Barış GÖKŞİN IMPROVING SHORT-TERM MEMORY PERFORMANCE USING ALPHA BAND NEUROFEEDBACK AGU 2018

IMPROVING SHORT-TERM MEMORY PERFORMANCE USING ALPHA BAND NEUROFEEDBACK

A THESIS
SUBMITTED TO THE DEPARTMENT OF ELECTRICAL AND COMPUTER ENGINEERING
AND THE GRADUATE SCHOOL OF ENGINEERING AND SCIENCE OF ABDULLAH GUL UNIVERSITY
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF
MASTER SCIENCE

By
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I hereby declare that all information in this document has been obtained in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all materials and results that are not original to this work.

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M.Sc. thesis titled "Improving Short-Term Memory Performance Using Alpha Band Neurofeedback" has been prepared in accordance with the Thesis Writing Guidelines of the Abdullah Gül University, Graduate School of Engineering & Science.

Prepared By | Advisor

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ACCEPTANCE AND APPROVAL

M.Sc. thesis titled "Improving Short-Term Memory Performance Using Alpha Band Neurofeedback" and prepared by Barış GÖKŞİN has been accepted by the jury in the Electrical and Computer Engineering Graduate Program at Abdullah Gül University, Graduate School of Engineering & Science.

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ABSTRACT

IMPROVING SHORT TERM MEMORY PERFORMANCE USING ALPHA BAND NEUROFEEDBACK

Barış GÖKŞİN
MSc. in Electrical and Computer Engineering Department
Supervisor: Prof. Dr. Bülent YILMAZ

May 2018

Age-related memory degradation is a serious problem for individuals and there is no known satisfying medical treatment of memory disorders such as Alzheimer. Recent advances in BCI technology enable us to measure brain wave activity of individuals, and neurofeedback is one of the methods that uses BCI technology. Although there are many researches about applications of neurofeedback on psychological disorders, there exist limited research on the application of neurofeedback's effect on short-term memory performance.

This thesis explored the possibility of short-term memory improvement through alpha-band neurofeedback training. EEG signals were collected from 11 healthy male participants using a wireless EEG device. The neurofeedback paradigm was used to enhance alpha-band power in real-time. Before and after 5 neurofeedback training sessions, a memorization test using 10 words was applied to all participants in order to evaluate the short-term memory performance improvement due to neurofeedback.

The results indicated that 6 out of 11 participants were able to enhance their alpha-band power with respect to other bands in the frequency spectrum during neurofeedback sessions. However, there was no obvious improvement in their short-term memory performance.

We may conclude that neurofeedback training was beneficial for the participants to focus their minds consciously. However, it is not easy to mention that neurofeedback training certainly improves or is irrelevant with short-term memory performance.

Keywords: short-term memory, alpha band, neurofeedback, EEG

ÖZET

ALFA BANDI NÖRAL GERİBİLDİRİM YÖNTEMİYLE KISA DÖNEM HAFIZA PERFORMANSININ İYİLEŞTİRİLMESİ

Barış GÖKŞİN
Elektrik ve Bilgisayar Mühendisliği Bölümü Yüksek Lisans
Tez Yöneticisi: Prof. Dr. Bülent YILMAZ
Mayıs 2018

Hafızanın yaşın ilerlemesi ile zayıflaması bireyler için önemli bir problemdir ve bu problemin Alzheimer'da olduğu gibi bilinen tatmin edici bir tıbbi tedavi yöntemi bulunmamaktadır. Beyin-bilgisayar arayüzü teknolojisindeki son gelişmeler bireylerin beyin aktivitesinin ölçülmesine olanak sağlamıştır, nöral geri bildirim de beyin bilgisayar arayüzünü kullanan metotlardan biridir. Nöral geribildirim metodunun psikolojik bozukluklar üzerine uygulanması hakkında birçok araştırma olmasına rağmen, kısa dönem hafıza performansı üzerine uygulamaları hakkında yapılmış sınırlı sayıda araştırma vardır.

Bu tez kişilerin alfa bandı nöral geribildirim eğitimi ile kısa dönem hafızalarının geliştirilmesinin mümkün olup olmadığını araştırmaktadır. 11 Sağlıklı erkek katılımcıdan kablosuz EEG cihazı ile EEG sinyalleri toplanmıştır. Nöral geri bildirim yöntemi alfa bandı gücünün gerçek zamanlı artırılması için kullanılmıştır. Nöral geribildirimin sağladığı kısa dönem hafıza performansındaki iyileşmenin ölçülmesi amacıyla 5 seanslık nöral geribildirim eğitimi öncesi ve sonrası 10 kelimeden oluşan ezber testi tüm katılımcılara uygulanmıştır.

Sonuçlar nöral geribildirim seansları esnasında 11 kişiden 6'sının alfa bandı gücünü spektrumdaki diğer bantlara göre artırabildiğini göstermiştir. Fakat kısa dönem hafıza performansında belirgin bir gelişme olmamıştır.

Sonuç olarak nöral geribildirimin katılımcıların zihinlerini bilinçli bir şekilde odaklayabilmesinde faydalı olduğu söylenebilir. Fakat nöral geribildirim eğitiminin kısa dönem hafızayı kesinlikle artırdığı veya alakasız olduğunu söylemek güçtür.

Anahtar kelimeler: kısa dönem hafıza, alfa bandı, nöral geribildirim, EEG

Acknowledgements

I would like to thank my advisor Prof. Dr. Bulent YILMAZ who taught me basics of neuroscience helped selecting the thesis topic, during the development of the system, reviewing the thesis and did not push me too much during my work. I would like also to thank Asst. Prof. Kutay IÇOZ for his support in the progress of the thesis, Assoc. Prof. Dr. Fatma LATIFOĞLU for reading my thesis, my brother Suleyman Taner GOKSIN who checked the English language in the thesis, graduate students of Abdullah Gul University who participated in the experiments and especially my family and all others who supported me.

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To clean minds

CHAPTER 1

INTRODUCTION

Human brain (cortex) emits electromagnetic waves in some defined bands: Delta (0.5-4Hz), Theta (4-7Hz), Alpha (8-13Hz), Beta (13-30) and Gamma (>35 Hz). With the development of electroencephalography (EEG) system, it has become possible to observe the electrical activity of the brain easily [1]. By measuring brainwaves, scientists try to diagnose psychological and physiological disorders, and even work on improving cognitive performance of the human brain.

It is a fact that humans' physical, physiological and psychological functions start to degrade with aging that causes a significant decrease in life quality [2]. Studies also show that aging causes individuals' cognitive abilities, such as the speed of cognitive process [3], a reduced visual side of view [4], visual search efficiency during distraction [5], some dysfunction in inhibitory processes (attention control, response suppression) [6], low cognitive plasticity [7] and decreasing short-term memory and working memory capacity [8]. Therefore, it is valuable to find a way to preserve these cognitive abilities for healthy aging.

Neurofeedback training (NFT) method has been studied for several decades as an alternative treatment to traditional medication for some psychological disorders, and it is also used to enhance cognitive performances of healthy participants. For example, some clinical application areas of NFT method are attention deficit hyperactivity disorder (ADHD) [9], substance addiction [10], epilepsy [11], and autism [12]. Besides its function in psychological disorders, NFT has some positive effects on cognitive performance of healthy individuals, e.g., musicians and surgeons [13,14].

As it is seen in figure 1.1.1, during NFT brain activity is measured from the scalp and some frequency band powers (such as alpha, beta, and gamma bands) are increased or decreased consciously by the participant himself intentionally via visual or auditory feedback.

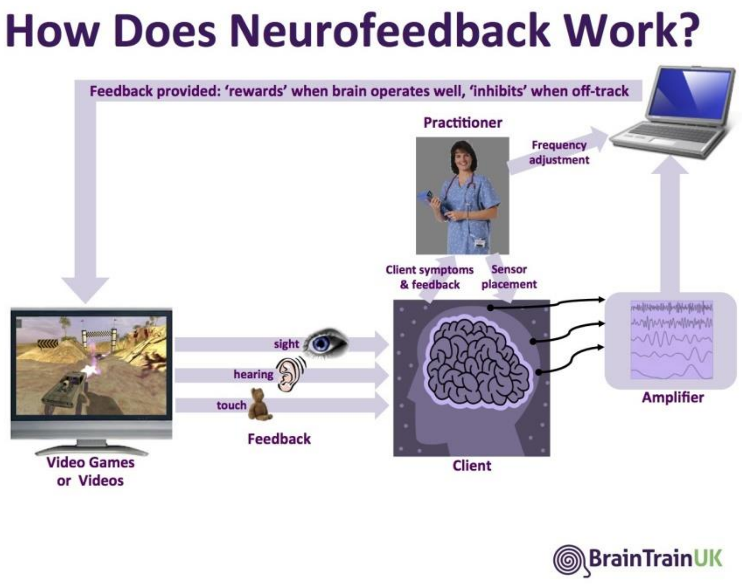

Figure 1.1.1 A neurofeedback application loop [15].

It is believed that brainwave bands have relations with some cognitive functions of the brain. As a result, the band to be used in NFT is determined according to the relation of that band with the targeted cognitive function. For example, there are many studies that aim enhancing human cognitive performance by changing alpha band power through NFT. Some of them are listed in Table 1.1.1, and some others are introduced in Chapter 2.

Considering all the cognitive functions of the brain, memory is likely to be one of the most important cognitive ability for individuals to continue their quality and productive lives. Today we see that science and technology could not be improved without a healthy brain, which is equipped with a good memory function. We know that memory is of a great importance even for finding our ways home e.g. Alzheimer patients [17].

According to scientists, human memory is a combination of sensory memory, short-term memory, working memory and long-term memory, which function together to fulfill a task [18].

	Site of treatment	Enhance/inhibit	Num. of sessions	Outcome
(Allen, Harmon-Jones, & Cavender, 2001)	F_3 ,F_4	Enhance alpha (8-13 Hz)	5	Impact of self-reported emotional responses and facial EMG
(Angelakis et al., 2007)	F_3	Enhance peak alpha (8-13 Hz)	31-36	Improve cognitive processing speed and executive function
(Hanslmayr, Sauseng, Doppelmayr, Schabus, &, Klimesch, 2005)	F_3 ,F_4, F_z P_3, P4, P_z	Enhance upper alpha	1	Improvement in cognitive performance
(Hardt&Kamilya, 1978)	O_2, O_1, C_3	Enhance alpha (8-13 Hz)	7	Decrease anxiety
(Hord, Tracy, Lubin, &, Johnson, 1975)	O_2	Enhance alpha		Help maintain performance such as counting and auditory discrimination
(Markovska-Simoska et al., 2008)	F_3 -O_1,F_4 – O_2	Enhance individual upper alpha	20	Increasing the quality of musical performance
(Martindale- Armstrong, 1974)	O_z ,P_4	Reduction alpha (7-13 Hz)	1	High creative
(Plotkin& Rice, 1981)	O_z	Enhance alpha	5-7	Decrease anxiety
(Regestein, Buckland, & Pegram, 1973)	Parietal-Occipital	Enhance alpha (8-13 Hz)	2	Decrease sleep need
(Zoefel, Huster, & Herrmann, 2011)	O_1 ,O_2, P_3, P4, P_z	Enhance individual upper alpha	5	Enhancement of cognitive performance

Table 1.1.1 Summary of studies using alpha protocol training [16].

Sensory memory is a kind of buffer that keeps the feelings received by our five senses after the original stimulant has disappeared. It retains information accurately, but for a very short duration [19]. Short-term memory stores the information temporarily, and working memory uses this temporary information to fulfill its task. For example, short-term memory keeps two numbers and working memory uses these two numbers during multiplication. Short-term memory and working memory are like brothers, the only difference is that working memory has an attentional component [20]. Long-term memory is another type of memory, which retains information for a long time period [19].

In the literature, it was reported that there was a relationship between memory performance and the alpha band activity [21]. When an individual's resting-state alpha activity is high, his/her memory performance is also high [22]. Although there are many studies, which support that NFT has positive effects on some areas including cognitive performance improvement using alpha band power [16], there are several studies, which showed the effects of NFT on short-term memory [20].

In this study, we first converted a simple wireless EEG device to a neurofeedback tool. Later, we examined whether it was possible to improve short-term memory performance of healthy participants, by increasing alpha band power using NFT. Before and after 5 days of neurofeedback training sessions, we measured the improvement on participants' short-term memory by performing a test, which consisted of memorizing and recalling some English words asked in GRE tests.

1.1 Thesis Outline

In Chapter 2, the topics covered were the following: Background on brainwaves and their associated psychological states, the definition of neurofeedback, how it is implemented, its use on psychological disorders and human memory performance, an introduction to our EEG device used for neurofeedback training and its applications in different areas, fundamental information about human memory, memory types, memory stages such as memory formation, storage, and retrieval. Chapter 3 presents all the information about how EEG signals were collected and processed during the neurofeedback training sessions. Chapter 4 and 5 demonstrate the results obtained in this study, and discussions, respectively.

Chapter 2

Background

2.1 Brainwaves

The electrical property of the human brain has been known for one hundred years. Dispersion of scalp electrical potential reminds an electrical activity caused by the cortex [1]. This dispersion of scalp potential can be measured with some pair of electrodes. The resultant signal is called electroencephalography (EEG). There are significant amount of information gathered by electrodes, and it is not easy to process all brainwaves.

There are five frequency bands that are especially prominent. *Delta* waves span the 0.5-4 Hz range of the frequency spectrum, and it is associated with the "deep sleep." However, if it occurs in the awaking state, it is interpreted as a deficiency in the brain. *Theta* waves span the 4-7 Hz range in the frequency spectrum. They generally have amplitude values higher than 20 μV. Theta waves are caused by low emotional states, such as "frustration or disappointment." They are also related to creative thinking and "deep meditation", and have a peak value around 7 Hz. *Alpha* waves span 8-13 Hz of the frequency spectrum. The amplitude of the waves changes between 30 μV and 50 μV. Alpha waves are related to the relaxed consciousness and not to the focusing state. In the frontal and occipital lobe of the brain, alpha waves have the highest peak values. The amplitude of these waves is larger when the eyes are closed than when they are open. *Mu* waves span "spontaneous" 8-12 Hz wave. They are related to the motor activity, and measured as the maximum value on the motor cortex. They disappear when someone moves or intends to move his/her limbs. Beta waves span the 13-30 Hz range of the frequency spectrum. The amplitude of the voltage changes between 5 μV and 30 μV. Beta waves are related to "active thinking", "active attention", "concentrating on the outer environment," and "resolving tangible problems". *Gamma* waves span 35 Hz and above.

It is considered that gamma band has some association between different brain functions, and it is related to consciousness [2]. Table 2.1.1 shows EEG bands and their associated physiological states.

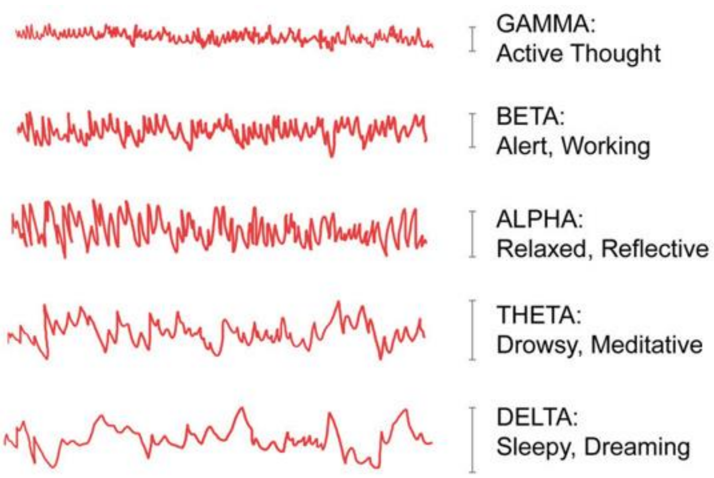

Figure 2.1.1 EEG frequency bands [3].

Common brainwave frequency	Frequency range (Hz)	General characteristics
Delta	1–4	Sleep, repair, complex problem solving, unawareness, deep-unconsciousness
Theta	4–8	Creativity, insight, deep states, unconsciousness, optimal meditative state, depression, anxiety, distractibility
Alpha	8–13	Alertness and peacefulness, readiness, meditation, deeply-relaxed
Lower alpha	8–10	Recalling
Upper alpha	10–13	Optimize cognitive performance
SMR (sensorimotor rhythm)	13–15	Mental alertness, physical relaxation
Beta	15–20	Thinking, focusing, sustained attention, tension, alertness, excitement
High beta	20–32	Intensity, hyperalertness, anxiety
Gamma	32–100 or 40	Learning, cognitive processing, problem solving tasks, mental sharpness, brain activity, organize the brain

Table 2.1.1 EEG bands and associated physiological states [4].

2.2 Neurofeedback

We have mentioned in the previous section that human brain emits some electromagnetic waves in certain bands. In neurofeedback, these waves are measured and given back to the person again, which is called feedback. Feedback may be via visual or auditory means. By the feedback the person could know the power of his brain waves in real-time. It is requested from the person to increase or decrease the chosen brainwave band power. For example, beta band is associated with concentration. Lower beta band power in frontal lobe depicts the lack of concentration. With neurofeedback approach, the person's beta band power is measured by electrodes placed on the frontal lobe, and the feedback is given to the person via visual image or auditory signal to inform the person about the state of his beta band power at that time. After that, it is requested from the person to increase the beta band power. In the visual feedback case, the person can see his beta band power on the screen, and he/she can define his emotional state at that time whether it increases or decreases. When band power decreases, he alters his emotional state or when band power increases he tries to continue increasing it. Shortly, in the neurofeedback method the person is informed about the chosen band power in real-time, which is related to his emotional state at that time. It is up to the person to change this power by himself. Thus, that person can learn to control his brain rhythm. The number of bands, which are requested to change their power, may be more than one. For example, in hyperactivity disorder in the frontal lobe, not only beta band power is lower but also theta band power is higher than normal. During the treatment of hyperactivity with neurofeedback, it is requested from the patient to increase beta band power while decreasing theta band power. This is accomplished generally by increasing the beta/theta ratio. Feedback is generally given by visual or auditory signals, which change with a neuro parameter. For example, as shown in Figure 2.2.1 the neuro parameter is related to the movement of the plane.

Figure 2.2.1 A neurofeedback game [5].

For instance, when the subject changes the beta band power neuro parameter here is beta band power. When the beta band power increases, the plane in the computer game accelerates. However, when this parameter value decreases the plane decelerates or stops.

Thus, that person can understand the state of beta band power, which is requested to change in real-time, and can adjust his emotional state according to that feedback.

2.2.1 Neurofeedback applications

2.2.1.1 Attention deficit hyperactivity disorder (ADHD)

ADHD is caused by some deficiency of the right frontal lobe processing. Some ADHD symptoms are "inattention, distractibility, hyperactivity and extreme dispassionateness." ADHD can be cured with drugs, but they have some side effects. However, neurofeedback is another another alternative for ADHD. ADHD patients have low beta activity and high theta activity in comparison to normal people [23].

2.2.1.2 Schizophrenia

Symptoms of schizophrenia are "illusion of auditory disorders, restlessness, non flexible muscle, confusion, and depression." Schizophrenic people can adjust their brainwaves with neurofeedback [24].

2.2.1.3 Insomnia

The patient who is treated with neurofeedback has some improvements in their "sleep patterns." The people treated with neurofeedback can sleep easily whereas they have to be prepared at least one hour before the sleep [25].

2.2.1.4 Learning Disability, Dyslexia, Dyscalculia

Neurofeedback has important treatment effects on learning disability, dyslexia, dyscalculia. Dyslexia patients have difficulties in reading and spelling especially in school age. Dyscalculia patients have some difficulties to understand and solve mathematical problems. Increasing alpha waves is used for the treatment of these disorders [26, 27].

2.2.1.5 Drug Addiction

Long-term use of drugs has deep effects on people's EEGs. Researchers show that neurofeedback has positive effects that help people quitting their drug addiction. People who are addicted to cocaine can be treated with neurofeedback and this way of treatment can also be applied to treat alcoholism and computer game addiction [28].

2.2.1.6 Performance Enhancement

Researchers believe that brain activity of professional athletes is different from the brain activity of nonprofessional athletes. It is thought that neurofeedback improves the athlete's psychomotor and self-regulation talents, self-confidence, and eventually the performance in the following contest [29].

2.2.1.7 Autism

Autistic people generally tend to choose introvert careers such as engineering, working with machines, and computers that look like obsessive concerns. The aim of neurofeedback with autistic children is to decrease theta/alpha ratio while increasing beta band power [30].

2.2.1.8 Epilepsy

Studies have shown that 1/3 of epilepsy patients are not responding to the medication. In the treatment of epileptic patients with neurofeedback, sensory motor rhythm (SMR, 12-15 Hz) is increased while decreasing synchronously or asynchronously "slow rhythms" (4-7 Hz). Reduced activity of gamma band in epileptic patients who experienced surgery is a good mark for the treatment of epilepsy. Studies have shown that seizure rate and uncontrollable epileptic attacks can be reduced by neurofeedback with SMR treatment [31].

2.2.1.9 Depression

Findings have shown that there is an inverse relationship between alpha asymmetry and parietal activation. In the treatment of depression with neurofeedback, the protocol includes increasing alpha and theta bands while reducing high beta frequencies. Studies have good signs of improvements in the depression disorder [32].

