Brian Computer Interfacing for Game Controlling

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Declaration

I declare that this dissertation does not incorporate, without acknowledgment of any material previously submitted for a Degree or a Diploma in any University and to the best of my knowledge and belief, it does not contain any material previously published or written by another person or myself except where due reference is made in the text. I also hereby give consent for my dissertation, if accepted, to be made available for photocopying and for interlibrary loans, and for the title and summary to be made available to outside organization.

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Date:

Dedication

Many decades' efforts of many talented individuals have resulted in the techniques of Artificial Intelligence occupying a central place throughout the discipline of computing. The capacity for intelligent behavior is now a central part of people's understanding of and experience with computer technology. Thus, this thesis work is dedicated to all the exceptional men and women who contributed to the growth of Artificial Intelligence.

Acknowledgement

I would like to express my gratitude to my supervisor Professor Asoka S Karunananda for the useful comments, remarks and engagement through the learning process of this master thesis. Furthermore I would like to thank him for introducing me to the topic as well for the support on the way. Also, I like to thank the participants in my evaluation, who have willingly shared their precious time during the process of data gathering. I would like to thank my family and friends, who have supported me throughout entire process, both by keeping me harmonious and helping me putting pieces together.

Abstract

The way human interacts with electronic games has changed in a dramatic manner in the past decade. Many individuals utilize mouse, keyboards, joysticks and even motion sensors in order to provide input commands to various computer gaming applications. Nonetheless, above mentioned modes of interaction has its confines when it comes to individuals with physical limitations such as handicapped and paralyzed. Thus, addressing this problem Neurogaming has become a hot topic in the past few years where brain wave signals namely electroencephalogram signals are used to control different aspects of an electronic gaming application, this approach eliminates the traditional hand coordinated interacting mechanisms allowing even a handicap to interact with a gaming interface with ease.

The main objective of the research has been to implement a system which enables usage of an available electroencephalogram device for instance NeuroSky mind wave mobile, in order to aid the individuals with physical limitations and also to provide near real time attention input, incorporating all parts of a functioning brain computer interface system. These parts are 1) acquiring the electroencephalogram signal 2) process and classify the electroencephalogram signal to extract the attention level and 3) use the attention to control a feature in a multi agent game.

This thesis report outlines the step-by-step design of the attention racer system which incorporate module level design and interactions among various components of the system. Furthermore, the implementation details of the attention racer system covers the core code segments and the flow of the system. The implemented system was evaluated using 15 participants. Initially they had to undergo through an attention span test and individual who scored more than 75% was selected for the second phase of the evaluation which was training data acquisition and attention racer valuation. After the attention span test 10 individuals were selected for final evaluation where they were evaluated for attention in different environments. The evaluation results asserted that system worked with 70% accuracy in detecting human attention level and using it to control the speed of the car.

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Chapter 1

Introduction

1.1. Prolegomena

As the proliferation of technology dramatically infiltrates all aspects of modern life, in many ways the world is becoming dynamic and complex that technological capabilities are overwhelming human capabilities to optimally interact with and leverage those technologies [1]. The human computer interaction (HIC) has also changed dramatically in the past decade. Human Computer Interaction has mingled with many different fields from artificial intelligence to sociology. Electroencephalography (EEG) equipment are becoming available and ever so popular in the public market, which has rouse the enthusiasm of many individuals to perform diverse research on this broad field [2]. The Brain-Computer Interface (BCI) community recognize the necessity for systems that make Brain-Computer Interface dynamic, user-friendly, manageable and real-time.

Therefore, this research seek such improvements, by exploring the possibility of using EEG signals emitted from the brain as an input command to control a computer game using artificial intelligence techniques such as machine learning and cognitive.

Why artificial intelligence? Why BCI? In answering these questions AI is thriving. Many decades' efforts of many talented individuals have resulted in the techniques of AI occupying a central place throughout the discipline of computing. The capacity for intelligent behavior is now a central part of people's understanding of and experience with computer technology [11]. Brain-Computer Interface (BCI) is an alternative mode of communication that enables an individual to send commands to a computer or a peripheral device using his brain activity [12].

This chapter introduces the project by elaborating its why, how and what. It presents the project background and motivation, problem in brief, aim and objectives, proposed solution and finally, an overview of the report structure is stated.

1.2. Background and Motivation

The area of games, especially, receives a lot of interest, as gamers are often among the first to adopt any new technology [8]. Many individuals utilize mouse, keyboards, joysticks and even motion sensors in order to provide input commands to various computer gaming applications. However, Neurogaming has become a hot topic in the past few years where brain wave signals namely electroencephalogram signals are used to control different aspects of an electronic gaming application, this eliminates the traditional hand coordinated interacting mechanisms allowing even a handicap to interact with a gaming interface with ease. This area of research had many drawbacks in the past due to infrastructure cost and set up complexity of electroencephalogram headsets. Nonetheless, EEG-based technology has become more popular in “serious” games design and development since new wireless headsets that meet consumer demand for wearability, price, portability and ease-of-use are available in the market [13] as an example NeuroSky mind wave mobile headset.

Despite the improvements in AI and BCI, as explained in others work (chapter 2) many researches done thus far has not effectively applied the human attention extracted from EEG signals for game controlling. Thus, with the widespread use of artificial intelligence techniques and ever gaining popularity of BCI the writer is highly motivated to research the possibilities of using human attention as an input for computer game controlling.

1.3. Problem in Brief

The research aims to address two thriving problems in human computer interaction for gaming. Firstly, traditional human computer interaction involves user utilizing a keyboard, a mouse, a joystick, or a Motion sensor to interact with gaming consoles. However, people with physical disabilities such as handicapped and paralyzed doesn’t have the luxury of using their hands to interact with a gaming interface. Thus, the research seeks to introduce an alternative approach of using human attention level as a mechanism of game controlling input command.

Secondly, the information transfer rate (ITR) of BCIs is still around up to 25 bits per minute [10], which is incomparable with keyboard speeds of over 300 characters per minute. Due to these limitations, there is still a big gap between the BCI games and traditional keyboard driven games. This research seeks to eliminate the gap by feeding attention level approximately every five hundred millisecond as an input to a gaming module. This can be considered as near real time input.

1.4. Aim and Objectives

To meet the objectives of this research it is vital to gain knowledge of the two domains, Brain-Computer Interface special methods for analyzing brain waves, and AI techniques for Game design. From this research, a prototype software application should be implemented that is able to read brain wave input from an EEG device, classify them, and make them be part of the, or the only, user input to a game.

BCI systems mainly rely on Electroencephalogram (EEG) recordings for measuring brain activity because EEG is one of the most convenient and cheapest brain imaging techniques among the existing non-invasive methods [14]. Thus, the research focuses on using real time attention level as an input for a multi agent video game by applying artificial intelligent classification techniques on EEG signals emitted from a human brain. Therefore, the entire research is oriented on below objectives.

1. The EEG signals are commonly decomposed into five EEG sub-bands: delta, theta, alpha, beta and gamma [15]. Hence, the research seek to study about these wave forms extensively to extract the human attention factor.

2. Furthermore, Support vector machines, decision trees and artificial neural networks are powerful machine learning techniques that can be used for EEG signal classification [16]. Among these classification techniques, artificial neural network is one of the most popular technique for EEG classification [17]. Thus, the research focuses on developing an artificial neural network for EEG attention classification.

3. Moreover, Autonomous Agent and Multi-Agent Systems is the key in game development [18]. Thus the research seek to develop a car racing game on a multi agent framework using 3D gaming platform.

1.5. Proposed Solution

It is hypothesized that human attention level can be used as an input parameter for computerized game controlling as a near real-time input. To prove this hypothesis, the research has taken various measures and used many techniques. The research will be using a NeuroSky mind wave mobile for EEG signal acquiring, as illustrated in Figure 1.1. EEG is a non-invasive technique recording the electrical potential over the scalp which is produced by the activities of brain cortex and reflects the state of the brain [13]. Then the acquired signal will be transmitted to a computer via Bluetooth technology. In order to process and classify the acquired signal, artificial neural network will be used. Once the attention level is extracted it is transmitted as game controlling input for multi agent based car racing game.

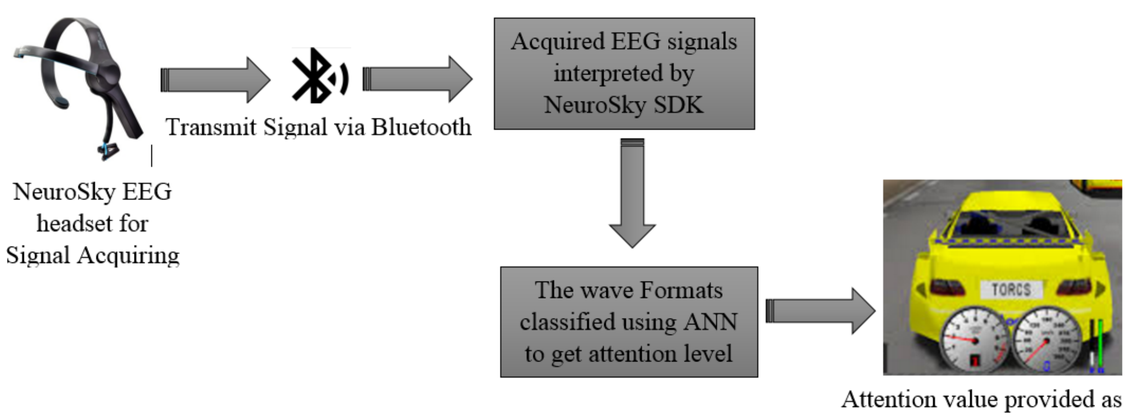


Figure 1.1: Input process output of the system

This EEG signals from brain acts as the input for the system and attention outputted from the neural network acts as the input for the gaming module to control its speed.

Several advance technologies will be used in this research. For brain wave activity monitoring EEG signals will be used. EEG captures the micro currents produced by the activity of neurons in the brain by placing sensors on scalp. The electrical activity of brain recorded by EEG is susceptible to noise which necessitates the development of robust signal processing algorithms and machine learning techniques for accurate identification of user's intention and successful operation of BCI. For purpose of signal classification artificial neural network is utilized. As previously explained the game module is developed using multi agent framework on 3D gaming platform this is elaborated in detail in Technology and Approach chapters. BCI research has recently started to focus on multimedia applications such as video games [19]. Video game play has greatly become a part of entertainment industry, and its positive effect on brain waves has been explored in literature [20]. Gamers would be the target audience and potential users of the system.

1.5. Report outline

This section describes the remaining chapters and the report structure.
Chapter 2 (Others` work): describes the related work and background for this project and identifies the most important research questions and method of approach.

Chapter 3 (Technology): explains the Technology that is adapt to solve the problem. By clearly pointing out how/why these techniques are appropriate to solve the given problem. For instance, explains how the EEG technology works, and the different brain activity patterns that are the foundation for EEG analysis.

Chapter 4 (Approach): in this chapter fist hypothesis is stated. Then how the technology is adopted to solve the problem with reference to users, inputs, outputs, process, technology of the implements the solution.

Chapter 5 (Analysis and Design): top level architectural design of the system is elaborated along with describing the modules in the architectural design asserting WHAT each module does and its interaction with other modules/components.

Chapter 6 (Implementation): Describes the implementation details of each module that are stated in the design diagram. In describing the implementation, software, hardware, flowcharts, algorithms, pseudo codes, code segments as per each module in the design are explained in detail.

Chapter 7 (Evaluation): explains how the solution is evaluated in order to verify whether the objectives were met. Experimental design, selection of participants, control experiments, interview techniques, design of questionnaire are also asserted.

Chapter 8 (Conclusion and Future Work): elaborates the overall achievements quantitatively. Moreover, achievement of each objective is asserted. Also problem encountered, limitations of the solution, and further work is stated in detail.

1.6. Summary

This chapter provided an overall view of the thesis, by elaborating the background and motivation, problem in brief, aims and objectives and the proposed solution. As the last section it outlined the structure of the thesis. Next chapter, focuses on others work in the fields related to thesis.

Chapter 2

Development in BCI for Gaming

2.1. Introduction

This chapter explains the comprehensive literature survey, done on others' approaches to solve similar problems. Furthermore, the chapter elaborates background for this research, and identifies the main research questions and methods. The section further expanse on drawbacks of existing systems lessons learned and how this thesis will address these drawbacks in the novel approach.

2.2. EEG for gaming from fist game to State of the Art

Successful games are often described with adjectives such as engaging, immersive or exciting [29]. Players might report playing them to "lose track of time" or be "completely focused". Games that do not engage players or create optimal experiences are often considered failures, costing businesses and video game players' time and money. They also cause game developers frustration. Researchers have attempted to measure and to predict how to create good and engaging gameplay experiences.

