A Wearable EEG-Based Serious Game for Focus Improvement and Diagnosing ADHD/ADD Patients by EEG Signals Classification

A thesis submitted to the
Graduate School of Natural and Applied Sciences

by

Alaa Eddin Alchalabi

in partial fulfillment for the
degree of Master's of Science

in

Electronics and Computer Engineering

İSTANBUL ŞEHİR UNIVERSITY

This is to certify that we have read this thesis and that in our opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master's of Science in Electronics and Computer Engineering.

APPROVED BY:

Prof. Dr. Shervin Shirmohammadi (Thesis Advisor) ....

Assist. Prof. Dr. Barış Arslan ....

Prof. Dr. Ahmet Ademoğlu ....

This is to confirm that this thesis complies with all the standards set by the Graduate School of Natural and Applied Sciences of İstanbul Şehir University:

DATE OF APPROVAL: 14.06.2017

SEAL/SIGNATURE:

Declaration of Authorship

I, Alaa Eddin ALCHALABI, declare that this thesis titled, "A Wearable EEG-Based Serious Game for Focus Improvement and Diagnosing ADHD/ADD Patients by EEG Signals Classification" and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Signed: [signature]

Date: 09/06/2017

"Life is tough, my friends."

-The Çamlıca Guys

A Wearable EEG-Based Serious Game for Focus Improvement and Diagnosing ADHD/ADD Patients by EEG Signals Classification

Alaa Eddin Alchalabi

Abstract

Attention Deficit Hyperactivity Disorder (ADHD), characterized by the lack of attention and focus, is one of the most spread cognitive disorders. Since electroencephalogram (EEG) signals carry extensive information about cognition skills, which include attention, then the potential of using EEG signals for people with low attention span can be quite significant. EEG can be read using the new wireless EEG reading devices often used by Brain-computer Interface (BCI) researchers.

In parallel, serious games have been recently utilized for rehabilitating various cognitive and emotional deficits. In this thesis, we put the two things together, and we design a virtual reality serious game controlled using a wireless wearable EEG device to improve the attentiveness ability of people with ADHD/ADD. Our preliminary experiments with healthy subjects show an average improvement of 10% in engagement and 8% in focus for people using our EEG-controlled game compared to using the same game but keyboard-controlled.

Furthermore, we investigate the integration of an EEG-controlled serious game that trains and strengthens patients' attention ability while using machine learning to detect their attention level. The pilot experiments with healthy individuals show an accuracy of up to 96% in classifying the EEG data to detect the correct attention state during gameplay, and the extended experiments with ADHD patients show an accuracy up to 98% in classifying the patients EEG data.

Keywords: EEG classification; Brain-Computer Interface; Brain-Controlled Games; Serious Games

Odaklanmanın Geliştirilmesi İçin Giyilebilen EEG Temelli Uygulamalı Oyun ve EEG Sinyal Sınıflandırması ile DEHB Hastalarına Tanı Koyma

Alaa Eddin ALCHALABI

Öz

Dikkat Eksikliği Hiperaktivite Bozukluğu (DEHB) dikkat ve odaklanma eksikliği ile karakterize edilir ve en yaygın bilişsel işlev bozukluklarından biridir. Elektroensefalogram (EEG) sinyalleri dikkatlilik gibi bilişsel yetenekler hakkında çok fazla bilgi taşıdığı için EEG sinyallerini dikkat eksikliği olan kişiler için kullanmak büyük önem gösterir. EEG, Beyin-bilgisayar Arayüzü (BBA) araştırmacıları tarafından sıklıkla kullanılan EEG okuyan kablosuz aletler kullanılarak okunabilir.

Buna parallel olarak, son günlerde uygulamalı oyunlardan muhtelif bilişsel ve duygusal eksikliklerin iyileştirilmesi bakımından faydalanılmıştır. Bu tezde, bir bu iki alanı birleştirdik ve DEHB'li insanların dikkat yeteneklerini geliştiren, giyilebilen kablosuz EEG aleti ile control edilen bir sanal gerçeklik uygulamalı oyunu tasarladık. Sağlıklı bireylerle yaptığımız ilk deneylerde, oyunumuzu klavye kullanarak ve EEG kullanarak oynayan kişileri karşılaştırdığımızda etkileşimde 10%'luk, odaklanmada ise 8%'lik bir gelişme gördük.

Buna ek olarak, hastaların dikkat yeteneğini kuvvetlendiren EEG-kontrollü uygulamalı oyunların entegrasyonunu incelerken bir yandan da onların dikkat seviyelerini ölçmek için makine öğrenmesini kullandık. Sağlıklı kişilerle yaptığımız pilot deneylerde EEG verilerini sınıflandırmada, oyun oynama esnasındaki dikkat seviyesini ölçmede 96%'ya ulaşan bir doğruluk payı elde ettik. Ayrıca DEHB hastaları ile yaptığımız sonraki deneylerde de EEG verilerini kıyaslamada 98% doğruluk elde ettik.

Anahtar Sözcükler: EEG sınıflandırması; Beyin-Bilgisayar Arayüzü; Beyin-Kontrollü Oyunlar; Uygulamalı Oyunlar

To my martyred uncle, Aiman Alchalabi, and grandfathers, Youssef Alchalabi and Khalil Haddal, who would have been proud . . .

To my extended family scattered all over the world who I haven't met in years out of Syria . . .

Acknowledgments

I would like to express my wholehearted gratitude to Prof. Shervin Shirmohammadi for the tremendous support during the past years. He was a great mentor, an awesome motivator, and an elder friend. Without his tutelage, this thesis would not have been written.

I also want to address some of the people who I would not have made it to this point without them. I want to thank my brother and friend, Dr. Mohammed Elsharnouby for being always there when I needed support, and a special thanks to the his wife, Ebra Uraloğlu for the consultation in the Psychology field and for her help with ADHD patients. I thank my fellow labmates Amer Noureddin and Khaled AlSaleh for being a great company during our sleepless nights of working in the Neurotechnology Lab. A special thanks goes to the Technology Transfer Office and to Mr. Önder Yılmaz for his support and patience. I would like also to thank Ayşe Rumeysa Mohammed and all my other fellow teammates in the Erasmus project for Intelligent Serious Games for Social Competence for their encouragement, support and stimulating discussions.

Dearest of all is my family, who are behind me on each step and are my greatest source of strength. I want to acknowledge the endless love and support they have been giving.

Last but not least, I want to thank my friend Taha Moiz and all my other friends for making the past two years in Istanbul the best years of my life so far. Thanks for making me feel at home, or more precisely, making Istanbul my new home.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Motivation

In their famous survey, Rego et al. [1] attention is classified as one of the cognitive skills along with concentration, problem-solving, judgment, language, etc. Attention Deficit Hyper Activity Disorder (ADHD) is a psychiatric disorder that is related to levels of inattention, impulsivity, and hyperactivity [2]. ADHD is common in children and adults while the former have a higher probability of being symptomatic. According to a survey conducted by the Centers for Disease Control and Prevention (CDC), 11% of children in the US (4-17 years) had been diagnosed with ADHD as of 2011 [3]. ADHD's presence in children is manifested by hindering academic achievement and social interactions.

Cognitive training with different duration and intensity has also been used with the elderly since they deal with a declination in the cognitive abilities. However, while encouraging the engagement, illuminating the repetitive monotonic scenes, adapting the difficulty level and stimulating the users' interests are considered the main challenges in this context. With the help of new technologies such as serious games during cognitive therapies, users' reinforcement is no longer an obstacle, accommodating different spans of ages and various cognitive impediments.

In this thesis, one of the motivations behind this work is proposing an EEG-controlled serious game aimed at training individuals diagnosed with ADHD/ADD to improve their attentiveness levels. Moreover, to ensure the acceptance of the medical community, the game is built as an attempt to digitally mimic few existing clinical and rehabilitation therapies.

Since the brain-controlled FOCUS game [4] has recorded a 10% increase in engagement and a 8% in focus over the keyboard-controlled game with healthy subjects, we hypothesize that it will be effectively used with those diagnosed with low attentiveness and ADHD. Along with the previous work, testing with healthy subjects acts as a milestone for reaching our long-term goal of diagnosing ADHD, and hopefully becoming a rehabilitation alternative.

After obtaining the acceptance of İstanbul Şehir University's Ethics Committee for testing the game with ADHD subjects, the game was tested with 4 ADHD subjects and the same diagnostic machine learning classification models were applied on the recorded data of the ADHD subjects. The classification models obtained a classification accuracy up to 98%.

This serious game has been developed in the context of the European project titled ``Erasmus+: Intelligent Serious Games for Social and Cognitive Competence'' [5].

1.2 Problem Definition

State-of-the-art therapies for individuals dealing with low attention levels aims at increasing focusing skills while compromising the motivation techniques. When dealing with children, the existing dilemma of maximizing the attentiveness level in therapies is a recent optimization research problem. The new wireless EEG recording devices could fill this gap. The integration of brain EEG signals and serious games is a recent research trend. Because the brain generates EEG signals, they carry extensive information about cognition skills, and since attention is one of those skills, then the potential of using EEG signals for people with low attention span and ADHD treatment/diagnosis can be quite significant.

Additionally, serious games not only promote inclusivity but also helps to influence knowledge, discoveries, and challenges. Studies have proven the ability of serious games to be used in sustainability, education, and nutrition. But the amount of information in EEG signals could be vast, too much for human processing. Machine learning (ML) techniques, which nowadays are more accurate in classifying data with the advancement of learning algorithms and the availability of big amounts of data, can help process EEG data to find useful results. Recent works use ML and statistical techniques in diagnosing different neurological diseases, such as, Epilepsy and Becker Muscular Dystrophy (BMD) [6], and psychological disorders, such as ADHD [6–8] , schizophrenia [9], and Autism [8], although none do so within a serious game.

1.3 Methodology

We propose to integrate and exploit three different components: the ability of serious games to increase engagement, the importance and the accuracy of the EEG data to cognitive disorders, and the intelligence of the machine learning classification models.

We also lay the ground for the integration of the aforementioned serious game that is aimed at providing training to augment attentiveness and a classification model that identifies to different game control modes (brain-controlled, keyboard-controlled) of non-ADHD subjects. This is achieved by a pre-designed game (FOCUS Game) that adopts various techniques which digitally mimic existing clinical and rehabilitation approaches [4], as well as using an ML classifier, using multiple models, that can diagnose different attentiveness levels characterized by the game control mode (brain-controlled, keyboard-controlled).

The serious game was designed using Unity Game Engine as an attempt to digitally mimic few existing clinical and rehabilitation therapies. The design decisions and implementation details are discussed in later chapters. The wearable wireless EEG device, EMOTIV, was used to control the the serious game via the open source SDK provided by the company. Lastly, the raw EEG data was recorded during the testing sessions and classification models were trained on it.

1.4 Contributions

This thesis presents a wearable EEG-Based serious game aimed at improving the attentiveness skills of ADD/ADHD patients, which was designed according the standards of the European project, Erasmus+: Intelligent Serious Games for Social and Cognitive Competence. The designed game used an EEG wireless device for controlling the movement of the avatar, and for the first time, we have laid the ground for integrating a machine learning classifier with a serious game to detect ADHD patients.

Several contributions are included in this research, which are as follows:

- A user-friendly EEG-controlled serious game that targets improving the focus of ADHD diagnosed individuals.
- Adaption of traditional tasks in order to stimulate the enhancement of attentiveness, in addition to using wearable sensors.

- Handling player movement using the cognitive skills through the EEG pattern recognition, and handling the rotation using a wearable gyroscopic sensor on the scalp.
- A 10% improvement in engagement and 8% in focus recorded during gameplay in the preliminary results with healthy subjects.
- An up-to 96% accuracy obtained in classifying EEG data to detect the correct attention state characterized by the type of game control (Emotiv-control, and Keyboard-control)
- An up-to 98% accuracy obtained in detecting ADHD patients by classifying EEG recorded data during gameplay.

1.5 Research Publications

The peer reviewed publications related to the topic of this thesis are given below.

Journal Papers:

Alaa Eddin Alchalabi, Shervin Shirmohammadi, Amer Nour Eddin, and Mohamed Elsharnouby. "FOCUS: Detecting ADHD Patients by An EEG-Based Serious Game," IEEE Transactions on Instrumentation and Measurement, (submitted), 2017. [10]

Conference Publications:

Alaa Eddin Alchalabi, Mohamed Elsharnouby, Shervin Shirmohammadi, and Amer Nour Eddin. "Feasibility of Detecting ADHD Patients' Attention Levels by Classifying Their EEG Signals," The 12th Annual IEEE International Symposium on Medical Measurements and Applications, (accepted, to appear), 2017. [11]

Alaa Eddin Alchalabi, Amer Nour Eddin, and Shervin Shirmohammadi. "More Attention, Less Deficit: Wearable EEG-Based Serious Game for Focus Improvement," The 5th IEEE Conference on Serious Games and Applications for Health (SeGAH '17), Perth, Australia, April 2017. [4]

Other Conference Publications:

These publication are not related to this thesis, but was published within the duration of the author's Masters studies.

> Alaa Eddin Alchalabi, Mohammed Elsharnoby, and Saed Khawaldeh. "Rightscope: Detecting search campaingns positive and negative queries," International Conference on Machine Learning and Cybernetics (ICMLC), pp. 290-295. IEEE, 2016. [12]

> Alaa Eddin Alchalabi, Ayşe Rumeysa Mohammed, and Onur Guzey, "Bringing Engineering and Management Education Together in the Age of Big Data," Portland International Conference on Management of Engineering Technology 2017 (PICMET '17), (accepted, to appear), 2017.