2.2.1.10 Anxiety

In medicine, anxiety has symptoms of high-level muscle tension. It is considered that reducing alpha band can calm people who have an anxiety disorder down [33].

2.2.1.11 Pain Management

“Studies have shown that brain alters its functional organization in somatocortex in chronic pain patients and with neurofeedback, it is considered that patients can learn to self-regulate their brains and reduce pain perception [34].

2.2.2 Neurofeedback applications on memory Performance

Wang and Hsieh investigated whether an increase in the frontal midline theta band power might improve attention and cognitive performance in younger and older subjects or not [6]. In EEG experiments, Fz electrode was used, and an audio-visual feedback approach was employed. After 12 neurofeedback training sessions, they have shown that subjects could increase theta band power and improve attention and working memory performance.

Lecomte and Juhel investigated whether increasing upper alpha band (10-12 Hz) power over theta band (4-7 Hz) power could improve short-term memory performance [7]. In EEG experiments, C3, C4, and Cz (ref) electrodes were used, and again an audio-visual feedback was employed. After 4 neurofeedback training sessions, they have shown that subjects could increase alpha band power and alpha/theta band power, however, there was no memory performance improvement in elderly participants.

Xiong et al. examined whether increasing the theta/alpha band power ratio could improve working memory performance [8]. In EEG experiments, Fz, FCz, Cz, C1 and C2 electrodes were used, and an audio-visual feedback was employed. After 15 neurofeedback training sessions, they have shown that participants were able to increase theta/alpha ratio, and improve working memory performance.

Kober et al. examined whether increasing the SMR (12-15 Hz) band power or upper alpha (10-12 Hz) band power could improve short-term memory performance in post-stroke patients [9]. In EEG experiments, Cz electrode was used for SMR, Pz electrode was used for upper-alpha training, and a visual feedback was employed. After 10 neurofeedback training sessions, they have shown that participants who took the SMR training could improve their visuo-spatial short-term memory performance, and participants who took the upper-alpha training could improve their working memory performance.

Reddy et al. investigated whether increasing the alpha (8-12 Hz) band power and decreasing the theta (4-7 Hz) could improve "verbal and visual learning memory in a patient with traumatic brain injury" [10]. In EEG experiments, O1 and O2 electrodes were used, and a visual feedback was employed. After 20 neurofeedback training sessions, they have shown that subject was able to improve both his verbal and his visual learning memory performance.

Reis et al. examined whether increasing alpha and theta band powers could improve cognitive performance in older adults [11]. In EEG experiments Pz, Fz, Fp1 and Fp2 electrodes were used, and a visual feedback was employed. After 8 neurofeedback training sessions, they have shown that participants could increase alpha and theta band powers and improve their working memory performance.

Nan et al. investigated whether increasing the individual alpha band power could improve the short-term memory performance [12]. In EEG experiments, only Cz electrode was used, and a visual feedback was employed. After 20 neurofeedback training sessions, they have shown that participants could increase their individual alpha band power and improve the short-term memory performance.

Escolano et al. examined whether increasing the upper alpha band power could improve the working memory performance [13]. In EEG experiments, P3, Pz, P4, and O1 electrodes were used and visual feedback was applied. After 5 neurofeedback training sessions, they have shown that the participants could increase the upper alpha band power and improve the working memory performance.

Staufenbiel et al. investigated whether increasing gamma and beta band powers could improve cognitive performance and brain activity in elderly [14]. In EEG experiments, only Fz electrode was used, and an audio feedback was employed. After 8 neurofeedback training sessions, they have shown that the participants could increase brain activity, however, they did not observe any effects on cognitive performance.

Zoefel et al. examined whether increasing the upper alpha band power could improve cognitive performance [15]. In EEG experiments, O1, O2, P3, P4, Pz, and FCz (ground) electrodes were used. After 5 neurofeedback training sessions, they have shown that the participants could increase upper alpha band power and improve cognitive performance.

Wang examined whether increasing the alpha band power could improve the working memory performance in the students with ADHD [16]. In EEG experiments, only FCz electrode was used. After 10 neurofeedback training sessions, he has shown that the participants could increase alpha band power and improve working memory performance.

2.3 EMOTIV Epoc

EMOTIV system is a commercial grade EEG system with 14 electrodes and 2 gyro sensors. Electrodes have contact with the scalp without the need for a gel, unlike other EEG systems used in the field. However, they need a moisturizing liquid, which contact lens users employ for sanitation. Sensor data collected with EMOTIV system can be processed with MATLAB, Java, and C++. EMOTIV Epoc specifications are given below in Table 2.3.1.

	EEG HEADSET
Number of channels	14 (plus CMS/DRL references P3/P4 locations)
Channel names (international 10-20 locations)	AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4
Sampling method	Sequential sampling. Single ADC
Resolution	128 SPS (2048 Hz internal)
Bandwidth	0.2-45 Hz, digital notch filters at 50 Hz and 60 Hz
Filtering	Built in digital 5th order Sinc filter
Dynamic range (input referred)	8400 μV
Coupling mode	AC coupled
Connectivity	Proprietary wireless, 2.4GHz band
Power	LiPoly
Battery life (typical)	12 hours
Impedance measurement	Real-time contact quality using patented system

Table 2.3.1 EMOTIV Epoc specifications [35].

2.3.1 EMOTIV Applications

EMOTIV is cheaper than other EEG systems on the market; therefore it finds a wide range of use in EEG community. There are many applications in which EMOTIV system was recently used for different purposes. Below a survey of projects has been mentioned:

2.3.1.1 Implicit detection of relevance decisions and affect in web search

In a project performed by Gwizdka and Cole, which led them to win Google's Research Award in 2011, the researchers attempted to uncover interest decisions using eye movement and pupil size, galvanic skin response, and EEG [17].

2.3.1.2 Brain-controlled car

Sensor signals obtained by EMOTIV system was used to control a real car. When the car reached a predefined point automatically a new direction could be chosen by this headset. However, system's lag was thought to be a huge problem for real life use [36].

2.3.1.3 NeuroPhone

This project included calling someone in the address book of an iPhone using the EMOTIV system. Images of the contacts were shown for a short period of time, and when the target person's image appeared on the screen a P300 signal was detected in the EEG signals in real-time [37].

2.3.1.4 Five-axis robotic arm

This project used EMOTIV "built-in patterns" to control a 5-axis robotic arm [17].

2.3.1.5 Design and evaluation of musical neurofeedback software in matlab

This project used an EMOTIV Epoc headset as a neurofeedback device. It was applied on several patients with depression. Designed system increased or decreased the volume of the song according to the emotional state of the patients. Thus, the patients could adjust the volume by altering their emotional state using sound feedback [38].

2.4 Human Memory

The first day in school, the most delicious food that you taste, the birth of your children, the death of your relative, learning to ride a vehicle and like this, these are memories that make you who you are and shape your future.

Every event, which you find yourself in, launches a life cycle in itself with visible and invisible actors. From that moment on every new event in your lifetime will construct your memory.

If you face new problems, previous experiences will guide you. Only if you have learned a lesson from them. But if have not, it means you are going to be bitten from the same hole again and again.

To be valuable, it is necessary to be able to recall memories that are stored in different times in the past. Therefore, both the short-term memory and the long-term memory are crucial for our brain's working system [18].

Figure 2.4.1 shows how the information from the stimulus stage to the long-term memory settles in the brain. The figure includes several memory types, such as sensory memory, short-term memory, working memory, and long-term memory. The details of these memory types are explained below.

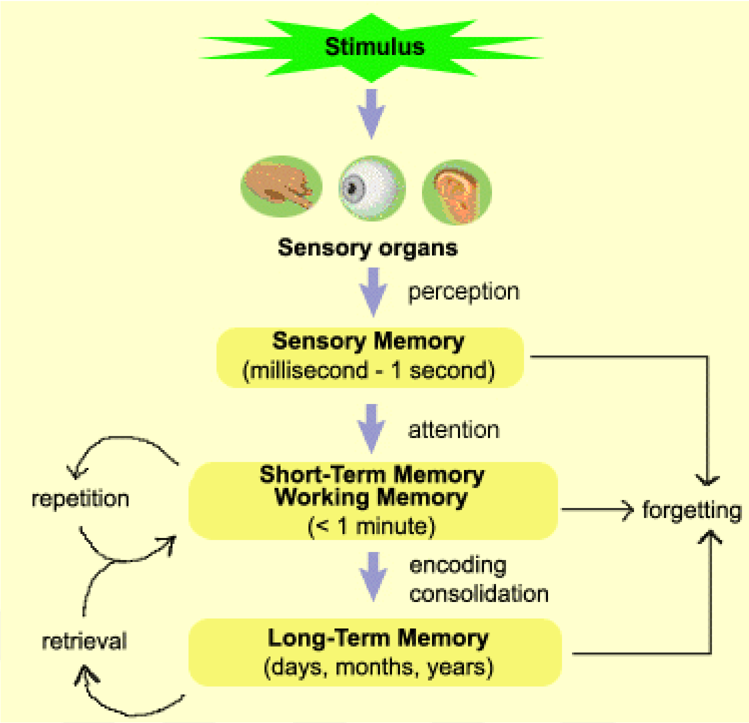

Figure 2.4.1 Stages of memory formation [19].

2.4.1 Sensory memory

Sensory memory is formed naturally from our perceptions. For the most part, it vanishes in very short durations. It incorporates two sub-frameworks: visual perceptions and sound-related perceptions [19].

2.4.2 Short-term memory

In a regular day of our life, there are many instants that you have to keep some portion of data in your mind for very short durations. One common instance of short-term memory use is the duty of repeating a list of elements that have been said to you, in their original sequence [19]. Short-term memory has a limit; it can keep around seven things in mind for 20 or 30 seconds [20].

2.4.3 Working memory

Working memory is an extension of the idea of short-term memory. Working memory is utilized to perform cognitive procedures of the things that are briefly stored in it. It is subsequently vigorously engaged with cognitive forms that require thinking, like reading, composing, and performing calculations. One instance of the utilization of working memory is the duty of repeating the names of things that have recently been listed to you, yet in the inverse of their original sequence. Another instance is the duty of simultaneous translation, where the translator must store data in one language while orally making an interpretation of it into another [19]. Another good example of working memory is that a chess master who can investigate a few possible arrangements intellectually before picking the one that will prompt checkmate [39].

Data stream between short-term and long-term memory. According to the way of the stream, various types of thoughts occur. For instance, when data streams from short-term memory into long-term memory, it causes learning. Data can likewise stream from long-term memory into short-term memory. This occurs whenever we consider a formerly known certainty, individual, or occasion, that we call recognition, recall, or remembering [40].

2.4.3.1 Brain regions for short-term and working memory

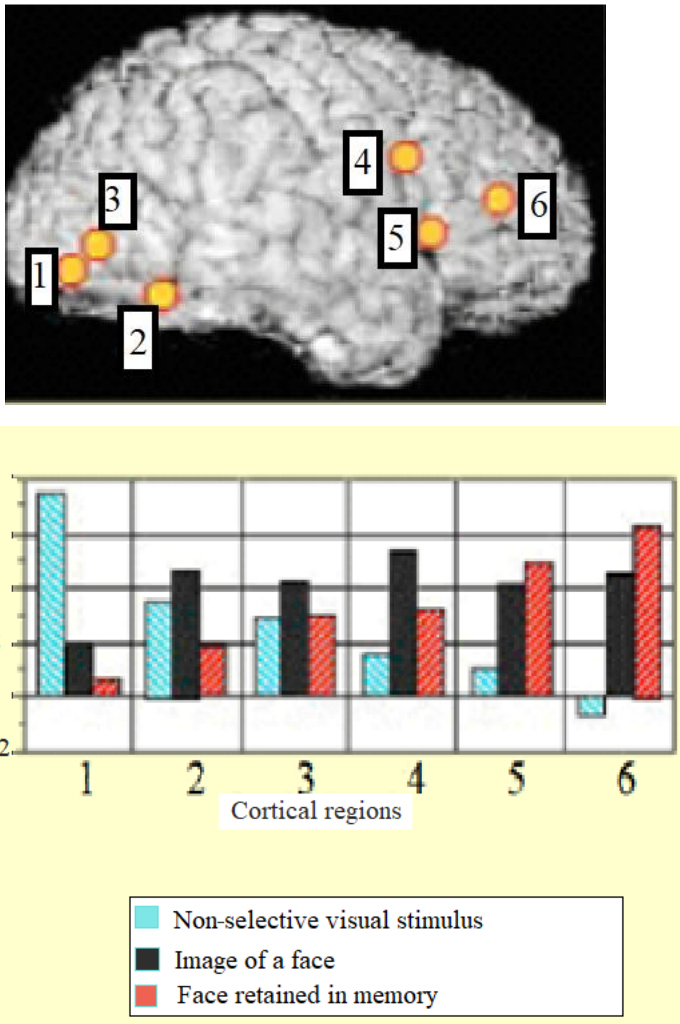

Figure 2.4.3.1.1 Different activation regions for different stimulants [41].

The results of the research study presented in Figure 2.4.3.1.1 [41] depict how different regions of the subjects' cortices adjust their activation levels as the subjects are shown different visual stimuli. When a blurry image was shown to the participants the activation level (illustrated by the blue bars in the chart) was elevated in area 1, the visual cortex. When a face image was shown to the participants cortical activities (dark bars) were noticeably higher in the associative and frontal areas (4, 5, and 6). Finally, when the participants were keeping an image of a face in their working memory, cortical activities (red bars) was noteworthy in the frontal areas, while the visual regions were barely stimulated at any moment.

The prefrontal cortex has an important role in the working memory. It enables the individuals to keep data accessible for their present thinking task. For this reason, the prefrontal cortex must collaborate with different parts of the cortex from which it gets data for brief periods. Finally, these data go into the long-term memory, the limbic system plays an important role [23]. The aforementioned brain regions are shown in Figure 2.4.3.1.2.

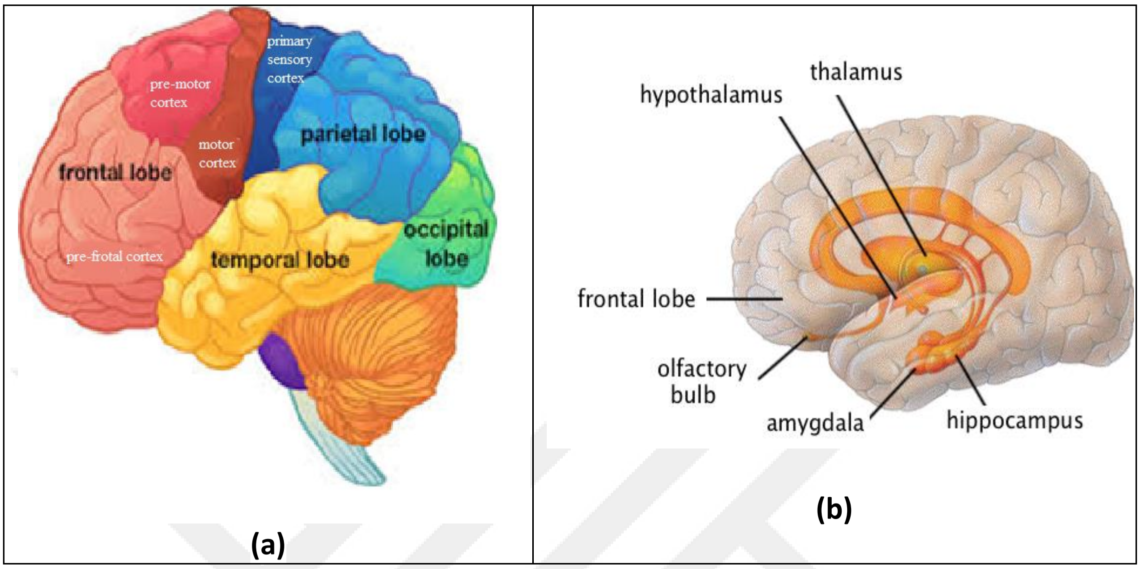

Figure 2.4.3.1.2 (a) Brain lobes and (b) Limbic system [42].

2.4.4 Long-term memory

Critical data is progressively conveyed from the short-term memory into the long-term memory. The more the data is repeated or utilized, the more probable it is to be finally finished in the long-term memory, or to be "held." Unlike sensory and short-term memory, which are time-limited and fade quickly, long-term memory can save the boundless quantity of data indefinitely.

Individuals can accumulate more effortlessly material on subjects that they definitely know something about, since the data has more significance to them and can be intellectually associated with related data that is saved in their long-term memory earlier. That is the reason why somebody who has a normal memory might have the capacity to recall profoundly of data around one specific subject [41].

Long-term memory can be divided into different subtypes, such as episodic memory and semantic memory. However, these different subsystems communicate with each other all the time. Episodic memory gives you a chance to recall occasions that you personally experienced at a particular time and location. Semantic memory refers to the huge depot of information that humans have readily. It includes the knowledge of facts, events, ideas, and concepts [46].

2.4.4.1 Brain regions for long-term memory

The hippocampus assumes an essential part in the consolidation of short-term memory to long-term memory. The name was given to the hippocampus since it looks like a seahorse. Hippocampus originates from the Greek hippos, "horse," and kampos, "sea monster." Humans have double hippocampi, one in the left side of the cerebrum, and another one in the right side of the cerebrum. [47].

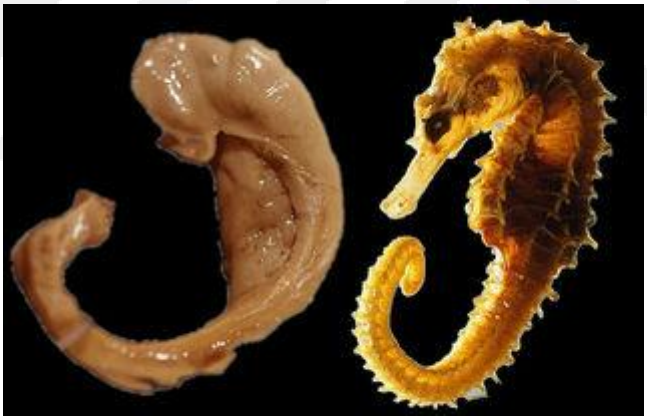

Figure 2.4.4.1.1 Hippocampus [26].

As mentioned in [48], Hippocampus is “critical to learning and remembering relationships that characterize spatial layouts, items in particular context in which they have been experienced, and other associative, sequential or logical relationships among experiences.” The hippocampus makes connections easy between different areas of the cerebrum. What may cause such connections to be reinforced and ultimately sent to the long-term memory generally depends on “limbic” factors [41].

2.4.5 Memory Stages

The stages of memory are encoding, consolidation, storage, and retrieval. In this part, each concept will be explained in a certain detail.

2.4.5.1 Encoding

Encoding is the initial phase of making a memory. It is a biologic event established in the senses that starts with perception. When a young man meets his first love, his visual system enrolls physical components, for example, the color of her eyes and hair. The auditory system might grab the sound of her laugh. Each of these different sensations go to the piece of his brain called the hippocampus, which incorporated these observations as they are happening into one single experience, which is his experience of that particular individual.

Specialists consider that the hippocampus, along with the other pieces of cerebrum called the frontal cortex, are in charge of examining these different sensory information sources and choosing whether they are worth recollecting. If so, they may turn out to be a piece of your long-term memory. As demonstrated before, these different pieces of data are then put away in various parts of the brain. How these pieces of information are later recognized and recovered to shape a related memory, nonetheless, is not yet known.

To appropriately encode a memory, a person should be focused first. Because s/he cannot focus on everything at the same time, the vast majority of what s/he experiences each day is essentially sifted through, and just a couple of stimulus go into his/her cognizant awareness. If that person recalls everything that s/he sees, his/her memory will be overloaded before s/he exits home in the morning.

The formation of a memory starts with its perception. The booking of data at the perception happens in the concise sensory stage that generally lasts for just a fraction of a second. It is the sensory memory that permits a perception, for example, a visual instance, a sound, or a touch to stay for a concise time after the excitation is finished. After that initial flare, the sensation is put away in the short-term memory [49].

2.4.5.2 Consolidation

Consolidation is the procedures of strengthen a memory pattern after the first obtainment. It is normally taught to comprise of two particular procedures, synaptic consolidation (which happens inside an initial couple of hours of learning or encoding) and system consolidation (where hippocampus-dependent recollections come to be independent from the hippocampus over a time of weeks to years).

Neurologically, the procedure of consolidation uses a marvel called long-term potentiation, which enables a synapse to increment in power as expanding quantities of impulses are transferred between the two neurons. Potentiation is the procedure in which synchronous ignitions of neurons make firing those neurons together easier later on. Long-term potentiation happens when a similar set of neurons fire together so regularly that they turn out to be for all time stimulated to each other. As new encounters gather, the cerebrum makes an ever-increasing number of associations and pathways, and may "re-wire" itself by re-directing associations and re-regulating its association.

Accordingly, a neuronal pathway, or neural system, is navigated again and again, a persevering trace is embedded and neural messages will probably stream along such accustomed ways of slightest resistance. This procedure is accomplished by the generation of new proteins to remake the neural connections in the new shape, without which the memory stays delicate and is easily dissolved with time. For instance, if a piece of music is played again and again, the rehashed ignition of the specific neural connections in a specific order in your cerebrum makes it simpler to rehash this ignition later on, with the outcome that the performer turns out to be better at playing the music, and can play it speedier, with less inaccuracy.

