128 * \text{Window_length}$.

Still, we need to reach the *Window_length_samples* frontier in order to stream and process the EEG data correctly according to the user's configuration. That is the reason why in the *neurofeedback.m* script we check this inside the main loop.

```
%We wait until we have the full window we need to compute the
parameters

if actual_length > Window_length_samples

%Actualize buffer values

    actualize_begin_sample_index
```

Inside *actualize_begin_sample_index* we change the *begsample* value in order to start properly next time we read from buffer.

4.4.2 The main loop

Finally, the main loop will be as follows:

```
global start_neurofeedback

start_neurofeedback = 0;

%Start Loop (Control-C to stop it)

while ~user_stops

%Read & Show data from buffer
```

```

read_data_eeg

%We wait until we have the full window we need to compute the
parameters

if actual_length > Window_length_samples

%Actualize buffer values

    actualize_begin_sample_index

%Compute waves

    wave_computation

if ~start_neurofeedback

%Show GUI with EEG signal

    eeg_axes(signal, signal_filt_fft_a, signal_filt_fft_b,
signal_filt_fft_d...
        , signal_filt_fft_t, signal_filt_fft_g);

else

%Open Configuration window

    configuration_script

if strcmp('Yes', response)

if ready == 1

%Start Neurofeedback

    musical_neurofeedback

end

end

end

else

    ready = 1;

end

```

end

When the user pushes the button *Start Neurofeedback* then we call the *configuration_script.m* where the configuration window is opened. Once all the parameters have been adjusted and the user push the Start button (response = 'Yes'), we call to the *musical_neurofeedback.m* script and the neurofeedback session starts.

4.4.3 Configuration

One of the most interesting parts related to the configuration process are the processes related to the extraction of the equation from the config file, and how it is interpreted. When the user opens a new configuration file in the Configuration Window (Figure 4.5) it calls to the script *extract_equation.m*. There, all the values written in the equation are substituted by alphabetic letters ordered in the usual way {a,b,c,d...} and a string value where a representation of the equation is stored in this way: $@(a,b,c)(a*b)-c$. Finally, we also store in two different variables, for each value (a,b,c,...) two values; one related to a number assigned to the name of the electrode (for example, 1 to 'AF3', 2 to 'F7',etc.) and the other one related to the type of EEG wave (1 to 'Delta', 2 to 'Theta',etc.).

Finally all this data is stored in a cell array called *config_cell_param{}*, where each file represents a different parameter, and in each column stored the name, the equation, a matrix nx2 with the different values associated with the electrode and the waves and a string with 'TS', 'V' or 'OV' depending of the process the parameter is going to control. During the musical neurofeedback session, where each value of the equation is actualized, the final results for each parameter are computed in the *User_parameters_computation.m* script. Here, we use the *str2func* function to convert the equation string in a function handle and then, after computing for each electrode and each frequency band, the energy related to any different variable we compute the result of the equation.

```
fh = str2func(final_eq);

for j=1:length(var_electrodes)

    vars_aux{j} = waves_fft{var_waves{j}};

    vars_{j} = sum(abs(vars_aux{j}(var_electrodes{j},:)).^2);

end

mode = config_cell_param(i,5);

if strcmp(mode,'TS ')

    param_1(m) = fh(vars_{:});

else

    if strcmp(mode,'V ')

        param_2(m) = fh(vars_{:});
```

end

end

So, depending on the mode associated with each parameter we will compute the result for param_1 (which is the parameter that controls time stretching) or param_2 (the parameter that controls the volume).

4.4.5 Musical Neurofeedback

All the process carried out during the neurofeedback session is made in the *musical_neurofeedback.m* script, including the computation of the user's parameters explained in the last chapter. In the next lines of code we can see a review of all the different processes:

```
%We normalize data and start computing parameters for
%neurofeedback

if steps >= Window_length

% Computation of the user parameters extracted from the config file

    User_parameters_computation

% Normalization of parameter values

    Normalization

% Play & Modify Music parameters

    Play_alter_music

% Compute graphs for visual parameters

    Visualization_parameters_computation

% Time Intervals Computation

    Interval_computation

% Display results in real-time

    neurofeedback_gui(param_1(m),log_pot_beta, log_pot_alpha,...

        tabla_arousal,norm_param1, min_p1, max_p1, tabla_valence,...

        param_2(m), min_p2, max_p2, norm_param2, bol, arousal_path,
bol_end_song)

% Increase time counter

    m = m + 1;
```

```

% If user renormalizes, we re-start everything
if bol_renormalize || bol_end_song
    bolwaitbar = 0;
    bol = 0;
    param_2 = 0;
    param_1 = 0;
    m=0;
    bol_path_arousal = 0;
    arousal_path = 0;
    bol_renormalize = 0;
if hsin1 ~= 0
    %release(hsin1);
    release(Player);
end
    init_var;
end

else
    steps = steps + 1;
    waitbar(steps/Norm_time, h, [num2str(steps*hopSize) 'sec']);
end