1.6 Thesis Outline

Due to the diversity of technical/medical terms and concepts, Chapter 2 will contain a background on these terminologies and concepts. Then, Chapter 3 will present the related works. Following that, Chapter 4 will illustrate the design decisions of the proposed game along with the implementation details. Chapter 5 will illustrate data collection methodology, data pre-processing, and will also discuss the proposed classification models along with experiments and results. Finally, the thesis is concluded in the last section where the future work opportunities are also presented.

Due to the lack of time and the difficulty of accessing ADHD patients in the early stages of this work, we will start by presenting the preliminary study with the healthy subjects which served as a motivation to test our models with actual ADHD patients that will be presented later.

Major parts of Chapter 3 and Chapter 4 are taken from the recently published paper [4] at The 5th IEEE Conference on Serious Games and Applications for Health (SeGAH 2017). Chapter 5 also represents another published work [11] at The 12th Annual IEEE International Symposium on Medical Measurements and Applications (MeMeA 2017), while the other chapters use some parts from both papers. Some of the work in the end of Chapter 5 is also submitted as an extended journal paper of [11] to the MeMeA 2017 Special Issue of IEEE Transactions on Instrumentation and Measurement (TIM) at the same time this thesis was submitted [10].

Chapter 2

Background

In this chapter, we will go over some of the technical and medical terms/concepts that are used in this research. It will act as a strong technical foundation for the readers to refer to.

2.1 EEG

Neurofeedback, as a biofeedback technology, as originated in the late 1960s [13] and was utilized to train the capability of self-control using a real-time analysis of EEG brain signals, magnetoencephalography, and real-time functional magnetic resonance imaging [14]. Therapeutic enhancements following neurofeedback training (NFT) have been recorded in association with a normalization of the Quantitative EEG (QEEG) frequency ranges, which is a protocol used in Signal Processing of EEG signals [15]. An example of the wireless EEG reader, Emotiv headset, is shown in action in Figure 2.1 below. EMOTIV EPOC+, a 14 channel wireless EEG system by EMOTIV Inc., is designed for research related to brain-computer interface. The device can record raw EEG data and EEG frequency bands data via open source software provided by the company [16].

The EEG signals are divided into multiple frequency bands: Delta δ band ($<$4 Hz), Theta θ band 4-7 Hz, Alpha α band 8-12 Hz, Beta β band 12-30 Hz, and Gamma γ band $>$30 Hz. These frequency bands generated by Emotiv have 0.5 second time step and 2 seconds of data window size. Each frequency band is associated with a unique brain function: δ band is dominant in children during sleeping and is related to linguistic acquisition [17], θ band is predominant in EEG during drowsiness states, α band is important in relaxation, β band is linked to fast activities, and γ band is related to problem-solving and memory [18]. Figure 2.2 illustrates the different frequency bands.

FIGURE 2.1: The EMOTIV EPOC+ EEG Reader.

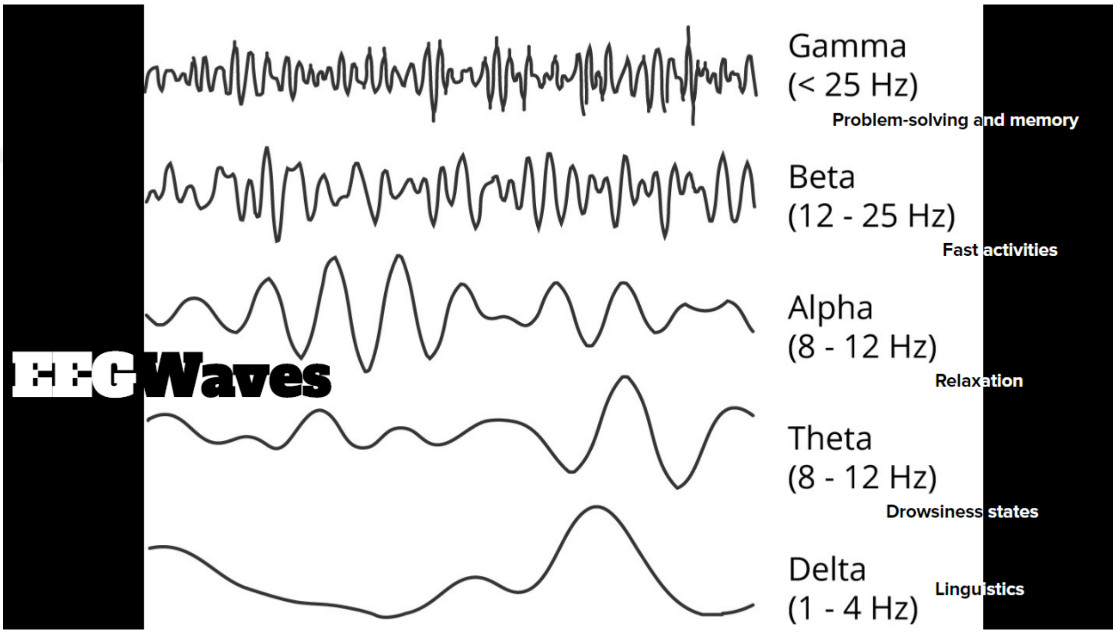


FIGURE 2.2: The EEG Frequency Bands.

2.2 ADHD & ADD

Attention Deficit Hyperactivity Disorder (ADHD) is a cognitive disorder that is linked with levels of inattentiveness, impulsivity, and hyperactivity [2]. It is widely common in children, while symptoms may take effect in later adultery stages. ADD, Attention Deficit Disorder, is similar to ADHD with the absence of hyperactivity.

2.3 ASD

Autistic Spectrum Disorder (ASD) is a psychological disorder which symptomatic individuals often suffer social problems include difficulties with communication and interaction with others, some repetitive behaviors, and limited activities or interests [19, 20].

2.4 GAD

Generalized Anxiety Disorder (GAD) is a common mental disorders characterized by the irrationally and extremely uncontrollable anxiety about normal life activities without distinguishable cause for panic.

2.5 SVM

Support Vector Machines (SVMs) are machine learning supervised learning models that are used for linearly non-probabilistic binary data classification. SVMs have the ability to fit a hyperplane that separates between 2 different classes. SVM performs well with non-linearly separable data using the kernel trick which maps data inputs to higher dimensional spaces of features in which they are easily separable. An example of an SVM model using a linear kernel is illustrated by Figure 2.3 below.

The black hyperplane separates the two classes, resulting in the maximum margin between their closest samples

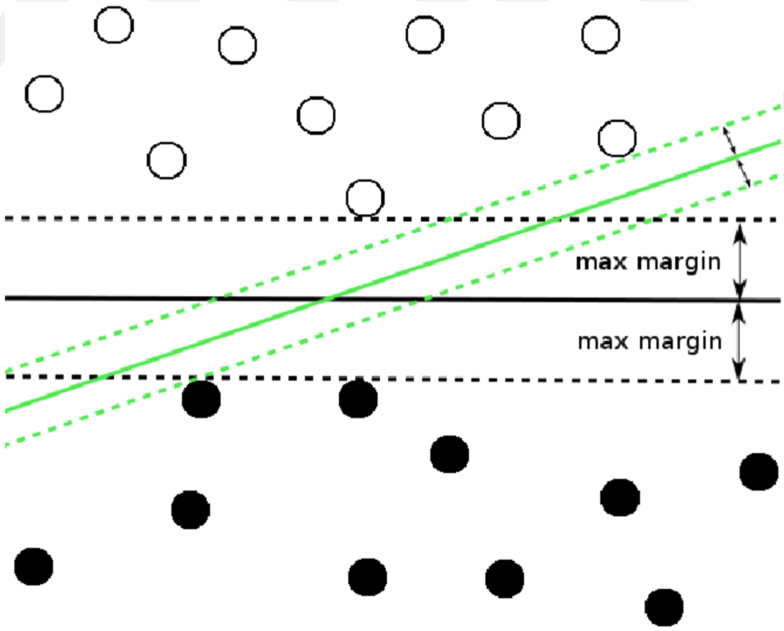


FIGURE 2.3: Binary classification using an SVM hyperplance that maximizes the margin between the two classes [21].

The Radial Basis Function kernel (RBF kernel) was used for obtaining better accuracy with dealing with complex and a high number of features. Figure 2.4 shows an example of an EEG classification task. SVMs have a soft margin parameter C which controls the margin of the separating hyper-plane.

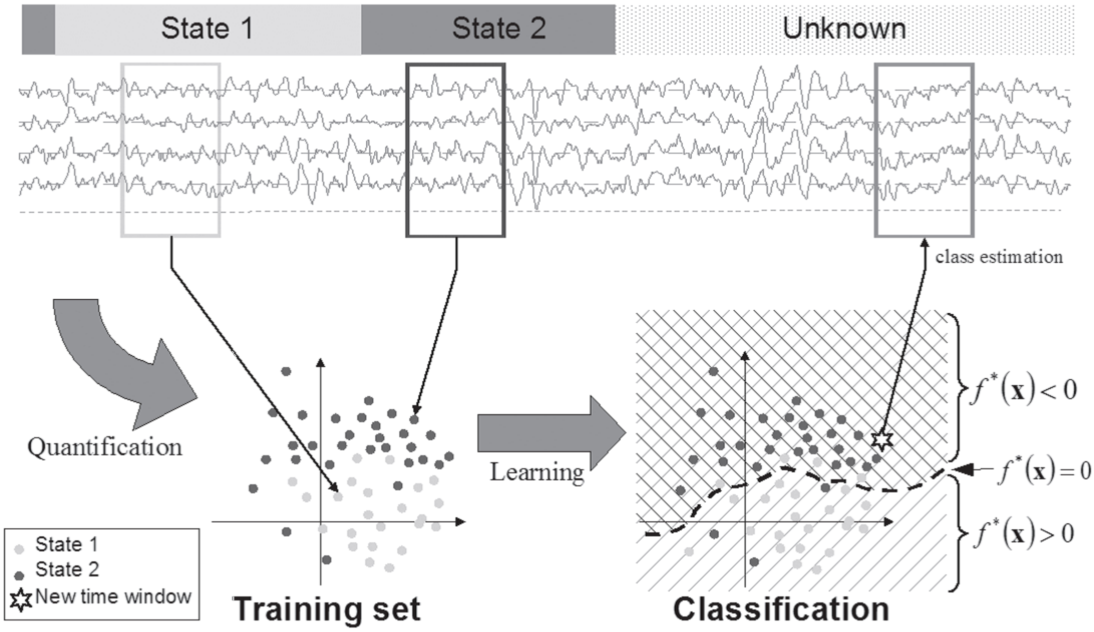


FIGURE 2.4: Binary classification of EEG recordings using each time window as a point in a multidimensional space [22], used with permission.

2.6 KNN and DTW

K-Nearest Neighbors is a supervised classification technique that classifies samples according to the k-nearest samples that have known classes as shown in Figure 2.5. The distance is calculated by an algorithm that is usually used in digital signal processing called Dynamic Time Warping (DTW) [23]. DTW can compare waves that are non-aligned and differently scaled and find the optimal match within a specified window as shown in Figure 2.6. DTW has shown significant results with KNN classification [24].

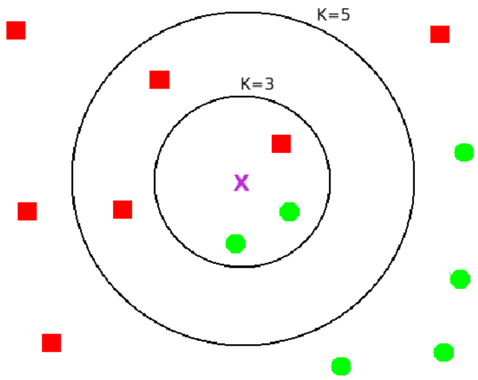


FIGURE 2.5: A classification model using a KNN model [21].

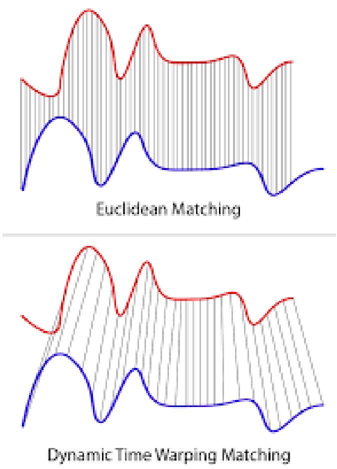


FIGURE 2.6: The difference between matching waves using Euclidean distance and using DTW [25].

2.7 Cross-validation

Cross-validation is a performance measurement technique used for many machine learning models. It is done by splitting data into k-folds, and iteratively repeat taking a single fold as a test set while training on the other k-1 folds for k different models as shown in Figure 2.7. This is considered a reliable way of reporting results by averaging the k accuracies obtained.

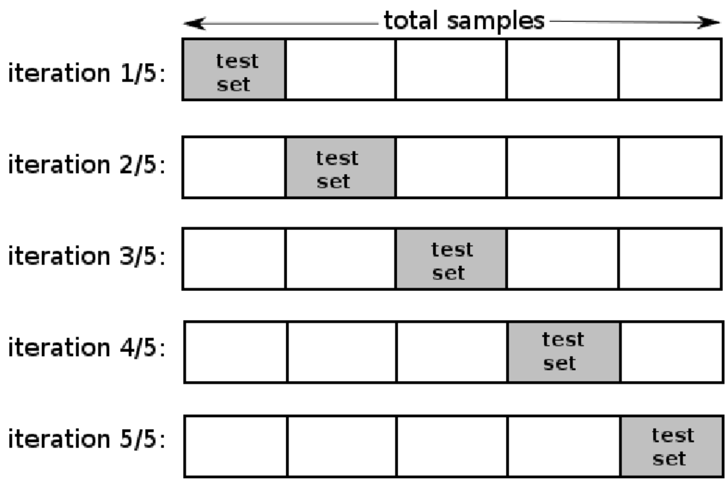


FIGURE 2.7: An exmaple of 5-folds Cross-validation [21].