Thusly, the cerebrum composes and redesigns itself according to experiences, making new recollections provoked by experience, instruction or training. The capacity of the association, or synapse, between two neurons can change in power so the synaptic transmission is known as the synaptic plasticity or neural plasticity, and it is one of the critical neurochemical establishments of memory and learning.

We should remember that every neuron makes a huge number of associations with different neurons, and memories and neural associations are commonly interconnected in amazingly complex ways. In this way, various recollections might be encoded inside a unique neural system, by various examples of synaptic associations. Alternately, a unique memory may include initiating a few different set of neurons in totally different parts of the cerebrum.

Sleep (especially slow wave, or profound sleep, during the initial couple of hours) is additionally thought to be critical in enhancing the solidification of data in memory. Also activation traces in the sleeping cerebrum, which reflect those recorded at the learning of lessons from the earlier day, recommend that new recollections might be hardened through such reactuation and practice.

Memory re-consolidation is the procedure of beforehand solidificated recollections being remembered and afterward effectively combined once more, with a specific end goal to fortify and alter recollections that are previously saved in the long-term memory. A few retrievals of memory might be required for long-term memory to keep going for a long time, according to the deepness of the initial processing. In any case, these individual retrievals can occur at expanding intervals, as per the guideline of spaced rehearsal (this is natural to us in the way that "packing" the night prior to an exam is not as successful as learning at intervals over an any longer traverse of time).

However re-consolidation may change the intial memory. As a specific memory trace is reactivated, the power of the neural associations may change, the memory may progress toward becoming related with new passionate or environmental conditions or subsequently obtained information, desires instead of real occasions may come to be noticeably consolidated into the memory, and so forth [50].

2.4.5.3 Storage

Storage is a very inactive ability of keeping information in the brain, it may be placed in the long-term memory, short-term memory or sensory memory. The probability of keeping the information to be held increases with repeating or utilization.

After consolidation, a set of neurons that are fired together in a similar way which first experience coded such as neurons store an image in the visual cortex, neurons store feelings in amygdala, and so on. In reality, experiences are coded in different areas of the cortex a few times. So that, in the event one memory trace is erased from other copies the memory can be recovered [51].

2.4.5.4 Retrieval

The recall of memory indicates the re-accessing of past incidents or data, which have been already encoded and stored in the cerebrum (known as remembering). During the recall, the brain "replays" an example of a neural action that was first produced because of a specific event, echoing the impression of the cerebrum during the real event [52].

A recent research made by MIT scientists on a group of mice shows that memory formation and memory retrieval have two distinct neural pathways in the hippocampus, whereas it was assumed that both memory formation and retrieval have the same circuit in the hippocampus. It is reported that this research shows that Alzheimer diseased patients can learn new things but can’t recall them appropriately, although there is not any research on this subject. One can ask why there are two distinct pathways in the brain to learn and retrieve. A researcher who was interviewed says that in this case, it is easy to recall previously known things and connect them with new things during learning [53].

Chapter 3

Methodology

It is known from the literature that alpha waves are associated with the human memory performance. In this thesis work, we have explored whether “it is possible to improve short-term memory capacity of Turkish graduate students in order to learn new English words by increasing their alpha band power with the neurofeedback methodology” or not.

3.1 Participants

The 11 subjects who participated in the experiments were all chosen among male graduate students, with an aveage age of 29, and with standard deviation of ±3.04. One participant was left-handed and 5 of them wore glasses.

3.2 EMOTIV System as an EEG Device

In the experiments, the EMOTIV system was used as the hardware, and as the software a MATLAB file called “eeglogger.m,” which was produced by the manufacturer, was used. Several modifications in this .m file were made in order to be able to use this system as a neurofeedback tool.

“eeglogger.m” collects data from 14 EEG channels and two gyro sensors, and yields an output matrix including sensor data and sampling time. In our project we used only P8 electrode, and the code used in the project was given in appendix 1, 2 and 3. P8 was chosen because it was one of the good places to record alpha band, and it was not affected significantly from eye-blinks. Eye-blinks affect the electrodes on the frontal lobes.

As it can be seen in Figure 3.2.1, only EMOTIV system’s two reference electrodes and P8 electrode were active during the experiments. Green label on the electrode location shows that the contact quality is good enough for recording.

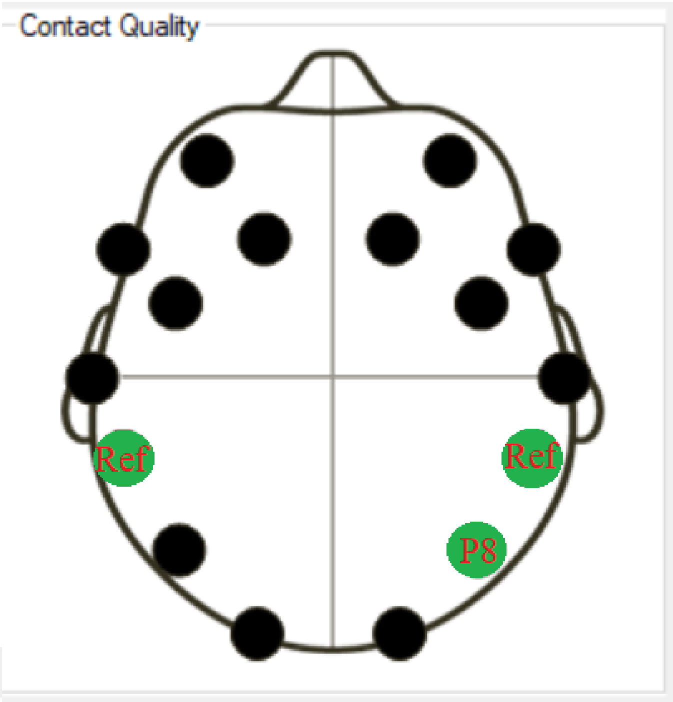

Figure 3.2.1 Active electrode locations.

3.3 EEG Preprocessing

Before performing the spectrum analysis of the EEG signals obtained, a preprocessing step was applied.

An EEG data coming from a participant is given below. As it can be seen in Figure 3.3.1, an offset existed in the data around 4150 uV.

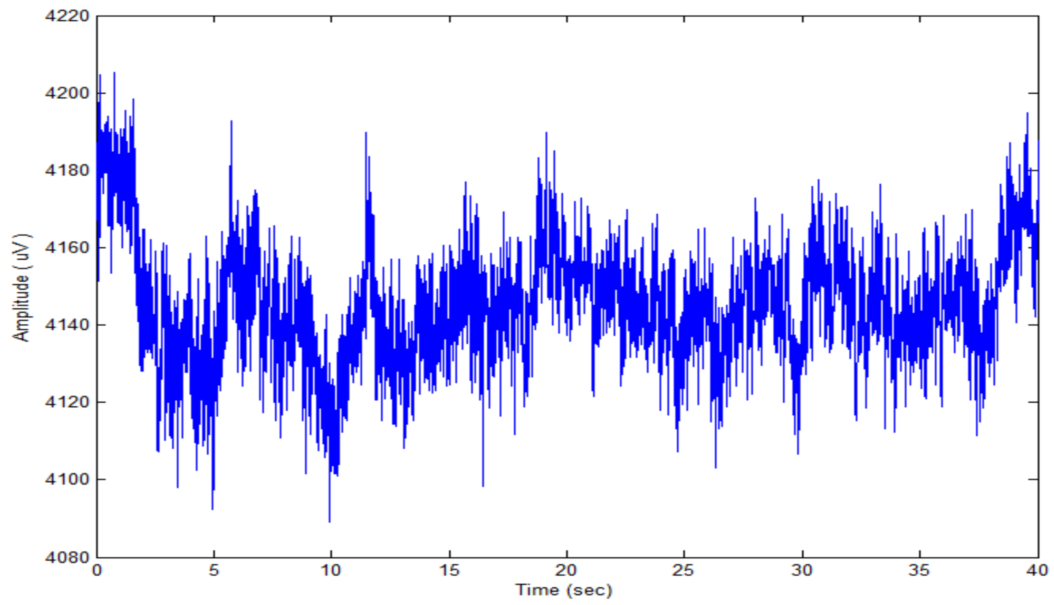

Figure 3.3.1 Sample EEG signal with an offset.

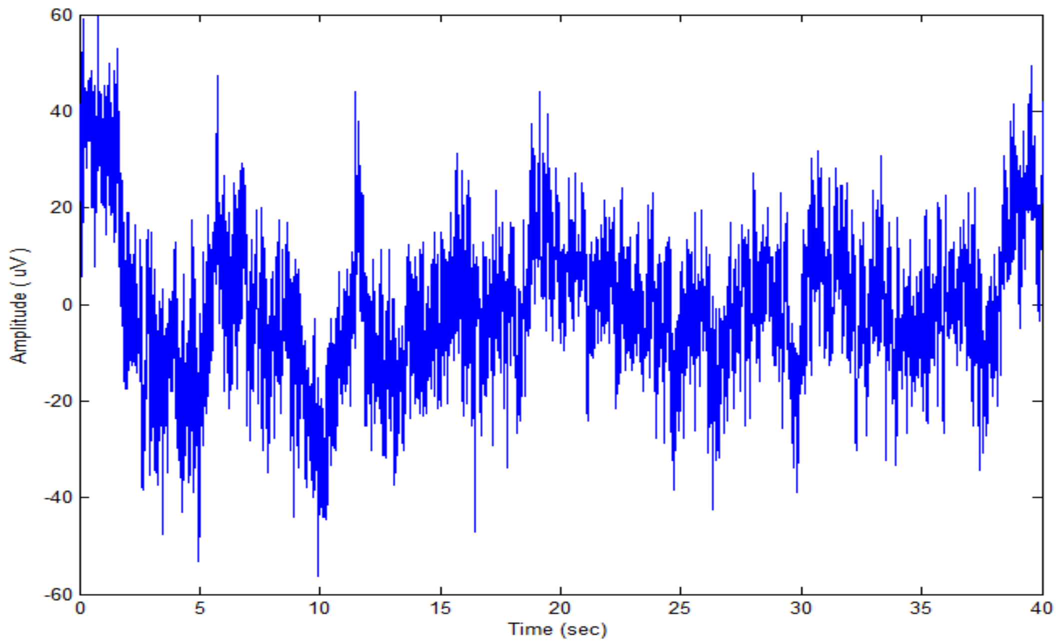

Figure 3.3.2 The same EEG signal after offset removal.

In the preprocessing step, the offset was removed by subtracting 4150 from each value in the dataset as shown in Figure 3.3.2. After offset removal, the signal was fed into a 5th-degree Butterworth high-pass filter whose cut-off frequency was 3 Hz. Because we were only interested in alpha band power we selected this cut-off in order not to affect any spectral coefficients in that band. In addition, if not removed excessive low-frequency power caused other spectral coefficients becoming not visible. The filtered signal, power spectra of signals before and after high-pass filtering can be seen in Figure 3.3.3, Figure 3.3.4 and Figure 3.3.5, respectively.

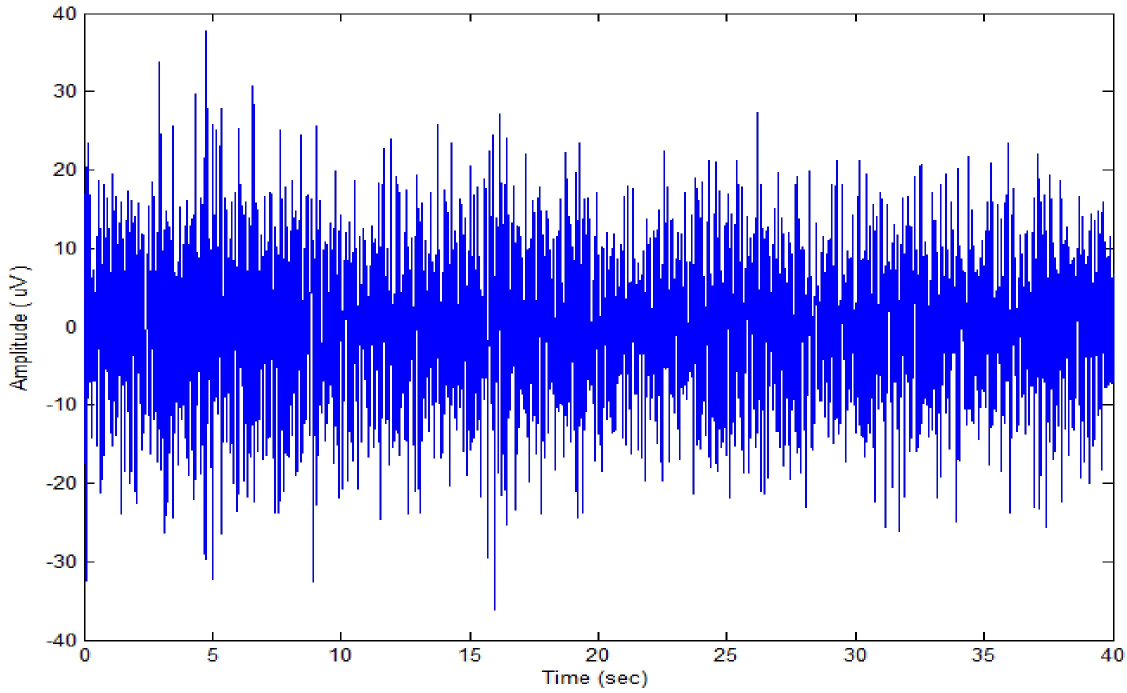

Figure 3.3.3 Filtered signal.

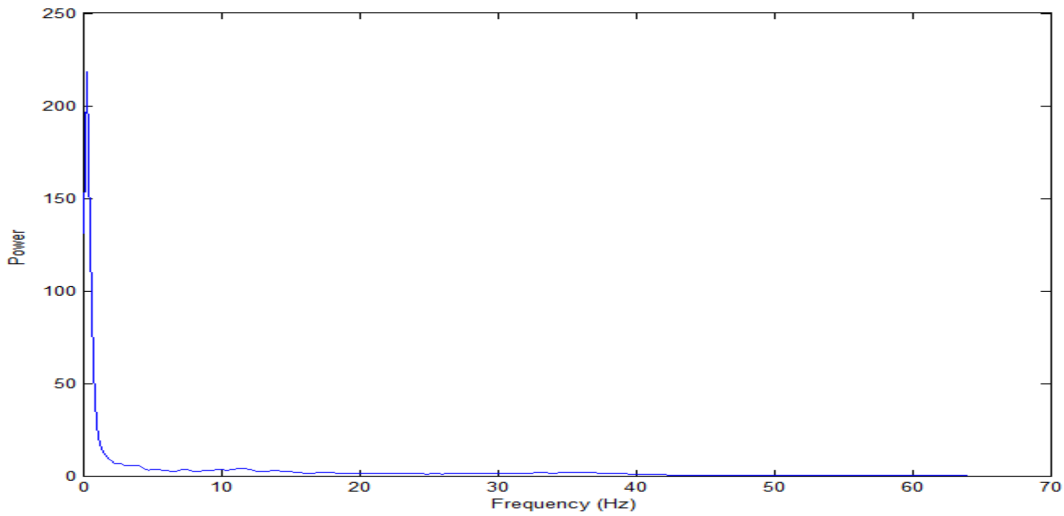

Figure 3.3.4 Unfiltered EEG signal spectrum.

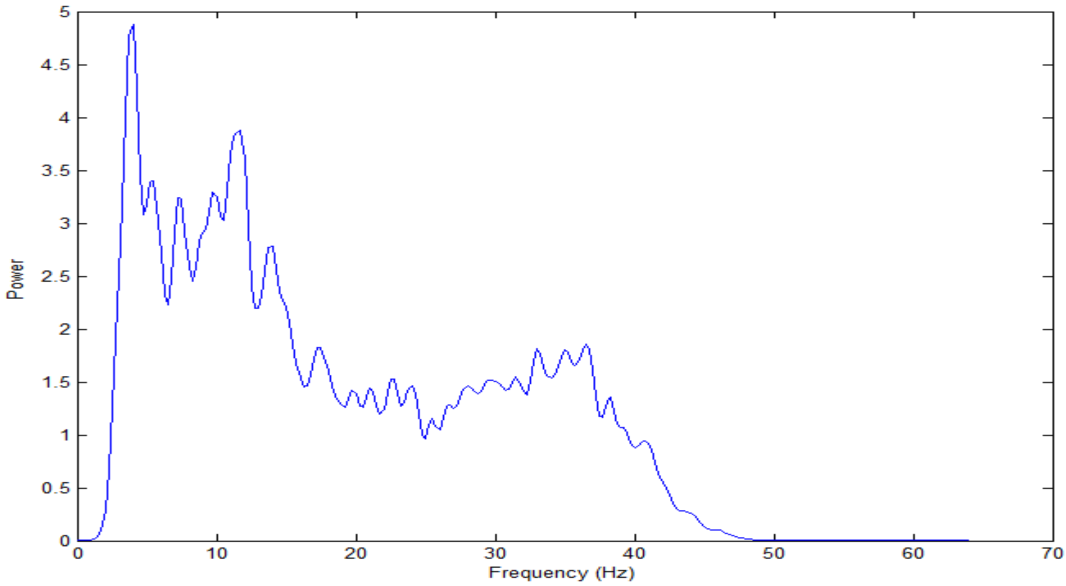

Figure 3.3.5 Filter applied EEG signal spectrum.

3.4 Power Spectral Density Methods

While calculating spectrum we investigated the use of three methods, such as Burg's, FFT, and Welch's methods. Explanations of these power spectral density computation methods are given below.

3.4.1 FFT method

The aim of the Fourier Transform is to separate a signal into its periodic basis functions. A digital system like computer samples the continuous signal, so the signal becomes discrete and has a finite bandwidth. Discrete Fourier Transform (DFT) plays an important role by getting definite number of instants of the signal and converts them to a definite number of frequency components. However, DFT requires a vast number of calculations when the number of the instants (N) reaches big numbers. Therefore, FFT decreases the number of calculations required by N samples from $2N^2$ to $2N\log_2 N$. Shortly, FFT is an effective version of DFT [54].

3.4.2 Welch's method

Welch's method first divides data into windows. Adjacent windows have some overlap between each other, and the method calculates the spectrum of these windows. Finally, averaging is applied to compute the spectrum of the data [55].

3.4.3 Burg's method

Burg's method first applies an autoregressive model to the data, and finds the best model reducing "the forward and backward prediction errors." The spectrum resolution of this method is good only for low amount of data [56]. However, we have observed several disadvantages of Burg's and FFT methods, which are given in detail in the Results section. Thus, we concluded that Welch's method was better than others for this thesis work.

Welch's method MATLAB command is given below.

[pxx,f] = pwelch(x,window,noverlap,f,fs)→ original command in MATLAB

[Pxx,f]=pwelch(y1,200,100,4*128,128)→the command used in our experiments.

Here, pxx is the power spectral density estimate, f is the frequency vector (cycle/second), x is our input signal, window divides the signal into segments, noverlap is the number of samples overlap from segment to segment, f = 4*fs means that we will calculate the spectrum coefficients for every 0.25 Hz (frequency resolution of power spectrum values), and fs is number of samples acquired in one second (fs was 128 Hz for this system).

3.5 Band Power Computation

In this thesis work, not the whole alpha band (7-13 Hz) was used. During the design stage, we recorded EEG data on a person with closed and open eyes a few times, found the intersection of these two cases. The data collected with open and closed eye method made it possible to observe alpha band synchronization and desynchronization which can be used to figure out alpha frequency band by using band crossings [12]. We found that open and closed eyes spectrums intersect at approximately 7 Hz and 11.5 Hz so we decided to use the 7-11.5 Hz band for all the participants in our experiment.

During the experiments, 45-second sensor data was collected using the EMOTIV system. Before we had started computing alpha band power values in real-time, enough data had to be collected. The first computed spectrum value was seen on the screen once we acquired 700 samples. During the spectrum computations, the last 512 samples were used (1 sample required 7,81 ms to be collected). In addition, in real-time computations, there was no artifact removal.

When calculating band power, relative band power (RBP) was used as shown in Equation 3.51.

$$RBP = \frac{Absolute\ Band\ Power\ of\ [7.5\ Hz - 11\ Hz]}{Absolute\ Band\ Power\ of\ [3.5\text{Hz} - 35\text{Hz}]} \quad \textbf{(3.5.1)}$$

3.6 Neurofeedback Experiments

3.6.1 Experimental medium

Experiments were done in a silent library room as seen in the below image.