Using brain signals to control the aspects of a computer game is a novelty approach that's revolutionized human computer interaction when engaging with a computer game. Some Neurogaming software use a player's brain waves, heart rate, expressions, pupil dilation, and even emotions to complete tasks or affect the mood or aspects of the game. The next few paragraphs describe games designed using EEG technology.

Ever since the first Brain computer Interface game was implemented by Vidal in 1977 [5], BCI for game controlling has become a hot research topic. In this game, the user can move in four directions in a maze and Vidal utilized online artifact rejection and adaptive classification. The user can walk through the maze using a brain-computer interface based on visually evoked potentials (VEP). User can move in four directions by fixating on one of four fixation points off-screen. VEP is classified and used to move in the maze. However, the major drawback in this system was the operation of BCI depends on the ability to make eye movements. Making eye movements to control the game causes frustration to the end-users.

Another approach in mingling EEG signals in games is based on the interpretation of broadband frequency power of the brain, such as Beta, Gamma, Alpha, and Theta. Brian ball [7] is an example for using broadband frequencies. This is a game that can be best described as an anti-game; the goal is to achieve nothing, there are no sounds, blinking lights and no action. Using a headband the EEG of the players is measured and a relaxation score is derived from the ratio between alpha and beta activity in the EEG signal. One attractive feature in this game is that when a player gets exited his relaxation level goes down and he loses the game. One Key drawback to note in these game designs is that mastering control over brain signals is often the goal of the game, as opposed to using a BCI as an input device similar to a gamepad or a joystick.

A 3D game based on EEG biofeedback is presented by Mingyu et al [30]. The EEG band power in the major frequency bands is used to determine the speed of a spaceship racing with two other spaceships. The main draw back in this is that game is controlled by detecting the movement and interaction of the user via EEG. Thus, HCI concepts of this game is poor.

Lalor E [32] developed “Mind Balance” a 3-Dimensional Game for developing balanced brainwave. The game used Steady State Visual Evoked Potential to control the game. It was proposed that performance on the BCI game detailed below will be sensitive to neurological disorders such as Attention Deficit/Hyperactivity Disorder and thus may aid in its rehabilitation. The objective of the Mind Balance game was to control the balance of an animated character on a tightrope using only the player’s EEG. A checkerboard is positioned on either side of character Figure 2.1. Results of the study indicate that successful binary control using Steady State Visual Evoked Potentials is possible in an uncontrolled environment and resilient to any ill effects potentially incurred by a rich detailed visual environment as in the Mind Balance game. The authors also propose to extend the results of the preliminary trials of this study to covert visual attention, in which subject's direct attention to one of two bilateral stimuli without eye movement. However, balancing the mind is a tedious task for the game user.

Figure 2.1: Mind balance game

Beom-Soo Shim [31] has developed a 3-Dimensional Game for developing balanced Brain wave. It is an analysis game which analyzes raw brain wave gathered. By comparing the power value of the left and right cerebral hemisphere, Subjects can train the way they use their brain stably with the help of this game. The merit of this algorithm is it will help researchers gather brain wave data which is stable and balanced. The main drawback in this approach is that user needs to balance the power of the brain waves in left and right hemisphere.

J. A. Pineda [31] developed 3-D first-person shooter game. The goal of their study is to examine the mu rhythm and to determine the effects on learning while using a complex visual representation of the brain signal. In this case, the signal was mapped to navigational movements (i.e., left or right) within a 3-dimensional (3-D) first person shooter video game. Subjects were placed in a soundproof chamber and asked to look straight ahead at a computer monitor that displayed a high-resolution 3-D first-person shooter video game. During the free running period, subjects were asked to explore the game by pressing the “s” key on the keyboard to move forward and the “x” key to move back. Right and left movements were controlled by “high” and “low” mu respectively. At the end of the free-running period, subjects began either the left- or right- movement period. Subjects were instructed not to touch the keyboard (thus keeping the environment on the screen stationary), but to attempt to rotate it left or right by producing “low” or “high” mu respectively. For a left movement, the subject was told to focus on rotating the environment only to the left (Thus making counter-clockwise circles). Similarly, for a right movement, the subject was told to focus on rotating the environment only to the right (thus making clockwise circles). When the subject completed the three periods of training, the session for that day ended. The results of this study indicate that subjects learn to control levels of mu very quickly, but especially when this learning involves producing similar mu levels (whether high or low) over each hemisphere which is a tedious task and this was one of the main limitations of the game.

T. A. Lin, L. R. John [30] implemented a system that Quantifying Mental Relaxation with EEG for use in Computer Games. The aim of this study was to investigate methods for
The implementation of EEG based measurement of mental relaxation, and to demonstrate the potential of the interface with a simple game, where a simulated ball is controlled to move left or right based on player’s mental relaxation level. This is the first study that attempted to measure mental relaxation state using one channel (Fp1-Fp2) EEG for game implementation. The EEG results indicate that the sum alpha + theta, and sum of alpha + beta + theta are good indices for the measurement of neurological relaxation. Game testing also reflects that these indices have the capability to measure the basic level of relaxation in at least half of the players.

Palke, Amy [31] completed a research on Enhancing Brainwave Control Through Brain-Controlled Game Play. The goal of this project was to create a different type of application for the Modular EEG device. In the spirit of Brain ball, a competitive Neuro feedback game was designed and developed. In addition to a software game, the aim was to build a reusable library of EEG acquisition and analysis components that could be used to build other applications for use with the Modular EEG device. The game application was also designed to be easily extended if other programmers wanted to create different Neuro feedback games.

The data from one-player and two-player games was also analyzed separately to determine if either mode was more effective in increasing alpha activity. Although the player's average alpha amplitude was higher for those who played alone, both modes resulted in increased alpha activity with repeated game play.

Guobin implemented a Mind-controlled Android Racing Game [34] using Brain Computer Interface Figure 2.2. However, in this implementation the in-built e-sense attention value transmitted by NeuroSky and has caused a major failure.

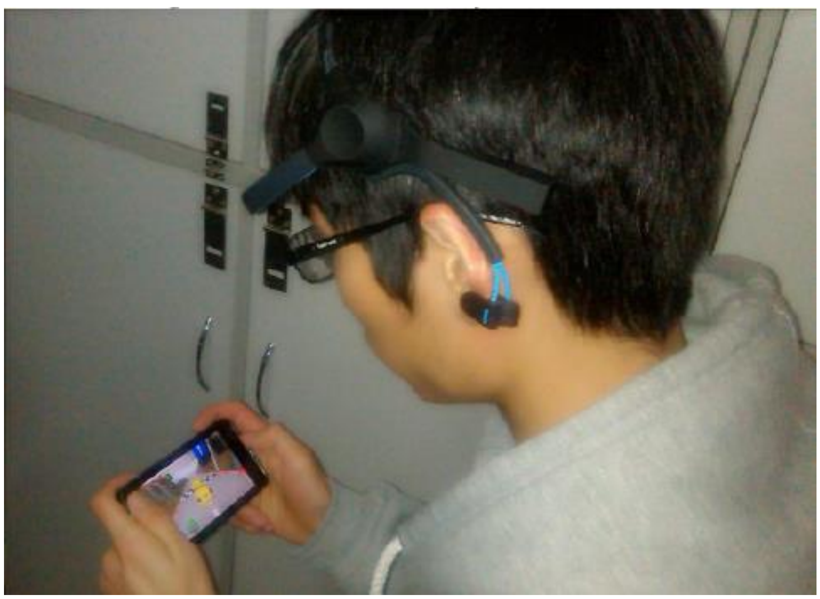


Figure 2.2: Android Racing Game using BCI

According to the research other games have mimicked the concept of relaxation as main interaction. The below Table 2.1 provides an overview of the BCI Games.

- F: represents feedback settings, in which the user has to adapt by modifying broadband power,
- VEP: task relevant stimuli and visually evoked potentials.
- In the sensors column, E indicates EEG sensors, M indicates EMG measurements.

Work Done by	Paradigm	Sensors	Number of electrodes
Palke	F	E	1
Mingyu et al.	F	E	3
Vidal	VEP	E	5
Martinez et al.	VEP	E	6
Pineda et al	M	E	3
Kaul	F	E ,M	3
Shim et al	F	E	4

Table 2.1: BCI Game classification Source: The State of the Art [33]

2.2.1. Neurogaming

“Neurogaming” was coined five years ago and put together a small San Francisco conference around the concept, “neurogaming” proved to be an effective meme for gathering a lot of like minded individuals coming from across a wide variety of professions and industries who were interested in leveraging neurosciences and new digital engagement technologies.

Neurogaming can be classified into many subsections;

- Therapeutic neurogaming
- Wellness neurogaming
- Educational neurogaming
- Entertainment neurogaming

In this research we are oriented on Entertainment neurogaming.

2.2.2. Related work disscussion

Existing BCI games are often just proofs of concept, where a single BCI paradigm is the only possible means of control, such as moving a paddle in the game Pong to the left or right with imaginary movement of the hands [9].

These BCIs are weak replacements for traditional input devices such as the mouse and keyboard: they cannot achieve the same speed and precision. The information transfer rate (ITR) of BCIs is still around up to 25 bits per minute [10], which is incomparable with keyboard speeds of over 300 characters per minute. Due to these limitations, there is still a big gap between these research games and games developed by the games industry at this time.

We now need to continue this trend to move beyond prototype tests, and focus on the role that BCI can play in improving the gaming experience. One of the key aspects of this research is to calculate the attention level dynamically in order to improve the information transfer rate. Thus, to meet the research objective EEG signals should be classified effectively by means of Artificial Intelligence technologies. Since, the performance and dynamic classification is required, utilizing Artificial Neural Networks is essential. These techniques are explained in Technology chapter.

2.3. Summary

This chapter highlighted the related work done on Neurogaming, the attractive features of those systems and the possible drawbacks. The chapter further evaluated critically about EEG acquisition devises and on a concluding note a research discussion was made summarizing the findings. Next chapter focus on the Technology used in this research.

Chapter 3

Neurogaming Technology

3.1. Introduction

This chapter provides an in depth explanation about the technology adopted to solve the problem at hand. It also elaborates the rationalization behind the choice of each technology. As explained in previous sections the proposed solution can be categorized into four segments as shown in below Table 3.1.

Solution Segment	Technology Adopted
Brain Signal Acquisition	For signal acquisition process EEG is utilized.
Signal Transformation	FFT analysis is used for signal transformation process.
Signal classification	In order to classify the attentive and non- attentive status Artificial Neural network is utilized.
Gaming module	Multi agent technology is used in order to control the racing game.

Table 3.1: Solution segments and technology adopted

3.2. Brain Signal Acquisition

Brain signal acquisition is a complex operation and many technologies are available readily at hand for signal acquisition. The following sections elaborate on signal acquisition mechanisms, background study on EEG signals. Electrode placement for signal acquisition, EEG signal wave formats and classifications and finally end with a discussion on rationalization behind using EEG.

3.2.1. EEG signal acquisition mechanisms

Hans Berger, who discovered the human EEG, speculated in his first comprehensive review of his experiments with the ‘‘Electroencephalography “(1929) about the possibility of reading thoughts from the EEG traces by using sophisticated mathematical analyses [6].

Brain–computer interfaces allow control of computers or external devices with regulation of brain activity alone. Invasive BCIs, almost exclusively investigated in animal models using implanted electrodes in brain tissue, and noninvasive BCIs using EEG recordings in humans are described [6]. The EEG signal is a voltage signal that arises from synchronized neural activity, that is, the coordinated firing of millions of neurons in the brain. It can be measured by non-invasively placing an electrode on or near the scalp, and for greater accuracy, by implanting an electrode in the skull [21] as illustrated in Figure 3.1.

Figure 3.1: EEG signal acquisition methods

There are many different companies producing EEG equipment for data collection that vary in reference points or number of electrodes. Recordings may be done with a dense electrode array of 132 electrodes [23], 62 electrode caps [24], 19 electrodes caps [25], 16 electrodes as in the consumer-price EPOC Emotive system [26], 10 electrode caps [27] or even as few as 1 electrode and references as in the consumer-price NeuroSky systems [28]. Introducing multiple electrodes can increase spatial resolution but increase the cost of the system and it may also increase complexity of the analysis, depending on the technique used.

Placing multiple electrodes in the skull for EEG acquisition has been one of the major drawbacks for advancement in EEG based systems. The conventional wet adhesive electrodes used almost universally in clinical applications today provide an excellent signal but are cumbersome and irritating for mobile use [22]. But the recent availability of low-cost EEG devices makes it feasible to take this technology from the laboratory into informal environments such as schools and homes. The benefits of such devices are affordability and ease of use. Several types of low-cost EEG devices exist commercially in the market today. For example, the NeuroSky mindwave mobile Figure 3.2 an EEG headset equipped with a single, dry EEG sensor. It uses the Bluetooth technology to transfer signal samples wirelessly to the host computer. More details in appendix A.