Chapter 3

Related Work

In this chapter, we will review few medical therapies that are EEG-Based for various cognitive problems, and EEG-based serious games for ADHD, then we will talking about some of the limitations of the presented work and our contribution. In this context, clinical methods for treating ADHD are beyond the scope of this thesis; readers interested in learning about traditional and clinical ADHD therapies can refer to [26] for more details.

3.1 EEG-Based Therapies

For various cognitive disorders, NFT was proven to be a non-invasive side-effect-free substitute [13]. EEG remains a strong candidate for a spot in the clinical setting, depending on continued efforts – via multivariate analyses and advanced studies of EEG signal generators – to capture additional sources of heterogeneity in ADHD [27]. NFT has commonly been used with ADHD patients and it has been observed to be associated with:

- Improved concentration and attention span
- Decline in hyperactivity and impulsiveness
- Enhanced academic performance
- Increased retention, mood stability and memory
- Relaxed sleep patterns

For most learning disabilities, NFT showed a positive results after evaluating pre-NFT and post-NFT treatment. An increase of an average of 9 IQ points were recorded following NFT [13–15, 28]. The treatment effect that NFT has on ADHD is significant as [29] observed several abnormal behaviors from the EEG distortions of ADHD patients characterized by the ratio of θ/β frequency bands. Furthermore, a distortion in slow cortical potential (SCP), which is direct-current and slow event-related vacillations in the EEG signals measured from the upper cortical membrane [30], was observed in [31]. Good therapeutic results on ADHD could be attained by SCP and NFT trainings [18, 31], while GAD patients could also have positive results by regularizing and suppressing the α bands generated by EEG [32].

Some other experiments was done on an 8 years old girl with ASD [18, 29] through a simple experiment of eye-blinking showed an abnormal activity in the α and θ bands of the EEG, while the NFT training aimed at resolving the abnormalities and regularizing the signals. Twenty-one sessions later, the patient was observed to have a better attention span and reduced the ASD symptoms. A similar experiment on autistic individuals was done using NFT with typical Quantitative EEG (QEEG) protocol which observed a decline in the θ band power at the frontal and central zone of the brain of the patients [20].

A study employed quantified EEG data to analyze subjects learning status during the experiment. The optimum classification results are obtained when five of the frequency bands features are used simultaneously. However, each of the features has a different influence on the classification accuracy. Delta value is recorded to have the most significant effect on the classification accuracy by up to 6%. The study results indicate the EEG signals of attention are easier to identify compared to those of inattention [7].

Another study mentioned that during an attentive state, subjects with ADHD are characterized by an under activated state in the EEG with subtype-specific differences. Findings may provide a rationale for applying NFT protocols targeting Theta activity and Theta/Beta ratio in subgroups of children with ADHD to achieve an attentive state [33].

A similar study on ADHD most reliably associating it with the growth of front-central Theta band activity and increased Theta to Beta (θ/β) power ratio during rest compared to non-ADHD. Significant EEG variety also exists across ADHD-diagnosed subjects. Intensive re-analysis of existing EEG study data can better describe the neurophysiological differences between and within ADHD and non-ADHD subjects, and lead to more accurate diagnostic measures and effective NF approaches [34].

There has been much work done on EEG in the instrumentation and measurement community, but none have focused on attention measurement for ADHD. For example, analysis and detection of seizure have been performed using EEG [35, 36]. In [37], authors propose a method to remove EEG artifacts occurring during concurrent recordings of EEG and functional magnetic resonance imaging (fMRI). [38] uses SVM and develops a classifier to recognize the cognitive and resting state of the brain. As a final example, the authors in [39] build an implantable micro-apparatus encompassed under the scalp for monitoring and retrieving electrical cerebral activities.

Other studies used wearable EEG recording devices with the elderly in order to improve epilepsy detection and ambulatory monitoring [40]. NFT also has been used for age-related memory impairments in a form of a rehabilitative software [41]. Out of the medical applications, NFT can also improve the mental abilities of a normal healthy person.

3.2 EEG-Based Serious games for ADHD

The newly introduced EEG wireless recording devices have revolutionized research in the area of rehabilitation therapies, and since serious games used to have a big share in this area, the inclusion of wireless EEG devices in serious games made them more effective [42]. The same study [42] classified serious games into: neurofeedback EEG-based games and e-learning based games. Another research surveyed the different BCI-based serious games that are built for ADHD treatment, then they proposed a design that balances the entertainment and training levels [43].

A group developed a game that are controlled by the player's attention via EEG signals. It asks the player to remember a set of numbers in a given matrix, empty the matrix, and then, via the players attention, tries to fill the matrix again [44].

Another group designed a BCI-controlled spacecraft game that the player should avoid obstacles using his mental abilities. The controllers are built based on phase tagging and steady state visually evoked potentials (SSVEP). The game is built for children that suffer from attention deficits with Neurofibromatosis Type 1. They tested the game with healthy individuals and reported a 95% of accuracy for 5-seconds trails [45].

A recent study used P300 event related potential (ERP) and sensorimotor rhythms in order to control the falling objects of the well-known 2D Tetris game. The BCI-controlled Tetris was tested with children with ADHD and the game has been experimentally validated to be effectively controlled by the EEG signals.

3.3 Limitations of Related Work, and Our Contribution

EEG-controlled gaming is relatively a new concept. EEG-based therapy in the medical field traditionally use the wired devices to record EEG signals which puts constrains on the therapists due to the need of the special laboratory equipment to extact the raw EEG data from the brain. Additionally, a Fast Fourier Transform (FFT) should be run on the data in order to obtain the EEG power bands. The new wireless EEG recording devices; i.e., Emotiv EPOC can be a possible choice that will ease dealing with EEG data.

As noticed from the serious games in the literature, games built for ADHD lack the Virtual Reality (VR) option with a humanoid avatar, which could improve the engagement and, therefore, the attention span. Using more than a stimulus in a single game will also enhance the level of interaction. In the proposed game, EEG signals were used to control the avatar forward movement, while for turning right and left, the built-in gyroscope in the Emotiv EPOC was utilized.

Additionally, the difficulty level in most of the existing serious games such as, memory games, obstacle avoidance games, or time limited games could create a more stressful environment to the patient that to help him focus. Therefore, our choice of game design was to simplify the gameplay that will illuminate the side-effect on the player's concentration.

Finally, using a fuzzy colored avatars, robots, cubes, or other cartoonish avatars as the player's character will cause an stress and annoyance stimulants for people with ADHD. The choice of light and simple colors avoiding harsh colors was considered, while the desgin details will be discussed in later stages.

Chapter 4

Proposed Game: Design, Implementation, Preliminary Test

In this chapter, the design decisions and the implementation details of the developed serious game will be presented. Additionally, a preliminary test with healthy subjects will be presented and analyzed.

4.1 Game Design

For the game developed, an initial level of difficulty was only developed. The player in this level is asked to collect the cubical pick-ups that exist in the environment within the shortest time possible. The controls used were the mental commands using the Emotiv kit; i.e., the "push" and the "neutral" states which will be discussed in detail later. Adding some extra rules to the game to increase the difficulty, such as, collecting cubes in order, is left as a future work.

4.1.1 Environment and the avatar

Since the targeted group has a relatively short attention span, the choice of the environment should be a self-relieving and alleviating environment. For this reason a calm and serene nature-like environment was chosen. The environment design contains a square shaped floor centered in a jungle, as shown in Figure 4.1 below. The dominant color was green since according to [46] green has a calmative effects on humans' cognition, and therefore, no distractions exist.

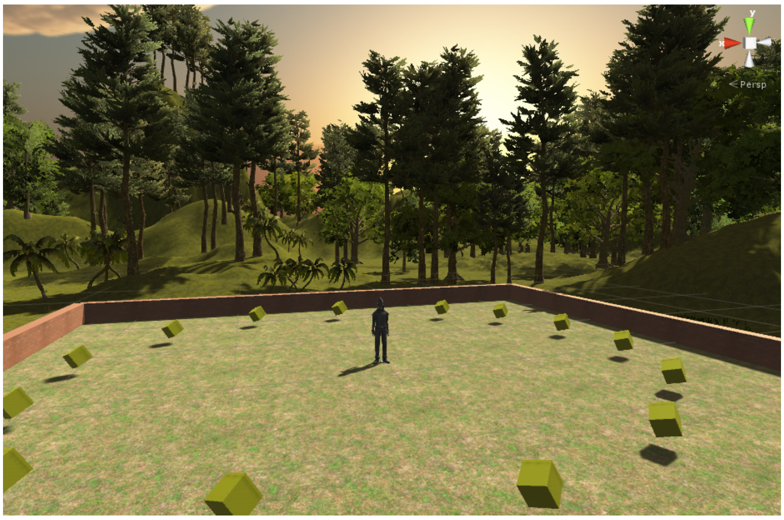


Figure 4.1: The proposed game's environment

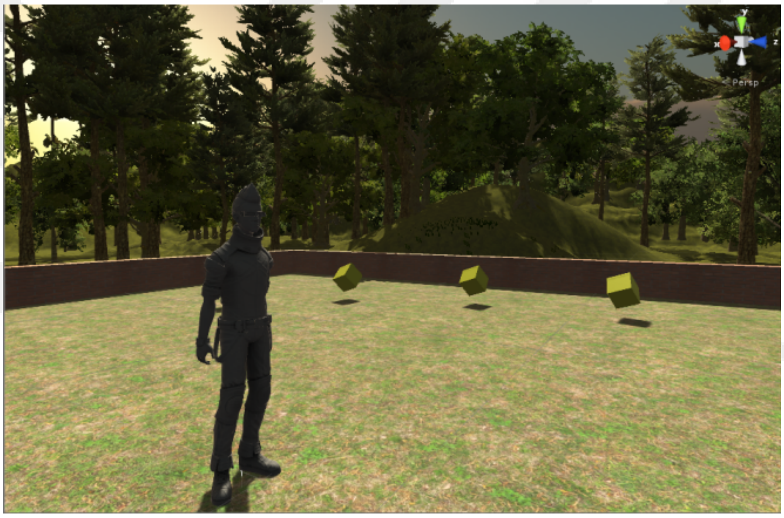


Figure 4.2: The Proposed Game's Avatar

A humanoid character was chosen for this game, as shown in Figure 4.2, opposing to the games' typical choice of a cartoonish avatar or a 3D polygon shape for the following reasons:

- People with ADHD/ADD prefer a simple muted character, since a highly warm-colored fantasy avatar could create distraction and anxiety rather than maintaining attention.
- The Humanoid avatar is preferred due to the taste of realism it imposes stimulating and emboldening real-life attention skills.
- The Humanoid avatar is preferred to 3D geometric objects due to the ability to convey a deeper level of engagement in the player's mind since it is easier for training the cognitive abilities.

The grey color of the avatar was chosen for avoiding any expected distraction generated by energetic and warm colors [46]. A background music in accordance with the overall game's theme on order to improve patients' attention span. Emotiv Cloud, shown in Figure 4.3, allows users to save the settings and the users' trainings in order to load them later. Using the EMOTIV ID, the save and load options could be utilized.

FIGURE 4.3: The profile logging fields

An open-sourced software called "Emotiv Xavier Controlpanel" helps Emotiv developers with checking the sensors' connectivity and reporting performance metrics (focus, engagement, stress, relaxation, interest, and excitement levels).

4.1.2 Initial Setup

To challenge the cognitive ability of the player, the game scenario was built to challenge the player to finish the task in the shortest time possible. Therapist should assure that the Emotiv kit is well installed before the game starts, and the kit's electrodes have good connection using the EMOTIV Controlpanel [16], as shown in Figure 4.4.

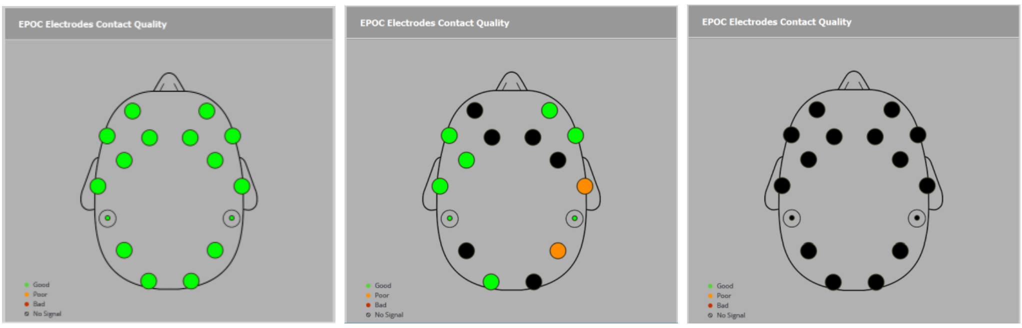


FIGURE 4.4: The Emotiv control panel connectivity status. Right: perfect connectivity, middle: some lack of connectivity, left: bad connectivity.

The sensors' indicators on the control panel are better be green lighted for the best results. The Emotiv sensors should be watered by a special liquid which comes with the kit to increase the electrical conductance. Then, the executable file should be run by the therapist after completing the initial setup.

4.1.3 Training and Gameplay

The game initializes by creating the humanoid character to the user and by showing some instructions for using the headset to play the game. The training phase is a crucial stage that challenges researchers in the field of EEG-based serious games. Since the EEG signals of different people might have some mutual characteristics, EEG signals are highly personalized and it is impossible to have a single universal trained system that works on different people.