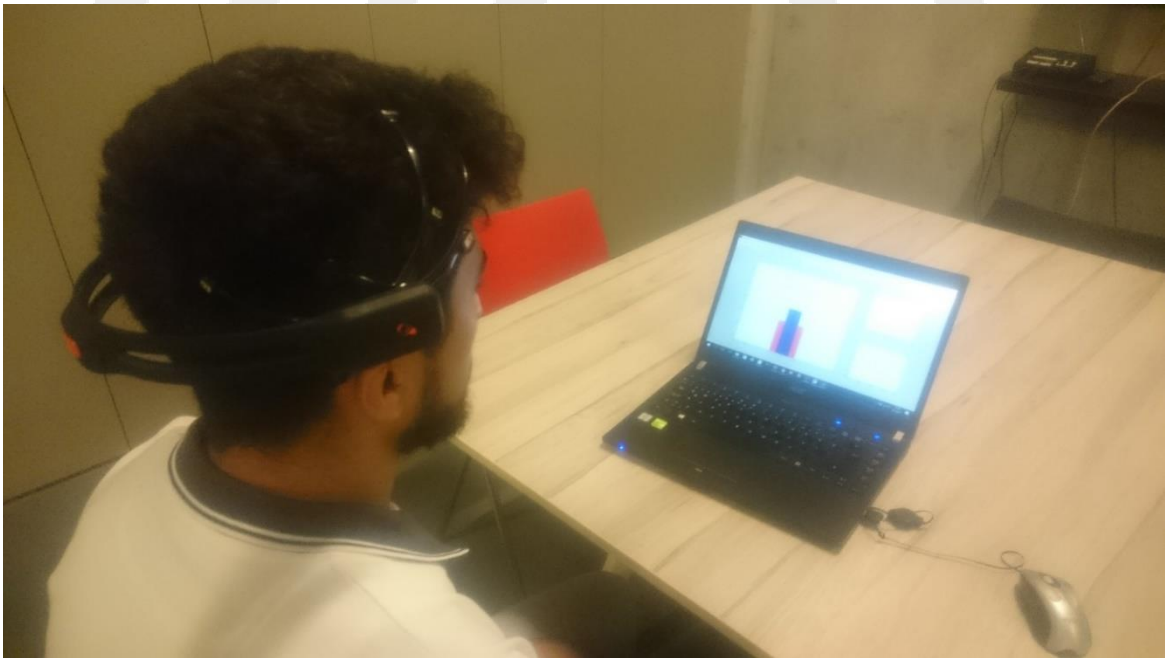

Figure 3.6.1.1 Experimental medium.

3.6.2 Memorizing words

Before the neurofeedback training sessions were started, pre-memory test was given to the participants. This test included 10 words asked in GRE examinations as given below:

English	Turkish
Exigency	zorunluluk
Innocuous	zararsız
Inspid	tatsız
Intractable	inatçı
Paucity	yetersizlik
Penchant	tutku
Equivocate	kelime oyunu yapmak
Discerning	zeki
Desultory	düzensiz
Audacious	gözü pek

Table 3.6.2.1 English words used in the pre-memory test.

After the neurofeedback training sessions, an after-memory test was given to the participants. This test also included 10 words asked in GRE examinations as given below:

English	Turkish
Elegy	ağıt
Ameliorate	düzeltmek,iyileştirmek
Impervious	su geçirmez
Contention	çekişme
Ebullient	coşkun
Imperturbable	soğukkanlı
Delineate	tasvir etmek
Arduous	çetin
Erudite	bilgili
Ephemeral	fani

Table 3.6.2.2 English words used in the after-memory test.

Firstly, the participant memorized the words. At first one word was shown on the screen followed by its meaning, then another word was shown followed by its meaning, and so on. Then, it was requested from the participant to remember the words. In the recall part of the memory tests, a word was given and the participant had to say the meaning. No multiple choice type approach was followed (see Figure 3.6.3.1 and Figure 3.6.3.2).

Learning time, recall time, and the number of accurate words were recorded manually except for the two of the participant. For those participants, recall times were not measured, and they were indicated as N.A. in the charts, which are given in the Results section.

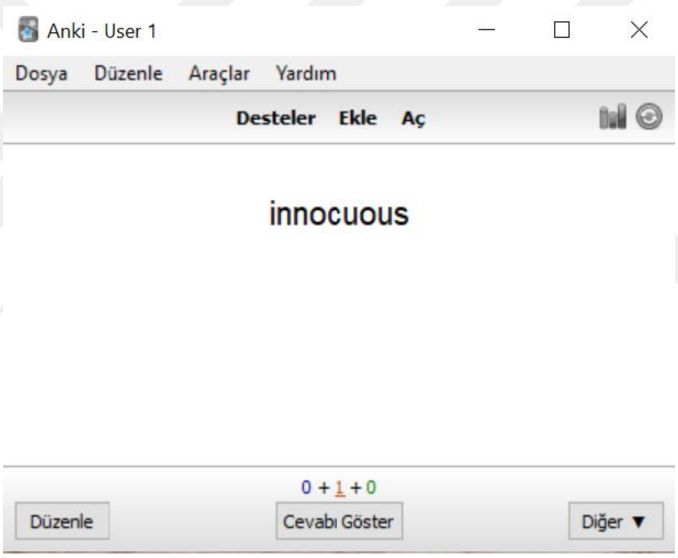

Figure 3.6.3.1 English word test screen without answer.

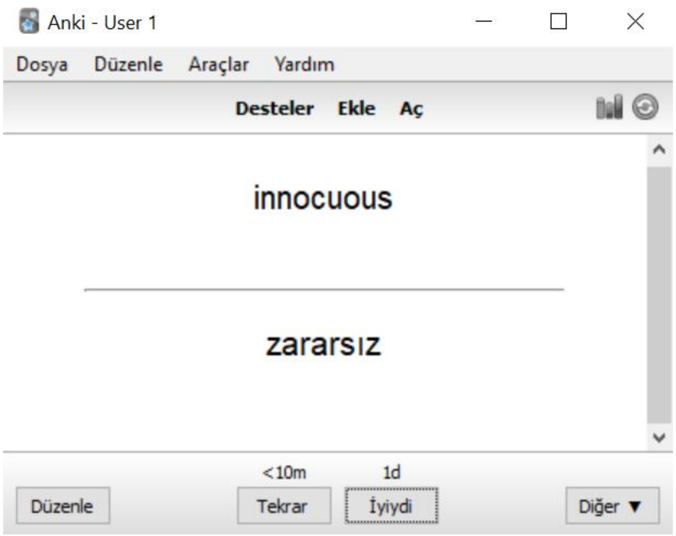

Figure 3.6.3.2 English word test screen with the answer.

3.6.4 Graphical user interface used in neurofeedback training

During the training, the participants were able to see the panels shown below in Figure 3.6.4.1. The blue bar indicated the dynamically changing relative alpha band power, and the red bars depicted the mean value of the relative alpha band power, which was measured at the baseline recordings. The mean power values were updated after each training subsession. The participants tried to increase the blue bar's level to pass the red bars (baseline level), which worked as a visual feedback. We also used an audio feedback as a beep sound when the level was surpassed. Some participants wanted to make sound off, because they thought that it was distracting their concentration. In the large panel on the left, the red, blue and green lines showed some levels that the participant could challenge. They were put there in order to be able to motivate the participants. On the right panel, the dashed pink line showed relative alpha band power, and the blue line indicated the absolute alpha band power. We asked participants to focus on the left panel only.

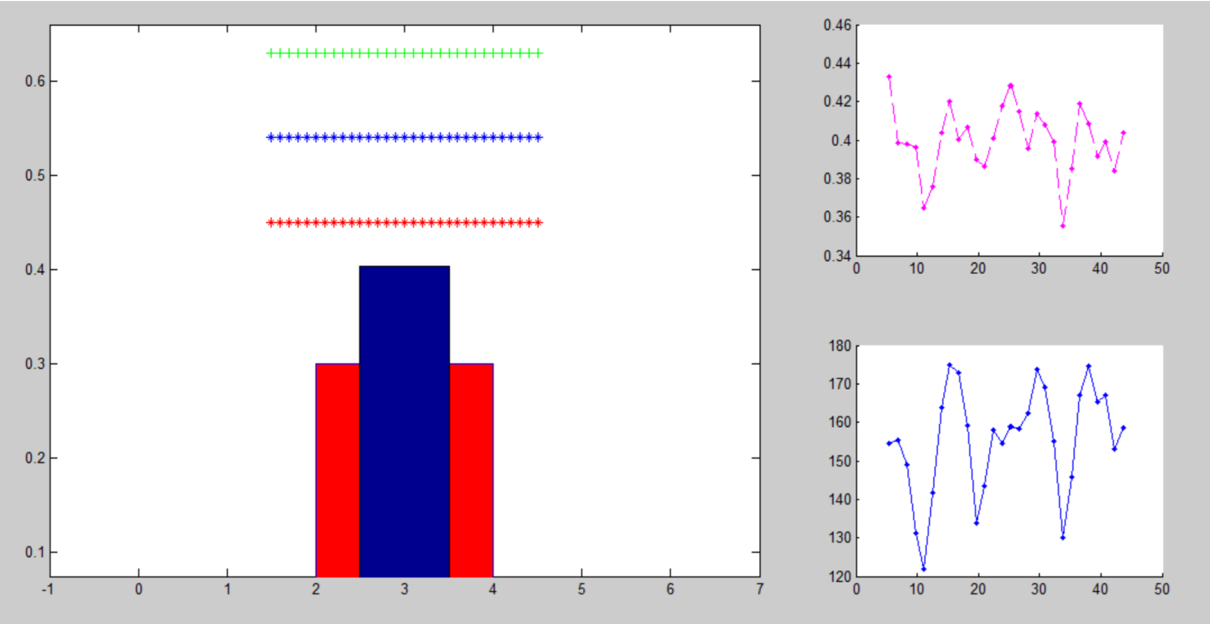

Figure 3.6.4.1 User interface of neurofeedback training during the experiment.

3.6.5 Training

After the pre-memorizing test, 5 sessions of neurofeedback training were applied. No more than one session was applied on the same day, and the training sessions lasted at most for 10 days according to the availability of the participants.

One-day training (one session) included 3 subsessions. Five trials constituted one subsession. As a result, one training session included 15 trials. Each trial lasted for 45 seconds, and 10 seconds were placed between two adjacent trials. After every 5 trials (1 subsession) the participants had enough time to rest, approximately 1-2 minutes. In Table 3.6.5.1 we can see the paradigm we used during the training sessions.

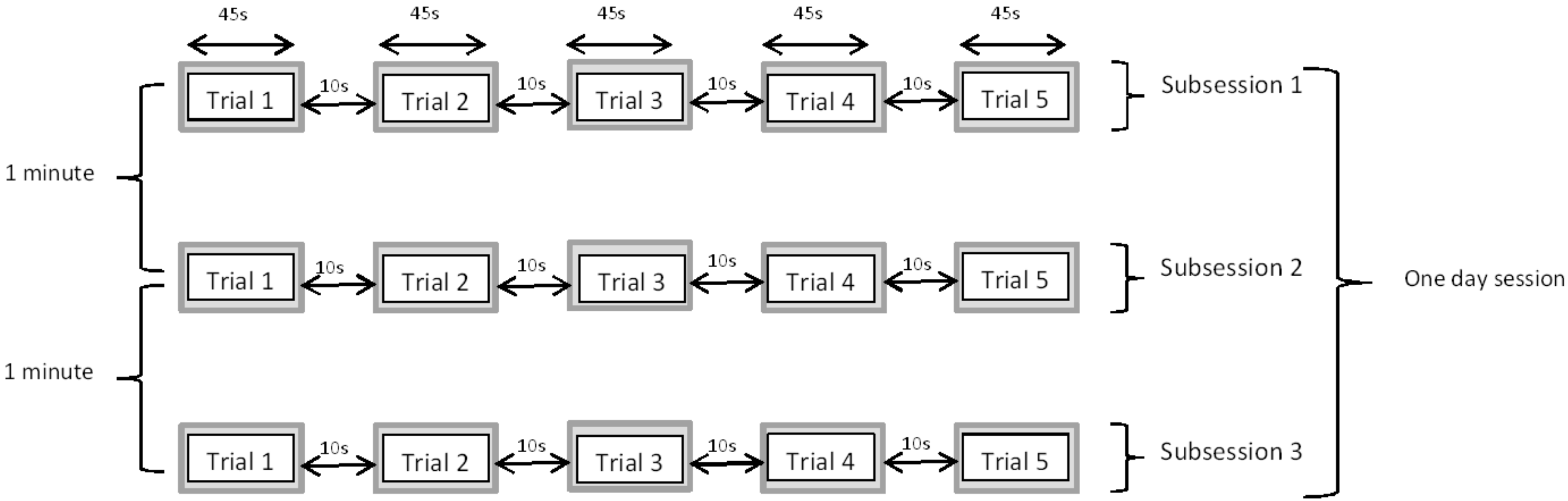

Table 3.6.5.1 Experimental paradigm used for neurofeedback training.

At the end of the subsessions, the participants were able to see their performances as shown in the Figure 3.6.5.2.

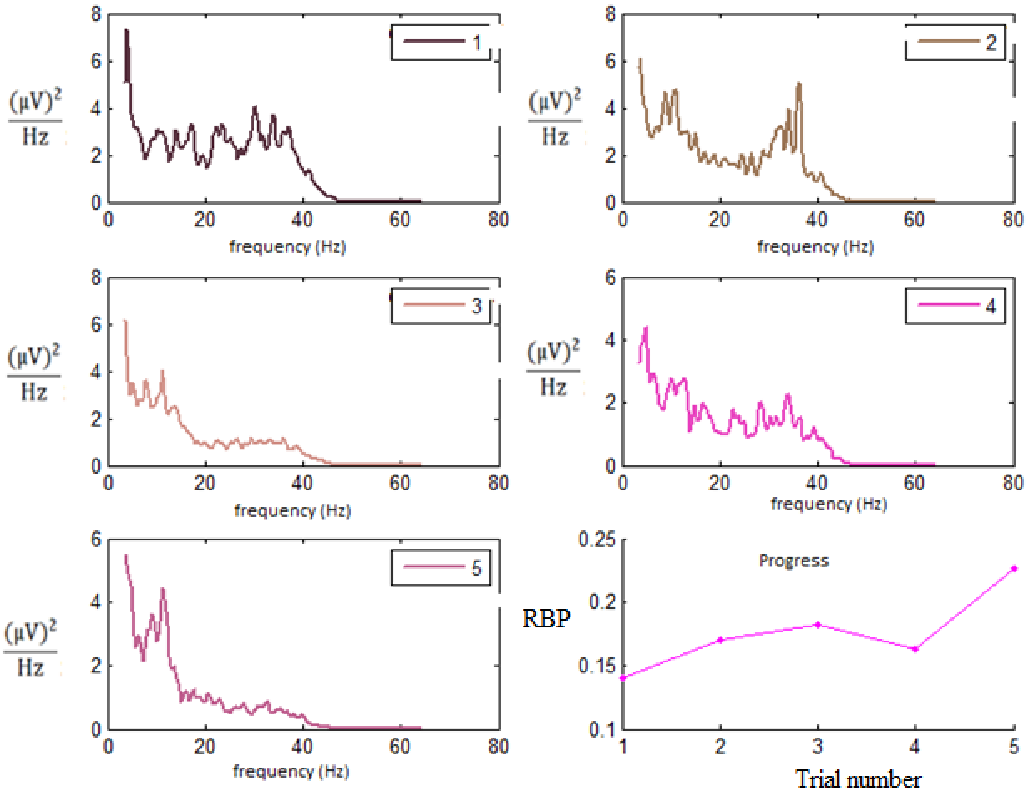

Figure 3.6.5.2 A participant's performance graphics for one subsession.

Before the training session started, several thinking strategies were advised to the participants. For example, the alpha power generally is related to the relaxation process, and positive thinking such as thinking of the family, friends and natural scenes increase the alpha power. In the first 2nd and 3rd sessions (2-3 day training) it was requested from the participants to determine the best thinking strategy that had increased their alpha power. However, in the 4th and 5th sessions, it was requested from them not to find any new thinking strategies but to focus on what they had figured out before, shortly, try to increase the alpha power as much as they could.

The items below were reported during the training.

- When focusing on one thinking strategy another disturbing thinking style was intervening.
- The participants could not synchronize with the screen.
- It was hard to maintain a thinking style for the whole trial duration for 45 seconds.

Participants indicated that they could not fully synchronize with the blue bar during training. Here synchronization means, they were not sure whether one type of thinking style increased or decreased the alpha power. However, at the end of the trial, they mentioned that a particular thinking style was generally useful in increasing the alpha power. During the training sessions, when we observed an alpha power increase we asked the participant what he was thinking of. The answers generally complied with positive thinking, however, some of them mentioned that they thought about the processes of their job, the meal they ate, the characters that they read from a novel or of someone they were angry with.

Data including the participants' EEG, pre-test, and after-test data were saved. The statistical graphics belonging to the participants were given in the results section.

For the experiment, there was no payment to the participants except for a piece of chocolate for every session.

CHAPTER 4

Results

In this chapter, we present the comparison of spectral methods which were tested during the EEG signal processing of this thesis work, and the analysis outcomes of neurofeedback sessions for each individual participant.

4.1 Comparison of spectral methods

In this section, three spectral analysis approaches (FFT, Burg's, and Welch's methods) were compared using a simulated combined sinusoidal signal and an EEG signal that was collected during our experiments.

For the first comparison, a signal was simulated using the equation (4.1.1) as shown below in Figure 4.1.1. This signal was a linear combination of 5, 10 and 15 Hz sine waves with equal amplitudes (0.3). This signal worked as a simulated EEG signal.

$$z = 0.3*\sin(2*pi*5*t)+ 0.3*\sin(2*pi*10*t) +0.3*\sin(2*pi*15*t) \qquad (4.1.1)$$

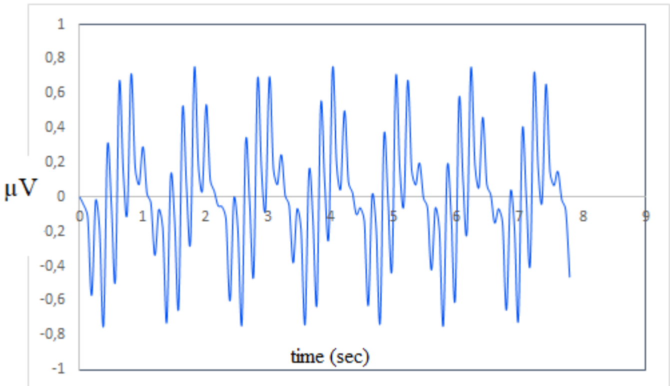

Figure 4.1.1. Simulated signal.

Later, this signal was filtered using the 5th order Butterworth filter with a cut off frequency of 3 Hz, which was the case in the neurofeedback sessions. We expected to see three spikes at 5, 10 and 15 Hz with equal amplitudes. The frequency spectra of simulated EEG are depicted in Figures 4.1.1, 4.1.2, and 4.1.3 for FFT, Burg's and Welch's methods, respectively. These figures show that the best spectrum was obtained using Burg's method for the simulated signal.

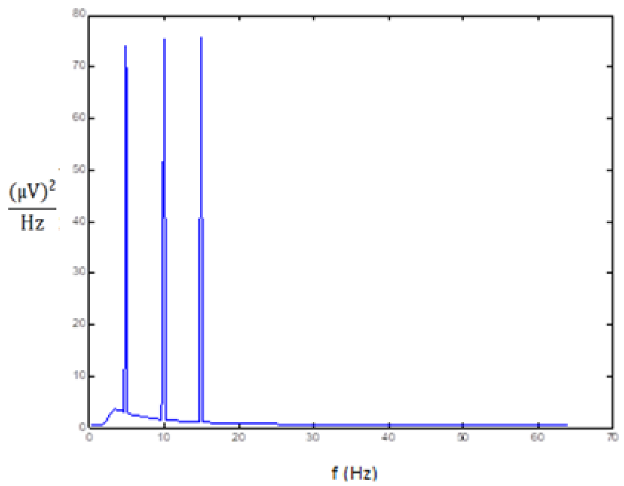

Figure 4.1.2. Frequency spectrum of the simulated signal using FFT method.

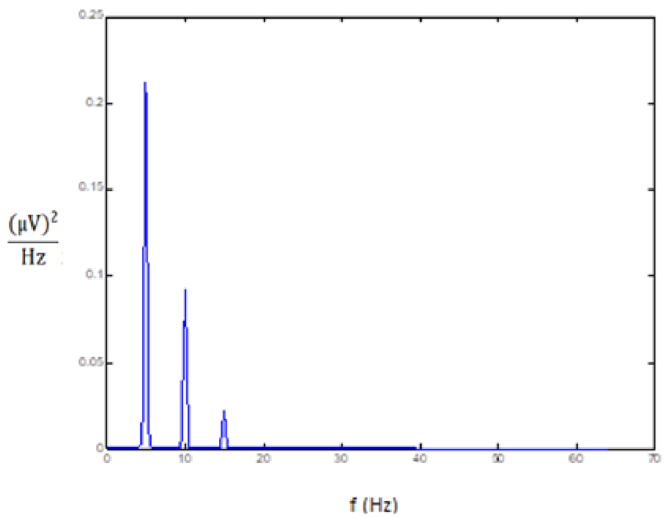

Figure 4.1.3. Frequency spectrum of the simulated signal using Burg's method.