```

The first step of this process is to compute the user parameters in order to normalize them later. Once the values have been normalized, we call to the *Play_alter_music.m* script in order to reproduce music in real time and alternate it with signal processing techniques.

In the script called *initialize_gen.m* we create an audio player object, *Player*, using *dsp.Audioplayer*, that will allow us to play audio samples using an output device in real-time.

```
[hsin1,fs] = audioread(nameFile);
```

```
framelength = fs*hopSize;  
Player = dsp.AudioPlayer('SampleRate', fs);
```

Now, in order to write audio to audio output device, we will use the step method with the audio in *y* as it follows.

```
step(Player,y);
```

On the other hand, we use the *wsolaTSM.m* method from the TSM Toolbox to time stretch our signal.

```
y = wsolaTSM(y, stretch);
```

As we can see, *y* is the audio signal we want to write, while *stretch* is the stretch value we want to assign and it depends on the normalized value between 0 and 1. By default, when the normalized value is equal to 0 the audio is stretched in a 1.3 factor, but when the normalized value is equal to 1, it is stretched in a 0.7 factor.

5. Evaluation

5.1. Introduction

In this chapter we are going to talk about the different experiments we realized in order to evaluate, not only the performance of our software from a user perspective, but also the validity of musical neurofeedback as a treatment for depression displayed in a clinical case with real patients.

In the first part we will present the methodology of an experiment realized with healthy users in order to determine whether musical feedback could be a powerful tool helping users to self-regulate their emotional states. In the second and third part, we present the results of various experiments realized in order to determine which features seem to reflect better the emotional state of the user. Finally, we will expose the methodology and the results obtained during a 7 days neurofeedback therapy on an adolescent with depression, accompanied by its corresponding discussion.

5.2. SystemEvaluation

5.2.1 Methodology

We tested our system with 15 subjects (9 male and 6 female) with an average age of 24 years. Subjects were instructed to remain seated with their eyes closed and avoiding movement while the Emotiv Epoc device was placed over their head even before the experiment started (in order to have correct normalization values).

During the experiment, subjects were asked to follow the orders of the instructor and to try to achieve the mental state requested by the instructor. After 30 seconds the subject had a 30 seconds rest to set a neutral emotional state before starting with the next exercise.

The emotional states the patients needed to reach were four: high valence, low valence, high arousal and low arousal. The order of the exercises was random and different for each subject. We can see the schematized process of the experiment in Figure 5.1.

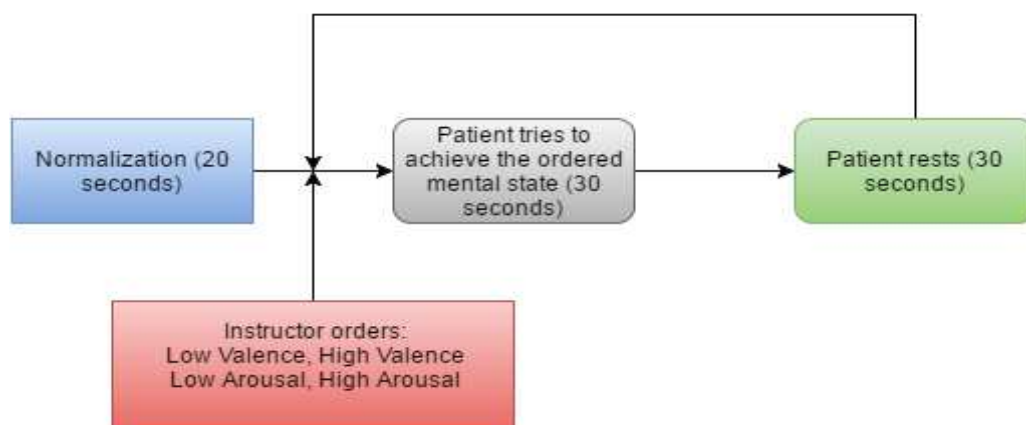


Figure 5.21 Schematized process of the experiment without music

After this, we repeated the experiment for each subject but using music feedback as reinforcement this time. Subjects chose a song and they were asked to modify different musical parameters as volume and tempo associated with different mental states. The different associations between music parameters and emotional states were represented in Table 1.