Figure 3.2: NeuroSky mindwave mobile with single dry electrode [38]

3.2.1.1 Discussion on EEG signal acquisition

Thus, based on the above critical review, due to low cost and ease of use, this thesis utilizes a NeuroSky mindwave mobile device for EEG signal acquisition. Protocol information about the device, how it works and the concepts behind it is explained extensively below.

3.2.2. Background on Electroencephalography.

The EEG signal is a voltage signal that arises from synchronized neural activity, that is, the coordinated firing of millions of neurons in the brain. It can be measured by non-invasively placing an electrode on or near the scalp, and for greater accuracy, by implanting an electrode in the skull [21]. Invasive and non-invasive approaches gives different perspectives and enables us to look inside the brain. To observe what happens In EEG, brain-related electrical potentials are recorded from the scalp.

Pairs of conductive electrodes are used to read this electricity. The difference in voltage between the electrodes are measured, and since the signal is weak (30-100 micro volt) it has to be amplified as shown in Figure 3.3.

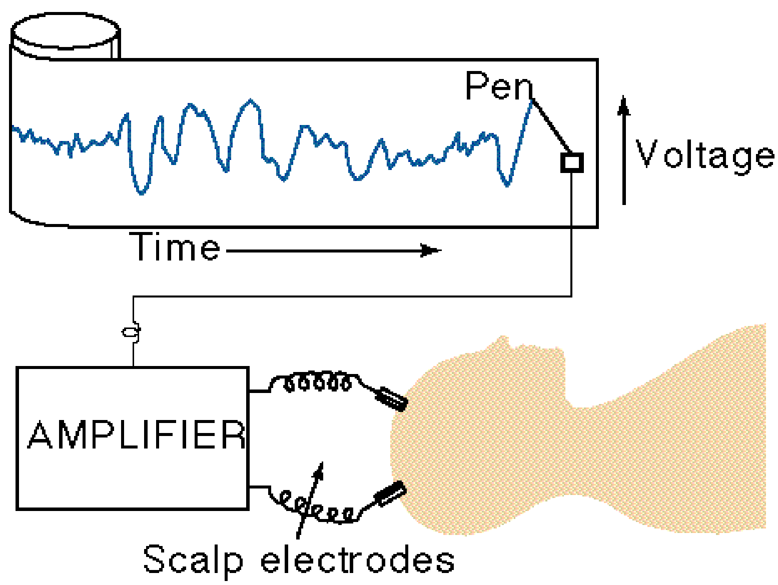


Figure 3.3: EEG Recording system

Current occurs when neurons communicate. The simplest event is called action potential, and is a discharge caused by fast opening and closing of *Na*+ and *K*+ ion channels in the neuron membrane. If the membrane depolarize to some threshold, the neuron will “fire”. Tracking these discharges over time reveals the brain activity.

3.2.3. Electrode placement for Signal Acquisition

Recordings of EEG may be done with a dense electrode array of 132 electrodes [23], 62 electrode caps [24], 19 electrodes caps [25], 16 electrodes as in the consumer-price EPOC Emotive system [26], 10 electrode caps [27] or even as few as 1 electrode and references as in the consumer-price NeuroSky systems [28]. Nonetheless, for accurate EEG capturing the electrodes should be placed in precise locations. The 10/20 system or international 10/20 system is an internationally recognized method to describe the location of the scalp electrodes. This system is defined based on the coordinates or placement of an electrode and the underlying area of cerebral cortex. The number "10" and "20" indicate the 10 and 20 percentage of the total front-back or right-left distance from the skull as illustrated in Figure 3.4 and Figure 3.5.

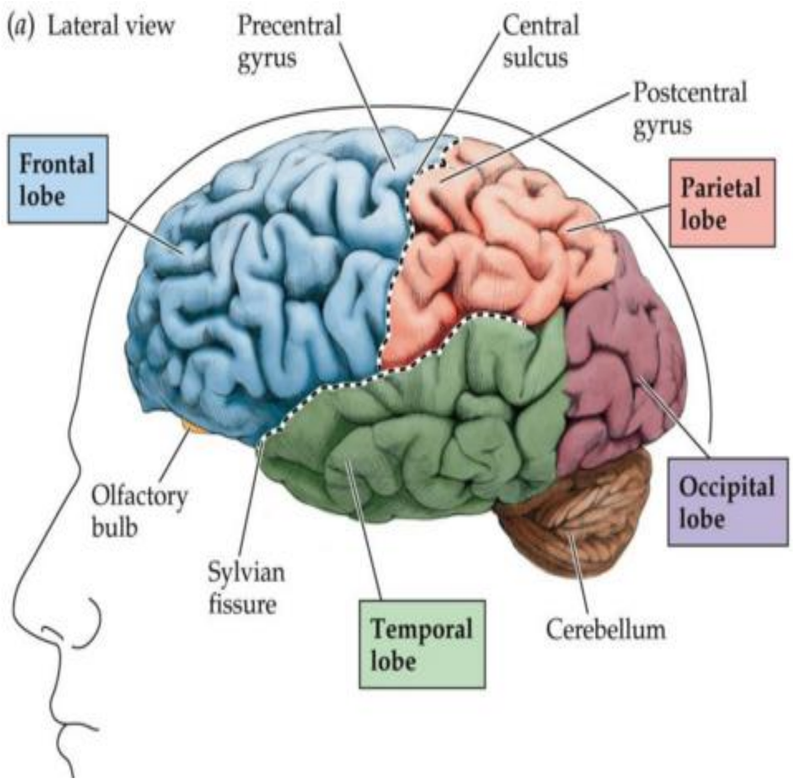


Figure 3.4: Brain 10/20 system [39]

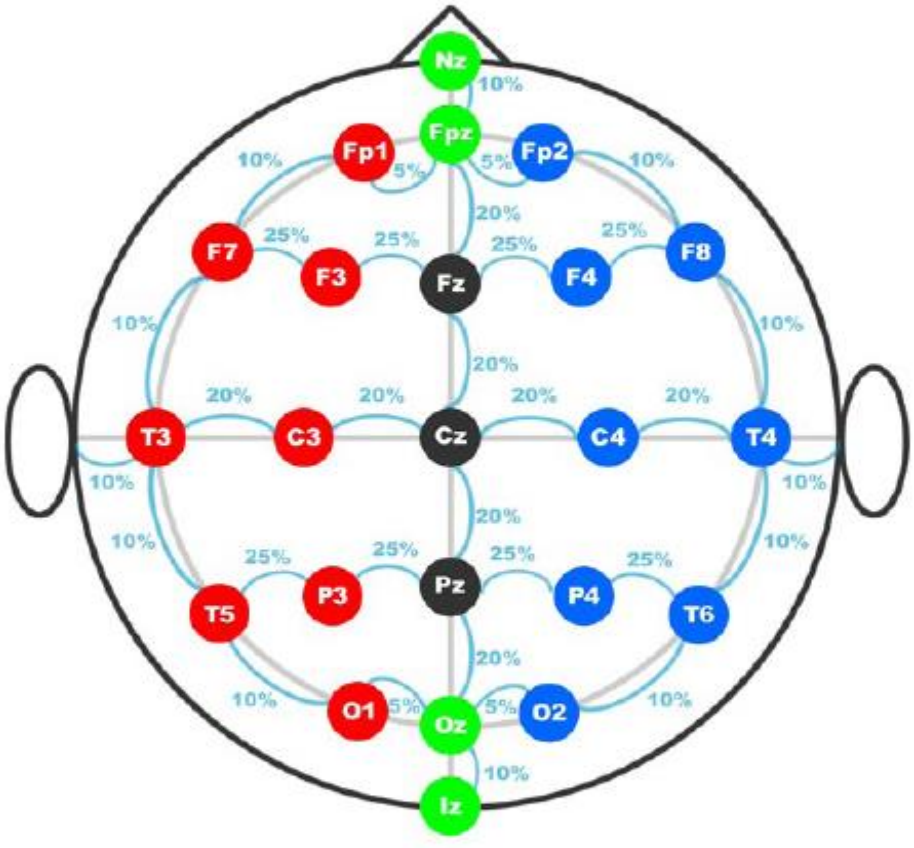


Figure 3.5: International 10/20 system [39]

Each electrode has a letter to identify the lobe and number to identify the hemisphere location Table 3.2.

Electrode	Lobe	
F	Frontal	Even numbers 2,4,6,8 refers to electrode positions on right hemisphere
T	Temporal	Odd numbers 1,3,5,7 refers to electrode positions on right hemisphere
C	Central	* used only for identification purpose
P	Parietal	
O	Occipital	

Table 3.2: Electrodes and Lobe [39]

Since the focus of this research is oriented on attention and as explained in chapter 2 the research will be utilizing a single electrode mind wave mobile headset. Thus, tapping to Fp1 would be suffice. As illustrated in Figure 3.6 this research will be targeting on FP1 electrode placement.

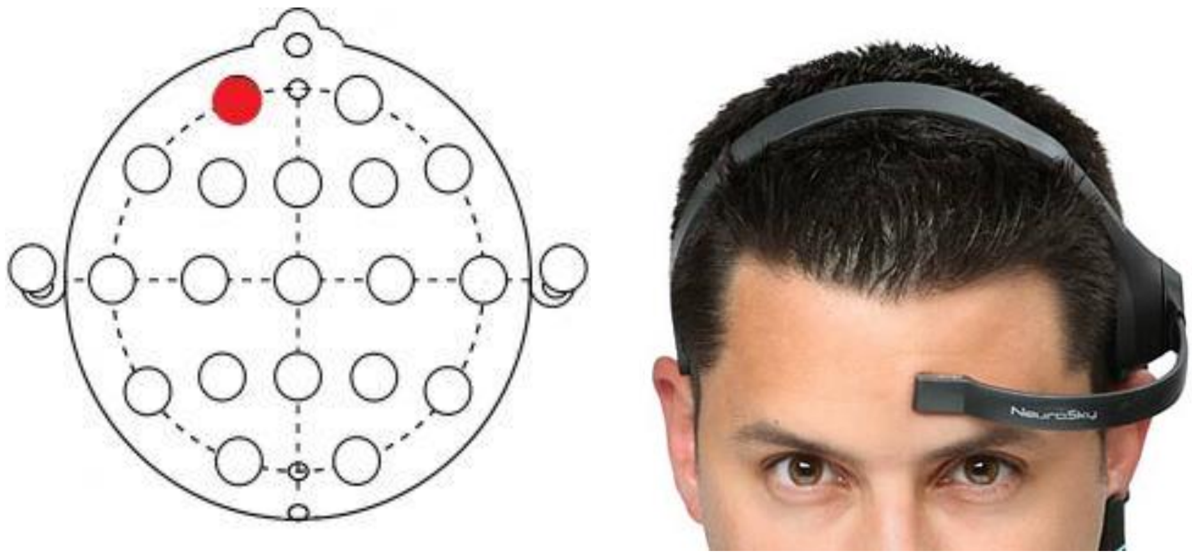


Figure 3.6: Tapping to Fp1 for Attention acquisition

3.2.4. EEG signal wave formats and classifications.

Different electrical frequencies could be linked to actions and different stages of consciousness. This was done by observing subjects performing different task, like solving mathematical problems, while recording their EEG. The below Table 3.3 represents different wave formats associated with EEG based on frequency and amplitude.

Wave	Frequency Range	Amplitude	Emotions	Wave Format
α **Alpha**	8 - 13 Hz	30 - 50 µV	• Consciousness • Quiet, or At Rest • Thinking • Blinking	

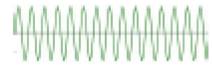
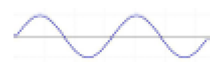
β **Beta**	14 - 30 Hz	5 - 20 µV	• Consciousness • Alert • Thinking	
θ **Theta**	4 - 7 Hz	30 µV	• Emotional Pressure • Interruptions Of Consciousness • Deep Physical Relaxation	
δ **Delta**	0.5 - 3 Hz	100 -200 µV	• Deep Sleep • Unconscious • Anesthetized	
γ **Gamma**	31 - 50 Hz	5 - 10 µV	• Cognition And Perceptual Activity	

Table 3.3: EEG Wave Formats [38]

3.2.5. Rationalization behind using EEG over EOG and EMG

Electorooculogram (EOG) is used to detect eye movements, Electromyogram is used to capture muscle tension and Electroencephalogram is used to measure consciousness of an individual. Since this project focuses on human attention the most suitable signal format would be using EEG.

3.3. Signal Transformation

The NeuroSky mindwave mobile device measures the raw signal, power spectrum (alpha, beta, delta, gamma, and theta), attention level, mediation level and blink detection. The raw EEG data received at a rate of 512 Hz. Other measured values are made every second. Therefore, raw EEG data is the main source for calculating attention value rapidly for gaming input.

However, these raw signals are in time domain and should be transferred to frequency domain. In order to accomplish this there are several algorithms.

- Fourier Transform (FT) Method
- Wavelet Transform (WT) Method
- Continuous Wavelet Transform (CWT) Method

The best suited transformation method for this research would be Fourier Transform [35].