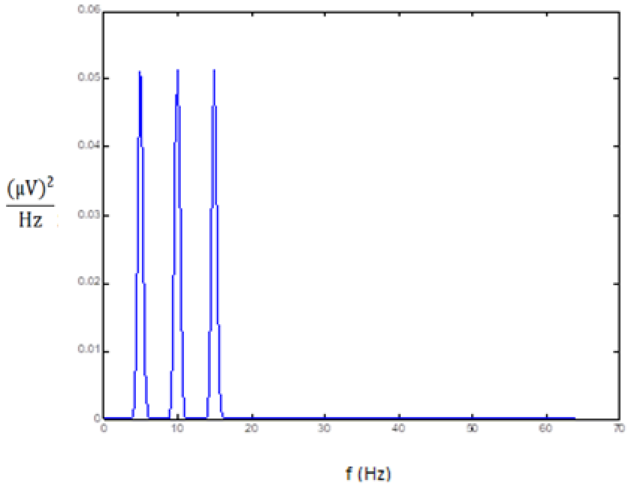

Figure 4.1.4. Frequency spectrum of the simulated signal using Welch's method.

We have repeated the frequency spectra determination using the same approaches on a real EEG signal that was acquired during our experiments. The results are demonstrated in Figures 4.1.4, 4.1.5, and 4.1.6 for FFT, Burg's and Welch's methods, respectively. Due to the fact that Burg's method did not give true amplitudes in simulated signal, and spectrum obtained using FFT method was highly spiky when applied to the original EEG signal, we decided to use Welch's method for the processing of EEG signals in real-time neurofeedback experiments. The MATLAB code used for this part is available in the appendix 4.

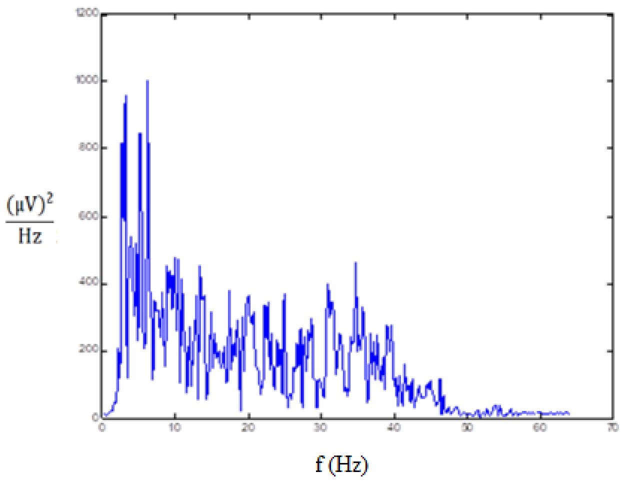

Figure 4.1.5. Frequency spectrum of the EEG signal using FFT method.

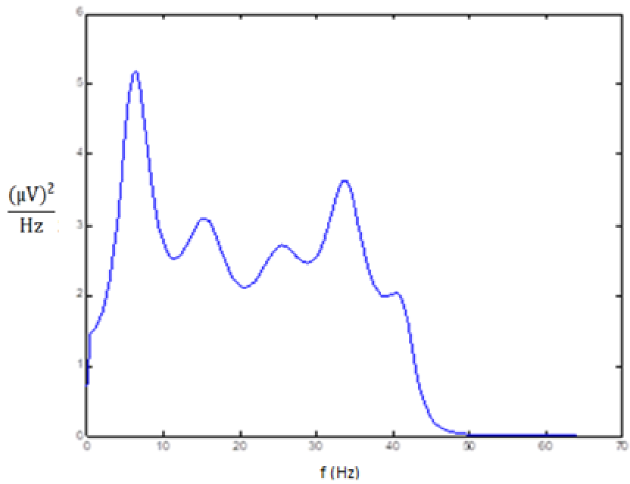

Figure 4.1.6. Frequency spectrum of the EEG signal using Burg's method.

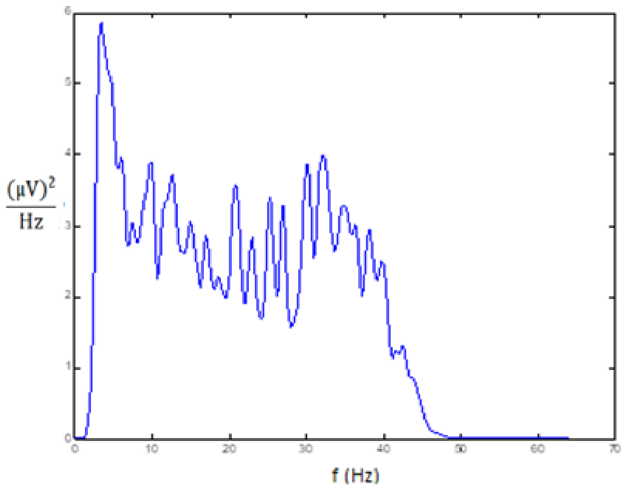

Figure 4.1.7. Frequency spectrum of the EEG signal using Welch's method.

4.2 Experimental results

In this part of the thesis, experimental results obtained from 11 participants are given. In the tables presented below (from 4.2.1 to 4.2.12), average alpha band power for the baseline recordings and all neurofeedback subsessions are summarized. The sessions were repeated for 5 days, and 3 subsessions per day. The mean alpha band power values for the baseline and each day were also depicted in the tables and in the figures below the tables. In these tables, one can see several memory related durations and number of words that were correctly remembered before and after the sessions.

Subsession	Day1	Day2	Day3	Day4	Day5
1st Subsession	0.189	0.223	0.170	0.179	0.201
2nd Subsession	0.217	0.217	0.178	0.301	0.238
3rd Subsession	0.188	0.161	0.205	0.275	0.246
Mean	0.198	0.200	0.184	0.252	0.228
Baseline	0.160				
	Memorization Duration (sec)	**Recall Duration (sec)**	**Num. of Correct Answers (?/ 10)**		
Pre-test	95	Not available	3		
After-test	123	59	9		

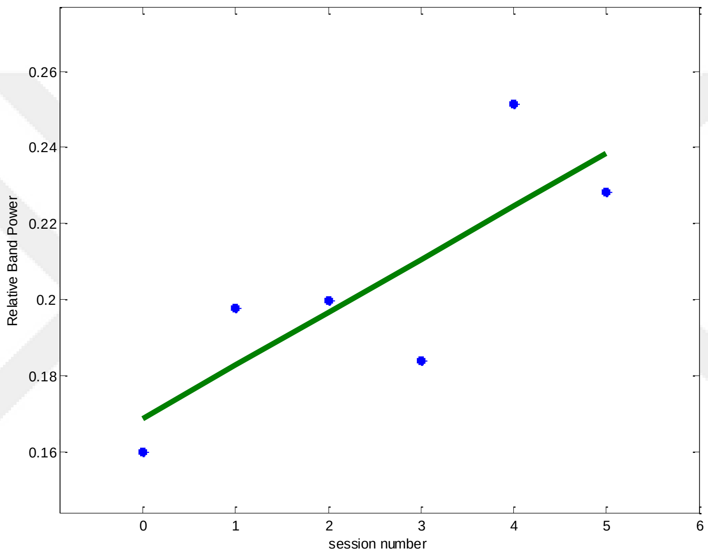

Table 4.2.1 Experimental results obtained during neurofeedback sessions from participant #1.

Subsession	Day1	Day2	Day3	Day4	Day5
1st Subsession	0,1404	0,1655	0,1906	0,1779	0,1772
2nd Subsession	0,158	0,1523	0,2024	0,1714	0,1903
3rd Subsession	0,1489	0,176	0,1882	0,1685	0,1979
Mean	0,1491	0,1646	0,1937	0,1726	0,1885
Baseline	0,1071				
	Memorization Duration (sec)	**Recall Duration (sec)**	**Num. of Correct Answers (?/ 10)**		
Pre-test	86	120	3		
After-test	91	136	2		

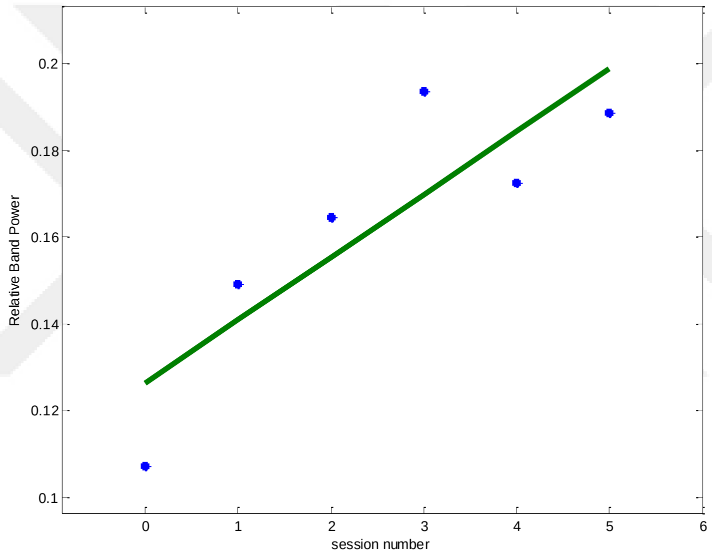

Table 4.2.2 Experimental results obtained during neurofeedback sessions from participant #2.

Subsession	Day1	Day2	Day3	Day4	Day5
1st Subsession	0,1876	0,1641	0,224	0,2029	0,2229
2nd Subsession	0,2049	0,2385	0,2409	0,1774	0,2519
3rd Subsession	0,2239	0,2402	0,2074	0,2032	0,2397
Mean	0,2055	0,2143	0,2241	0,1945	0,2382
Baseline	0,2128				
	Memorization Duration (sec)	Recall Duration (sec)	Num. of Correct Answers (?/ 10)		
Pre-test	46	69	1		
After-test	75	61	7		

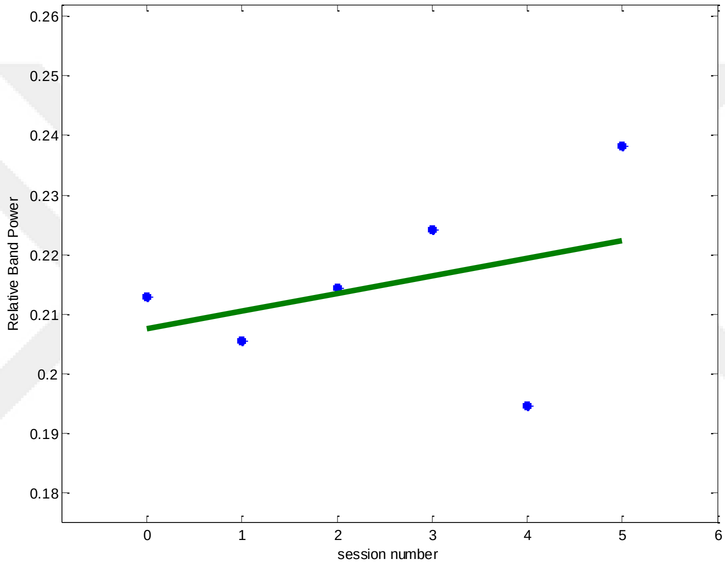

Table 4.2.3 Experimental results obtained during neurofeedback sessions from participant #3.

Subsession	Day1	Day2	Day3	Day4	Day5
1st Subsession	0,1855	0,1939	0,2035	0,1985	0,2005
2nd Subsession	0,2546	0,1929	0,1934	0,1955	0,2218
3rd Subsession	0,1948	0,1809	0,2031	0,1911	0,2331
Mean	0,2116	0,1892	0,2	0,195	0,2185
Baseline	0,1759				
	Memorization Duration (sec)	Recall Duration (sec)	Num. of Correct Answers (?/ 10)		
Pre-test	117	103	2		
After-test	182	105	8		

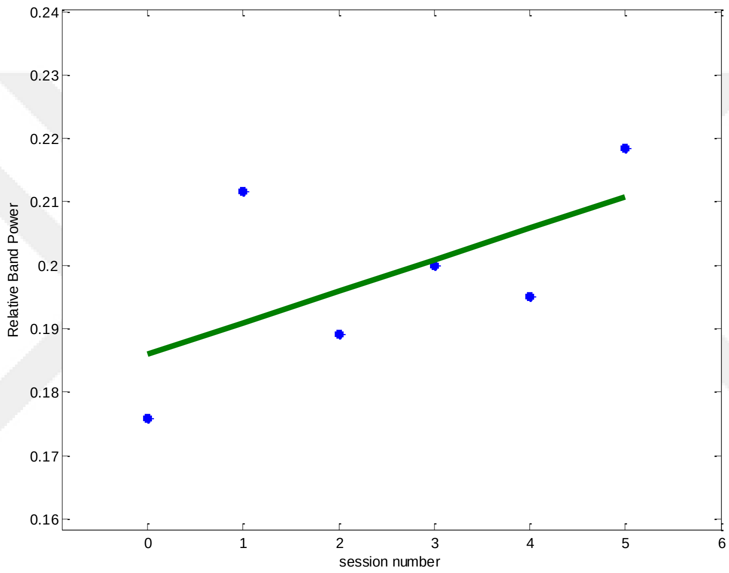

Table 4.2.4 Experimental results obtained during neurofeedback sessions from participant #4.

Subsession	Day1	Day2	Day3	Day4	Day5
1st Subsession	0.2336	0.2265	0.2047	0.2278	0.2168
2nd Subsession	0.2466	0.2290	0.2200	0.2575	0.1808
3rd Subsession	0.2572	0.2048	0.1923	0.2605	0.1717
Mean	0,2458	0,2201	0,2057	0,2486	0,1897
Baseline	0,2158				
	Memorization Duration (sec)	Recall Duration (sec)	Num. of Correct Answers (?/ 10)		
Pre-test	42	45	4		
After-test	45	85	1		

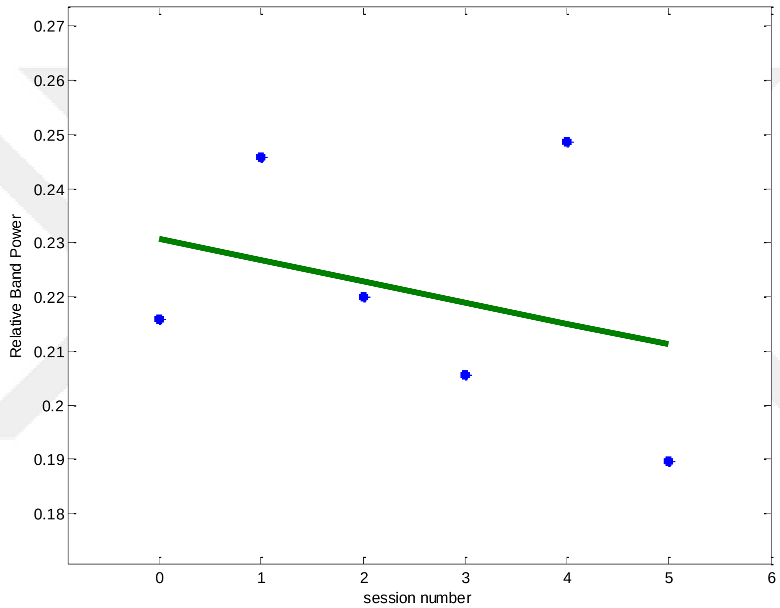

Table 4.2.5 Experimental results obtained during neurofeedback sessions from participant #5.

Subsession	**Day1**	**Day2**	**Day3**	**Day4**	**Day5**
1st Subsession	0,1527	0,1565	0,1496	0,1776	0,1517
2nd Subsession	0,1515	0,1706	0,1421	0,1595	0,1588
3rd Subsession	0,1496	0,1597	0,1578	0,1551	0,1409
Mean	0,1513	0,1622	0,1498	0,1641	0,1505
Baseline	0,1567				
	Memorization Duration (sec)	**Recall Duration (sec)**	**Num. of Correct Answers (?/ 10)**		
Pre-test	82	113	2		
After-test	116	105	4		

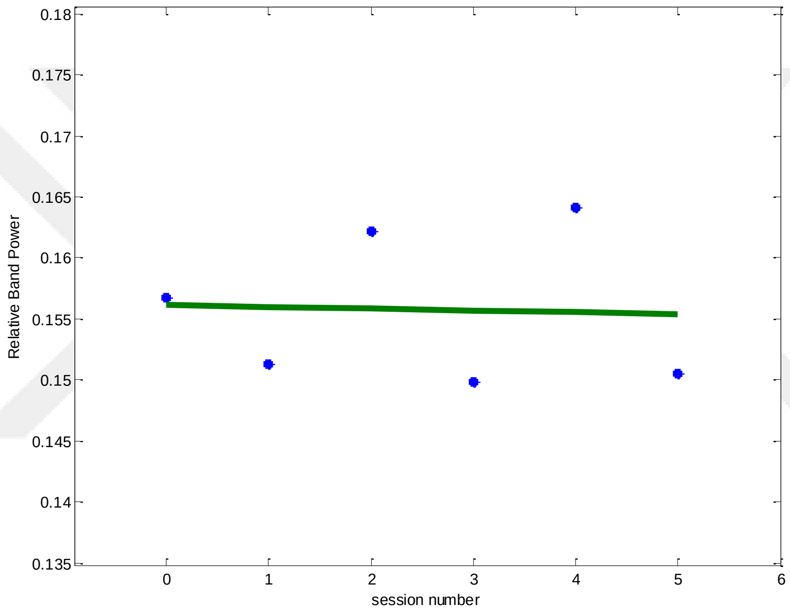

Table 4.2.6 Experimental results obtained during neurofeedback sessions from participant #6.

Subsession	Day1	Day2	Day3	Day4	Day5
1st Subsession	0,2001	0,184	0,1791	0,1883	0,1862
2nd Subsession	0,2131	0,1907	0,1807	0,1914	0,2197
3rd Subsession	0,2196	0,1814	0,2128	0,2276	0,206
Mean	0,211	0,1854	0,1909	0,2024	0,204
Baseline	0,1429				
	Memorization Duration (sec)	Recall Duration (sec)	Num. of Correct Answers (?/ 10)		
Pre-test	139	Not available	4		
After-test	241	78	8		

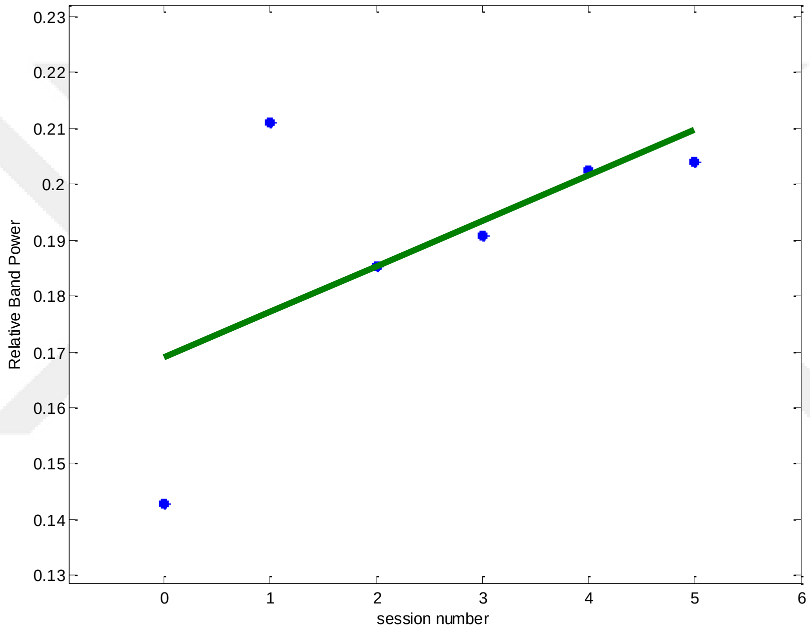

Table 4.2.7 Experimental results obtained during neurofeedback sessions from participant #7.

Subsession	Day1	Day2	Day3	Day4	Day5
1st Subsession	0,3018	0,3466	0,3978	0,3795	0,4302
2nd Subsession	0,3377	0,389	0,4112	0,4184	0,4206
3rd Subsession	0,2876	0,454	0,4544	0,4712	0,4582
Mean	0,309	0,3965	0,4211	0,423	0,4363
Baseline	0,2797				
	Memorization Duration (sec)	**Recall Duration (sec)**	**Num. of Correct Answers (?/ 10)**		
Pre-test	90	62	8		
After-test	159	51	8		

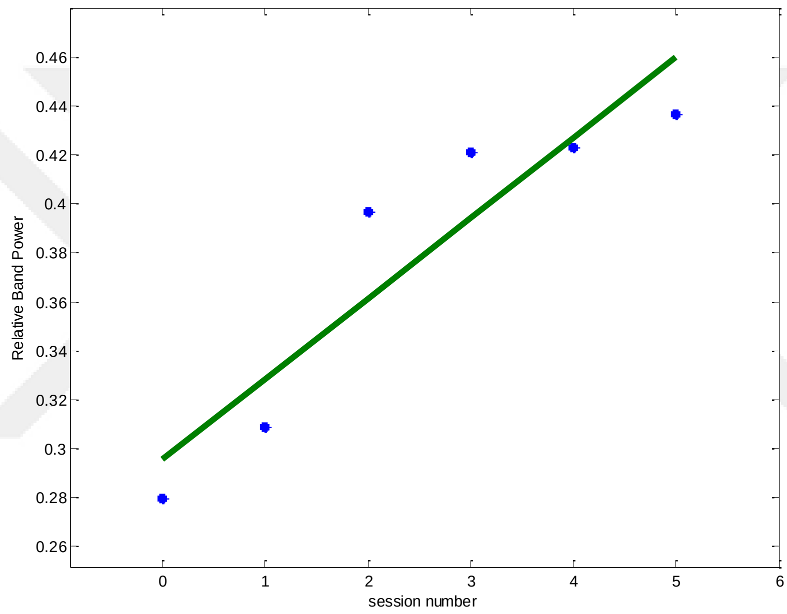

Table 4.2.8 Experimental results obtained during neurofeedback sessions from participant #8.