Musical Parameter	Emotional State	Direction
Volume	Valence	Increase volume --> High Valence
		Decrease volume --> Low Valence
Tempo	Arousal	Increase tempo --> High Arousal
		Decrease tempo --> Low Arousal

Table 5.2 Association between music parameters and emotional states

During the 30 seconds break between each exercise of both experiments, patients also rated how well they believed they accomplished the results in a 1 to 5 score.

For this experiment we computed Valence and Arousal as it follows:

$$Valence = \alpha F3 - \alpha F4$$

$$Arousal = \frac{1}{\alpha F3 + \alpha F4 + \alpha AF3 + \alpha AF4}$$

With a window length of 5 seconds and a hop size equal to 1 second.

5.2.2 Results and Discussion

We can see the results of the experiment with and without music in Table 1.

The percentage we see in the first column (Time > 0.75) is the time subjects reached their objectives while trying to achieve the ordered mental state. We have to remember that valence and arousal values are normalized before each session between 0 and 1. We considered an achievement the fact that the user was able to surpass the 0.75 barrier when trying to increase his arousal or valence, or to decrease them below 0.25 when ordered. We can then, compare the real performance of the users with the results of their self-evaluation in the other columns.

Without music	Time (>0.75 or <0.25)	Self-Evaluation Mode	Self-Evaluation Mean
Arousal	30%	3	2.66
Valence	14%	4	3.42
With music	Time (>0.75 or <0.25)	Self-Evaluation Mode	Self-Evaluation Mean
Arousal	26%	2	1.71
Valence	21%	1	1.57

Table5.3 Results with and without music

According to our definition of achievement, the probability of achieving the correct mental state by chance is 1/4. This means, that is difficult to extract any significant difference from the performance results when subjects were trying to regulate their mood by their own, or with the help of a musical feedback. What we found was a decrease in the score of their self-evaluation, suggesting that they trusted more in the feedback provided by the system (which most part of the time was not in harmony with the mental state they tried to achieve) rather than in their own judgment.

Considering the results we can extract three different conclusions:

- We are using bad emotional state indicators. There are other different indicators found in the literature for Arousal or Valence which have not been taken into account.
- Subjects were incapable to self-regulate their emotional state (at least in just only 30 seconds).
- Both

In the next evaluation experiments we are going to try to study empirically all these issues.

5.3. Evaluation with a Yoga Kundalini teacher

We thought that in order to test our hypothesis it should be interesting to study the brain of an expert meditator during meditation. If we assume that the brain during meditation is in a state of profound relaxation (low arousal) and great satisfaction (high valence) then, we should

be able to extract useful information about which features are the most important when trying to characterize those mental states.

We recorded one minute of the brain activity in normal state and another one during meditation of a Yoga teacher from the Kundalini branch. Results corresponding with the difference in alpha and beta power can be seen in Table 5.2 and 5.3.

Arousal	Beta Waves (AF3,AF4,F3,F4)	Alpha Waves (AF3,AF4,F3,F4)	Beta/Alpha (AF3,AF4,F3,F4)
Power difference	-15%	+6%	-20%

Table 5.4 Power difference between brain activity in a normal state and during meditation.

Valence	$\alpha F4 - \alpha F3$	$\beta F3/\alpha F3 - \beta F4/\alpha F3$
Power difference	+5.6%	0.645%

Table 5.5 Power difference between brain activity in a normal state and during meditation.

What we can see in Table 5.2, is the power difference between brain activity in a normal state and during meditation of three different arousal indicators. As we can see, each indicator seems to represent well the direction of the mental state. In this case, it seems that arousal could be better represented by taking into account the high decrease of power in the beta band rather by an increase of power in alpha band. This could give us the clue that we should not underestimate the beta reduction as an indicator for arousal and thus the indicator Beta/Alpha seems to be the best option.