By starting the game, there are 2 different states in the game's algorithm that need to be trained: "push" and "neutral" states. On the left side of the game's screen, the player could use 2 buttons to initiate the trainings: "Train Push", and "Train Neutral" that can be seen on Figure 4.5. Instructions will be shown during the game to assist the player during the training phase.

In order to train the algorithm to push the avatar and make it move, the player is asked to imagine the avatar walking forward while the kit is recording the brain signals. By training the neutral state, the player is asked to be idle since the neutral training is essential for detecting the other state ("Push state"). It is important during the training phase that players should carefully not associate any facial muscles movement, such as blinking or raising eyebrows because it generates a different pattern of EEG signals that the algorithm can easy distinguish.

Figure 4.5: The training buttons

By finishing the training, players should be able to use their mental commands to control the character forward. the gyroscope of the EPOC headset was associated to turning the avatar such that players could turn the avatar by turning their heads right and left, as shown in Figure 4.6. Introducing the head movement to turn the avatar will maximize the player's engagement with the game.

FIGURE 4.6: The game subject playing the game with the Emotiv kit.

4.1.4 Implementation

The platform used for developing the game was Unity3D along with the EMOTIV open source SDK. The data collection was done using a 14 channel EPOC kit, then the data was wirelessly sent to the computer using Bluetooth as shown in Figure 4.7.

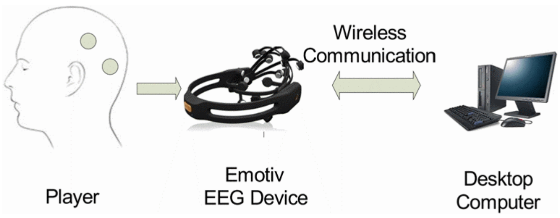


FIGURE 4.7: Data Collection Diagram. Source: [18], used with permission

The open source SDK library was used to detect the "push" state using a simple busy-wait loop that keeps iterating until it detects a "push" signal. Then, the animation of the avatar was programmed to move if any "push" event was detected. On the other hand, rotating the avatar right and left was done by detecting the difference in the gyroscope readings and then it was linked to the avatar's rotation and animation.

4.2 Experimentation and Results

4.2.1 Test Methodology

Before the testing starts, each of the testing subjects is explained how to use to game. Then, the therapist should install the Emotiv headset on the subject's scalp. By starting the game and the timer, the Emotiv Xavier Controlpanel's performance metrics detection is run on the background.

The player starts by training the "push" and "neutral" commands in order to be able to control the avatar with the Emotiv kit. The time each player takes to collect all the cubical pickups is measured. While the game is being played, the performance metrics detection which is run in the background is recording the brain activity of each player. Figure 4.8 has a sample of the focus levels pre-training, during training, and after the training using the Emotiv controlled game. The peak attentive value was measured during the training.

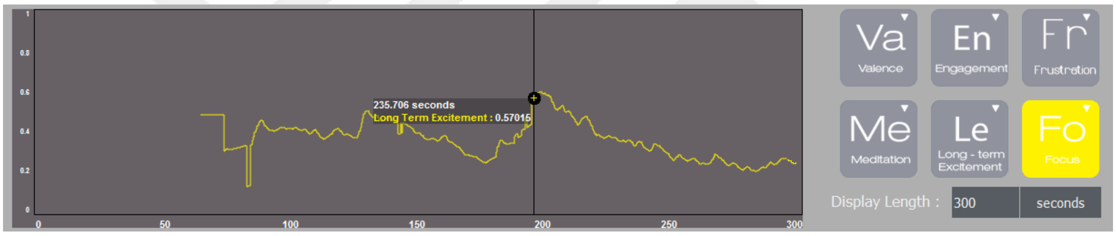


FIGURE 4.8: The performance metrics of the subject's focus

To test the inclusion of Emotiv control to the game's effectiveness, the testing methodology developed will compare the Emotiv-control to the traditional keyboard-control of the same game. Therefore, players are asked to play the game using the keyboard arrows to control the character movement instead of the using Emotiv kit for control. Similarly, the performance metrics detection was run on the background.

Using the Emotiv Xavier Controlpanel, there are options to perform the brain analysis performance metrics for certain activities such as studying, brainstorming, gaming, and etc. The analysis results report a level of each of the following performance metrics: focus, stress, relaxation, interest, excitement, and engagement. Before the the recording starts, the software should be calibrated for each person by recording a base EEG session while the eyes-open and eyes-closed states. The type of recording activity was set to "Gaming", and then the recording starts. The software graphs the live metrics during the recording session as shown in Figure 4.9.

When the recording session is halted by the therapist, the performance report is automatically generated showing the levels of metrics. The report represents the EMOTIV

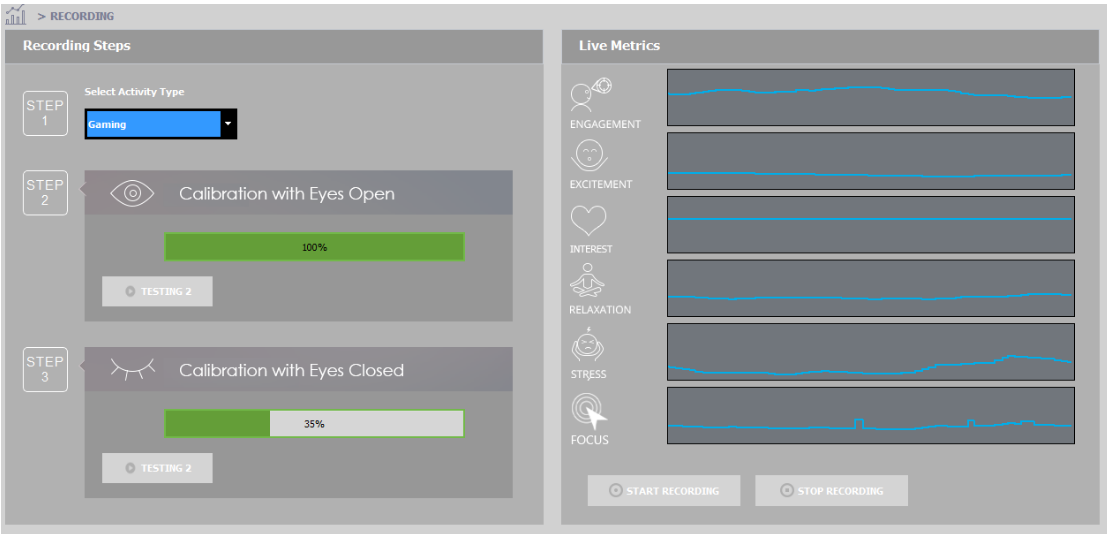


FIGURE 4.9: Calibration and recording

predefined measures which takes into account the ratio between the various frequency power bands in order to calculate the reported measurements. Figure 4.10 shows a sample of the generated report. After the measurements are presented, the data is collected for each subject, compared and analyzed.

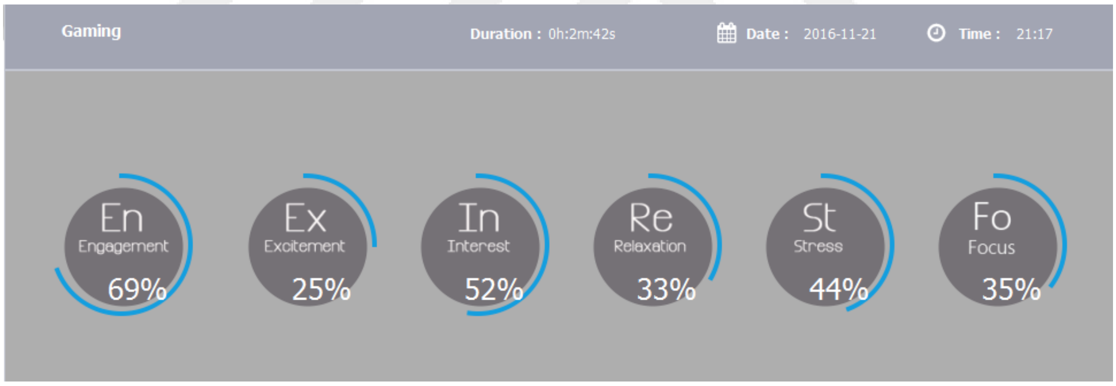
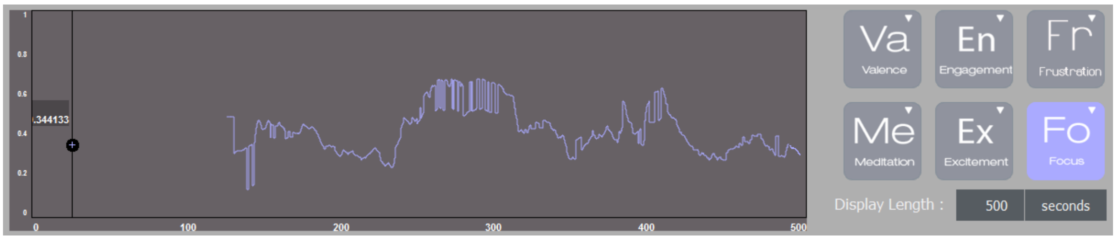


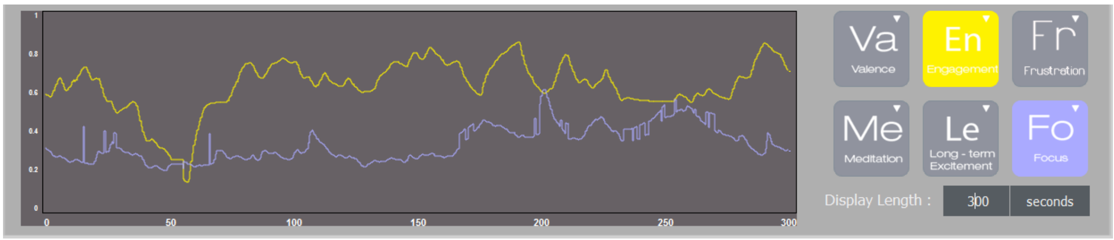
FIGURE 4.10: A sample recording for the Emotiv-tested game.

4.2.2 Preliminary Testing Results

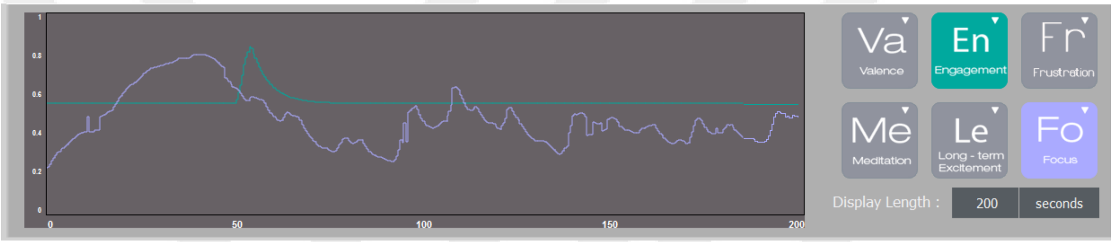
The aforementioned testing methodology was done on 4 healthy subjects due to the inability to have the access and the approval to test the game with ADHD patients. This test serves as an initial attempt to prove the effects of the proposed serious game. Future tests presented in later chapters will contain more test subjects and will include ADHD patients. For the confidentiality, the test subjects will be referred by S1, S2, S3, and S4. The focus levels of subjects while playing the Emotiv-controlled game are shown in Figure 4.11 (a) through (d) respectively.



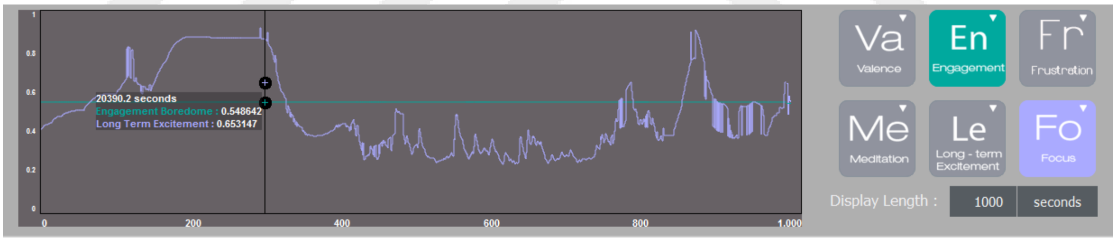
(a)



(b)



(c)



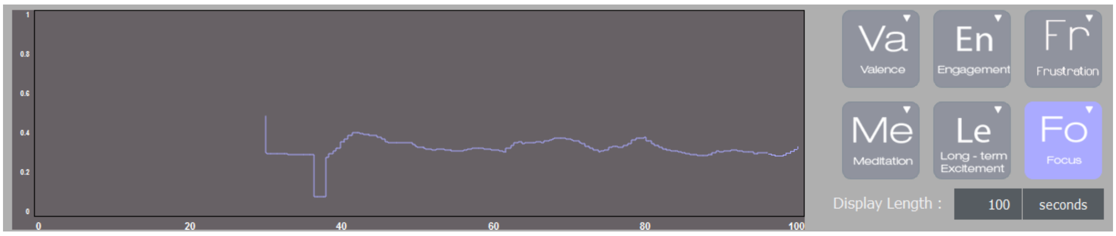
(d)

FIGURE 4.11: The focus levels for the Emotiv-tested game

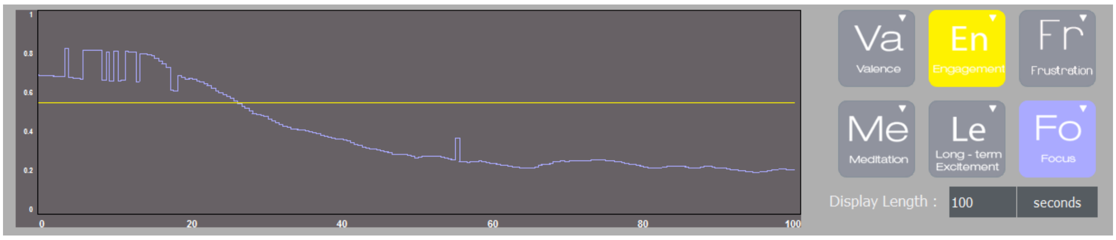
Similarly, The focus levels of subjects while playing the keyboard-controlled game are shown in Figure 4.12.