Subsession	Day1	Day2	Day3	Day4	Day5
1st Subsession	0,1933	0,1829	0,1829	0,1742	0,1818
2nd Subsession	0,1881	0,1814	0,1757	0,1885	0,1879
3rd Subsession	0,1848	0,1901	0,1914	0,1825	0,1882
Mean	0,1887	0,1848	0,1833	0,1817	0,186
Baseline	0,1789				
	Memorization Duration (sec)	**Recall Duration (sec)**	**Num. of Correct Answers (?/ 10)**		
Pre-test	64	Not available	1		
After-test	101	86	5		

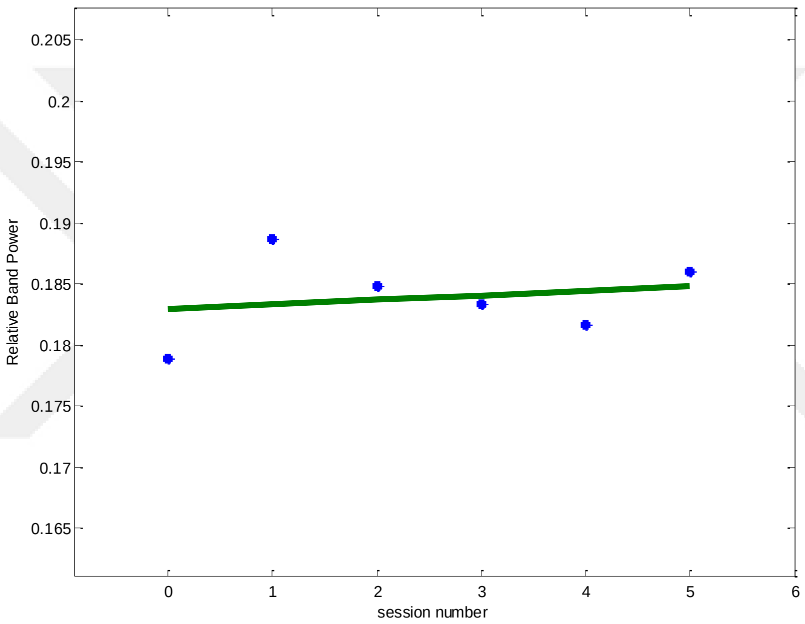

Table 4.2.9 Experimental results obtained during neurofeedback sessions from participant #9.

Subsession	Day1	Day2	Day3	Day4	Day5
1st Subsession	0,1976	0,3021	0,3011	0,3239	0,3125
2nd Subsession	0,2331	0,3114	0,3138	0,34	0,3353
3rd Subsession	0,2596	0,3255	0,3065	0,2851	0,3222
Mean	0,2301	0,313	0,3071	0,3163	0,3233
Baseline	0,3039				
	Memorization Duration (sec)	**Recall Duration (sec)**	**Num. of Correct Answers (?/ 10)**		
Pre-test	88	Not available	4		
After-test	153	62	9		

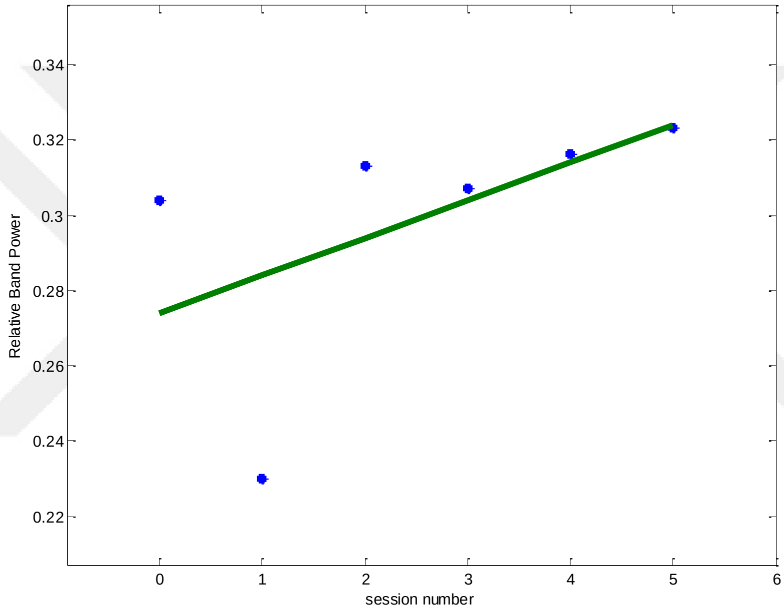

Table 4.2.10 Experimental results obtained during neurofeedback sessions from participant #10.

Subsession	Day1	Day2	Day3	Day4	Day5
1st Subsession	0,1663	0,1203	0,1545	0,187	0,1613
2nd Subsession	0,1326	0,1419	0,2064	0,2052	0,1423
3rd Subsession	0,1597	0,1559	0,1768	0,1858	0,1799
Mean	0,1529	0,1394	0,1792	0,1926	0,1612
Baseline	0,1073				
	Memorization Duration (sec)	**Recall Duration (sec)**	**Num. of Correct Answers (?/ 10)**		
Pre-test	94	103	4		
After-test	162	94	7		

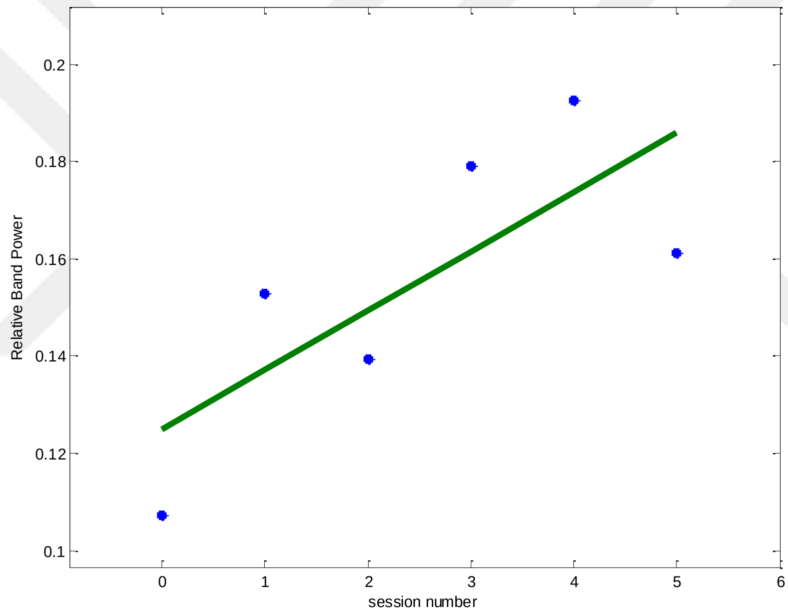

Table 4.2.11 Experimental results obtained during neurofeedback sessions from participant #11.

In Table 4.2.12 one can see the relative alpha band power levels, memorization durations and the number of words which were truly recalled before and after the neurofeedback training sessions.

Participant	Baseline	Day1	Day2	Day3	Day4	Day5	Pre-test Memorization Duration (sec)	After-test Memorization Duration (sec)	Pre-test Recall Duration (sec)	After-test Recall Duration (sec)	Pre-test Num. of Correct Answers	After-test Num. of Correct Answers
Participant#1	0.1601	0.1978	0.1999	0.1841	0.2515	0.2284	95	123	Not available	59	3	9
Participant#2	0.1071	0.1491	0.1646	0.1937	0.1726	0.1885	86	91	120	136	3	2
Participant#3	0.2128	0.2055	0.2143	0.2241	0.1945	0.2382	46	75	69	61	1	7
Participant#4	0.1759	0.2116	0.1892	0.2	0.195	0.2185	117	182	103	105	2	8
Participant#5	0.2158	0.2458	0.2201	0.2057	0.2486	0.1897	42	45	45	85	4	1
Participant#6	0.1567	0.1513	0.1622	0.1498	0.1641	0.1505	82	116	113	105	2	4
Participant#7	0.1429	0.211	0.1854	0.1909	0.2024	0.204	139	241	Not available	78	4	8
Participant#8	0.2797	0.309	0.3965	0.4211	0.423	0.4363	90	159	62	51	8	8
Participant#9	0.1789	0.1887	0.1848	0.1833	0.1817	0.186	64	101	Not available	86	1	5
Participant#10	0.3039	0.2301	0.313	0.3071	0.3163	0.3233	88	153	Not available	62	4	9
Participant#11	0.1073	0.1529	0.1394	0.1792	0.1926	0.1612	94	162	103	94	4	7
Mean	0.1856	0.2048	0.2154	0.2217	0.2311	0.2295	82	129	-	-	3.27	6.18

Table 4.2.12 Results obtained during neurofeedback experiments combined in one table.

4.3 Performance results

In this section, the most successful and the most unsuccessful participants' first and last trials' EEG spectra are given.

In Figure 4.3.1 one can see the EEG spectrum obtained from the most unsuccessful participant during the first day, first subsession, and first trial. Figure 4.3.2 shows the EEG spectrum from the same participant during the neurofeedback in the last day, last subsession, and the last trial. As can be seen from these figures, the participant was able to reach approximately 2 $\frac{(\mu V)^2}{Hz}$ alpha band power in the first trial, and in the last trial the level increased up to approximately 2.7 $\frac{(\mu V)^2}{Hz}$.

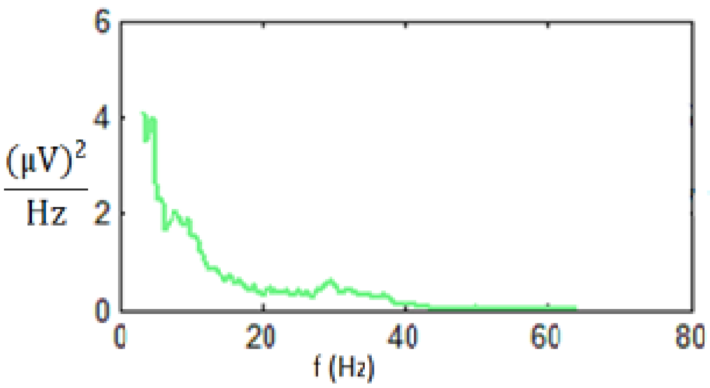

Figure 4.3.1 EEG spectrum of the most unsuccessful participant's first day, first subsession, and first trial.

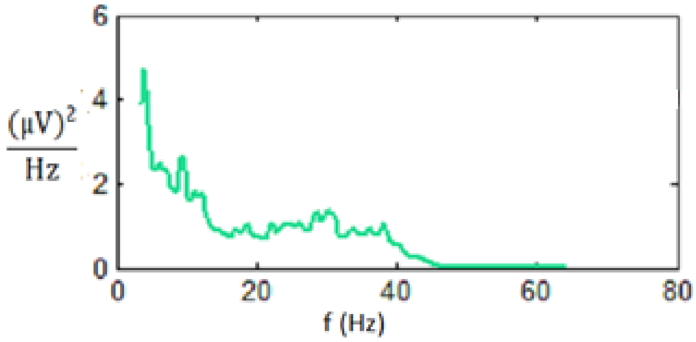

Figure 4.3.2 EEG spectrum of the most unsuccessful participant's last day, last subsession, and the last trial.

Figure 4.3.3 depicts the EEG spectrum of the most successful participant obtained during the first day, first subsession, and the first trial, and in Figure 4.3.4 one can see the EEG spectrum of the most successful participant during the last day, last subsession, and the last trial. This participant was able to reach approximately 12 $\frac{(\mu V)^2}{Hz}$ alpha band power during the first day, approximately 22 $\frac{(\mu V)^2}{Hz}$ alpha band power in the last day.

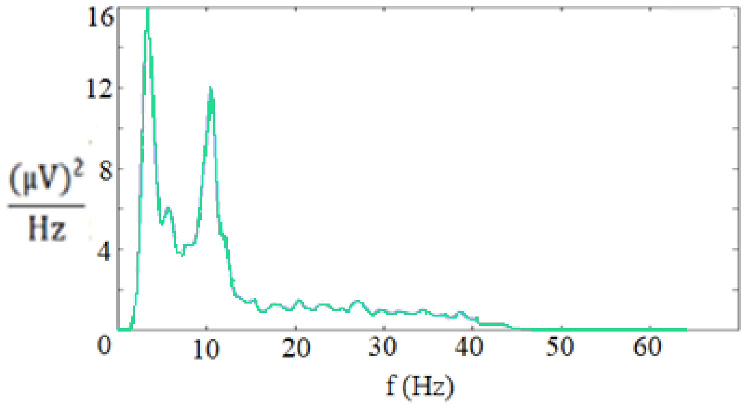

Figure 4.3.3 EEG spectrum of the most successful participant obtained during the first day, first subsession, and the first trial.

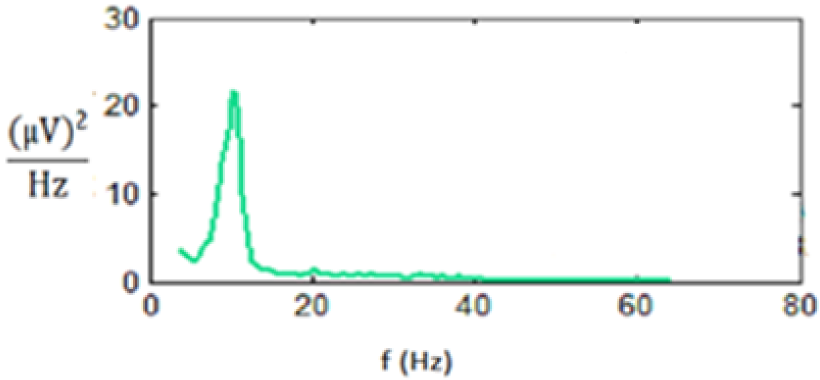

Figure 4.3.4 EEG spectrum of the most successful participant during the last day, last subsession, and the last trial.

Participants generally had a peak performance at the third or fourth trial in a subsession. One sample performance can be seen in Figure 4.4.1, which belonged to the tenth participant at the first day third subsession. In the bottom-right panel the relative band power values are demonstrated in a comparative manner.

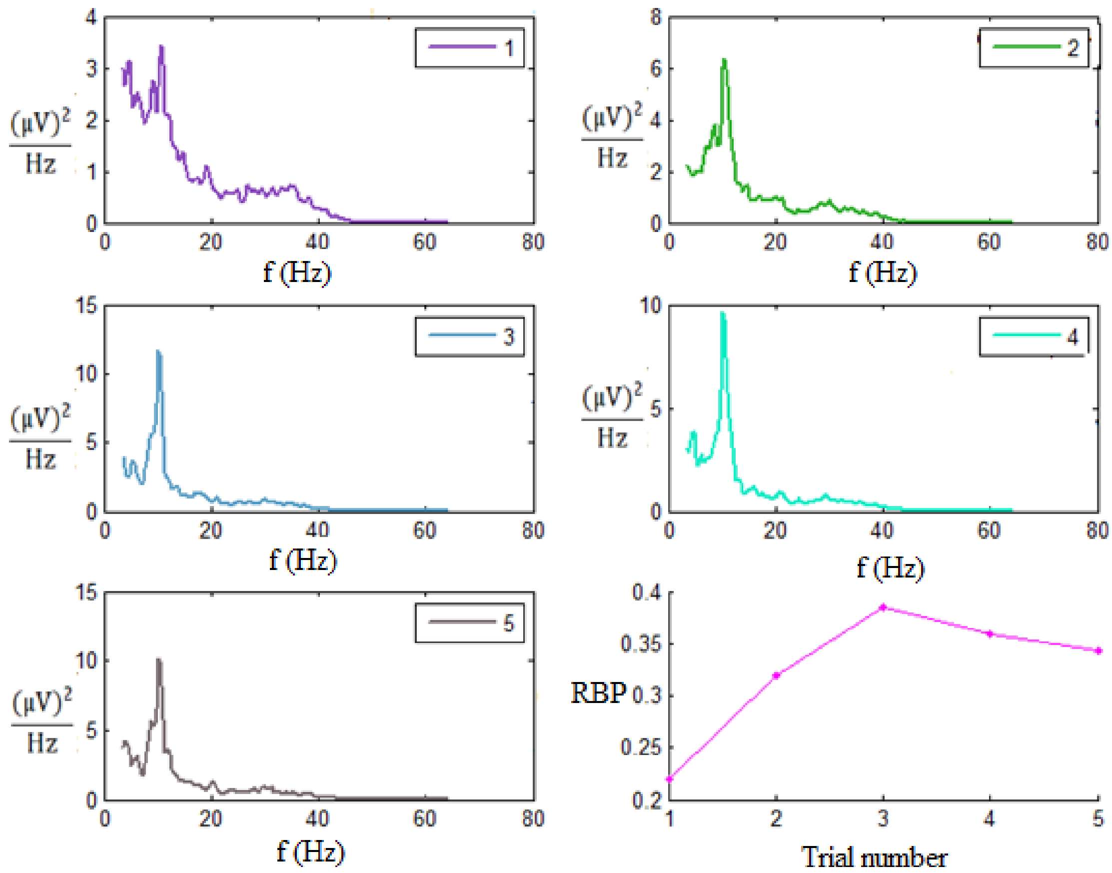

Figure 4.4.1 EEG spectra of the participant #10 from the first day, third subsession five trials. Relative band power (RBP) is also shown on the bottom-right panel.

4.4 Observations

Here, we would like to summarize several observations extracted from the neurofeedback sessions:

Six out of eleven participants were able to increase their alpha band power between 2.7% and 11.75%. Three participants slightly increased their alpha band power approximately 1%. Two participants slightly decreased their alpha band power below approximately 1%. Taking all participants into consideration, we observed that the alpha band power increase was on average 4.4%. Including only successful participants, who increased alpha power over 1%, they were able to increase the alpha band power 7.73% on average.

Five participants who increased alpha band power were also able to increase the number of the correct recalls, which they increased their recall performance between 2 to 4 folds. One of the successful participants could not increase or decrease the number of correct recalls. One participant increased the alpha band power (>1%), but decreased the number of the correct recalls. Two participants who were able to slightly increase alpha band power could increase the number of correct recalls (5 to 7 folds). One participant who was able to slightly increase alpha band power decreased the number of correct recalls. Two participants decreased their alpha band power, but increased the number of correct recalls (2 to 2.25 folds). When all participants were considered, they were able to increase the number of correct recalls 2.63 fold on average. All subjects increased after-test memorization duration compared to the pre-test memorization duration 4.76 seconds per word.

During the experiments we noticed that when concentrating on some positive scenes (for example, inspecting a flower closely in mind) the alpha band power increased in comparison to other bands. In addition, we observed during the training that participants focused on one type of thinking style increasing the alpha band power, and later the power decreased with the same style, as shown in Figure 4.4.1. Most of the participants complained about the following: When they tried to maintain the same thinking style some disturbing interventions came to their minds. Some participants complained about the bar-graph. They offered that it would be better to play a challenging game in which the level went up and down.

In the neurofeedback literature, during the experiments participants were requested to find their way to synchronize with the feedback signals (visual or auditory) by themselves. There was an "aha" point which participants could understand and synchronize with the screen or the sound [57]. However, in our study, due to the limited number of sessions we advised some thinking strategies to the participants before the neurofeedback training.

Chapter 5

Discussion

In this thesis we asked two related questions about the alpha band power during neurofeedback training sessions and short-term memory improvement.

The first question was the following: “Is it possible to increase the alpha band power selectively with respect to other bands (theta, beta, and gamma bands) of the EEG spectrum?” According to our results, the answer to this question may be positive. More than half of the participants were able to increase their alpha band power when compared to the other bands. We found that the participant who increased alpha band power slightly with respect to the baseline, which is obtained before neurofeedback sessions, he was able to increase alpha band power by only 2.7% on average. The participant who increased alpha band power maximally with respect to the baseline was able to increase it by 11.75% on average. When we assessed all successful participants’ alpha band power levels, we noticed that those values increased by 7.73% on average when compared to the mean baseline as shown in Figure 5.1. When we assessed all participants’ alpha band power, there was a 4.4% increase on average when compared to the mean baseline as depicted in Figure 5.2.

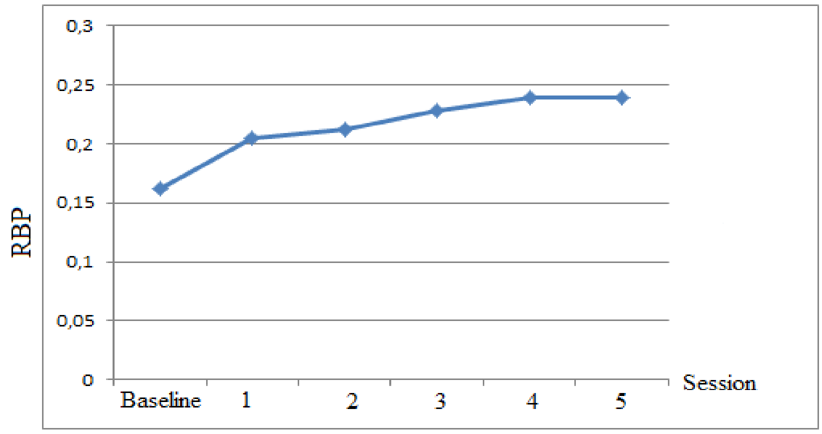

Figure 5.1 Successful participants' average relative alpha band power enhancement day-by-day.