3.3.1. Fast Fourier Transform Method

Fast Fourier transforms are widely used for many applications in engineering, science, and mathematics. The basic ideas were popularized in 1965, but some algorithms had been derived as early as 1805. A Fast Fourier Transform (FFT) algorithm computes the Discrete Fourier Transform (DFT) of a sequence. Fourier analysis converts a signal from its original domain to a representation in the frequency domain. An FFT rapidly computes such transformations by factorizing the DFT matrix into a product of sparse factors. As a result, it manages to reduce the complexity of computing the DFT from $O(n^2)$, which arises if one simply applies the definition of DFT, to $O(n \log n)$, where n is the data size. The execution time for FFT depends on the length of the transform. It is fastest for powers of two.

3.4. Signal Classification

The signal classification cannot be done using algorithmic approach. Thus machine learning techniques need to be utilized. There are several approaches available for EEG signal classification [3, 4].

- Linear classification using support vector machines
- Nonlinear Bayesian classifiers
- Nearest neighbor classifiers,
- Artificial Neural Networks

However, for this research Artificial Neural Networks is utilized for EEG signal classification.

3.4.1. Artificial Neural Network.

An artificial neuron is a computational model inspired in the natural neurons. Natural neurons receive signals through synapses located on the dendrites or membrane of the neuron. When the signals received are strong enough (surpass a certain threshold), the neuron is activated and emits a signal though the axon. This signal might be sent to another synapse, and might activate other neurons Figure 3.7.

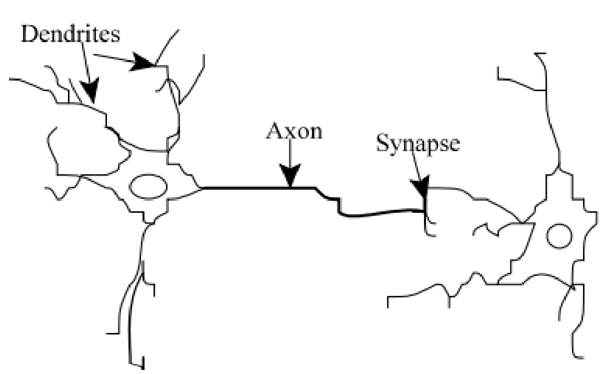


Figure 3.7: Natural Neuron

The complexity of real neurons is highly abstracted when modelling artificial neurons. These basically consist of inputs (like synapses), which are multiplied by weights (strength of the respective signals), and then computed by a mathematical function which determines the activation of the neuron.

3.4.1.1. Artificial Neural Network Learning Mechanisms

ANN works with three major learning paradigms. These are supervised learning, unsupervised learning and reinforcement learning. Each of these paradigms corresponds to a particular abstract learning task (Table 3.4 learning paradigms).

Supervised learning	Unsupervised learning	Reinforcement learning
In supervised training, both the inputs and the outputs are provided. The network then processes the inputs and compares its resulting outputs against the desired outputs. Errors are then calculated, causing the system to adjust the weights which control the network. This process occurs over and over as the weights are continually tweaked	Unsupervised learning is the machine learning task of inferring a function to describe hidden structure from unlabeled data. Since the examples given to the learner are unlabeled, there is no error or reward signal to evaluate a potential solution. However unsupervised learning also encompasses many other techniques that seek to summarize and explain key features of the data.	Reinforcement learning is an area of machine learning inspired by behaviorist psychology, concerned with how software agents ought to take actions in an environment so as to maximize some notion of cumulative reward.

Table 3.4: Learning paradigms

3.4.1.2. Artificial Neural Network Activation Functions

Activation functions controls whether a neuron is “active” or “inactive”. Activations function are needed for hidden layer of the NN to introduce nonlinearity. Without them NN would be same as plain perceptions. If linear function were used, NN would not be as powerful as they are. Below tables describes the activation functions.

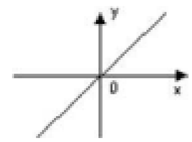
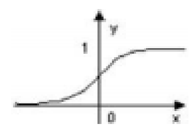
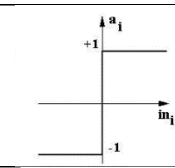
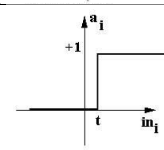
Activation Function	Mathematical Equation	2D Graphical Representation
Linear	y = x	
Sigmoid	$y = \frac{1}{1 + e^{-x}}$	
Sine	sin(*x*)	
Step	$\begin{Bmatrix} 0 & x < 0 \\ +1 & x \geq 0 \end{Bmatrix}$	

Table 3.5: Activation function

3.4.1.3. Multi-layer perceptron

A multilayer perceptron (MLP) is a feed forward artificial neural network model that maps sets of input data onto a set of appropriate outputs. An MLP consists of multiple layers of nodes in a directed graph, with each layer fully connected to the next one. Except for the input nodes, each node is a neuron (or processing element) with a nonlinear activation function. MLP utilizes a supervised learning technique called back propagation for training the network. MLP is a modification of the standard linear perceptron and can distinguish data that are not linearly separable.

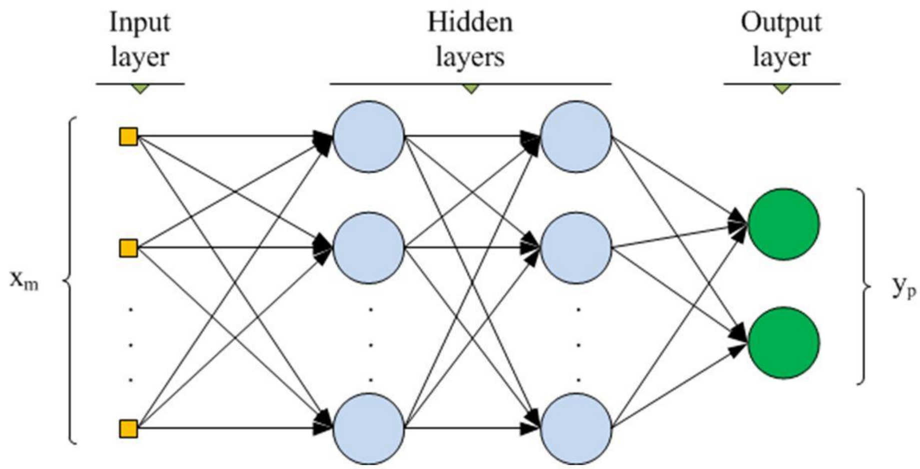


Figure 3.8: Multi-layer Perceptron

3.4.1.4. Back propagation algorithm

One of the most popular ANN algorithms is back propagation algorithm. BP algorithm could be broken down to four main steps [37]. After choosing the weights of the network randomly, the back propagation algorithm is used to compute the necessary corrections.

The algorithm can be decomposed in the following four steps:

i) Feed-forward computation
ii) Back propagation to the output layer
iii) Back propagation to the hidden layer
iv) Weight updates

The algorithm is stopped when the value of the error function has become sufficiently small.

3.4.2. Rationalization using Artificial Neural Network over support vector machine

Support vector machines, decision trees and artificial neural networks are powerful machine learning techniques that can be used for EEG signal classification [16]. Among these classification techniques, artificial neural network is one of the most popular and fasted technique for EEG classification [17]. Thus, the research utilizes artificial neural Networks.

3.4.3. Artificial Neural Network Configuration

The below sections elaborates in details the artificial neural network configuration. The number of layers the weight settings play an important part in this design.

3.4.3.1. Number of Nodes and Layers

Choosing number of nodes for each layer will depend on problem NN is trying to solve, types of data network is dealing with, quality of data and some other parameters. Number of input and output nodes depends on training set in hand.

3.4.3.2. Setting Weights

The way to control NN is by setting and adjusting weights between nodes. Initial weights are usually set at some random numbers and then they are adjusted during NN training

3.5. Gaming Module

The gaming module is a car racing game which requires intelligent behavior. The competitive cars need to accelerate and control its speed autonomously in various stages of the race. The completive cars need to adopt to the environment conditions and create obstacles and barriers to the users' car when required. Thus, to model the racing game Agent technology is utilized.

3.5.1. Agent Technology

Autonomous Agent is the key in intelligent game development [18]. Thus the research seek to develop a car racing game on a multi agent frame work using 3D gaming platform.

Multi-agent systems consist of agents and their environment. Typically multi-agent systems research refers to software agents. Agents can be divided into different types ranging from simple to complex. Some categories suggested to define these types include:

- Passive agents or agent without goals
- Active agents with simple goals

In this research active agents (Autonomous car agents) will be used to control the game.

3.5.2. .NET, Open GL, Shadow Engine

The research will be programmed over .NET frame work 4.0 and for advance simulations and animations Open GL and shadow engine will be utilized.

3.6. Summary

This chapter focused on the technology being used in this research project. For attention acquisition EEG signals are used over EOG and EMG. For signal transformation FFT algorithm is been used. Artificial Neural network is preferred over support vector machine due to its popularity and performance. Finally agent technology is used to model the gaming module. Next, chapter explains the Approach of the research.

Chapter 4

Approach for BCI Framework via MAS and ANN

4.1. Introduction

This chapter asserts the hypothesis or the premise of this thesis. Furthermore, the chapter elaborates on the inputs and outputs of the attention racer system. Moreover, the chapter explains about the features and users of the system.

4.2. Hypothesis

It is hypothesized that human attention level can be used as a near real time input parameter for computerized game controlling, this can be illustrated in other words as using brain computer interfacing for game controlling. The mentioned hypothesis seeks to resolve two problem areas. Firstly, providing the ability for individuals with physical limitations to interact with a computer game and secondly, to overcome the one second barrier of attention calculation in the NeuroSky. In order to test the above hypothesis several steps are been followed as exemplified in this chapter.

4.3. Inputs to the system

Primary task of this system is to capture the attention level of a human brain and use it as an input parameter for game controlling. In order to accomplish this objective Mind-wave mobile from NeuroSky will be utilized. The Mind-wave mobile head set illustrated in Figure 4.1 has the ability to capture the EEG signal from human brain and to transmit it to any receiver.

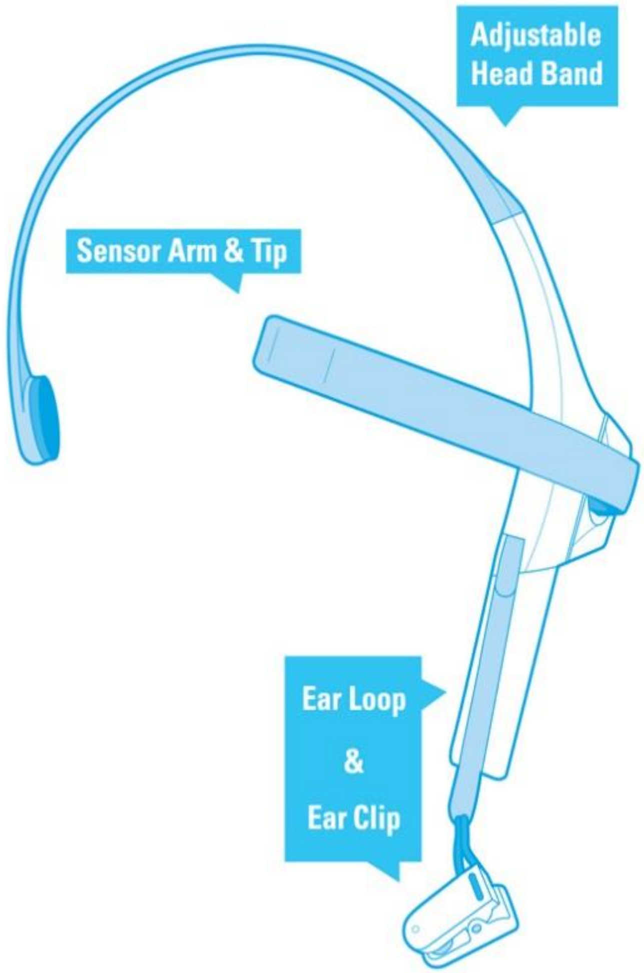


Figure 4.1: Mind-wave mobile head set from NeuroSky. [38]

In order to capture the transmitted EEG signals, the headset will be paired with a laptop via Bluetooth and a Microsoft .NET mindset interface library will be used this is depicted in Figure 4.2. Mindset interface library acts as the bridge connecting the computer and Mindset via Bluetooth technology. In addition to above feature the Mindset interface library has the ability to handle connections, disconnections and to receive EEG waves such as Delta, Alpha, Beta and Gamma which are important in calculating the attention level of a human.

Figure 4.2: Laptop paired with headset and Mindset interface library captures the EEG signals

Thus, Alpha, Beta, Theta, Delta will be used as inputs for an artificial neural network in calculating the attention value which is explained in the process section. Furthermore, the calculated attention value will be used as input for speed controlling in a computer game.