It is noticed from the graphs that the focus levels recorded during the Emotiv-controlled game are higher on average. Also, it is observed that keyboard-controlled recordings have less fluctuations.

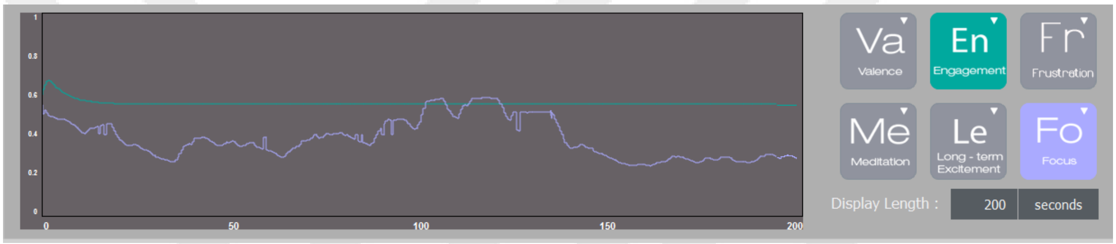
On the other hand, the activity-based recording software was run in the background for all subjects. The results has been collected and are presented in Table 4.1 below. The Emotiv-controlled recordings has average improvement in engagement of 10.25%, while the focus levels has a 8.25% improvement over the keyboard-recordings.



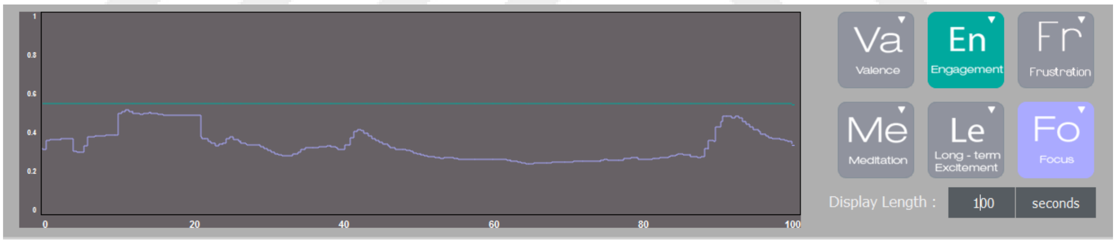
(a)



(b)



(c)



(d)

FIGURE 4.12: The focus levels for the keyboard-tested game

TABLE 4.1: Performance Metrics Initial Testing Results

Subject	Metrics	Focus	Stress	Relaxation	Interest	Excitement	Engagement
	Key %	.30	.27	.28	.46	.19	.56
S1	Emo %	.35	.44	.33	.52	.25	.69
	Diff.	+ .05	+ .17	+ .05	+ .06	+ .06	+ .13
	Key %	.32	.35	.33	.62	.21	.55
S2	Emo %	.35	.38	.32	.62	.25	.64
	Diff.	+ .03	+ .03	- .01	0	+ .04	+ .09
	Key %	.30	.35	.33	.54	.22	.55
S3	Emo %	.41	.54	.33	.63	.26	.65
	Diff.	+ .11	+ .19	0	+ .09	+ .04	+ .10
	Key %	.30	.42	.33	.62	.19	.54
S4	Emo %	.44	.61	.33	.62	.26	.63
	Diff.	+ .14	+ .19	0	0	+ .07	+ .09

After the positive results obtained from the preliminary testing, testing on a wide samples of subjects that suffer from ADHD symptoms was set as the next milestone. Additionally, newer testing methodologies should be developed. Another milestone is enhancing the game to support multiplayers, but due to the technical complexity of creating a multiplayer EEG-controlled serious game, as the first of its kind, it will be kept as a future goal.

To conclude this chapter, the proposed EEG-based serious game proved its ability to augment the attentive abilities of the ADHD symptomatic people. The design decisions and the implementation has been discussed. The preliminary testing results of using the Emotiv kit as a game controller with healthy individuals showed an average improvement of 10% in the engagement measurement and 8% in the focusing measurement compared to using the same people playing the same via the keyboard buttons.

Chapter 5

Proposed Classification Models, Experiments, and Results

We designed a serious game called "FOCUS" that targets improving the attention of individuals with low attention spans and those diagnosed with ADHD [4]. The aforementioned game is BCI-controlled and should be played using the EMOTIV EPOC+ kit. The game challenges the players to move an avatar, using mental commands and focus abilities, to collect all the cubical pickups in the shortest time possible. Using the training buttons on UI, the user can start associating his mental commands to the actions of the avatar. The study in [4] showed that the brain-controlled had a 10% increase in engagement and a 8% in focus over the keyboard-controlled game with healthy subjects, and that acted as a motivation for building more classification models to better understand the recorded data.

In this chapter, the focus will be on the machine learning classification models that was built using the data recordings of the test subjects. We will start by explaining the data wrangling techniques applied on the data. Since the access to ADHD patients was not possible, as a preliminary study we tried to classify between the data recorded using the Emotiv Kit and the data recorded using the Keyboard control as they represent different types of attention levels. Then we will continue by explaining and analyzing the proposed ADHD classification models.

5.1 Data Wrangling

For the models built in this study, some data wrangling techniques were applied to enhance the models' performance to obtain the best detection accuracy.

5.1.1 Frequency Bands Data Filtering

Frequency bands recordings were only used for training the models. Data provided by the frequency bands is more compact in size, while it conserves the same wave information as a result of applying Fast Fourier Transform. Raw data recordings were disregarded and kept for future studies.

5.1.2 Data Windowing

We employed data windowing to improve the accuracy of the initial models. From each recording session file, a window of n-rows (representing a time step) were considered a single data sample instead of the recording session as a whole. The windows are not overlapping to eliminate the duplication of waves. Also, since we had 50 recordings for models presented in Section 5.2, taking windows of signals increased the data samples from 50 recordings to approximately 20,000 data samples in a window of size 5. Additionally, after adding the ADHD subjects' data, the total number of data samples was 57,790 samples.

5.1.3 Feature Extraction (Extra Attributes)

In this context, we would name the extracted features as attributes in order not to cause confusion with the features that are input to the model. Since raw data were eliminated for models built in this study, data attributes represent only the 5 frequency bands. According to [33] the ratio between Theta and Beta bands reflected the attention levels of the test subject. Other studies [34] showed that individuals with ADHD produce comparatively less of the higher frequency band (Beta) and more of the lower frequency band (Theta), and as a result, the ratio Theta/Beta carries valuable information. Other studies [47] proved that the ratio between Alpha and Beta bands is as important and reflects the attention levels. The data recorded contained High Beta and Low Beta, and consequently, 4 attributes were added: Theta/High Beta, Theta/Low Beta, Alpha/High Beta, and Alpha/Low Beta.

5.1.4 Data Flattening

This step was done because the models used require each input data sample to be represented as a vector of features. As we have 5 frequency bands per sample, we flatten all the bands sequentially in a vector. With the addition of extra data attributes, the vector length will be calculated by the window size multiplied by the total number of attributes as in equation 5.1.

$$Vector\ Length\ =\ Window\ size \times Num\ of\ Attributes \tag{5.1}$$

After applying the data wrangling techniques, each of the data points was labeled and input to the training model. The model will be trained accordingly on the training data folds, then the model will be tested on the remaining fold.

5.2 Proposed Models: Emotiv-control VS. Keyboard-control Classification

In this section, we lay the ground for the integration of a serious game that's aimed at providing training to augment attentiveness and a classification model that identifies to different game control modes (brain-controlled, keyboard-controlled). This is achieved by a pre-designed game (FOCUS Game) that adopts various techniques which digitally mimic existing clinical and rehabilitation approaches, as well as using an ML classifier, using multiple models, that can diagnose different attentiveness levels characterized by the game control mode (brain-controlled, keyboard-controlled). Since the brain-controlled FOCUS game has recorded a 10% increase in engagement and a 8% in focus over the keyboard-controlled game with healthy subjects, we hypothesize that it will be effectively used with those diagnosed with low attentiveness and ADHD. Along with the previous work, this stage acts as a milestone for reaching our long-term goal of diagnosing ADHD, and hopefully becoming a rehabilitation alternative.

We used two different models to classify the EEG signals according to their attention states, a.k.a. labels, which in our case are two labels: keyboard controlled and EMOTIV controlled. Our presumption, according to the previous study, is that the latter requires more attention, and hence the EEG signals for players using EMOTIV should look more like each other, compared to the EEG signals for players using the keyboard.

This section uses the study presented on [11] which aims at complementing the conclusions obtained in the previous study in order to have a better understanding of the recorded EEG data. Since the brain-controlled recording sessions showed noticeable results, it acted as a motivation for extending the previous work to classify the 2 different game control modes by utilizing some machine learning techniques.

Due to the fact that the Ethics Committee Approval of Istanbul Sehir University was not obtained at this stage of time, the access to ADHD patients was not possible. Alternatively, healthy people were tested by assigning them tasks which require levels of attentiveness. Since keyboard-controlled recordings showed lower attention levels than Emotiv-controlled recordings, detecting the control type of the game gives a powerful insight into the ability to classify EEG recordings based on concentration levels.

5.2.1 Pre-recording Instructions

Subjects were instructed on how to play the FOCUS game using both the keyboard and the Emotiv for control. Subjects played a non-recorded Emotiv-controlled game in the beginning to remove the training effect. Once the subjects were confident of controlling the avatar via Emotiv, actual recording was initiated.

5.2.2 Data Recordings

By the time of conducting this study we were not able to clear ethics approval for testing with ADHD patients, so we used 5 healthy subjects (males, age range 19-26). Each test subject was asked to play the FOCUS game using the arrow buttons on the keyboard to control the avatar collecting the pickups. After that, the subject was asked to play the same game using the EMOTIV kit to control the avatar movement. The subject was asked to repeat the 2 games for 5 times producing 5 recording sessions for each of the keyboard-controlled and Emotiv-controlled games, resulting in 10 recordings per person and 50 sessions in total. The average time measured for a single keyboard-controlled recording was around 1 minute, as for Emotiv-controlled recordings the average duration was approximately 2.5 minutes.

While the subjects were playing the game during the recording session, 2 different scripts were running in the background to collect raw EEG data from the electrodes and the EEG frequency bands (Alpha, Beta, Theta, and Gamma).

5.2.3 Data Labeling

Before designing the model, data was labeled according to the game control type (Keyboard and Emotiv). Since playing the FOCUS game with Emotiv rather than the keyboard leads to a significant improvement in focus and attention abilities of healthy individuals, we could say that the ability to detect the game control type with healthy subjects by EEG data is, conceptually, similar to detection and diagnosis of attention deficit individuals.

5.2.4 Model 1: Support Vector Machine (SVM)

In this model, we employ an SVM classifier to classify data samples to one of two labels: Keyboard-controlled and Emotiv-controlled. Different SVM models were implemented to increase the prediction accuracy by tuning the models' parameters. Data windowing, data subsampling, data shuffling, introducing extra attributes and cross-validation were utilized and explained in details earlier.

It is important to mention that the SVM's C parameter (the regularization parameter that prevents data overfitting and/or underfitting) was tuned iteratively without overfitting the data and obtaining the best validation test accuracy, which occurred at C set to 3. Also, the accuracies obtained are calculated simply by dividing the true positives over the total number of data points as in 5.2. The true positives include the correctly classified samples from both brain-controlled and keyboard-controlled data points. We have also recorded the precision, the recall and the F1-score for some models.

$$Accuracy = \ True\ Positive\ /\ Total\ Data\ Points \tag{5.2}$$

We then designed 6 different SVM models, in order to analyze the data and find what approach would work best for attention classification. These are described next.

5.2.4.1 Linear Kernel Model

This was the first model built which had only 50 data samples such that each data sample is a complete recording session. Since the data recordings had different lengths, samples were trimmed to match the shortest. Keyboard ranged from 1000 to 3000 rows of data, while Emotiv recordings ranged from 1000 to 7000 rows. The last 1000 rows of each recording data were chosen and shuffled, then the model was trained on the flattened data features.

The model was trained on 80% of the data (40 samples) and was tested on the other 20% (10 samples). The model was run 300 times, and the average, standard deviation, min, max and median of the accuracies on the 10 test samples are shown in Table 5.1. The mean accuracy was **61.97%.**

Table 5.1: Linear Kernel Model Results

Count	Mean	STD	Median	Max
300	0.6197	0.1402	0.6	1.0

The low accuracy could be explained by the small number of data samples in the data set where the number of features to samples were comparatively huge due to data flattening. Also, linear kernels are too simple kernels which cannot easily separate complex distribution of data points. Without subsampling, the data waves' fluctuations need more sophisticated models to be classified. Data trimming resulted in losing a big amount of meaningful data which could have carried more correlated information.