On the other hand, what we can see in Table 5.3, is that the power difference between both hemispheres before and during meditation was not as significant as with arousal indicators although power difference was shown in the right direction. What we can extract from these results is that the difference of power in beta, could play a less important role than alpha when trying to detect valence.

Still, we need many more subjects in order to conclude something about which valence indicator is the best one. At the same time, our first assumption that meditation offers great satisfaction and high valence values during the process of meditating could not be true and that is the reason that could explain such a small power difference. In the next chapter, we will introduce a new methodology that will allow us to clarify our doubts.

5.4. EEG feature evaluation for valence

In *Detecting emotions from EEG signals using the Emotiv Epoc device* [31], Ramírez and Vamvakousis proposed a mood induction procedure, based on emotion-annotated sounds from the IADS library [53], in order to record valuable EEG data from subjects using the Emotiv Epoc device. In Figure 3 we can see an illustration of the different steps of their approach.

After the experiment they trained a classifier with the following form:

- $ValenceClassifier(EEGdata([t, t + c])) \rightarrow \{positive, negative\}$

Where $c = 1$ second and $t = 0.625$. They also estimated the valence value in a person using alpha and beta asymmetry:

$$valence = \beta F3/\alpha F3 - \beta F4/\alpha F4$$

As we see, even with the good results obtained (80.11% accuracy with SVM), one of the most important limitations of this previous work, regarding our unknowns, is the comparison between different valence estimators. In this chapter we are going to reproduce the previous work adding all the considered modifications we need.



Figure 5.22 Schematic view of the system [31]

5.4.1 Methodology

The method we used did not differ excessively from [31], so we are going to focus on the main differences (Table 5.5).

Ramírez and Vamvakousis, 2012	This work, 2016
6 healthy subjects (3 males and 3 females) with average age of 30.16	7 healthy subjects (4 males and 3 females) with average age of 26.57
Subjects were instructed to look at a cross in the computer screen and to do not blink or move.	Subjects were instructed to close their eyes and to do not move.
12 sound stimuli were randomly presented each one for five seconds and a 10 second silent rest is inserted between stimuli. Sound stimuli were situated on each one of the extremes of the arousal/valence plane.	6 sound stimuli were randomly presented each one for five seconds. Users also listened to music chosen by them with a considered high-valence evoking potential. After each stimuli (including the chosen music), subjects were instructed to rate their valence value during the stimuli in a 1 to 5 score, being 3 a neutral value. Sound stimuli were chosen from the extremes of the valence values.
c=1 second and t = 0.625 seconds	c = 1 second and t = 0.1 seconds
<p>Estimation of valence according to:</p> $\beta F3/\alpha F3 - \beta F4/\alpha F4$	<p>Estimation of valence according to different indicators:</p> $\beta F3/\alpha F3 - \beta F4/\alpha F4$ $\beta F3 - \beta F4$ $1/\alpha F3 - 1/\alpha F4$ $1/\theta F3$ <p>Then, with the use of attribute selection techniques we choose the best indicator for each subject.</p>
<p>Classifiers used:</p> <p><i>SVM with linear Kernel</i></p> <p><i>SVM with Radial Basis Function</i></p> <p><i>LDA (Linear Discriminant Analysis)</i></p>	<p>Classifiers used (in Weka):</p> <p><i>NN Neural Networks</i></p> <p><i>SVM with Radial Basis Function</i></p> <p><i>J48 Decision Tree</i></p>

Table5.6 Table of differences between the methodology used in this experiment compared to Ramírez and Vamvakousis , 2012.

As we can see, there are some main differences that deserve an explanation. First, during the performance of the experiment, we found that some subjects found funny some sounds, from the IADS library, which were rated with a negative valence value. This fact, made us to considerate asking the users to rate their valence value during the stimuli, in order to discard useless data. We also found, how some sounds rated with a high valence value, were actually excerpts from classical music. As we know, music can shift frontal EEG in depressed adolescents which means, that music could be a powerful tool evoking positive emotions in subjects. Even so, each particular subject has its own well-defined music preferences, and we thought, that the inclusion of classical music in the IADS library could have a certain Western bias. That is the other reason why, we decided to include music chosen by them in the experiment.