4.4. Output of the system

The overall output of the system would be that a speed of a computer game racing car will be controlled based on the end user attention level. The entire system will contain two main modules the attention level calculation module and computer control gaming module.

- Attention Module: responsible to generate Attention level as Output by acquiring EEG signals.
- Gaming Module: takes attention level as input and controls the car speed as output.

4.5. Process

The process of the brain computing interface for game controlling has been summarized in the below Figure 4.3.

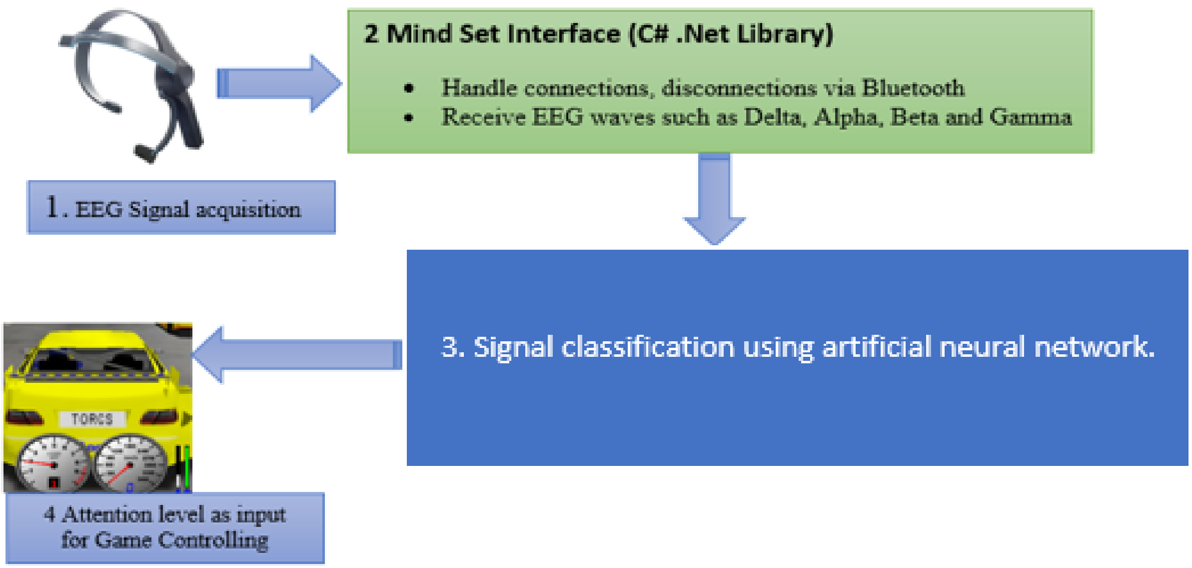


Figure 4.3: The big picture of the system.

As illustrated above, initially a Mind wave mobile head set from NeuroSky will be placed on the users head and will be paired with a laptop via Bluetooth technology. As headset transmits the EEG signals the mindset interface used in our system will capture the raw EEG signals. Then FFT analysis will be performed on raw input signals to convert them from time domain to frequency domain.

Then the filtered signals are used as the input for three layer artificial neural network which is composed of one input layer, one Output layer and the hidden layer. Based on the artificial neural network neuron firing the attention level will be calculated in a range for 0 to 100. Where 0 defines the lowest attention level while 100 defines the maximum attention level.

The calculated attention level is propagated as input for the computer gaming module. The .NET based game is a racing car game where the speed of the car will be determined by the input attention level.

4.6. Features

One of the major features of the design system is real time attention level calculation. Every 500 millisecond second the attention module will feed the gaming module with latest attention value which will improve the user experience. Furthermore, the system will be utilizing minimum resources, thus the system can run even on machine which has minimum configurations.

4.7. Uses of the system

Computer gamers and people with disabilities who cannot used keyboards and joysticks can use this system to interact with computer games more effectively and in an innovative manner.

4.8. Summary

The chapter explained the approach to the proposed solution in terms of inputs as to how EEG signals will be fed into the system as input data, outputs was elaborated in two stages where attention level as internal output and the speed of the car as primary output of the system. Process elaborated the entire flow of the system. Finally the chapter sums up by explaining the features and users of the system. The next chapter focuses on the design of the system.

Chapter 5

BCI Framework and Attention Racer Design

5.1. Introduction

This chapter emphasizes on the design of the attention racer system by elaborating on the component, interface, architectural and data design aspects. The attention racer system is composed of 12 modules which collaborates to produce the desired output of the system. Below diagram 5.1 depicts the high level architecture (component interaction) of the attention racer system.

Figure 5.1: Frame work components

As illustrated in the below component diagram Figure 5.2 EEG raw data is initially acquired by the "EEG Raw signal acquisition" module. Then the acquired raw information is sent through a "FFT analysis module" to convert raw information to Frequency Domain. Once FFT is applied the resulting data is passed through Wave filter module to filter Alpha, Beta, and Gamma etc... Band Frequencies.

The filtered wave is initially sent to Artificial Neural Network Training Data store module where the data will be saved in .EEG file. Once files are saved Artificial Neural Network training module will kick-in to train the artificial neural network via supervised training and serialize the trained network.

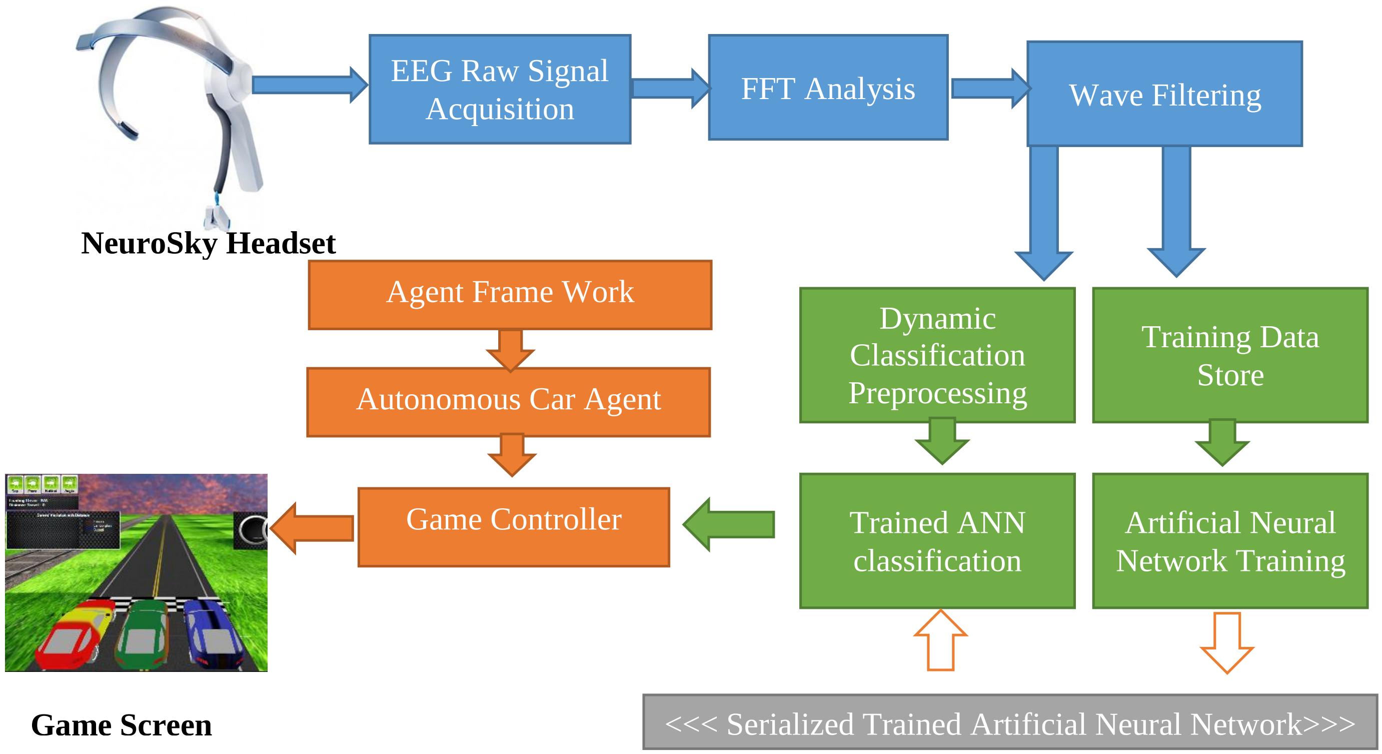


Figure 5.2: Component Interaction Design of attention

Once the ANN is trained "Trained ANN classification" module will calculate the dynamic attention values and pass it as an input to Game Controller. Finally, the game controller will utilize the attention value to control the speed of the user car in attention racing game.

5.2. Attention Racer Framework Modules

The modules collaborate with each other to work as a single functioning system. Below sections describe about the frame modules.

5.2.1. EEG Raw signal acquisition module

The raw signal acquisition module is responsible to acquire signal from NeuroSky headset. NeuroSky SDK acts as the device interface and handles connection, disconnection and raw data updates Figure 5.3.

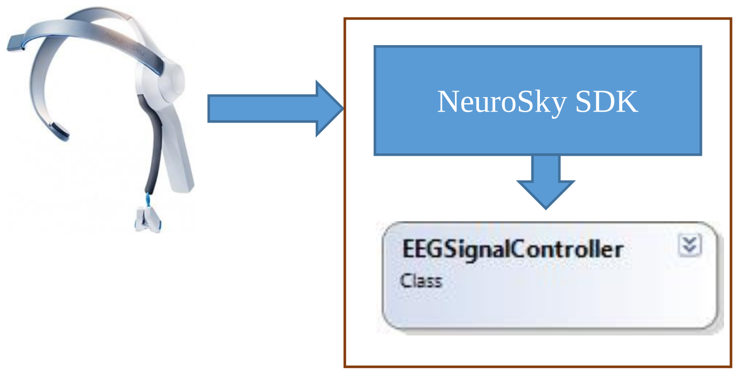


Figure 5.3: EEG Raw signal acquisition module

When the EEG signals are received by adhering to the NeuroSky signal strength standard EEG signal controller will filter out the Noise signals. The signal strength value ranges from 0 to 255. Any non-zero value indicates that some sort of noise contamination is detected. The higher the number, the more noise is detected. A value of 200 has a special meaning, specifically that the Headset electrodes aren't contacting a person's skin.

The NeuroSky SDK supports below data types

- ESense Attention value.
- ESense Meditation value
- Poor signal quality
- EEG band powers (delta, theta, alpha, beta, and gamma)
- Raw EEG wave samples (at 512Hz)

For this research we will be using only the Raw EEG wave value by ignoring others. Thus, once the noise is filtered the EEG signal controller will buffer the updated raw values for 500 milliseconds before passing it through FFT analysis.

5.2.2. FFT analysis and Wave Filtering

The FFT analysis module Figure 5.4 is responsible to convert the raw signal values from its original domain to frequency domain.

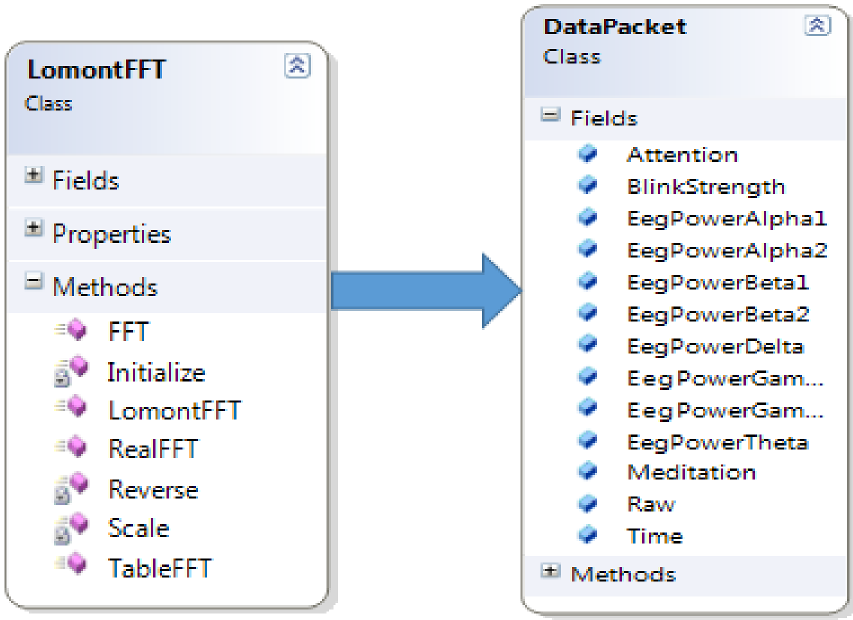


Figure 5.4: FFT analysis and Wave Filtering

In order to accomplish this task it will receive the buffered raw values every 500 milliseconds. Once, the signals are converted to frequency domain the result would be filtered to Alpha, Beta, Gamma, Thetas and etc... According to below band frequencies.