5.2.4.2 RBF Kernel Model

To enhance the accuracy of the previous model, a more sophisticated kernel was used, in addition to introducing the non-overlapping windows. Data was split into windows of a range of 50, 20, and 5 steps resulting in approximately 2000, 5000, and 20,000 data samples respectively. Data samples were shuffled, flattened, and then inputted to the model. Data balancing was applied by removing samples from the class that has more data sample to make the number of data samples equal, so it does not affect the accuracy.

The model was tested by 5-folds cross validation. The average, standard deviation, min, max and median of the accuracies on the test samples of the 5 folds are shown in Table 5.2.

Table 5.2: RBF Model Results

Window size	Count	Mean	STD	Median	Max
50	5	0.8110	0.0179	0.8129	0.8295
20	5	0.8769	0.0068	0.8761	0.8840
5	5	0.8926	0.0016	0.8927	0.8944

To validate the accuracies obtained previously, the confusion matrix of the model with window size 5 was calculated. The confusion matrix accounts the precision, recall, and f1-score of each keyboard and Emotiv labels. The average precision obtained is **89%**, while the average recall is **89%**, and the average f1-score is **89%** as well.

Table 5.3: Confusion Matrix of RBF Model (W Size = 5)

Labels	Precision	Recall	F1-Score	Samples count
Keyboard	0.86	0.92	0.89	1900
Emotiv	0.93	0.86	0.89	2115
Avg. / **Total**	0.89	0.89	0.89	**4015**

5.2.4.3 RBF Kernel Model with Extra Attributes

We implemented some enhancements on the previous model to increase the classification accuracy. Since the window size of 5 gave the best average accuracy, the model was adopted. We added the 4 extra attributes to the data which increased the attributes count to 9.

Data samples were shuffled, balanced, and inputted to the model. 5-folds Cross-validation test was used. The accuracies' mean obtained was **96.1%**. The accuracies' summary on the test samples of the 5 folds is shown in the Table 5.4.

Table 5.4: RBF Model with Extra Attributes Results

Window size	Count	Mean	STD	Median	Max
5	5	0.9610	0.0027	0.9601	0.9644

5.2.4.4 One Subject Data Holdout

This was built to have a deeper understanding of the data. We implemented the same previous model with a different testing methodology. Similar to cross-validation, the model was trained on data from 4 different subjects and tested on the 5th subject's data. The goal was to verify the ability of the model to generalize on data from individuals were not seen before.

The model was iterated 5 times, taking each person's data as a testing set and training on the other 4 persons' data. Since we iterate over all the subjects' recordings, it is similar to a cross validation approach which averages out the accuracies. The results of the 5 folds were: **70.86%**, **62.45%**, **60.66%**, **58.56%**, and **46.39%**, with an average of **59.78%**.

The low accuracies could be justified by the fact that EEG data differs from a person to another. As a result, creating a single classifier for different EEG data from different people will require a huge data set that covers a different type of people, which is impractical.

5.2.4.5 Personalized Models: Model Per Subject

Further testing was done on the data to prove the previous claim by building 5 different models for each person. The goal was to compare the accuracies to the previous results. Each subject's model used his recorded data where the training set-test set ratio was 80:20. Testing data was not shuffled to keep the sequential order of the data.

The testing results of the 5 different models were: **94.38%**, **86.05%**, **81.44%**, **79.91%**, and **75.75%** with an average of **83.50%**.

The average of the accuracies obtained by the personalized models was much higher than the one subject holdout models. Comparing the results to the previous model proves that EEG data is highly personalized.

5.2.4.6 Model for Attributes Importance

To rank the attributes based on their importance, we built different models and comparatively presented them to measure the importance of the features to the assigned label, and conceptually attention levels. Except for the training and testing data, all the other parameters were the same (RBF Kernel, window size = 5, single subject, data shuffled, 80% training and 20% testing, 5-folds).

Except for the training and testing data, the other parameters were similar (RBF Kernel, window size = 5, single subject, data shuffled, 80% training and 20% testing, 5-folds). Table 5.5 below presents the average f1-score for each model.

Table 5.5: The Models for Attributes Importance' F1-Score

Attributes used	**F1-score**	**Attributes used**	**F1-score**
Alpha only	75%	Gamma/High Beta only	59%
Theta only	75%	Gamma/Theta only	67%
Low Beta only	74%	Alpha/Theta only	57%
High Beta only	78%	Theta/Low Beta only	73%
Gamma only	77%	Theta/High Beta only	80%

From the table above, we can conclude that the model based on the single attribute "Theta/High Beta" relatively has the highest f1-score average. These results support the conclusions by [33, 34] which illustrates the relation of Theta/Beta bands to levels of attention.

5.2.5 Model 2: Dynamic Time Warping (DTW) and K-Nearest Neighbours (KNN) Classifier

This additional model was built applying the supervised KNN classification using DTW as a distance function. Using the results obtained by the models earlier, KNN classifiers were created using the "Theta/High Beta" values only. The goal of the model built here is trying to measure the temporal similarity of Theta/High Beta waves for different subjects.

For this KNN classifier, we decided to make a similar model to the SVM "One Subject Data Holdout" model but using the KNN classifier along with the DTW function. The window size step was set to 100, the number of neighbors was 3, and the Max warping window was 15. These values were selected based on a series of trials showing the best results. This model is trained on the "Theta/High Beta" data from 4 different subjects, and it was tested on the 5th subject.

The testing was done iteratively 5 times for all subjects and the models were built on the other 4 subjects' data. The resulting test accuracies of the 5 folds were: **66%**, **75%**, **59%**, **71%**, and **61%**, with an average of **66.4%**.

Comparing the SVM model to the KNN model, the latter had a better accuracy than the same type of a model implemented in SVM. The reasoning goes to the ability of DTW function to measure the distance between two sequences of non-aligned and differently scaled waves.

5.2.6 Summary

As our results and previous research showed, EEG signals are highly personalized. The significant findings support the previous outcomes that emphasize the importance of the Theta/Beta ratio as an indication of attention. The preliminary experiments with healthy individuals show an up to **96%** accuracy in classifying the EEG data at their correct attention state during gameplay. This promising result serves as motivation to test our models further with actual ADHD patients.

5.3 Proposed Models: ADHD VS. non-ADHD Classification

In this section, we will present the ML classifiers that aims to diagnose ADHD patients. Using the same serious game (FOCUS Game) that provide training of attentiveness skills, the same methodology explained earlier was applied with 4 ADHD subjects. Since the Keyboard-controlled and the Emotiv-controlled recordings were separable using SVM, the same testing methodology was applied for ADHD patients where they were asked to play the game using both control methods: keyboard and Emotiv. Two different classifiers were built separately using the data recorded from the 2 different methods.

This section uses the study presented on [10] which aims at investigating the ability of classifying ADHD patients using their EEG data. Since the keyboard-controlled and brain-controlled recording sessions showed noticeable results of classification, this acted as a motivation for extending the previous work to classify ADHD patients by utilizing some machine learning techniques.

The extended experiments done in this section include testing the game with 4 subjects: 2 males(18 and 23 years old) , and 2 females (21 and 22 years old), who were clinically diagnosed of suffering from ADHD. After obtaining the approval of the ethics committee at İstanbul Şehir University, which is attached in Appendix A, it was possible to access ADHD patients and test the game with them. Similarly, the subjects were asked to play the FOCUS game using with 2 different ways of controlling the avatar: keyboard-control and Emotiv-control. Each subject was asked to play the game 6 times using each of the controlling methods. That results 12 recording sessions per subject and 48 in total for the ADHD subjects

5.3.1 Data Recordings and Data Labeling

The same pre-recording instructions were presented to ADHD patients before the recording sessions start. Subjects played a non-recorded Emotiv-controlled game in the beginning to make sure that patients are confident how to control the game and to remove the training effect. Once they are confident of controlling the avatar using the Emotiv, the recorded sessions can start.

Similar to the previous section, each test subject was asked to play the FOCUS game using the arrow buttons on the keyboard to control the avatar collecting the pickups. After that, the subject was asked to play the same game using the EMOTIV kit to control the avatar movement. The subject was asked to repeat the 2 games for 6 times producing 6 recording sessions for each of the keyboard-controlled and Emotiv-controlled games, resulting in 12 recordings per person and 48 sessions in total. The average time measured for a single keyboard-controlled recording was around 1 minute, as for Emotiv-controlled recordings the average duration was approximately 4 minutes which is higher than the time recorded with the healthy subjects.

Also, while the subjects were playing the game during the recording session, 2 different scripts were running in the background to collect raw EEG data from the electrodes and the EEG frequency bands (Alpha, Beta, Theta, and Gamma).

Before designing the model, data was labeled according to the subject (non-ADHD - 0, ADHD - 1). Since ADHD patients have lower attention spans and therefore have different EEG patterns, our goal is to try to detect ADHD patients using the EEG data that is recorded during gameplay since attention deficit individuals have, conceptually, similar EEG patterns that could be diagnosed.

5.3.2 ADHD Classification Model: Support Vector Machine (SVM)

In this subsection, all the classification models targets the diagnosis of ADHD using different ways of dividing the data into training set and testing set. Data samples will be labeled accordingly (0 for non ADHD sample, 1 for ADHD sample). Since recording sessions were using 2 different control methods, all of the models that uses different data division will be done separately on keyboard-controlled and Emotiv-controlled data. Accordingly, the results will be compared on this basis.

Since the RBF kernel gave the best results in the models presented above, all of the upcoming models will use the same kernel. Also, in most of the models the extra attributes were also used since they are proven to increase the accuracy in previous models.

Since we had 5 non-ADHD subjects and 4 ADHD subjects, the non-ADHD samples were slightly more than the ADHD samples. The 4 ADHD subjects will be referred to as P1, P2, P3, and P4, while the 5 non-ADHD subjects will be referred to as S1, S2, S3, S4, and S5.

5.3.2.1 RBF Kernel with Extra Attributes

Firstly, the model was trained on the data from Emotiv-controlled sessions. The total number of data samples resulted after applying data wrangling techniques on Emotiv recording sessions was 37,725 samples, where each model has 7545 samples in each fold of the 5-fold cross validation to test the model on.

Data samples from the 2 classes were balanced throughout the folds (7545 total samples) such that in each fold non-ADHD samples were ranged between 4126 - 4176 samples (54.68% - 55.35%) while ADHD samples were ranged between 3378 - 3419 samples (44.77% - 45.31%). Also, a 5-folds cross-validation was applied as a testing methodology for the model.

The mean of the accuracies obtained was 98.62% for the 5-folds cross-validation applied. The average, standard deviation, min, max and median of the accuracies on the test samples of the 5 folds are shown in Table 5.6.

Table 5.6: RBF Kernel - ADHD Classification Model Results Using Emotiv Data

Count	Mean	STD	Median	Max
5	0.98624	0.0016	0.98701	0.98754

For the keyboard-controlled sessions, the total number of data samples resulted after applying data wrangling techniques on Keyboard recording sessions was 16,065 samples, where each model has 3213 samples in each fold of the 5-fold cross validation to test the model on.

Similarly, data samples from the 2 classes were balanced throughout the folds (3213 total samples) such that in each fold non-ADHD samples were ranged between 1922 - 2016 samples (59.82% - 62.75%) while ADHD samples were ranged between 1197 - 1291 samples (37.25% - 40.18%). Also, a 5-folds cross-validation was applied as a testing methodology for the model.

The mean of the accuracies obtained was 98.23% for the 5-folds cross-validation applied. The average, standard deviation, min, max and median of the accuracies on the test samples of the 5 folds are shown in Table 5.7.

Table 5.7: RBF Kernel - ADHD Classification Model Results Using Keyboard Data

Count	Mean	STD	Median	Max
5	0.98232	0.0027	0.98381	0.98382

5.3.2.2 One ADHD Subject's Data Holdout

Similar to what was done previously, one of the ADHD subject's data will be held out of the training phase and then the model will be tested on. This process will be iterated 4 times taking each of the ADHD subjects as a test set while the non-ADHD subjects' data is all kept in the training set. This way of testing will help us draw some conclusions about the ability of classification algorithms and how it performs on data from a subject that it did not encounter and was not trained on. Similar to the other models, the same process was repeated twice; once with Emotiv-controlled recordings and another with the keyboard-controlled sessions.

The results obtained from the 4 models were somehow different from each other, for both Emotiv-controlled based models and keyboard-controlled.

For Emotiv-controlled data, Table 5.8 will illustrate the obtained test accuracy and the number of samples in the test set for each of the subjects.

Table 5.8: 1-Hold Out - ADHD Classification Model Results Using Emotiv Data

Subject held-out	**P1**	**P2**	**P3**	**P4**
Test Accuracy	0.7219	0.3875	0.8671	0.8124
No. of Test Data Samples	6310	4356	1648	4681

The total number of data samples is 37,725 samples, and the number of test data samples was presented in order to validate the credibility of the accuracies obtained. Test data ranged between 4.37% - 16.73% of the whole data.

Test accuracies varied from a subject to another. For P1, P3, and P4, at least two-thirds of the data was labeled as ADHD data, and therefore, the subjects should be diagnosed as ADHD subjects. Generally, the line should be draw at 50% of the data, but that is still a naive assumption due to difficulty of accessing ADHD subjects and collecting more data.

The results obtained by the subject P2 was around 39%, which means around two-fifths of his data was predicted to be an ADHD subject data. Since there is not enough data, we could go with the assumption that around 40% of the data is enough to diagnosis a person with ADHD. Another justification to the result is that P2 was clinically taught few techniques that helps him to bypass the obstacles of the ADHD effects, while the other subjects were not. P2 was diagnosed of ADHD since he/she was young and since the early stages he/she was going to a therapist and learning the techniques to conserve attention. The results in the upcoming models will support this claim.