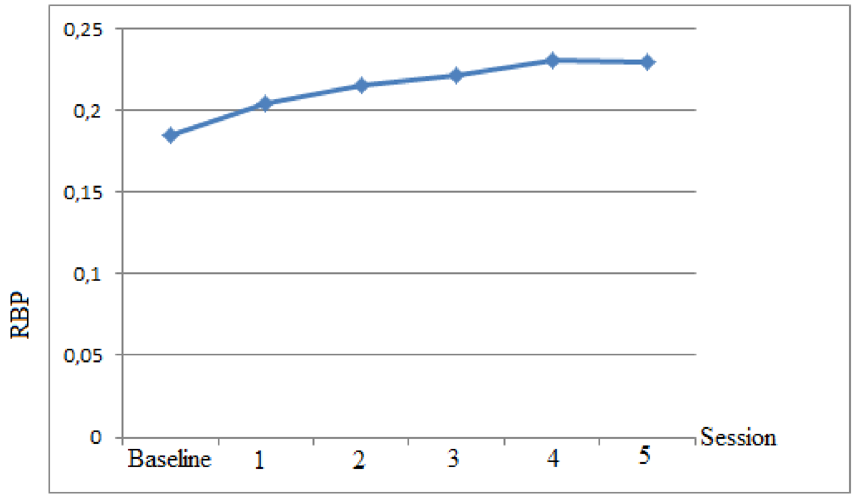

Figure 5.2 All participants' average relative alpha band power enhancement day-by-day.

The second question we investigated was the following: "Could participants, who increased alpha band power, also improve short-term memory performance?" Eight out of eleven participants in the experiment were able to increase the number of words correctly remembered (correct recalls). However, for the successful participants, only four of them were able to increase the number of correct recalls. Therefore, we were not able to give a positive answer to this question. This did not mean that neurofeedback training was not related to short-term memory performance. These findings comply with the results of the study undertaken by Lecomte and Juhel [7]. In that study, a group of elderly participants experienced four neurofeedback training sessions, and the participants were requested to memorize a list of words. They found that the participants were able to increase alpha band power; however, there were not any improvements in the memory performance.

We should note that the participant who had the highest improvement in the alpha band power was not the same person who had the most improved short-term memory performance. According to our results, the number of correct words remembered by the most successful participant was equal in the pre and after-test conditions. This finding may be due to the fact that the number of correct words remembered by the most successful participant was high enough in the pre-test. He had already remembered 8 out of 10 words, thus, the room for improvement was narrow. In addition, the participant who had the least increased alpha band power was not the same person who had the least improved short-term memory performance. Among the successful participants, one reduced the number of correctly remembered words 33%. This may be due to the fact that participant might not feel well himself at that day or could not focus during the test. In contrary, two unsuccessful participants increased the number of correctly remembered words. This may be due to fact that the struggle which the participants tried to revive their mental activity during the training, may extricate his brain from inertia so that he could use his brain in a more focused manner.

One of the limits of this study was that the duration of the word memorization at the pre and after-test were not equal. When we compares durations between pre-test and after-test, after-test memorization durations were longer, however, less than 4.76 seconds per word on average. Other limitations of our study were the session number and their durations. Although there were experiments with 5 sessions, the number of training sessions and session durations might not be sufficient for some participants to adapt with the environment, and explore themselves to control their brain in parallel with the aim of the study, which was increasing the alpha band power. However, we thought that if we increased the number of sessions or durations the participants would get bored, and this might affect the results negatively. Some subjects got bored of seeing bar graphs in all training sessions. If we were to use a game in the neurofeedback sessions, it would be more interesting and motivating for the participants, and they might have been more enthusiastic about the sessions.

Feedback from the participants revealed that positive thinking such as thinking of the family, friends, beautiful scenes and so forth was effective in increasing the alpha band power. However, not only positive thinking increases alpha band power but also some participants used negative motives such as getting angry with someone or something in order to improve the desired band power. This finding complies with the study of Nan et al [12]. Another finding was that when some subjects focused on one type of thinking style, this increased their alpha band power first, but decreased later. As seen below in Figure 5.3, alpha band power firstly increased, and then decreased after the third trial of a subsession. This observation was generally true especially after the third and fourth trials. This finding might have arisen due to the exhausting of the brain while thinking about the same feeling or object for a long time. Therefore, it may be useful for someone to have a rest during the neurofeedback sessions by changing the thinking style or the work which he did from one session to another. One neurological explanation of this suggestion might be that the activation of another neural network might help the exhausted one rest. During training sessions, most of the participants complained about getting disturbed by the thoughts coming to their minds when they tried to maintain the same thinking style for a long time. This finding may indicate that the human brain desires wandering around different neural networks especially when got bored [58]. However, if this wandering is very fast then the participants were not able to focus on anything.

In the literature, this is the first study in which Turkish students were trained via neurofeedback sessions in order to improve their short-term memory performances by using English words. Although there are few studies using EMOTIV system such as controlling a robotic arm or measuring P300 waves, there is no neurofeedback study reported using EMOTIV system in Turkey.

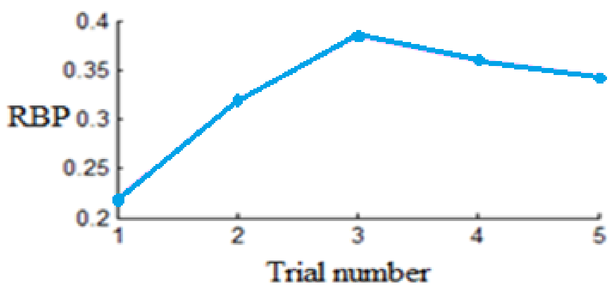

Figure 5.3 Relative band power vs. trial number.

According to the findings reported by Klimesch in 1997 [59] memory retrieval performance of subjects who had high resting state peak of alpha frequency, which is the frequency of maximum amplitude in alpha band, was better than others. In a future study, memory performance improvement may be examined by increasing the peak alpha frequency through neurofeedback training instead of increasing only the alpha band power.

In medicine, there is a method called Transcranial Magnetic Stimulation (TMS) which gives magnetic pulses to the patient's brain who has chronic depression as shown below in Figure 5.4. However, there is no electrical feedback obtained from patients during the treatment other than observing him. It may be a good idea to combine both Neurofeedback and TMS in one package. A micro coil which produces magnetic pulses is placed among EEG dry-electrode pins. While micro coil sends magnetic pulses to the patient's target brain area EEG dry- electrodes measure the brain wave changes on that area. Hence, a patient or a doctor could sense/or see the effects of TMS during the treatment. The effect may be measured with alpha wave changes. If the magnetic pulses cause discomfort to the patient, the TMS application area will be changed on the other hand, if it gives relaxation the treatment will continue by adjusting the power of the pulses.

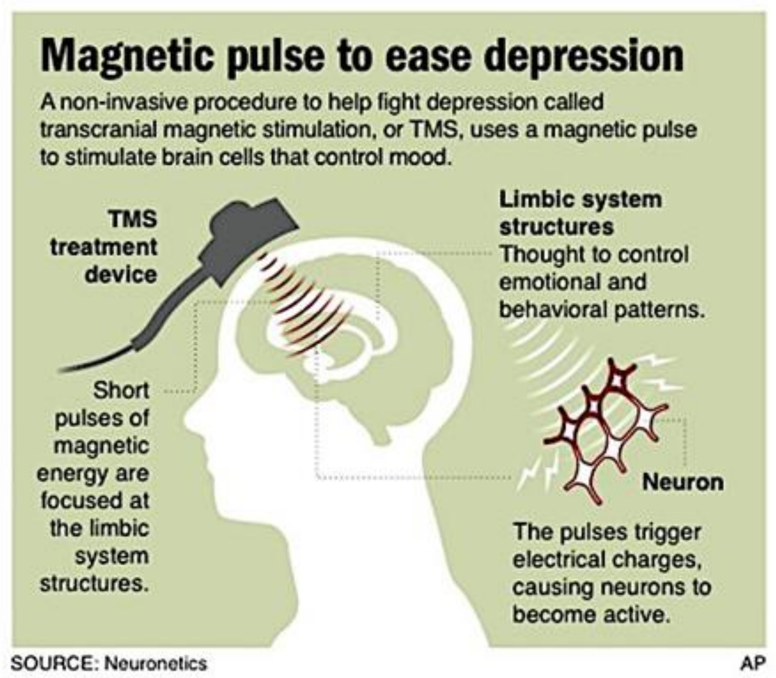

Figure 5.4 TMS treatment [60].

In conclusion, the findings of this study are neither sufficient to prove that neurofeedback training improves the short-term memory performance nor it is irrelevant with the short-term memory performance. However, we may mention that the neurofeedback training is beneficial for the subjects to orient their conscious minds to their goals.

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APPENDIX 1

```
% Baseline measurement

function [AllOK output_matrix nS P_rwelch] = eeglogger25(rectime,varargin)
% function [AllOK output_matrix nS] =
eeglogger(rectime,acqtime,lib_flag_popup, plot_popup)
%
%
% Francesco Tenore, JHU/APL - April 2010
%
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% Laboratory (JHU/APL).  All Rights Reserved.
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% AND IS NOT LIABLE FOR ANY DAMAGES OF ANY KIND ARISING
FROM THE USE
% OF THIS SOFTWARE.

%
% This function uses the Emotiv Epoc headset dll (edk.dll) to acquire the
% data contained in the EE_DataChannels_enum structure. The function mimics
% the EEGLogger.exe function that can be compiled and used to acquire the
% data using a C++ compiler.
% Additionally, it checks to make sure that the library hasn't been loaded
% yet. The function requires no inputs (4 optional) and produces 3 outputs
%
% Optional Inputs
% rectime: this is time, in seconds, of the data buffer size, default = 1
% acqtime: acquisition time, in seconds, default = 10 (for testing).
% lib_flag_popup: 1 = activates the libfunctionsview window, useful for
% looking at all the functions that were loaded from the dll. default = 0.
% plot_popup: 1 = plots the GyroX and GyroY signals after the data was
% recorded; 0 = no plot, default = 1.
%
% Outputs:
% AllOK: Everything worked fine in loading the library. If this is the case
% a ZERO (0) should be returned.
% output_matrix: a 25 (=length(EE_DataChannels_enum) by n matrix where n
=
% sampling_frequency * acquisition time. The sampling_frequency, as defined
% by Emotiv, is effectively 128 Hz.
% nS: provides you with the number of samples acquired (equivalent to
nSamplesTaken
```

```
% in the EEGLogger main.cpp function).

% data structures, copied and pasted from epocmfile.m
structs.InputSensorDescriptor_struct.members=struct('channelId',
'EE_InputChannels_enum', 'fExists', 'int32', 'pszLabel', 'cstring', 'xLoc', 'double',
'yLoc', 'double', 'zLoc', 'double');
enuminfo.EE_DataChannels_enum=struct('ED_COUNTER',0,'ED_INTERPOL
ATED',1,'ED_RAW_CQ',2,'ED_AF3',3,'ED_F7',4,'ED_F3',5,'ED_FC5',6,'ED_T
7',7,'ED_P7',8,'ED_O1',9,'ED_O2',10,'ED_P8',11,'ED_T8',12,'ED_FC6',13,'ED_
F4',14,'ED_F8',15,'ED_AF4',16,'ED_GYROX',17,'ED_GYROY',18,'ED_TIME
STAMP',19,'ED_ES_TIMESTAMP',20,'ED_FUNC_ID',21,'ED_FUNC_VALU
E',22,'ED_MARKER',23,'ED_SYNC_SIGNAL',24);
enuminfo.EE_CognitivTrainingControl_enum=struct('COG_NONE',0,'COG_ST
ART',1,'COG_ACCEPT',2,'COG_REJECT',3,'COG_ERASE',4,'COG_RESET',
5);
enuminfo.EE_ExpressivAlgo_enum=struct('EXP_NEUTRAL',1,'EXP_BLINK',
2,'EXP_WINK_LEFT',4,'EXP_WINK_RIGHT',8,'EXP_HORIEYE',16,'EXP_E
YEBROW',32,'EXP_FURROW',64,'EXP_SMILE',128,'EXP_CLENCH',256,'E
XP_LAUGH',512,'EXP_SMIRK_LEFT',1024,'EXP_SMIRK_RIGHT',2048);
enuminfo.EE_ExpressivTrainingControl_enum=struct('EXP_NONE',0,'EXP_ST
ART',1,'EXP_ACCEPT',2,'EXP_REJECT',3,'EXP_ERASE',4,'EXP_RESET',5);
enuminfo.EE_ExpressivThreshold_enum=struct('EXP_SENSITIVITY',0);
enuminfo.EE_CognitivEvent_enum=struct('EE_CognitivNoEvent',0,'EE_Cognit
ivTrainingStarted',1,'EE_CognitivTrainingSucceeded',2,'EE_CognitivTrainingFa
iled',3,'EE_CognitivTrainingCompleted',4,'EE_CognitivTrainingDataErased',5,'
EE_CognitivTrainingRejected',6,'EE_CognitivTrainingReset',7,'EE_CognitivAu
toSamplingNeutralCompleted',8,'EE_CognitivSignatureUpdated',9);
enuminfo.EE_EmotivSuite_enum=struct('EE_EXPRESSIV',0,'EE_AFFECTIV',
1,'EE_COGNITIV',2);
enuminfo.EE_ExpressivEvent_enum=struct('EE_ExpressivNoEvent',0,'EE_Expr
essivTrainingStarted',1,'EE_ExpressivTrainingSucceeded',2,'EE_ExpressivTrain
ingFailed',3,'EE_ExpressivTrainingCompleted',4,'EE_ExpressivTrainingDataEra
sed',5,'EE_ExpressivTrainingRejected',6,'EE_ExpressivTrainingReset',7);
enuminfo.EE_CognitivAction_enum=struct('COG_NEUTRAL',1,'COG_PUSH',
2,'COG_PULL',4,'COG_LIFT',8,'COG_DROP',16,'COG_LEFT',32,'COG_RIG
HT',64,'COG_ROTATE_LEFT',128,'COG_ROTATE_RIGHT',256,'COG_ROT
ATE_CLOCKWISE',512,'COG_ROTATE_COUNTER_CLOCKWISE',1024,'C
OG_ROTATE_FORWARDS',2048,'COG_ROTATE_REVERSE',4096,'COG_
DISAPPEAR',8192);
enuminfo.EE_InputChannels_enum=struct('EE_CHAN_CMS',0,'EE_CHAN_D
RL',1,'EE_CHAN_FP1',2,'EE_CHAN_AF3',3,'EE_CHAN_F7',4,'EE_CHAN_F
3',5,'EE_CHAN_FC5',6,'EE_CHAN_T7',7,'EE_CHAN_P7',8,'EE_CHAN_O1',9
,'EE_CHAN_O2',10,'EE_CHAN_P8',11,'EE_CHAN_T8',12,'EE_CHAN_FC6',1
3,'EE_CHAN_F4',14,'EE_CHAN_F8',15,'EE_CHAN_AF4',16,'EE_CHAN_FP2
',17);
```

```
enuminfo.EE_ExpressivSignature_enum=struct('EXP_SIG_UNIVERSAL',0,'E
XP_SIG_TRAINED',1);
enuminfo.EE_Event_enum=struct('EE_UnknownEvent',0,'EE_EmulatorError',1,
'EE_ReservedEvent',2,'EE_UserAdded',16,'EE_UserRemoved',32,'EE_EmoState
Updated',64,'EE_ProfileEvent',128,'EE_CognitivEvent',256,'EE_ExpressivEvent
',512,'EE_InternalStateChanged',1024,'EE_AllEvent',2032);

DataChannels = enuminfo.EE_DataChannels_enum;
DataChannelsNames =
{'ED_COUNTER','ED_INTERPOLATED','ED_RAW_CQ','ED_AF3','ED_F7','
ED_F3','ED_FC5','ED_T7','ED_P7','ED_O1','ED_O2','ED_P8','ED_T8','ED_FC
6','ED_F4','ED_F8','ED_AF4','ED_GYROX','ED_GYROY','ED_TIMESTAMP',
'ED_ES_TIMESTAMP','ED_FUNC_ID','ED_FUNC_VALUE','ED_MARKER',
'ED_SYNC_SIGNAL'};



optargin = size(varargin,2);
rectime = 1;
acqtime = 10;
lib_flag_popup = 1;
plot_popup = 1;


if optargin > 4
    error('Too many inputs');

elseif optargin == 4
 rectime = varargin{1};
    acqtime = varargin{2};
    lib_flag_popup = varargin{3};
    plot_popup = varargin{4};
elseif optargin == 3
 rectime = varargin{1};
    acqtime = varargin{2};
    lib_flag_popup = varargin{3};
elseif optargin == 2
 rectime = varargin{1};
    acqtime = varargin{2};
elseif optargin == 1
    rectime = varargin{1};
end
% Check to see if library was already loaded
if ~libisloaded('edk')
    [nf, w] = loadlibrary('edk','edk', 'addheader', 'EmoStateDLL', 'addheader',
'edkErrorCode');
```

```
 disp(['EDK library loaded']);
    if( lib_flag_popup )
        libfunctionsview('edk')
        nf % these should be empty if all went well
        w
    end
else
    disp(['EDK library already loaded']);
end
sampFreq = 128;
default = int8(['Emotiv Systems-5' 0]);
AllOK = calllib('edk','EE_EngineConnect', 'Emotiv Systems-5'); % success
means this value is 0

hData = calllib('edk','EE_DataCreate');
calllib('edk','EE_DataSetBufferSizeInSec',rectime);
eEvent = calllib('edk','EE_EmoEngineEventCreate');
readytocollect = false;
cnt = 0;


% initialize outputs:
output_matrix = zeros(acqtime*sampFreq,length(DataChannelsNames));
nS = zeros(acqtime*sampFreq,1);

cnt0=513;
cnt1=700;

fs=128;%sampling freuency 128Hz
ts=1/fs;%sampling period

P1=0;
P0=0;

tic

while(toc < acqtime)
    state = calllib('edk','EE_EngineGetNextEvent',eEvent); % state = 0 if
everything's OK
    eventType = calllib('edk','EE_EmoEngineEventGetType',eEvent);
    %disp(eventType);
    userID=libpointer('uint32Ptr',0);
    calllib('edk','EE_EmoEngineEventGetUserId',eEvent, userID);


    if strcmp(eventType,'EE_UserAdded') == true
```

```
        User_added = 1;
        userID_value = get(userID,'value');
        calllib('edk','EE_DataAcquisitionEnable',userID_value,true);
      readytocollect = true;
     end

  if (readytocollect)

      calllib('edk','EE_DataUpdateHandle', 0, hData);
      nSamples = libpointer('uint32Ptr',0);
        calllib('edk','EE_DataGetNumberOfSample',hData,nSamples);
        nSamplesTaken = get(nSamples,'value') ;
        if (nSamplesTaken ~= 0)
         data = libpointer('doublePtr',zeros(1,nSamplesTaken));
   %         for sampleIdx=1:nSamplesTaken
            for i = 1:length(fieldnames(enuminfo.EE_DataChannels_enum))
               calllib('edk','EE_DataGet',hData,
DataChannels.([DataChannelsNames{i}]), data, uint32(nSamplesTaken));
                data_value = get(data,'value');
%                  output_matrix(cnt+1,i) = data_value(sampleIdx);
                output_matrix(cnt+1:cnt+length(data_value),i) = data_value;

%y(cnt+1:cnt+length(data_value))=output_matrix(cnt+1:cnt+length(data_value)
,3);

                if (cnt>cnt1) %wait some time to process begin.
                 %   cnt0=cnt
                   cnt1=cnt+180;%slide the window

                y=output_matrix(cnt-512:cnt,12);%512 sample data window

fc=3;
n=5;
[b,a]=butter(n,fc/(fs/2),'high');
%freqz(b,a)
y=y-mean(y);
y1=filter(b,a,y);

               %---pwelch--
                [Pxx,f]=pwelch(y1,200,100,4*fs,fs);
                P1=sum(Pxx(round(7.5/.25):round(11/.25)));%total alpha power
7.5-11Hz band

                P_rband=P1/sum(Pxx(round(3.5/.25):round(35/.25)));%relative
band power
                P_rwelch(cnt)=P_rband;
```

```
                %---pwelch--

                    figure (2)
                    plot(cnt*ts,P1,'*');
                    hold on;

                 end
                  P0=P1
              end

              nS(cnt+1) = nSamplesTaken;
%                cnt = cnt + 1;
              cnt = cnt + length(data_value);
             % plot(output_matrix(8));
             % drawnow;
%             end
       end
 end
   %    pause(0.1);    % haven't played with this much...

end
% extract sampling rate (should be 128)
sampRateOutPtr = libpointer('uint32Ptr',0);
calllib('edk','EE_DataGetSamplingRate',0,sampRateOutPtr);
sampFreqOut = get(sampRateOutPtr,'value') % in Hz

calllib('edk','EE_DataFree',hData);
end_time = find(output_matrix(:,20)==0,1) - 1;

calllib('edk','EE_EngineDisconnect');
calllib('edk','EE_EmoEngineEventFree',eEvent);
end
% unloadlibrary('edk'); % unload the library after having turned off
% [int32, uint32Ptr] EE_DataGetSamplingRate (uint32, uint32Ptr)
% int32 EE_DataSetSychronizationSignal (uint32, int32)
% [int32, string] EE_EnableDiagnostics (cstring, int32, int32)
```

APPENDIX 2

```
%neurofeedback training measurement

function [AllOK output_matrix nS P_rwelch P_burg] =
eeglogger26(Thr,rectime,varargin)
% function [AllOK output_matrix nS] =
eeglogger(rectime,acqtime,lib_flag_popup, plot_popup)
%
%
% Francesco Tenore, JHU/APL - April 2010
%
% Copyright ? May 2010 The Johns Hopkins University Applied Physics
% Laboratory (JHU/APL).  All Rights Reserved.
% JHU/APL PROVIDES THIS SOFTWARE "AS IS" WITHOUT
WARRANTY OF ANY KIND
% AND IS NOT LIABLE FOR ANY DAMAGES OF ANY KIND ARISING
FROM THE USE
% OF THIS SOFTWARE.

%
% This function uses the Emotiv Epoc headset dll (edk.dll) to acquire the
% data contained in the EE_DataChannels_enum structure. The function mimics
% the EEGLogger.exe function that can be compiled and used to acquire the
% data using a C++ compiler.
% Additionally, it checks to make sure that the library hasn't been loaded
% yet. The function requires no inputs (4 optional) and produces 3 outputs
%
% Optional Inputs
% rectime: this is time, in seconds, of the data buffer size, default = 1
% acqtime: acquisition time, in seconds, default = 10 (for testing).
% lib_flag_popup: 1 = activates the libfunctionsview window, useful for
% looking at all the functions that were loaded from the dll. default = 0.
% plot_popup: 1 = plots the GyroX and GyroY signals after the data was
% recorded; 0 = no plot, default = 1.
%
% Outputs:
% AllOK: Everything worked fine in loading the library. If this is the case
% a ZERO (0) should be returned.
% output_matrix: a 25 (=length(EE_DataChannels_enum) by n matrix where n
=
% sampling_frequency * acquisition time. The sampling_frequency, as defined
% by Emotiv, is effectively 128 Hz.
```

% nS: provides you with the number of samples acquired (equivalent to nSamplesTaken
% in the EEGLogger main.cpp function).