- Delta: 1-3Hz
- Theta: 4-7Hz
- Alpha1: 8-9Hz
- Alpha2: 10-12Hz
- Beta1: 13-17Hz
- Beta2: 18-30Hz
- Gamma1: 31-40Hz
- Gamma2: 41-50Hz

The populated Data Packet with band frequencies is sent to Classification module for training or attention level calculation.

5.2.3. Attention Classification Training and Attention Level Detection Module

The classification and attention level detection module serves two purposes, firstly, it uses the above data packets for Artificial Neural Network Training and then in gaming mode it uses the trained network to calculate the attention level.

5.2.3.1. Artificial Neural Network Training Module

The designed Artificial Neural network is composed of three layers as illustrated in figure 5.5. Namely the input layer the hidden layer and output layer. The input layer contains 8 input nodes while output has one node. The number of nodes in hidden layer is decided at training time to get minimized error rate.

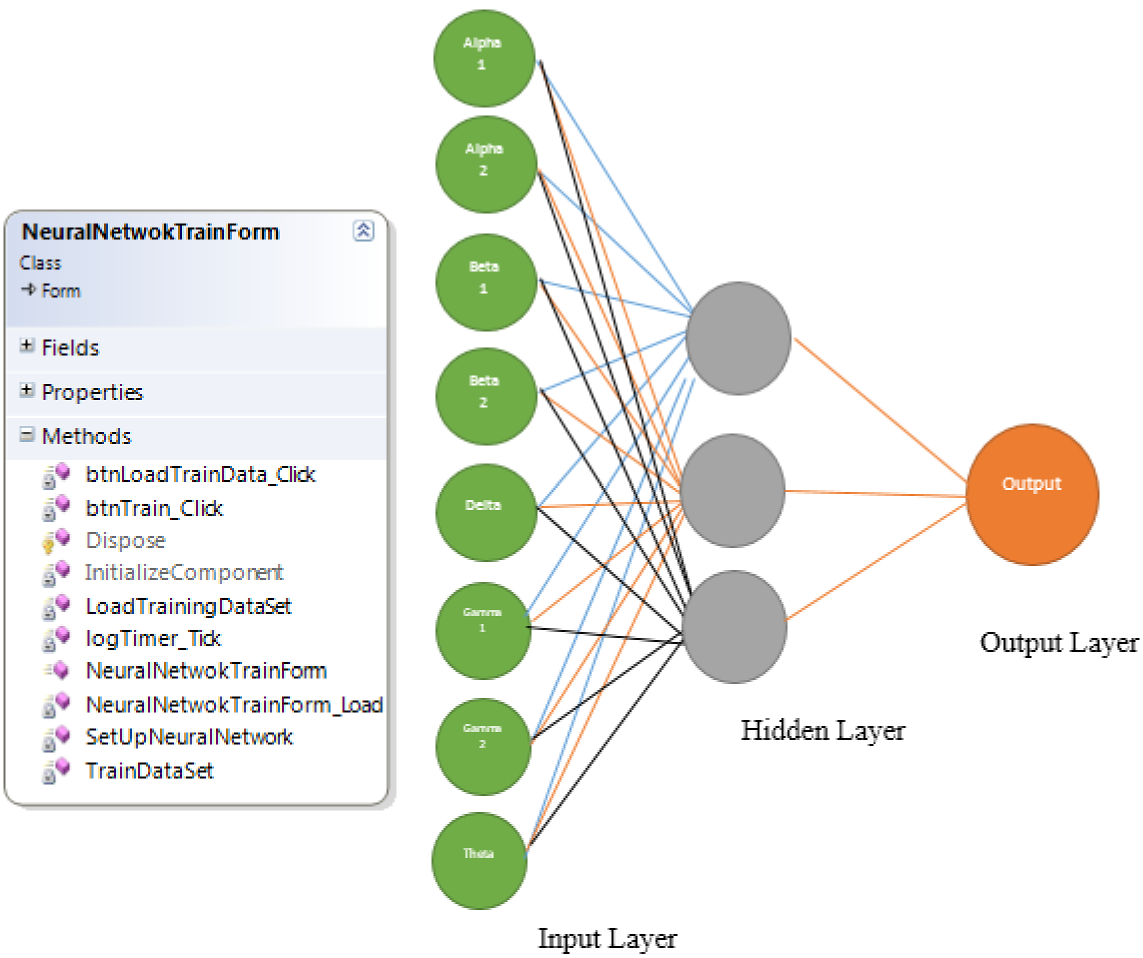


Figure 5.5: Artificial Neural Network and Training Module

The back propagation algorithm with supervised training is used for artificial neural network training and the trained network would be serialized for dynamic attention level detection.

5.2.3.2. Attention level detection Module

This module is responsible for attention level detection. In gaming mode the module would de-serialize the trained artificial neural network and input the data packet as input to get the computed attention value. The detected attention level is then passed on to the Gaming module for Speed control.

5.2.4. The Attention Racer Module

Racer module facilitates the game with an embedded multi-agent framework.

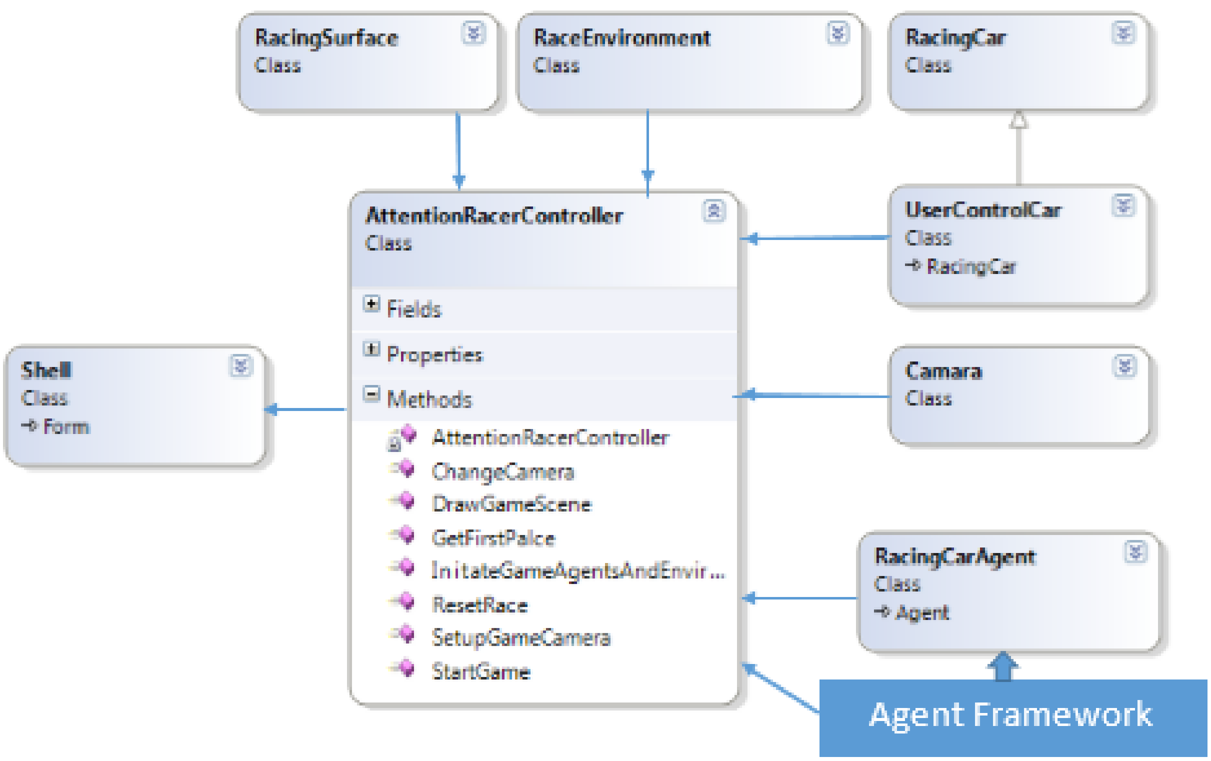


Figure 5.6: Attention Racer Game modules

Attention race controller module is responsible to setup the game environment which is composed of racing surface, game cameras, racing car agents and user controlled car. This module also controls the main game logic and flow of the game. When the attention value is provided by the classification module the attention race control module will use it to control the speed of the user racing car.

Moreover, racing car agent (Other competitive car) is an autonomous agent build upon a custom multi agent framework. The racing car agent works autonomously by depicting the racing car behavior such as cruise control, breaking and accelerating in different stages of the game.

5.3. Shell Design for Attention Racer

The attention racer shell screen (main screen) design is composed of three sections. Based on the component design as expressed in above section the top part of the shell consist of EEG connection handling and FFT analysis user control. The left side of the shell consist of the artificial neural network setup area. And finally the right side contains the main racing game surface as illustrated in below Figure 5.7.

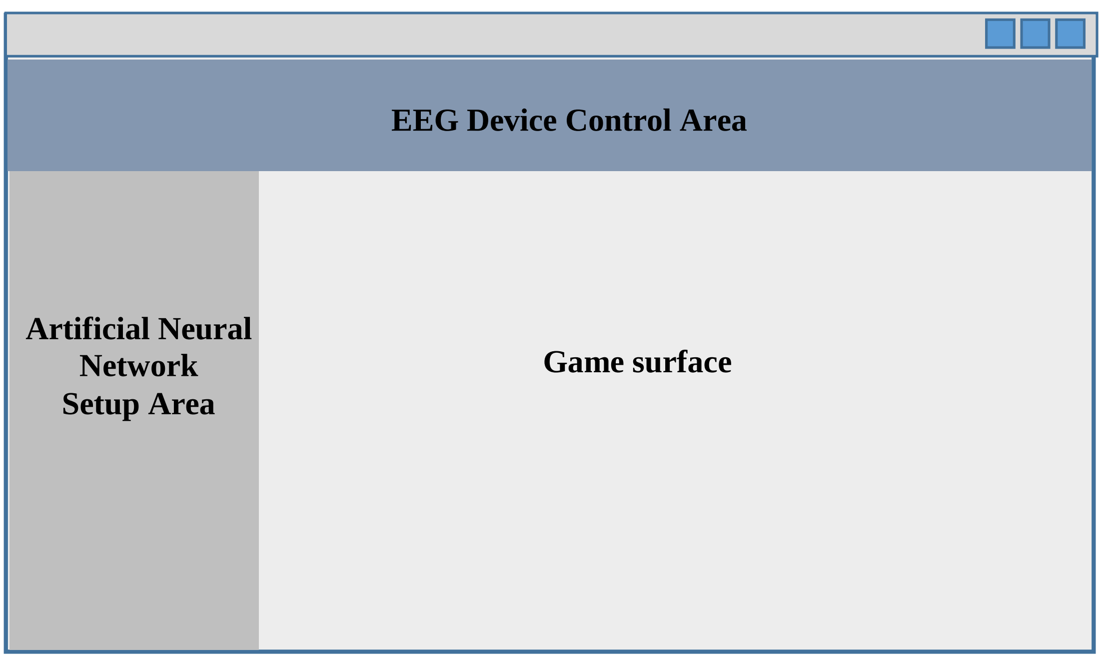


Figure 5.7: Shell Design for attention Racer

5.4. Summary

This chapter discussed about the twelve module design for attention racer application. Further it explained what each module dose, the internal architecture and how it interacts with the neighboring modules. Finally the shell design for the attention racer was illustrated. Next chapter focuses on the attention racer implementation.

Chapter 6

Implementation of BCI Framework for Gaming

6.1. Introduction

This chapter, explains the implementation details of each module in attention racer that are stated in the design chapter (chapter 5). In previous chapter the twelve modules were categorized into 3 sections;

- EEG raw data acquisition and FFT analysis modules
- Wave Classification and Training modules
- Attention racing game app modules

The implementation details for each section is elaborated in detail below.

6.2. EEG raw data acquisition and FFT analysis modules

As the first step in EEG raw data acquisition it is essential to handle connectivity with NeuroSky mind wave mobile headset. For connectivity handling we utilize NeuroSky ThinkGear DLL. With the aid of ThinkGear DLL we can handle the below connectivity statuses in Table 6.1.

Event Name	Description
DeviceConnected	Event is triggered when head set is connected with the system
DeviceConnectFail	Event is triggered when connection to headset fails after multiple attempts
DeviceDisconnected	Event is triggered when an established connection with the headset is lost.
DeviceFound	Event is trigged when the headset is found by system before connecting
DeviceNotFound	Event is triggered if headset cannot be found by the system
DeviceValidating	Event is triggered when validating the headset before connection

Table 6.1: Device Connection Statuses

Once the DeviceConnected event is triggered the EEG Controller module would receive EEG signals from NeuroSky mind wave mobile Headset. These signals contains a special Data packet namely **POOR_SIGNAL/SENSOR_STATUS.** This integer value (ranges from 0-200) provides an indication of how good or how poor the bio-signal is at the sensor. This value is typically output by all ThinkGear hardware devices once per second.
If this value is indicating that the bio-sensor is not currently contacting the subject, then any received RAW_DATA or EEG_POWER values during that time is treated as floating noise not from a human subject, and discarded.