On the hand, for keyboard-controlled data, Table 5.9 will illustrate the obtained test accuracy and the number of samples in the test set for each of the subjects.

Table 5.9: 1-Hold Out - ADHD Classification Model Results Using Keyboard Data

Subject held-out	**P1**	**P2**	**P3**	**P4**
Test Accuracy	0.9060	0.1513	0.7789	0.5529
No. of Test Data Samples	2426	1051	570	2154

The total number of data samples is 16,065 samples. Test data ranged between 3.55% - 15.10% of the whole data.

Test accuracies varied from a subject to another. For P1, P3, and P4, respectively 90%, 78%, and 55% of their data was labeled as ADHD data, and therefore, the subjects should be diagnosed as ADHD subjects.

The results of P2 showed only 15% of his/her data was labeled as ADHD data. This result supports our claim earlier, and it shows clearly that the data recorded from P2 is quite different that the other ADHD subjects.

By comparing Emotiv-based models to keyboard-based models, the earlier has an average accuracy of 69.72% for all subjects while the later has an average accuracy of 59.73%. Emotiv-based models clearly outperformed the keyboard-based models which complements the scope of the Emotiv-controlled based game in the treatment/diagnosis of ADHD subjects.

5.3.2.3 Two Subjects' Data Holdout (one ADHD and one non-ADHD)

In this type of model, two subjects were randomly chosen from each the ADHD and non-ADHD groups. The model was built using the data of the rest of the subjects, and then it was tested and evaluated using the two subjects' data. The goal here is to use the same testing methodology that was used earlier

Similar to the previous model, in this model, two subjects' data will be held-out of the training set and then will be used as a testing set. The process will be iterated 4 times, taking P1 and S1, P2 and S2, P3 and S3, P4 and S4 as testing sets respectively in each of the 4 iterated models.

This methodology of testing, which includes a non-ADHD subject's data to the test set, is important so we can generalize the results obtained earlier.

Table 5.10 contains the results obtains from the 4 Emotiv-based models, which contains the precision, recall, and f1-score for both the ADHD and non-ADHD classes.

Table 5.10: 2-Hold Out - ADHD Classification Model Results Using Emotiv Data

Subject held-out	**1- S1, P1**		**2- S2, P2**		**3- S3, P3**		**4- S4, P4**	
	Non	**ADHD**	**Non**	**ADHD**	**Non**	**ADHD**	**Non**	**ADHD**
Precision (avg)	0.49	0.69	0.41	0.44	0.96	0.53	0.55	0.52
	0.62		**0.43**		**0.85**		**0.54**	
Recall (avg)	0.39	0.77	0.43	0.42	0.73	0.90	0.15	0.89
	0.63		**0.43**		**0.77**		**0.53**	
F1-score (avg)	0.43	0.73	0.42	0.43	0.83	0.66	0.23	0.66
	0.62		**0.43**		**0.79**		**0.45**	
Test Accuracy	0.6327		0.4251		0.7713		0.5273	
Test Samples	3566	6310	4082	4356	4922	1648	4410	4681
	9876		**8438**		**6570**		**9091**	

While the total number of samples is 37,725, the test data samples ranged between 17.42% - 26.18% of the whole data. The overall testing accuracy is better than a random model with the exception of the second model, while the reasoning might be the data recorded by the subject P2. The highest accuracy obtained was 77.13%, while the lowest being 42.51%. Since ADHD is a psychological disorder, the low results obtained by the 4th model could be explained that S4 might suffer from ADHD while he is labeled as a non-ADHD subject in our experiment.

On the other hand, Table 5.11 contains the results obtains from the 4 keyboard-based models, which contains the precision, recall, and f1-score for both the ADHD and non-ADHD classes.

Table 5.11: 2-Hold Out - ADHD Classification Model Results Using Keyboard Data

Subject held-out	**1- S1, P1**		**2- S2, P2**		**3- S3, P3**		**4- S4, P4**	
	Non	**ADHD**	**Non**	**ADHD**	**Non**	**ADHD**	**Non**	**ADHD**
Precision (avg)	0.90	0.66	0.64	0.33	0.94	0.63	0.71	0.64
	0.77		**0.53**		**0.87**		**0.68**	
Recall (avg)	0.41	0.96	0.80	0.18	0.87	0.80	0.74	0.60
	0.71		**0.58**		**0.86**		**0.68**	
F1-score (avg)	0.56	0.78	0.71	0.23	0.91	0.71	0.73	0.62
	0.68		**0.54**		**0.86**		**0.68**	
Test Accuracy	0.7085		0.5763		0.8564		0.6815	
Test Samples	2054	2426	1897	1051	2084	570	2786	2154
	4480		**2948**		**2654**		**4940**	

While the total number of samples is 16,065, the test data samples ranged between 16.52% - 30.75% of the whole data. The overall testing accuracy is better than a random model with the highest being 85.6% and the lowest being 57.6%.

By comparing Emotiv-based models to keyboard-based models, the earlier has an average accuracy of 58.91% for all subjects while the later has an average accuracy of 70.57%. In this case, keyboard-based models performed better than Emotiv-based and the reasoning could be the existence of the subjects P2 and S4 whose data did not perform well while testing the classifier.

Chapter 6

Conclusion and Future Work

Taking into account the increasing number of ADHD/ADD diagnosed individuals, combined with the potential applications of the new wireless EEG devices in a variety of scenarios and with the advancement of machine learning algorithms and the field of serious games, it would be advantageous to make a good use of those technologies in order to create useful applications to ease the life of those with mental deficits.

In this work, the problems of detecting ADHD patients and improving the attentiveness skills are studied. The various state-of-the-art methods proposed by the literature are also reviewed. As detailed in the introduction chapter, there are various traditional methods that deals with ADHD patients, while such kind of therapies lose the motivation and the encouragement component in the long term. The new wireless EEG brain reading devices provide opportunities for researchers to create a more effective serious games that can revolutionize the serious games industry. Integrating the EEG wireless reading devices with serious game is a recent trend in research. EEG carries rich information about the cognition skills, and since attention is one of those skills, EEG signals have a huge potential to be effectively used for ADHD treatment/diagnosis. Cognitive trainings have been applied with different duration and intensity with the elderly as they deal with a declination in the cognitive abilities. With serious games, it is now possible to encourage more engagement, illuminate repetitive monotonic scenes, adapting levels, and stimulating the interest of the patients during the cognitive training. Studies have proven the ability of serious games to be used in sustainability, education, and nutrition. Machine learning techniques can now help with the classification of EEG data more accurately due to the advancement of the learning algorithms. For the case of ADHD, involving the cognition of the patient as a game-control during the therapy will directly affect the regularization of the EEG signals and results to treating the source of the deficit, not only its symptoms. Also, the use of machine learning techniques can be quite significant in the diagnosis of ADHD patients in this context. For this purpose, we designed a wearable EEG-based serious game that uses the EMOTIV kit for controlling the character to improve the attentiveness of people with ADHD. The game is built as an attempt to digitally mimic few existing clinical and rehabilitation therapies. The brain-controlled FOCUS game in [4] has recorded a 10% increase in engagement and a 8% in focus over the keyboard-controlled game with healthy subjects, that acted as a motivation to use it with those diagnosed with low attentiveness and ADHD. Due to the lack of time and the difficulty of accessing ADHD patients in the early stages of this work, we started by presenting the preliminary study with the healthy subjects. We laid the ground for a possible integration of the aforementioned game and an ML classifier using multiple models. By testing the game with healthy individuals, we tested the classifier's ability to diagnose different attentiveness levels characterized by the game control mode (brain-controlled, keyboard-controlled). After obtaining the acceptance of İstanbul Şehir University's Ethics Committee for testing the game with ADHD subjects, the game was tested with 4 ADHD subjects. The classifier was also fed with the data from the ADHD subjects, and its ability was tested to diagnose between ADHD and non-ADHD EEG data recordings. The pilot experiments with healthy individuals show an accuracy of up to 96% in classifying the EEG data to detect the correct attention state during gameplay, and the extended experiments with ADHD patients show an accuracy up to 98% in classifying the patients EEG data.

Planning to use more interactive game scenarios is one of the future goals of this research. More interactive scenarios might have a positive affect on ADHD patients' attention span. Additionally, creating serious games that are supported by the Virtual Reality glasses, such as the Oculus Rift and HTC VIVE, could also enrich the interaction and the engagement during the rehabilitation session. Lastly, creating a multiplayer platform that support EEG-based games is a long-term goal. Due to the technical complexity of creating the communication protocol for such a game, we leave it as a long-term future work.

Appendix A

Ethics Committee Decision

Appendix A contains İstanbul Şehir University's Research Ethics Committee Decision regarding testing the serious game with ADHD patients. The document is presented in the next page.

İSTANBUL
ŞEHİR
ÜNİVERSİTESİ

ARAŞTIRMA ETİK KURUL KARARLARI
(Research Ethics Committee Decision)

Toplantı Tarihi	: 22.02.2017
Toplantı Sayısı	: 09/2017
Toplantı Saati	: 11:00
Toplantıya Katılanlar	: Yrd. Doç. Dr. Elif ÇELEBİ Prof. Dr. Cem BEHAR Prof. Dr. Nihat BULUT Yrd. Doç. Dr. Sinem ELKATİP HATİPOĞLU Yrd. Doç. Dr. Eyyüp Said KAYA

Karar No 1:
İstanbul Şehir University Research Ethics Committee has reviewed the project named "Collecting EEG data for detecting cogntive problems using serious games." Prof. Dr. Servin Shirmohammadi"

According to the given information, To help diagnosis of cognitive deficiencies using EEG classification and the analysis of the deficiency levels to track the development of the patient's case after mutliple serious game sessions.

1- Testing pre-designed serious games for different cognitive rehabilitation in order to validate their usability.

2- Designing a customized classification tool which aimes to detect the levels of the cogntive problem using EEG data.

3- Find the significant features in the collected EEG data that is related to the cognitive impediment.

To implement existing clinical psychotherapies in the form of user-friendly therapeutic systems intended for cognitive disabilities and deficits, and as an extension to the EEG-based serious game, to build a customized classifier to diagnose individuals with a spceific cognitive impediment (ADHD, Social exclusion) via EEG brainwave frequency bands: Gamma, Beta, Alpha, Theta, and Delta.

1- The aim of the study is to test the pre-designed serious games with the people with special cognitive impediments in order to perform a comparative analysis of the data collected.
2- Collecting the patients (ADHD, Social exclusion) and test the games designed for detecing/treating the cognitive impediment.

3- EEG data will be collected as well and classification methods will be used to draw significant conclusions on the relation between EEG brainwaves and the patient's impediment.

Together with the summary section, please answer the questions below:

a) Does your research contain elements that could threaten the physical and/or mental health of the participants or cause stress to them? If yes, please explain. Please describe the measures to be taken in order to eliminate or minimize the effects of these elements.

Simply, the measures to be taken from the patients are mostly automatic. Patients won't be asked to fill a survey or even asked verbally. Patients will be playing a specific serious game and wear a brain headset which will collect the data. During the gameplay, the headset will collect the EEG brainwaves of the player without any intervention of the therapist.

b) Is it the case that the aim of the study partially or fully kept hidden from the participants? If yes, please explain the reasons. Please explain how this will be explained to at the end of data collection.

The aim of the study is not hidden.

c) Please explain how you will maintain the confidentiality of personal information of participants.

Personal information of the test group will not be used an the research and neither be shared with any

Followed by this information, undersigned Research Ethics Committee Members have seen no harm in view of ethics in the project entitled "Collecting EEG data for detecting cogntive problems using serious games." Prof. Dr. Servin Shirmohammadi

Yrd. Doç. Dr. Elif ÇELEBİ
President

Prof. Dr. Nihat BULUT
Member

Prof. Dr. Cem BEHAR
Member

Yrd. Doç. Dr. Sinem ELKATİP HATİPOĞLU
Member

Yrd. Doç. Dr. Eyyüp Said KAYA
Member

Bibliography

[1] P. Rego, P. M. Moreira, and L. P. Reis. Serious Games for Rehabilitation A Survey and a Classification Towards a Taxonomy. *The 5th Iberian Conference on Information Systems and Technologies*, pages 1–6, 2010. ISSN 2166-0727. doi: 978-1-4244-7227-7.

[2] M. Van Lambalgen, C. Van Kruistum, and E. Parigger. Discourse processing in Attention-Deficit Hyperactivity Disorder (ADHD). *Journal of Logic, Language and Information*, 17(4):467–487, oct 2008. ISSN 09258531. doi: 10.1007/s10849-008-9066-5. URL `http://link.springer.com/10.1007/s10849-008-9066-5`.

[3] Centers for Disease Control and Prevention. Key Findings: Newborn Screening for Critical Congenital Heart Defects Now Common Throughout United States | NCBDDD | CDC. URL `http://www.cdc.gov/ncbddd/heartdefects/features/kf-newborn-heart-screening-commom-us.html`.

[4] A. E. Alchalabi, A. Nour Eddin, and S. Shirmohammadi. More Attention, Less Deficit: Wearable EEG-Based Serious Game for Focus Improvement. *The 5th IEEE Conference on Serious Games and Applications for Health (SeGAH 2017)*, 2017.

[5] Erasmus + Strategic Partnership Project: Intelligent Serious Games for Social and Cognitive Competence. URL `http://www.isg4competence.com/`.

[6] K. Sadatnezhad, R. Boostani, and A. Ghanizadeh. Classification of BMD and ADHD patients using their EEG signals. *Expert Systems with Applications*, 38(3):1956–1963, 2011. ISSN 09574174. doi: 10.1016/j.eswa.2010.07.128.