The second difference, relates to the way we estimate valence. As we have seen, we still don't know exactly which indicators or which frequency bands give us the most valuable information when characterizing the valence dimension. Thanks to the use of attribute selection techniques like Information Gain Ratio together with the method Ranker in Weka, we can decide, between different features, which one could give us the better classification accuracy. This is the reason why, we have decided to compute different valence indicators, in order to check first, using attribute selection algorithms, which one is the best feature, for later, training a classifier using that specific one.

5.4.2 Results & Discussion

Classification accuracies for each subject can be seen in Figure 4. Each bar represents the accuracy of each one of the used classifiers in Weka (SVM, NN or J48).

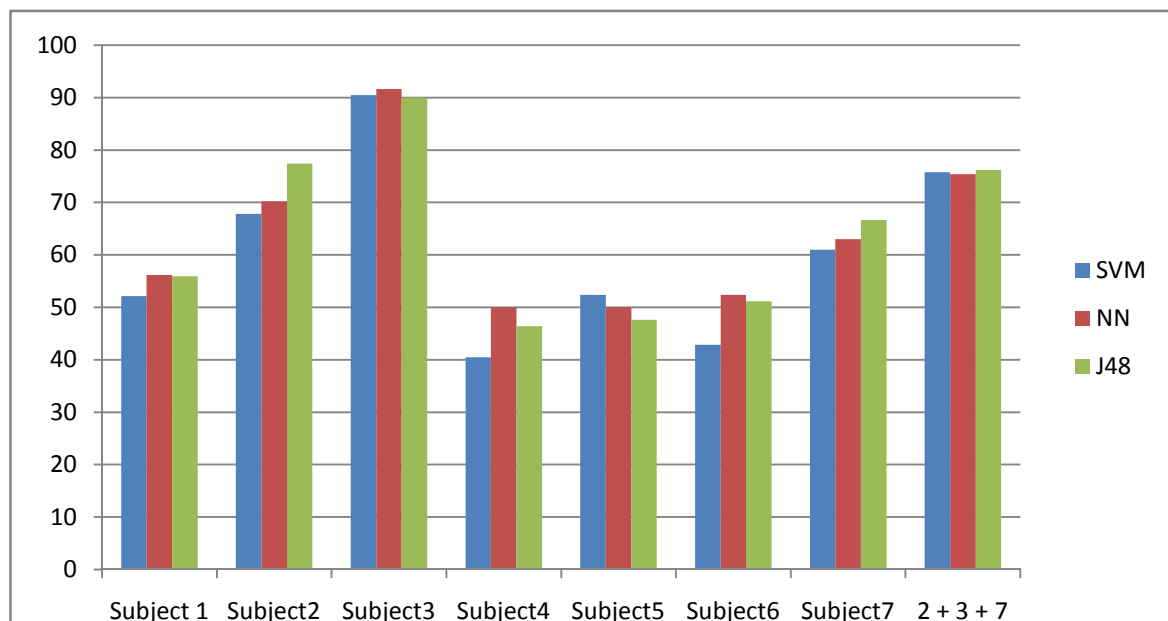


Figure 5.23. Classifiers accuracies for positive versus negative valence for all subjects.

As we can see, results were not as good as expected. For subjects 1, 4, 5 and 6 results were around 50%. Given that we are dealing with two-classification task and that the number of instances for each class is the same, it means that we were not able to find any significant difference between the two classes, using the chosen classifiers with the best attribute chosen with InfoGain and Ranker.

On the other hand, subjects 2,3 and 7 gave us significant results (77.381%, 91.66%, and 66.66% respectively with J48 decision trees). For all of them, the attribute selected as the best option was:

$$1/\alpha F3 - 1/\alpha F4$$

Which means that, Beta asymmetry or Theta power values in the left hemisphere, could not contribute to the recognition of valence values in subjects, while Alpha asymmetry could.

The last column named 2+3+7, is the result of the sum of all the different data from those subjects. Again, the best selected attribute was Alpha asymmetry with an accuracy of 76.19% with Decision Trees.

The fact of obtaining the same attribute for three of our subjects could be an important step in recognizing Alpha asymmetry as the most important indicator of valence we may know until the moment. Still, we need more subjects in order to test if it is true. Also, we may need to use more different sound stimuli to subjects (12 instead of 6 for example) in order to acquire more valuable data. Using only a half of the number samples used by Ramírez and Vamvakousis we obtained a lot of variability in the results, going from 50% until 91%. The sensitivity of people regarding to the sound stimuli can vary a lot between them, and adding more sound stimuli could smooth the results.