The system categorizes the signal strength according to below criteria.

Poor Signal Value	Description
0	This means that's signal strength is excellent
Between 1 and 49	Signal Strength is Good
Between 50 and 127	Signal strength is Moderate
Between 128 and 200	Signal Strength Poor and not connected to human

Table 6.2: Poor Signal Strength value and classification

The connection status and Signal strength is indicated in attention racer application as shown below in Figure 6.1.

Connection Status: connected **Signal Strength: Excellent**

Figure 6.1: Connection Status and Signal Strength Indication

If the device is connected and signal strength is excellent the EEG controller will receive below Data types from ThinkGear.

- ESense Attention value.
- ESense Meditation value
- Poor signal quality
- EEG band powers (delta, theta, alpha, beta, and gamma)
- Raw EEG wave samples (at 512Hz)

Except for Raw EEG wave signals all the other signals are updated every one second. However, as explained in chapter 2 since we require rapid values for attention calculation all these signals are neglected and only raw EEG value is taken into consideration.

The raw values are updated every 7.8 milliseconds. Thus, the EEG controller module will buffer the raw values for 500 milliseconds and send the array of raw values for FFT analysis to convert the raw signals to frequency domain. By using the raw values the attention racer system gains the 100% performance gain than using Band Waves (alpha, Beta, etc…) which is updated every 1 second. (Typical application using band waves will get attention update every 1 second however, the attention racer will get attention level every 500 millisecond).

As the next phase the buffered RAW signal is sent through FFT analysis. The LomontFFT class performs the required FFT transformation for buffered raw signals and signal conversion is illustrated in attention racer system as shown below Figure 6.2.

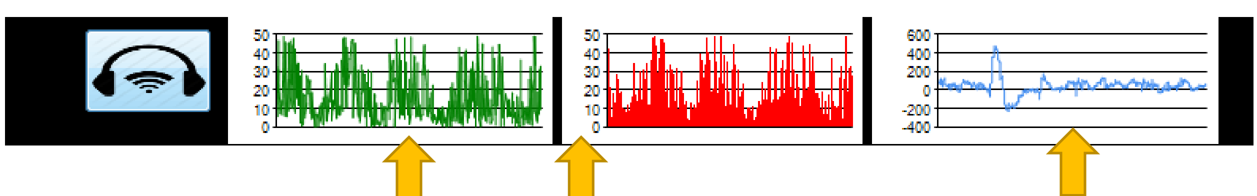


Figure 6.2: Raw Signal to FFT analysis Indicators

Once the FFT analysis is completed the Data Packet is created by categorizing the band frequencies. Once this is completed the data packet is passed to the next section Wave Classification and Training modules.

6.3. Wave Classification and Training modules

The above FFT analyzed data packet is composed of below fields.

- EegPowerDelta
- EegPowerTheta
- EegPowerAlpha1
- EegPowerAlpha2
- EegPowerBeta1
- EegPowerBeta2
- EegPowerGamma1
- EegPowerGamma2

This Data Packet can be used for attention level calculation via an artificial neural network. However, before the calculation the artificial neural network needs to be setup and trained.

6.3.1. Artificial Neural Network Training for attention Racer.

Before performing the training above Data packets needs to be acquired and stored in file. These data files are then used for supervised training, this requirement is facilitated by the below window Figure 6.3. Where Data packets are recorded for specified amount of time.

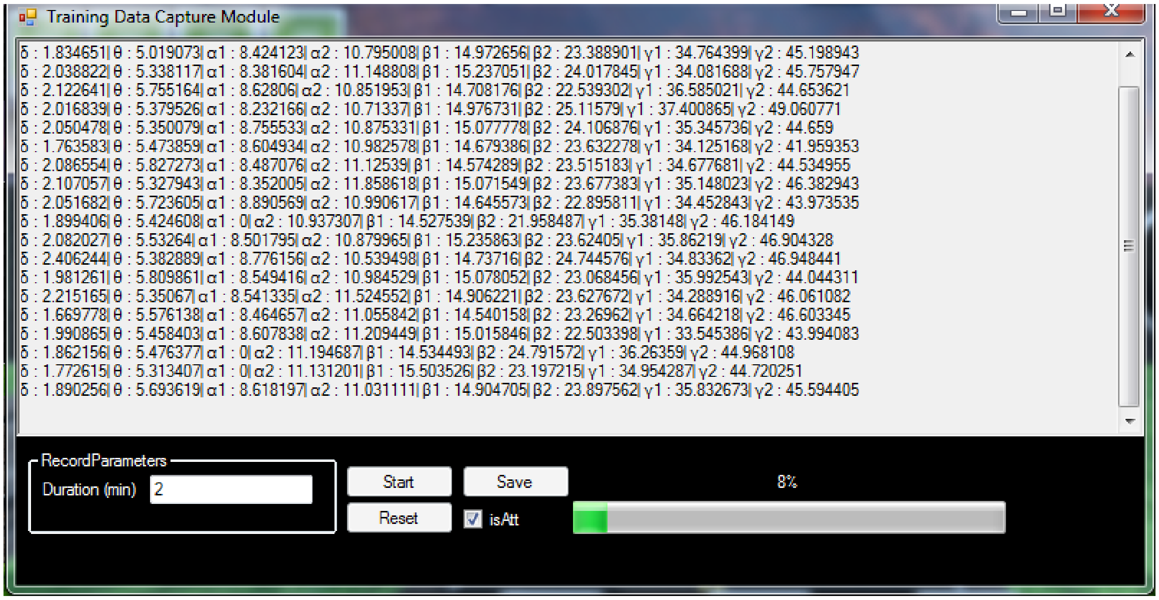


Figure 6.3: Training Data Capture Module

Once the data packets are populated for specified amount of time the data is saved to ".EEG" file Figure 6.4.

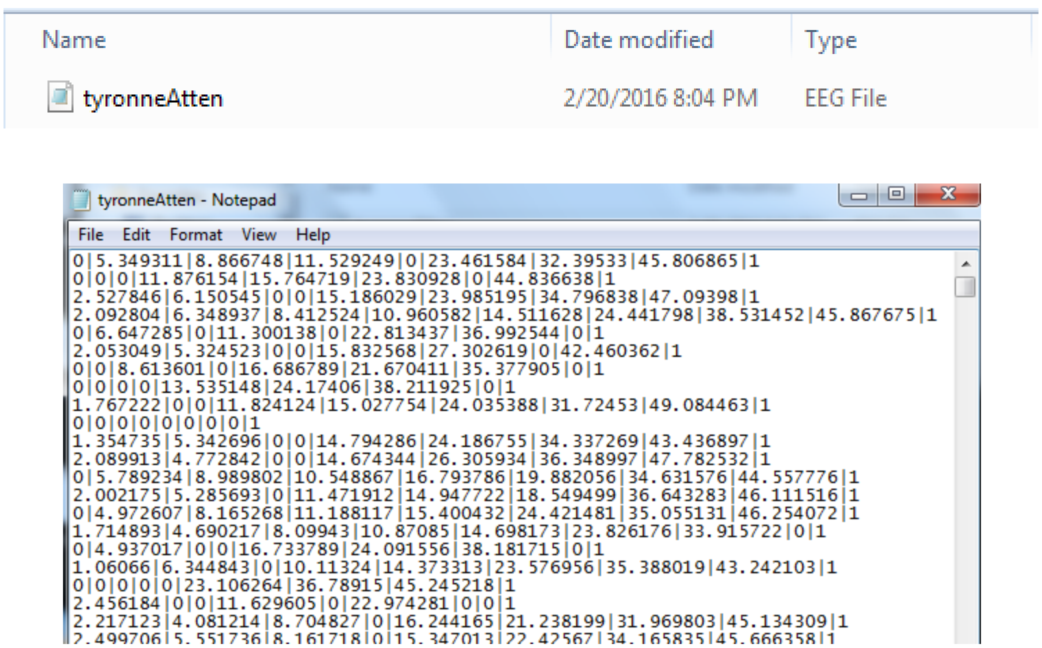


Figure 6.4: Captured EEG Data File

Once this is completed the neural Network needs to be setup and for this purpose we utilize the Encog-core DLL.

The neural network is composed of 8 input nodes as elaborated in chapter 5. For this training we utilized 10 hidden nodes and 1 output node which will produce the desired output. Sigmoid activation function was used along with learning rate of 0.4 and a momentum of 0.1. Back propagation algorithm was used along with supervised training. And below code segment expresses how the Neural Network was setup and how back propagation was used.

```
NeuralNetwork = new BasicNetwork();
///Set Up the Layers
ILayer outputLayer = null;
ILayer hiddenLayer = null;
ILayer inputLayer = null;

switch (cmbActivation.SelectedIndex)
{
    case 0:
    outputLayer = new BasicLayer(new ActivationSigmoid(), true, outputNodes);
    hiddenLayer = new BasicLayer(new ActivationSigmoid(), true, hiddenNodes);
    inputLayer = new BasicLayer(new ActivationSigmoid(), false, inputNodes);
    break;
    case 1:
    outputLayer = new BasicLayer(new ActivationLinear(), false, outputNodes);
    hiddenLayer = new BasicLayer(new ActivationLinear(), true, hiddenNodes);
    inputLayer = new BasicLayer(new ActivationLinear(), true, inputNodes);
    break;
    case 2:
    outputLayer = new BasicLayer(new ActivationStep(), false, outputNodes);
    hiddenLayer = new BasicLayer(new ActivationStep(), true, hiddenNodes);
    inputLayer = new BasicLayer(new ActivationStep(), true, inputNodes);
    break;
    case 3:
    outputLayer = new BasicLayer(new ActivationSIN(), false, outputNodes);
    hiddenLayer = new BasicLayer(new ActivationSIN(), true, hiddenNodes);
    inputLayer = new BasicLayer(new ActivationSIN(), true, inputNodes);
     break;
      }

//Add Layers
NeuralNetwork.AddLayer(inputLayer);
NeuralNetwork.AddLayer(hiddenLayer);
NeuralNetwork.AddLayer(outputLayer);

//Reset Structure and finalize
NeuralNetwork.Structure.FinalizeStructure();
NeuralNetwork.Reset();
```

```
if (dataSet != null && neuralNetwork != null)
{
    ITrain train =  new Backpropagation(NeuralNetwork, dataSet, learnrate, momentum);

     do
     {
        train.Iteration();
        String resultLine = "Iteration #" + train.IterationNumber + " Error:" + train.Error;
        trainData.Enqueue(resultLine);

     }
     while (train.Error > acceptableErrorRate);
}
```

Once the Artificial Neural network was setup the ".EEG" training data files were loaded and the network was trained until it reached a satisfactory error rate.

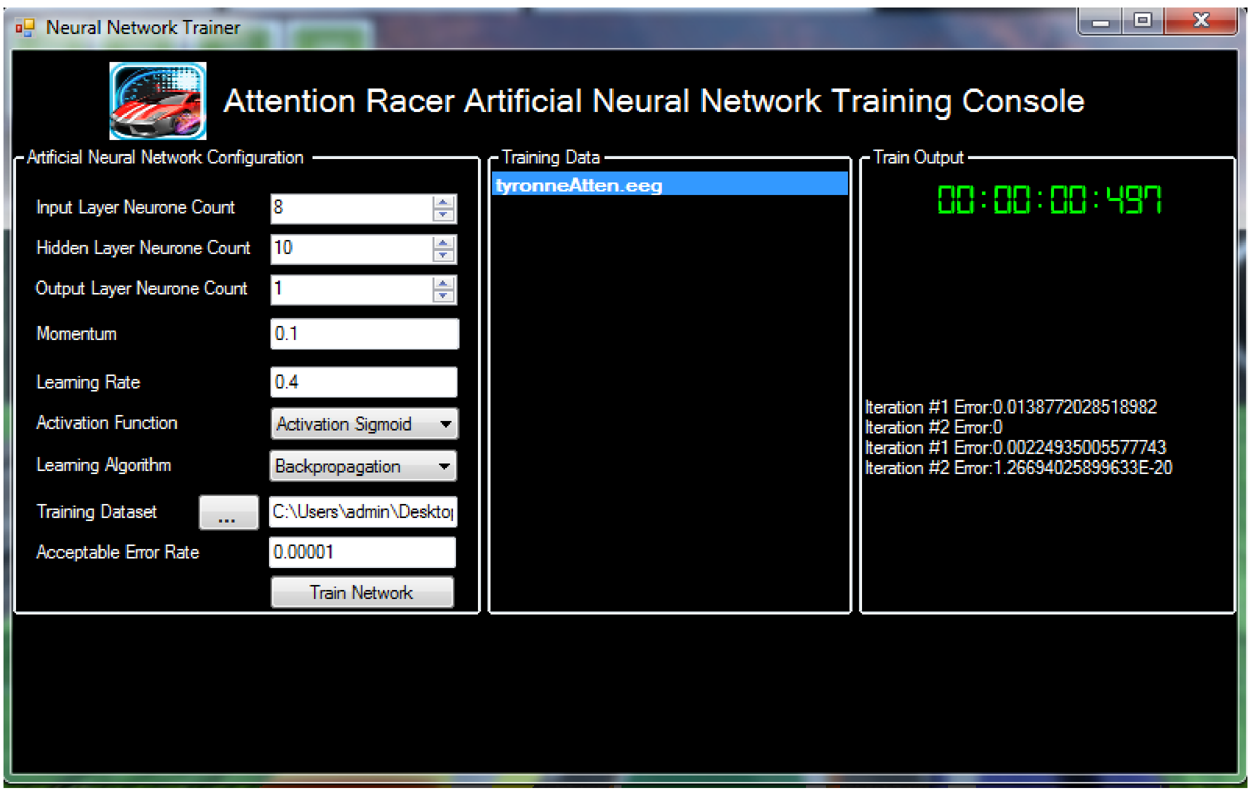


Figure 6.5: ANN Training Console

At the end of the training the trained Artificial Neural network was serialized for attention value calculation. The above features are facilitated by the above console Figure 6.5. Now the serialized trained network can be used for real time attention level calculation.