[7] N. H. Liu, C. Y. Chiang, and H. C. Chu. Recognizing the Degree of Human Attention Using EEG Signals from Mobile Sensors. *Sensors*, 13(8):10273–10286, aug 2013. ISSN 1424-8220. doi: 10.3390/s130810273. URL `http://www.mdpi.com/1424-8220/13/8/10273/`.

[8] M. Duda, R. Ma, N. Haber, and D. P. Wall. Use of machine learning for behavioral distinction of autism and ADHD. *Translational Psychiatry*, 6(2):e732, feb 2016.

ISSN 2158-3188. doi: 10.1038/tp.2015.221. URL http://www.ncbi.nlm.nih.gov/pubmed/26859815.

[9] M. Sabeti, S.D. Katebi, R. Boostani, and G.W. Price. A new approach for EEG signal classification of schizophrenic and control participants. *Expert Systems with Applications*, 38(3):2063–2071, 2011. ISSN 09574174. doi: 10.1016/j.eswa.2010.07.145.

[10] A. E. Alchalabi, S. Shirmohammadi, A. Nour Eddin, and M. Elsharnoby. Focus: Detecting adhd patients by an eeg-based serious game. In *IEEE Transactions on Instrumentation and Measurement*. IEEE, 2017.

[11] A. E. Alchalabi, M. Elsharnouby, S. Shirmohammadi, and A. Nour Eddin. Feasibility of Detecting ADHD Patients' Attention Levels by Classifying Their EEG Signals. *The 12th Annual IEEE International Symposium on Medical Measurements and Applications*, 2017.

[12] A. E. Alchalabi, M. Elsharnoby, and S. Khawaldeh. Rightscope: Detecting search campaingns positive and negative queries. In *Machine Learning and Cybernetics (ICMLC), 2016 International Conference on*, pages 290–295. IEEE, 2016.

[13] D. C. Hammond. What is neurofeedback? *Journal of Neurotherapy*, 10(4):25–36, 2007. ISSN 1087-4208. doi: 10.1300/J184v10n04_04.

[14] C. H. Han, J. H. Lim, J. H. Lee, K. Kim, and C. H. Im. Data-Driven User Feedback: An Improved Neurofeedback Strategy considering the Interindividual Variability of EEG Features. *BioMed Research International*, pages 1–7, 2016. ISSN 23146141. doi: 10.1155/2016/3939815. URL http://www.hindawi.com/journals/bmri/2016/3939815/.

[15] D. Vernon, T. Egner, N. Cooper, T. Compton, C. Neilands, A. Sheri, and J. Gruzelier. The effect of training distinct neurofeedback protocols on aspects of cognitive performance. *International Journal of Psychophysiology*, 47(1):75–85, 2003. ISSN 01678760. doi: 10.1016/S0167-8760(02)00091-0.

[16] EMOTIV. EMOTIV - Brainwear® Wireless EEG Technology. URL https://www.emotiv.com/.

[17] B. Penolazzi, C. Spironelli, and A. Angrilli. Delta EEG activity as a marker of dysfunctional linguistic processing in developmental dyslexia. *Psychophysiology*, 45(6):1025–1033, nov 2008. ISSN 00485772. doi: 10.1111/j.1469-8986.2008.00709.x. URL http://www.ncbi.nlm.nih.gov/pubmed/18803600.

[18] Q. Wang, O. Sourina, and M. K. Nguyen. EEG-based "serious" games design for medical applications. In *International Conference on Cyberworlds*, pages 270–276. IEEE, oct 2010. ISBN 9780769542157. doi: 10.1109/CW.2010.56. URL `http://ieeexplore.ieee.org/document/5656236/`.

[19] R. Coben, M. Linden, and T. E. Myers. Neurofeedback for autistic spectrum disorder: A review of the literature, 2010. ISSN 10900586.

[20] M. E. Kouijzer, H. T. Van Schie, J. M. De Moor, B. J. Gerrits, and J. K. Buitelaar. Neurofeedback treatment in autism. Preliminary findings in behavioral, cognitive, and neurophysiological functioning. *Research in Autism Spectrum Disorders*, 4(3): 386–399, 2010. ISSN 17509467. doi: 10.1016/j.rasd.2009.10.007.

[21] N. K. Chlis. *Comparison of Statistical Methods for Genomic Signature Extraction.* PhD thesis, TECHNICAL UNIVERSITY OF CRETE, 2013.

[22] M. Besserve, K. Jerbi, F. Laurent, S. Baillet, J. Martinerie, and L. Garnero. Classification methods for ongoing EEG and MEG signals. *Biological research*, 40(4):415–37, 2007. ISSN 0716-9760. doi: /S0716-97602007000500005. URL `http://www.ncbi.nlm.nih.gov/pubmed/18575676`.

[23] E. Keogh and C. A. Ratanamahatana. Exact indexing of dynamic time warping. *Knowledge and Information Systems*, 7(3):358–386, mar 2005. ISSN 0219-1377. doi: 10.1007/s10115-004-0154-9. URL `http://link.springer.com/10.1007/s10115-004-0154-9`.

[24] B. Hu, Y. Chen, and E. Keogh. Time series classification under more realistic assumptions. *SIAM International Conference on Data Mining*, (1):578–586, 2013. ISSN 13845810. doi: 10.1137/1.9781611972832.64. URL `http://epubs.siam.org/doi/abs/10.1137/1.9781611972832.64`.

[25] A. Yurtman and B. Barshan. Automated evaluation of physical therapy exercises using multi-template dynamic time warping on wearable sensor signals. *Computer methods and programs in biomedicine*, 117(2):189–207, 2014.

[26] S. R. Pliszka, C. L. Carlson, and J. M. Swanson. *ADHD with Comorbid Disorders: Clinical Assessment and Management.* Guilford Press, 1999. ISBN 1-57230-478-2.

[27] A. Lenartowicz and S. K. Loo. Use of EEG to diagnose ADHD. *Current psychiatry reports*, 16(11):498, nov 2014. ISSN 1535-1645. doi: 10.1007/s11920-014-0498-0. URL `http://www.ncbi.nlm.nih.gov/pubmed/25234074`.

[28] M. Linden, T. Habib, and V. Radojevic. A controlled study of the effects of EEG biofeedback on cognition and behavior of children with attention deficit disorder and learning disabilities 1. *Biofeedback and Self-Regulation, Applied Psychophysiology and Biofeedback Journal*, 21(1):35–49, 1996. ISSN 03633586. doi: 10.1007/BF02214148.

[29] R. J. Barry, A. R. Clarke, S. J. Johnstone, R. McCarthy, and M. Selikowitz. Electroencephalogram θ/β Ratio and Arousal in Attention-Deficit/Hyperactivity Disorder: Evidence of Independent Processes. 2009.

[30] G. Vossel, R. M. Stern, W. J. Ray, and K. S. Quigley. *Psychophysiological recording (2nd ed.)*, volume 15. 2001. ISBN 0195113586. doi: 10.1027//0269-8803.15.1.47.

[31] H. Gevensleben, B. Holl, B. Albrecht, D. Schlamp, O. Kratz, P. Studer, S. Wangler, A. Rothenberger, G. H. Moll, and H. Heinrich. Distinct EEG effects related to neurofeedback training in children with ADHD: A randomized controlled trial. *International Journal of Psychophysiology*, 74(2):149–157, nov 2009. ISSN 01678760. doi: 10.1016/j.ijpsycho.2009.08.005. URL `http://www.ncbi.nlm.nih.gov/pubmed/19712709`.

[32] C. Kerson, R. A. Sherman, and G. P. Kozlowski. Alpha Suppression and Symmetry Training for Generalized Anxiety Symptoms. *Journal of Neurotherapy*, 13(3):146–155, aug 2009. ISSN 1087-4208. doi: 10.1080/10874200903107405.

[33] H. Heinrich, K. Busch, P. Studer, K. Erbe, G. H. Moll, and O. Kratz. EEG spectral analysis of attention in ADHD: implications for neurofeedback training? *Frontiers in human neuroscience*, 8:611, 2014. ISSN 1662-5161. doi: 10.3389/fnhum.2014.00611. URL `http://www.ncbi.nlm.nih.gov/pubmed/25191248`.

[34] S. K. Loo and S. Makeig. Clinical utility of EEG in attention-deficit/hyperactivity disorder: a research update. *Neurotherapeutics : the journal of the American Society for Experimental NeuroTherapeutics*, 9(3):569–87, jul 2012. ISSN 1878-7479. doi: 10.1007/s13311-012-0131-z. URL `http://www.ncbi.nlm.nih.gov/pubmed/22814935`.

[35] R. Janca, P. Jezdik, R. Cmejla, R. Glajcar, P. Krsek, and A. Jahodova. Seizure onset zone detection and localization in iEEG using DTF. In *2011 IEEE International Symposium on Medical Measurements and Applications*, pages 93–97. IEEE, may 2011. ISBN 978-1-4244-9336-4. doi: 10.1109/MeMeA.2011.5966683. URL `http://ieeexplore.ieee.org/document/5966683/`.

[36] N. Mammone, A. Lay-Ekuakille, F. C. Morabito, A. Massaro, S. Casciaro, and A. Trabacca. Analysis of absence seizure EEG via Permutation Entropy spatio-temporal clustering. In *2011 IEEE International Symposium on Medical Measurements and Applications*, pages 532–535. IEEE, may 2011. ISBN 978-1-4244-9336-4. doi: 10.1109/MeMeA.2011.5966762. URL `http://ieeexplore.ieee.org/document/5966762/`.

[37] G. Frigo and C. Narduzzi. EEG gradient artifact removal by compressive sensing and Taylor-Fourier transform. In *2014 IEEE International Symposium on Medical Measurements and Applications (MeMeA)*, pages 1–6. IEEE, jun 2014. ISBN 978-1-4799-2921-4. doi: 10.1109/MeMeA.2014.6860079. URL `http://ieeexplore.ieee.org/document/6860079/`.

[38] R. F. Ahmad, A. S. Malik, H. U. Amin, N. Kamel, and F. Reza. Classification of cognitive and resting states of the brain using EEG features. In *2016 IEEE International Symposium on Medical Measurements and Applications (MeMeA)*, pages 1–5. IEEE, may 2016. ISBN 978-1-4673-9172-6. doi: 10.1109/MeMeA.2016.7533741. URL `http://ieeexplore.ieee.org/document/7533741/`.

[39] A. Lay-Ekuakille, G. Griffo, F. Conversano, S. Casciaro, A. Massaro, V. Bhateja, and F. Spano. EEG signal Processing and acquisition for detecting abnormalities via bio-implantable devices. In *2016 IEEE International Symposium on Medical Measurements and Applications (MeMeA)*, pages 1–5. IEEE, may 2016. ISBN 978-1-4673-9172-6. doi: 10.1109/MeMeA.2016.7533752. URL `http://ieeexplore.ieee.org/document/7533752/`.

[40] F. Pinho, J. H. Correiaa, N. J. Sousat, J. J. Cerqueirab, and N. S. Diast. Wireless and wearable EEG acquisition platform for ambulatory monitoring. In *2014 IEEE 3rd International Conference on Serious Games and Applications for Health, SeGAH 2014*, pages 1–7. IEEE, may 2014. ISBN 9781479948239. doi: 10.1109/SeGAH.2014.7067078. URL `http://ieeexplore.ieee.org/document/7067078/`.

[41] A. M. Portugal, D. Silva Ferreira, J. S. Reis, F. Pinho, and N. S. Dias. Cognitive intervention protocol for age-related memory impairments. In *2013 IEEE 2nd International Conference on Serious Games and Applications for Health (SeGAH)*, pages 1–6. IEEE, may 2013. ISBN 978-1-4673-6165-1. doi: 10.1109/SeGAH.2013.6665310. URL `http://ieeexplore.ieee.org/document/6665310/`.

[42] O. Sourina and Y. Liu. EEG-Based Serious Games. In *Subconscious Learning via Games and Social Media*, pages 135–152. Springer Singapore, 2015. ISBN 978-981-287-407-8. doi: 10.1007/978-981-287-408-5_10.

[43] J. Y. Kim and J. H. Bae. A Study on Serious Game Technology Based on BCI for ADHD Treatment Typical Types of Serious Games. 46:208–211, 2014.

[44] K. P. Thomas, A. P. Vinod, and C. Guan. Design of an online EEG based neuro-feedback game for enhancing attention and memory. *35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2013:433–436, jul 2013. ISSN 1557170X. doi: 10.1109/EMBC.2013.6609529. URL `http://ieeexplore.ieee.org/document/6609529/`.

[45] R. Parafita, G. Pires, U. Nunes, and M. Castelo-Branco. A spacecraft game controlled with a brain-computer interface using SSVEP with phase tagging. In *SeGAH 2013 - IEEE 2nd International Conference on Serious Games and Applications for Health, Book of Proceedings*, pages 1–6. IEEE, may 2013. ISBN 9781467361651. doi: 10.1109/SeGAH.2013.6665309. URL `http://ieeexplore.ieee.org/document/6665309/`.

[46] S. Turis. A Soothing Setting for the Anxious ADHD Child, 2016. URL `http://www.additudemag.com/adhdblogs/27/10005.html`.

[47] C. Hasegawa and K. Oguri. The effects of specific musical stimuli on driver's drowsiness. In *2006 IEEE Intelligent Transportation Systems Conference*, pages 817–822. IEEE, 2006. ISBN 1-4244-0093-7. doi: 10.1109/ITSC.2006.1706844. URL `http://ieeexplore.ieee.org/document/1706844/`.