% data structures, copied and pasted from epocmfile.m
structs.InputSensorDescriptor_struct.members=struct('channelId', 'EE_InputChannels_enum', 'fExists', 'int32', 'pszLabel', 'cstring', 'xLoc', 'double', 'yLoc', 'double', 'zLoc', 'double');
enuminfo.EE_DataChannels_enum=struct('ED_COUNTER',0,'ED_INTERPOLATED',1,'ED_RAW_CQ',2,'ED_AF3',3,'ED_F7',4,'ED_F3',5,'ED_FC5',6,'ED_T7',7,'ED_P7',8,'ED_O1',9,'ED_O2',10,'ED_P8',11,'ED_T8',12,'ED_FC6',13,'ED_F4',14,'ED_F8',15,'ED_AF4',16,'ED_GYROX',17,'ED_GYROY',18,'ED_TIMESTAMP',19,'ED_ES_TIMESTAMP',20,'ED_FUNC_ID',21,'ED_FUNC_VALUE',22,'ED_MARKER',23,'ED_SYNC_SIGNAL',24);
enuminfo.EE_CognitivTrainingControl_enum=struct('COG_NONE',0,'COG_START',1,'COG_ACCEPT',2,'COG_REJECT',3,'COG_ERASE',4,'COG_RESET',5);
enuminfo.EE_ExpressivAlgo_enum=struct('EXP_NEUTRAL',1,'EXP_BLINK',2,'EXP_WINK_LEFT',4,'EXP_WINK_RIGHT',8,'EXP_HORIEYE',16,'EXP_EYEBROW',32,'EXP_FURROW',64,'EXP_SMILE',128,'EXP_CLENCH',256,'EXP_LAUGH',512,'EXP_SMIRK_LEFT',1024,'EXP_SMIRK_RIGHT',2048);
enuminfo.EE_ExpressivTrainingControl_enum=struct('EXP_NONE',0,'EXP_START',1,'EXP_ACCEPT',2,'EXP_REJECT',3,'EXP_ERASE',4,'EXP_RESET',5);
enuminfo.EE_ExpressivThreshold_enum=struct('EXP_SENSITIVITY',0);
enuminfo.EE_CognitivEvent_enum=struct('EE_CognitivNoEvent',0,'EE_CognitivTrainingStarted',1,'EE_CognitivTrainingSucceeded',2,'EE_CognitivTrainingFailed',3,'EE_CognitivTrainingCompleted',4,'EE_CognitivTrainingDataErased',5,'EE_CognitivTrainingRejected',6,'EE_CognitivTrainingReset',7,'EE_CognitivAutoSamplingNeutralCompleted',8,'EE_CognitivSignatureUpdated',9);
enuminfo.EE_EmotivSuite_enum=struct('EE_EXPRESSIV',0,'EE_AFFECTIV',1,'EE_COGNITIV',2);
enuminfo.EE_ExpressivEvent_enum=struct('EE_ExpressivNoEvent',0,'EE_ExpressivTrainingStarted',1,'EE_ExpressivTrainingSucceeded',2,'EE_ExpressivTrainingFailed',3,'EE_ExpressivTrainingCompleted',4,'EE_ExpressivTrainingDataErased',5,'EE_ExpressivTrainingRejected',6,'EE_ExpressivTrainingReset',7);
enuminfo.EE_CognitivAction_enum=struct('COG_NEUTRAL',1,'COG_PUSH',2,'COG_PULL',4,'COG_LIFT',8,'COG_DROP',16,'COG_LEFT',32,'COG_RIGHT',64,'COG_ROTATE_LEFT',128,'COG_ROTATE_RIGHT',256,'COG_ROTATE_CLOCKWISE',512,'COG_ROTATE_COUNTER_CLOCKWISE',1024,'COG_ROTATE_FORWARDS',2048,'COG_ROTATE_REVERSE',4096,'COG_DISAPPEAR',8192);
enuminfo.EE_InputChannels_enum=struct('EE_CHAN_CMS',0,'EE_CHAN_DRL',1,'EE_CHAN_FP1',2,'EE_CHAN_AF3',3,'EE_CHAN_F7',4,'EE_CHAN_F3',5,'EE_CHAN_FC5',6,'EE_CHAN_T7',7,'EE_CHAN_P7',8,'EE_CHAN_O1',9,'EE_CHAN_O2',10,'EE_CHAN_P8',11,'EE_CHAN_T8',12,'EE_CHAN_FC6',1

```
3,'EE_CHAN_F4',14,'EE_CHAN_F8',15,'EE_CHAN_AF4',16,'EE_CHAN_FP2
',17);
enuminfo.EE_ExpressivSignature_enum=struct('EXP_SIG_UNIVERSAL',0,'E
XP_SIG_TRAINED',1);
enuminfo.EE_Event_enum=struct('EE_UnknownEvent',0,'EE_EmulatorError',1,
'EE_ReservedEvent',2,'EE_UserAdded',16,'EE_UserRemoved',32,'EE_EmoState
Updated',64,'EE_ProfileEvent',128,'EE_CognitivEvent',256,'EE_ExpressivEvent
',512,'EE_InternalStateChanged',1024,'EE_AllEvent',2032);

DataChannels = enuminfo.EE_DataChannels_enum;
DataChannelsNames =
{'ED_COUNTER','ED_INTERPOLATED','ED_RAW_CQ','ED_AF3','ED_F7','
ED_F3','ED_FC5','ED_T7','ED_P7','ED_O1','ED_O2','ED_P8','ED_T8','ED_FC
6','ED_F4','ED_F8','ED_AF4','ED_GYROX','ED_GYROY','ED_TIMESTAMP',
'ED_ES_TIMESTAMP','ED_FUNC_ID','ED_FUNC_VALUE','ED_MARKER',
'ED_SYNC_SIGNAL'};



optargin = size(varargin,2);
rectime = 2;
acqtime = 10;
lib_flag_popup = 1;
plot_popup = 1;


if optargin > 4
    error('Too many inputs');

elseif optargin == 4
 rectime = varargin{1};
    acqtime = varargin{2};
    lib_flag_popup = varargin{3};
    plot_popup = varargin{4};
elseif optargin == 3
 rectime = varargin{1};
    acqtime = varargin{2};
    lib_flag_popup = varargin{3};
elseif optargin == 2
 rectime = varargin{1};
    acqtime = varargin{2};
elseif optargin == 1
    rectime = varargin{1};
end
% Check to see if library was already loaded
if ~libisloaded('edk')
```

```
   [nf, w] = loadlibrary('edk','edk', 'addheader', 'EmoStateDLL', 'addheader', 
'edkErrorCode');
 disp(['EDK library loaded']);
   if( lib_flag_popup )
      libfunctionsview('edk')
      nf % these should be empty if all went well
      w
   end
else
   disp(['EDK library already loaded']);
end
sampFreq = 128;
default = int8(['Emotiv Systems-5' 0]);
AllOK = calllib('edk','EE_EngineConnect', 'Emotiv Systems-5'); % success 
means this value is 0

hData = calllib('edk','EE_DataCreate');
calllib('edk','EE_DataSetBufferSizeInSec',rectime);
eEvent = calllib('edk','EE_EmoEngineEventCreate');
readytocollect = false;
cnt = 0;


% initialize outputs:
output_matrix = zeros(acqtime*sampFreq,length(DataChannelsNames));
nS = zeros(acqtime*sampFreq,1);

cnt0=513;
cnt1=700;

fs=128;%sampling freuency 128Hz
ts=1/fs;%sampling period

count_artir=0;
P1=0;
P0=0;
P20=0;
P_rband=0;

amp=50 ;
fsamp=20500 ; % sampling frequency
duration=.08;
freq1=7000;
values=0:1/fsamp:duration;
a1=amp*sin(2*pi* freq1*values);
tic
```

```
%bar
figure (1)
subplot(2,3,[1,2,4,5])
x1=2.25;
Y1=Thr;
K=0.5;
bar1=bar(x1, Y1, 'FaceColor', 'r', 'EdgeColor', 'b');
set(bar1,'BarWidth',K);
hold on
x2=3.75;
Y2=Y1;
K=0.5;
bar2=bar(x2, Y2, 'FaceColor', 'r', 'EdgeColor', 'b');
set(bar2,'BarWidth',K);

%plot(1.5:.1:4.5,190*ones(length(1.5:.1:4.5)),'g')
x3=[2.5 3 3.5];
Y3=[Thr Thr Thr];
h=area(x3,Y3)
axis([-1 7 .25*Thr 2.20*Thr])
set(h,'YDataSource','Y3');
set(h,'XDataSource','x3');


plot((1.5:.1:4.5), 1.5*Thr,'r*');
plot((1.5:.1:4.5), 1.8*Thr,'b*');
plot((1.5:.1:4.5), 2.1*Thr,'g+');
%--bar

figure (1);
pause(0.00001);
frame_h = get(handle(gcf),'JavaFrame');
set(frame_h,'Maximized',1);

while(toc < acqtime)
   state = calllib('edk','EE_EngineGetNextEvent',eEvent); % state = 0 if
everything's OK
   eventType = calllib('edk','EE_EmoEngineEventGetType',eEvent);
   %disp(eventType);
   userID=libpointer('uint32Ptr',0);
   calllib('edk','EE_EmoEngineEventGetUserId',eEvent, userID);


   if strcmp(eventType,'EE_UserAdded') == true
      User_added = 1;
      userID_value = get(userID,'value');
```

```
      calllib('edk','EE_DataAcquisitionEnable',userID_value,true);
    readytocollect = true;
   end

 if (readytocollect)

    calllib('edk','EE_DataUpdateHandle', 0, hData);
    nSamples = libpointer('uint32Ptr',0);
      calllib('edk','EE_DataGetNumberOfSample',hData,nSamples);
      nSamplesTaken = get(nSamples,'value') ;
      if (nSamplesTaken ~= 0)
       data = libpointer('doublePtr',zeros(1,nSamplesTaken));
  %         for sampleIdx=1:nSamplesTaken
          for i = 1:length(fieldnames(enuminfo.EE_DataChannels_enum))
             calllib('edk','EE_DataGet',hData,
DataChannels.([DataChannelsNames{i}]), data, uint32(nSamplesTaken));
                data_value = get(data,'value');
%                  output_matrix(cnt+1,i) = data_value(sampleIdx);
                output_matrix(cnt+1:cnt+length(data_value),i) = data_value;

%y(cnt+1:cnt+length(data_value))=output_matrix(cnt+1:cnt+length(data_value)
,3);

                if (cnt>cnt1) %wait some time to process begin.
                 %   cnt0=cnt
                   cnt1=cnt+180;%slide the window

                y=output_matrix(cnt-512:cnt,12);%512 sample window
               % y2=output_matrix(cnt-500:cnt,10);
fc=3;
n=5;
[b,a]=butter(n,fc/(fs/2),'high');
y=y-mean(y);
%freqz(b,a)
y1=filter(b,a,y);
               % fft_y1=fft(y1,512);%
              %  fft_y2=fft(y2,512);
              % Thr=1.01*P_rmean;%threshold
              %



              %------------pwelch---
              [Pxx,f]=pwelch(y1,200,100,4*fs,fs);
              P1=sum(Pxx(round(7.5/.25):round(11/.25)));%total alpha power 7.5-
11Hz band
              P_bband(cnt)=P1;
```

```
P_rband=P1/sum(Pxx(round(3.5/.25):round(35/.25)));%relative band
power
P_rwelch(cnt)=P_rband;
  %figure (2)
  figure (1)
  subplot(2,3,3)
  if P0~=0

  hold on
  plot([(cnt-180)*ts cnt*ts],[P0 P_rband],'.--m')%
  hold off
  end




  %-----end pwelch----
    P2=P1;
  %---pburg---
   % [Pbb,F] = pburg(y1,12,256,128);
    %P2=sum(Pbb(15:27));
    P_burg(cnt)=P2;



   figure (1)
     subplot(2,3,6)
     if P20~=0
     hold on
     plot([(cnt-180)*ts cnt*ts], [ P20 P2],'.-b')
        hold off
     end
    P20=P2;


  %----end pburg----
 N=10;
for i=1:N
  Y3=[P0-i*(P0-P_rband)/N P0-i*(P0-P_rband)/N P0-i*(P0-
P_rband)/N];
  figure (1)
  subplot(2,3,[1,2,4,5])
  hold on
  refreshdata(h,'caller')
  drawnow;
  pause(.01)
```

```
                end
                 if P_rband>=Thr
                  sound(a1);
                 end


                  end
                   P0=P_rband;

               end

               nS(cnt+1) = nSamplesTaken;
%                  cnt = cnt + 1;
               cnt = cnt + length(data_value);
              % plot(output_matrix(8));
              % drawnow;
%              end
        end
 end
   %    pause(0.1);    % haven't played with this much...

end
% extract sampling rate (should be 128)
sampRateOutPtr = libpointer('uint32Ptr',0);
calllib('edk','EE_DataGetSamplingRate',0,sampRateOutPtr);
sampFreqOut = get(sampRateOutPtr,'value') % in Hz

calllib('edk','EE_DataFree',hData);
end_time = find(output_matrix(:,20)==0,1) - 1;

calllib('edk','EE_EngineDisconnect');
calllib('edk','EE_EmoEngineEventFree',eEvent);
end
% unloadlibrary('edk'); % unload the library after having turned off
% [int32, uint32Ptr] EE_DataGetSamplingRate (uint32, uint32Ptr)
% int32 EE_DataSetSychronizationSignal (uint32, int32)
% [int32, string] EE_EnableDiagnostics (cstring, int32, int32)

%this code used with Matlab 2012b 32 bit version.
```

APPENDIX 3

```
%run file

%%
%
clear
clc
close all

[all_ok, outputmatrix,ns, P_rwelch]=eeglogger25(1,1,35)%(rec_time,acq_time);
Baseline measurement
%Thr=.08*mean(P_alf);%first threshold
%%
%
zaman=2108 %date of the session for example, 21 August
name='baris'
  P_rmean=sum(P_rwelch)/length(find(P_rwelch~=0))
  session=1;
  fname = sprintf('%s-%d-baseline.mat',name, zaman);
  save(fname)
  %save
%%
%
close all
clc
clear P_rwelch
%clear P_rmean1
amp=50 ;
fsamp=20500 ; % sampling frequency
duration=.08;
freq1=18490;
values=0:1/fsamp:duration;
a2=amp*sin(2*pi* freq1*values);
k=0;
n=0;
Thr=P_rmean;
trial=5;
P_Rwelch=zeros(trial,16000);

%sound(a2)
figure (1);

figure (3);
```

```
pause(0.00001);
frame_h = get(handle(gcf),'JavaFrame');
set(frame_h,'Maximized',1);
for j=1:trial
   close figure 1
   sound(a2)
   pause(1)
   [all_ok, outputmatrix,ns, P_rwelch P_burg]=eeglogger26(Thr,2,2,45);
   Outputmatrix{j}=outputmatrix;
   Pburg{j}=P_burg;
   P_Rwelch(j,1:length(P_rwelch))=P_rwelch;
   P_rmean1(session,j)=sum(P_rwelch)/length(find(P_rwelch~=0));

   clear frame_h;
   fname = sprintf('%s-%d-%d%d.mat',name, zaman,session,j);%record name ??
gir
   save(fname)
%psd plot


fs=128;
nfft=fs*4;
fc=3;
n=5;

B=outputmatrix(1:end-1200,12)
B=B-mean(B);
[b,a]=butter(n,fc/(fs/2),'high');
%freqz(b,a)
Y=filter(b,a,B);
[pxx,f] = pwelch(Y,200,100,nfft,fs);

figure(3)
lg=sprintf('%d',j)
subplot(3,2,j)
plot(f(find(f==3.5):end),pxx(find(f==3.5):end),'Color',[rand rand
rand],'LineWidth',2,'DisplayName',lg)
legend('show')
text(50,7,sprintf('P_rmean=%f',P_rmean1(session,j)));
Pband=mean(pxx(find(f==7.5):find(f==11)));
text(50,4,sprintf('Pband=%f',Pband));
subplot(3,2,6)
hold on
plot(P_rmean1(session,1:j),'.-m')
%psd plot end
sound(a2)
```

```
    pause(11)
end
      P_rmean1
      P_RWelch=sum(P_Rwelch(1:trial,:))/trial;
     %P_rmean=sum(P_RWelch)/length(find(P_RWelch~=0))
    if length(find(P_RWelch>Thr))>.6*length(find(P_RWelch~=0))
       %P_rmean=1.1*P_rmean;
       Thr=1.1*Thr
        k=k+1
    else
        Thr=.9*Thr;
        n=n+1;
    end
    figure(3);
     figname = sprintf('%s-%d-%d.fig', name,zaman,session);
     saveas(gcf,figname)

    session=session+1;
```

APPENDIX 4

```
clear
 load('serhat-906-35.mat')% a real time EEG
close all
clc


fs=128;
acq_time=45;
ts=1/fs;
t=0:ts:acq_time;

%------------realtime eeg----------
%%
y=outputmatrix(1:end-500,12);
fc=3;
n=5;
[b,a]=butter(n,fc/(fs/2),'high');
y=y-mean(y);
%freqz(b,a)
X=filter(b,a,y);
%%
[Pxx,f]=pwelch(X,200,100,4*fs,fs);
figure (1)
plot(f,Pxx)

%%
[Pbb,F] = pburg(X,12,256,128);

figure (2)
plot(F,Pbb)
%%
Fs=128; k = 4;
L=Fs*k;
%NFFT = 2^nextpow2(L); % Next power of 2 from length of y
Y = fft(X,L);
ff = Fs/2*linspace(0,1,L/2+1);

% Plot single-sided amplitude spectrum.
figure (3)
plot(ff(2:end),abs(Y(2:L/2+1)))
```

```
%---------simulated eeg------
%%
z=0.3*sin(2*pi*10*t)+0.3*sin(2*pi*5*t)+0.3*sin(2*pi*15*t);
fc=3;
n=5;
[b,a]=butter(n,fc/(fs/2),'high');
z=z-mean(z);
%freqz(b,a)
Z=filter(b,a,z);
%%
[Pxx,f]=pwelch(Z,200,100,4*fs,fs);
figure (4)
plot(f,Pxx)

%%
[Pbb,F] = pburg(Z,12,256,128);

figure (5)
plot(F,Pbb)
%%
Fs=128; k = 4;
L=Fs*k;
%NFFT = 2^nextpow2(L); % Next power of 2 from length of y
Y = fft(Z,L);
ff = Fs/2*linspace(0,1,L/2+1);

% Plot single-sided amplitude spectrum.
figure (6)
plot(ff(2:end),abs(Y(2:L/2+1)))
```