5.5. Musical Neurofeedback for depressed adolescents: evaluation of a clinical case

In this section we offer a description of the methodology and the obtained results of seven 20 minutes sessions of musical neurofeedback with an adolescent diagnosed with depression.

5.5.1 Methodology

Our patient was 15 years old and female. She was diagnosed with depression and borderline personality disorder six months before the treatment. During the first sessions and before starting with the treatment, she presented the usual activation difference between the right and left prefrontal cortex that, as documented by Davidson [34], people with depression often show, and this is exactly what we tried to change. We used alpha asymmetry as the parameter that controlled the feedback because, as seen in chapter 4.2, was the best valence representation we found.

We recorded her valence state, one minute before and after each session in order to track the evolution of the difference of her valence state before and after each treatment. But still, our main goal, was not only trying to shift that alpha asymmetry but also to track the percentage

of time our patient is able during the sessions to achieve her goals, which could be a good indicator that she is learning how to regulate by herself his own brain activity.

The feedback we used for the sessions was chosen by her, and the aim was to increase the tempo of the song. We worked with 4 songs per session which were also chosen by her (the style consisted mostly in reggaeton and bachata), except during the three last sessions where we decided to introduce some "neutral music". The reason we decided to do that, was because although her frontal asymmetry was shifted during and after the session (as we will see in the next chapter), her training values were not changing. This fact made us think that she was not learning how to self-regulate her brain activity during the sessions but just showing the typical results of someone who is just listening to her favorite music.

5.5.2 Results and Discussion

We present the results of the seven 20 minutes sessions of musical neurofeedback with our subject in Figure 5.5.

In this figure we are representing the average alpha power difference (in Dbs) between 1/F3 and 1/F4 before, during and after each neurofeedback session. We think it could be interesting, to explain this data in context and related with the feedback we received from our subject. During the first and the second session, we found a negative frontal asymmetry before starting the session (in consonance with Davidson [34]), and we can see how her was able to shift her frontal EEG during the musical treatment. Valence values were always higher during the session than those recorded before and after without music, even though valence values recorded after the session were always higher than those recorded before. She said to us before starting Session 2 that she was specially sad that day, and we found that valence values recorded before the session corresponded with that, being even lower than those recorded before the first session.

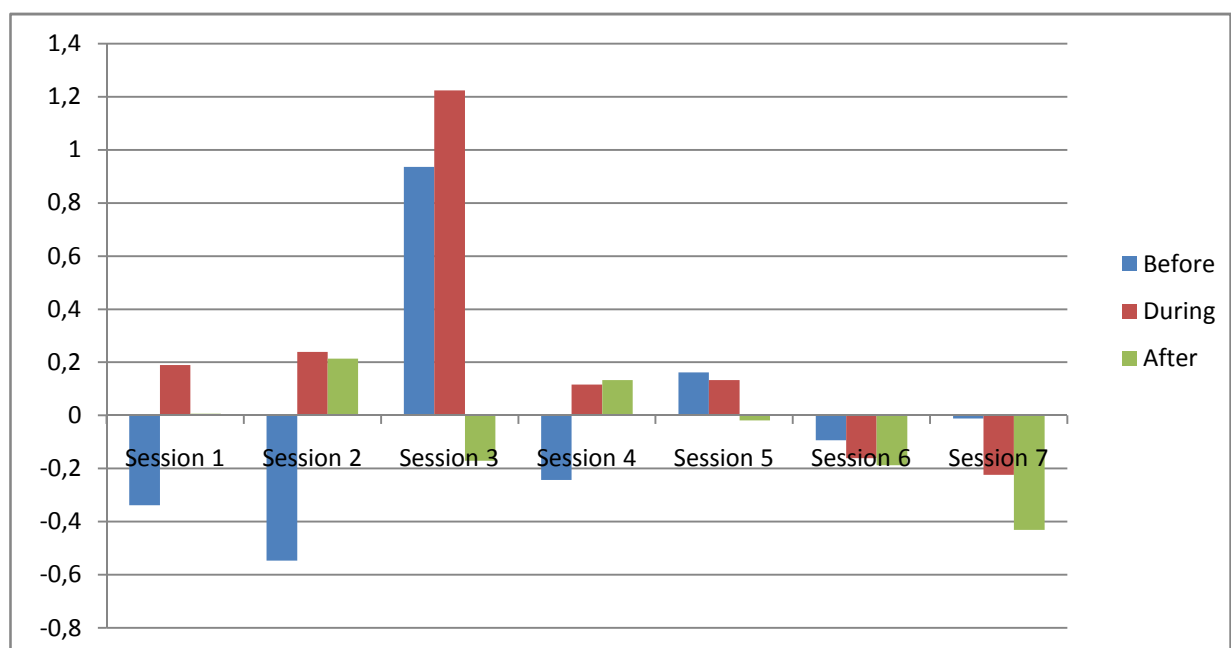


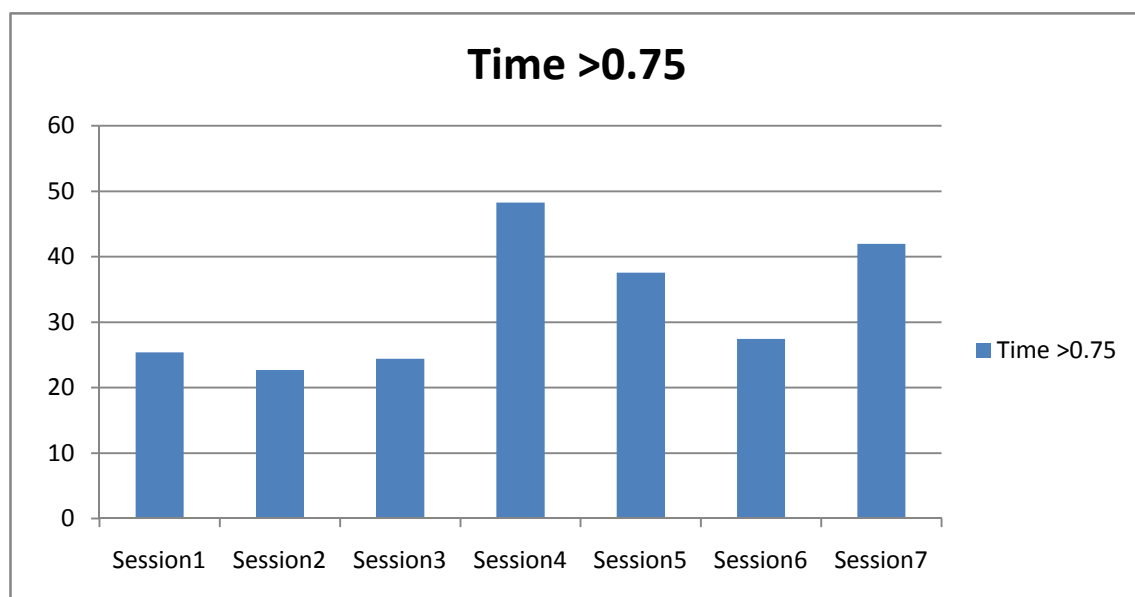
Figure 5.24Valence values registered before, during and after each session

Session 3 coincided with the same day summer vacation started and she said that her mood was magnificent, something that it was again corresponded with results. Still, we returned to find negative valence values after the session. She commented us, that being one minute in silence, with her eyes closed and trying not to move, was a really uncomfortable experience and that those 60 seconds were "eternal" to her. That is the reason why we decided, that probably it was enough to record only 30 seconds for the next sessions.

But something happened during sessions 5, 6 and 7. Here, for the first time, we started introducing "neutral music" in the session, music that was not chosen by her. We can see how her valence state was not higher anymore during the session compared with before and results after the session were always the worst. On the other hand, she also commented us that during those days she was having anxiety problems.

The reason we decided to introduce different music was because we were afraid that she was not learning how to self-regulate her mental state, and that the good results obtained during the session might be just the result of listening to music (as Tiffany documented [71]). In figure 6 we can see the percentage of time she was able to achieve her goals during each session.

As we can see, although we recorded the higher valence values in session 3, the training values were not different to those recorded in the last sessions. The reason of that is because we always normalize valence values before each neurofeedback training. So, we can have positive training results although valence values are negative. This just means that she was able to shift his frontal asymmetry enough for what was demanded even though valence results were not positive, they simply were less negative. This is also what happened in sessions 5, 6 and 7 where although we recorded negative valence values, we have higher training values than in the three first sessions.



5.25 Percentage of time our patient was able to increase her valence state above 0.75

Although seven days seem not to be enough time to extract conclusions about the therapy (neurofeedback therapies normally consist in 12 sessions as minimum), we can see a significant improvement on the ability of our subject to self-regulate her mood. Still, the introduction of neutral music sacrifices the emotional therapeutic effects of music listening which was one of the most important reasons of this work. Nevertheless, in session 4 our subject presented a really high level of training (almost 50%) accompanied with high valence values, even, valence values after the session were for the first time higher than during the session. It could mean, that the introduction of neutral music could have been an error as adolescents might be very sensitive when listening different music styles. We still need to test the system with a higher number of patients and with a minimum number of 12 sessions per subject in order to conclude something. It is also important to compare musical neurofeedback results with those achieved by a control group doing neurofeedback sessions as usual or, doing passive music therapy (subjects listening to music without any kind of feedback, while we record their EEG data).

6. Conclusions & Future Work

In this chapter we will explain how we have achieved each one of our proposed goals, which methods we have used, and what more is needed if we really want to explore all the different potentials that our system can provide.

6.1. Proposed Goals & Future work

6.1.1 Design of a musical neurofeedback software

One of the main goals of this work was to design a musical neurofeedback software. Concerning to the design, one of our main goals was to build an open and compact musical neurofeedback software, manageable, usable and easy to configure it for different therapies. Our software, as we have shown in chapter 4 is able to be configured easily for different therapies. At the same time, the fact of having designed a graphical user interface, makes our proposal accessible even to researchers or music therapists with low programming skills. Still, it would be interesting, with respect to research of musical brain-computer interfaces, to explore other environments like Simulink in Matlab (which is a block diagram environment for Model-based design. This kind of environments could help to make our code easier to understand and more flexible when introducing changes.

6.1.2 Experimental revision of important EEG features used for emotion recognition

Knowing the best way to represent the emotional state of a person through EEG data is of vital importance when dealing with patients with depression or emotional disorders. In this work we have realized two different methods for detecting emotions. Based on the dimensional perspective of emotions, we needed to detect which EEG features where the most important when measuring the arousal and valence levels in users.

First, working with the premise that meditation is a powerful tool to induce low levels of arousal, we have recorded and compared the EEG activity of a Yoga Kundalini teacher in normal state and while doing meditation. Results shown a biggest descend of beta and alpha activity in the frontal cortex, being the beta decline bigger when compared with alpha. This could mean that the beta and alpha ratio is the best descriptor when representing arousal rather than using each band separately. Still, research is needed with more yoga teachers in order to extract valuable information. No significant difference with regard to prefrontal asymmetry was found.

Secondly, we have replicated the paper of Ramírez and Vamvakousis, called *Detecting emotions from EEG signals using the Emotiv Epoc device* [31], where they proposed a mood induction procedure based on emotion-annotated sounds from the IADS library [53]. They found, in accordance with our last experiment, that beta and alpha ratio was a good descriptor of the arousal value of subjects. They also found, that this ratio was also a good descriptor when computing valence as the difference of activity of both hemispheres. Among the changes that we introduced in the methodology of the experiment, we wanted to use attribute selection algorithms like Information Gain and Ranker in Weka to compare between different valence descriptors so we can choose the most appropriate for our neurofeedback therapy. We found that for the three subjects which obtained significant results during the classification

process, alpha difference in the prefrontal cortex, instead of beta and alpha ratio, was the best valence descriptor for all of them. We also found that Decision Trees obtained significant results when compared with other methods like SVM or Neural Networks. Even so, more subjects will be needed in the future to confirm those results.

6.1.3 Pilot trial in patients with depression

Finally, we present the results of seven 20 minutes neurofeedback sessions realized to an adolescent with depression and emotional disorders. Results show the high impact music has on her valence values, and also show how this impact was very sensitive when music was not chosen by her. We also found a significant improvement in her abilities to self-regulate her emotional state during last sessions, although we sacrificed the emotional therapeutic effects of listening to her chosen music. Nevertheless, we also found some improvements in her capacity to self-regulate her mental activity in sessions where we were working with her music. We still need to test the system with a higher number of patients and with a minimum number of 12 sessions per subject in order to conclude something. It is also important to compare musical neurofeedback results with those achieved by a control group doing neurofeedback sessions as usual or, doing passive music therapy (subjects listening to music without any kind of feedback, while we record their EEG data).

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