6.3.1. Artificial Neural Network for Attention level detection

Serialized trained artificial neural network mentioned in previous section is loaded to the memory and the data packet composing of band waves are passed to the trained network to get the attention value. This is done by below code segment.

```
public static double GetComputedResult(double[] INPUT)
{
   if (trainedNN == null || INPUT == null)
       return 0;

     double[] OUTPUT = new double[1];
     trainedNN.Compute(INPUT,OUTPUT);
     return OUTPUT[0];
}
```

Calculated attention value is displayed in attention racer system as below Figure 6.6 and the value is passed on to the attention racer game controller.

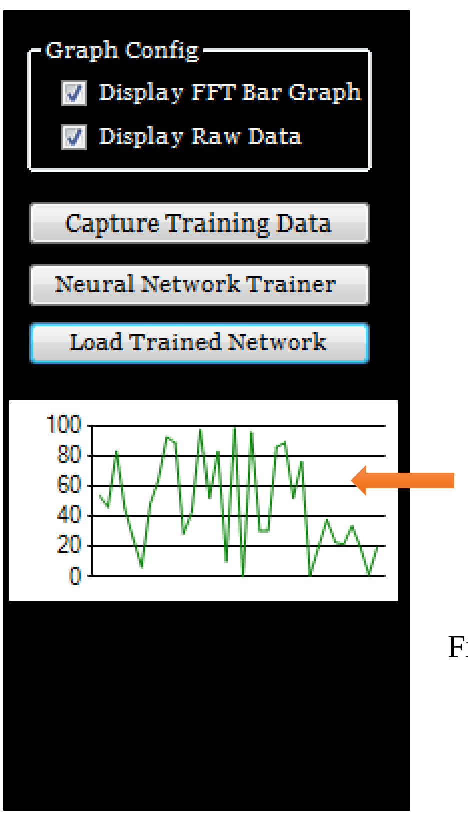


Figure 6.6: Attention Level Meter (0-100)

6.4. Attention Racing Game Application Module

The attention racing game module gets the attention as input value and used to control the speed of the users racing Car. However, before that the gaming environment, Gaming cameras and racing surface is set by Game controller. Open GL and Shadow Engine DLLs are used for these purpose and below code segment indicates how the Environment and cameras are setup. More details are appended to Appendix B.

```
public void DrawGameScene()
{
   //Environment
   gameEnvironment.DrawEnvironment();
   //draw the road
   racingSurface.DrawRacingSurface();
}

public void SelectCamaraView(CameraView camaraAngle)
{
    Gl.glMatrixMode(Gl.GL_MODELVIEW);
    Gl.glLoadIdentity();

      switch (camaraAngle)
      {
          case CameraView.Top:
           Glu.gluLookAt(0, 35, -15, 1, 0, -16, 0, 1, 0);
           break;
          case CameraView.Front:
           Glu.gluLookAt(3, 3, -47, 1, 0, 1, 0, 1, 0);
           break;
          case CameraView.Behind:
            Glu.gluLookAt(2, 3, 14, 2, 0, 5, 0, 1, 0);//Set View Angles
            break;
          case CameraView.BehindTop:
            Glu.gluLookAt(-2, 7, 10, 1, 3, 1, 0, 1, 0);
            break;
            }
}
```

When the environment setup is completed the game controller will place two autonomous racing car agents that would compete with the game user's car. Autonomous racing car agents utilizes an inbuilt agent framework and uses agent technology with ACL message passing. These car varies its speed and other aspects based on the state of the game. The speed control indication and two autonomous agents are represented as shown below in figure 6.7.

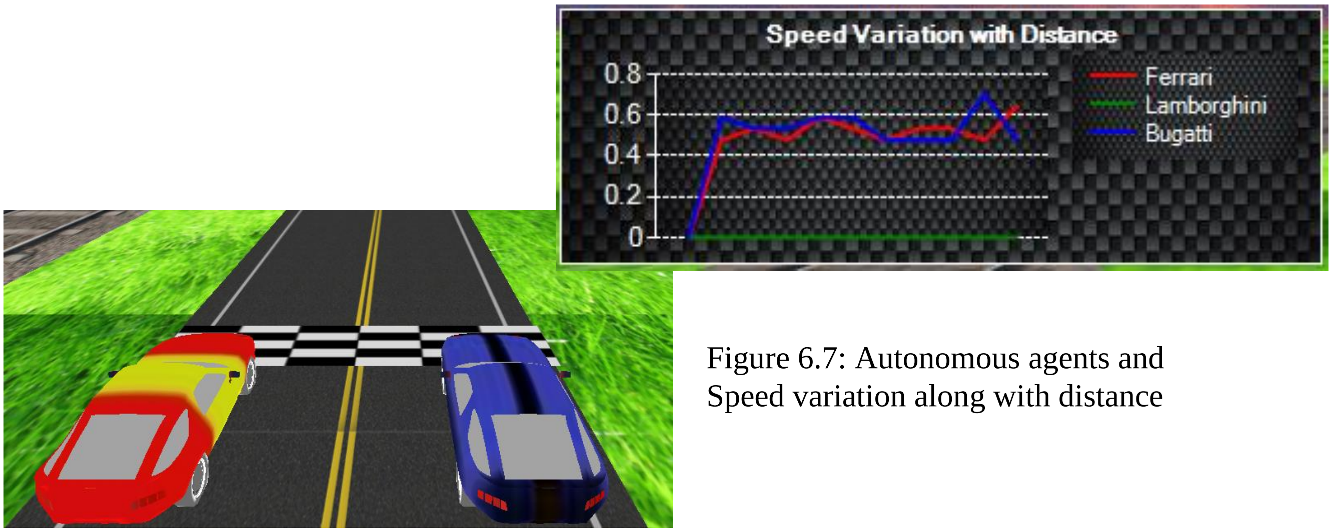


Figure 6.7: Autonomous agents and Speed variation along with distance

Finally the users racing car is placed on the gaming environment and is controlled by attention value.

6.5. Summary

This chapter elaborated on the implementation details of the attention racer application. It covered most important aspects of the system such as EEG signal gathering, Noise filtering, FFT analysis, Neural Network training, Attention value calculation and using the value to control the speed of the car. Next chapter focuses on the evaluation details of the system.

Chapter 7

Evaluation

7.1. Introduction

This chapter focuses on evaluating attention racer application to measure whether it works as anticipated in detecting attention level and whether it uses it effectively in game controlling. The chapter elaborates on data acquisition process using attention span test and utilizing the brain game to collect EEG data. Once the EEG data is obtained it was used to train the network. Then attention racer was evaluated in controlled experimental setup environment.

7.2. Experimental Design

The following section describes the evaluation process in detail by elaborating initial setup, Individual selection and module wise setup.

7.2.1. Initial Setup and Choice of individuals

Choice of individuals for evaluation process was done carefully by adhering to strict guidelines. As the first step in evaluation process the artificial neural network of the attention racer application should be trained accurately with attention data. It is crucial and vital that the neural network should be trained only and only with attention EEG data.

In order to accomplish this task initially the evaluation candidates had to go through an attention span test, by answering 10 question within 5 minutes honestly. The questions are hosted in "Psychology Today" web application, some sample questions are listed below Figure 7.1 and the entire questioner and URLs are attached to appendix C.

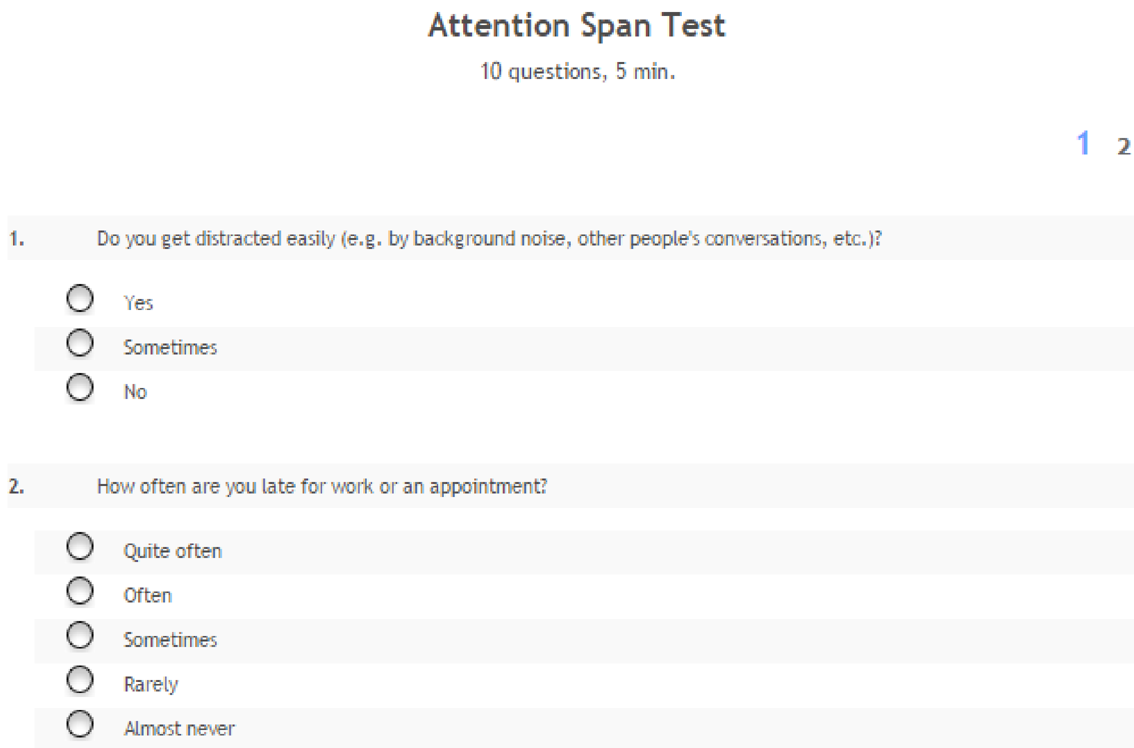


Figure 7.1: Attention Span Test Questions

15 individuals aged group from 25 to 40 participated in the test and those who obtained a score more than 75% on attention span test was selected for next phase of the evaluation. 10 individuals obtained scores more than 75% and 5 individuals scored below 75% in attention span test.

Each participants attention span score is listed in table 7.1 and individuals highlighted in red was rejected from participating in next phase of evaluation.

Participant	Attention Span Score
Udaya (Male)	68%
Tyronne (Male)	78%
Lakitha (Male)	82%
Tharindu (Male)	90%

Amila(Male)	61%
Roshini (Female)	50%
Vibeeshan (Male)	76%
Stephanie (Female)	78%
Praboda (Male)	75%
Samangi (Female)	80%
Hiran (Male)	64%
Ranmalee (Female)	77%
Uditha (Male)	89%
Tharika (Female)	90%
Vinusha (Male)	59%

Table 7.1: Participants' attention span score.

7.2.2 EEG data acquisition and Artificial Neural Network training

As mentioned in previous section (Subsection 7.2) 10 individuals were selected. It is vital that the ANN should be trained only with attention data. Thus, these 10 individuals were asked to wear the NeuroSky EEG headset and play an online Brian Game. In order to avoid them from playing this game from memory or previous experience they were allowed only to play this once and the writer made sure that they haven't played this game before.

The brain game was developed by "AARP brain games". The name of the game was "The Squeaking Mouse" and this game requires and individual to match the cries or noises of animals with their photographs. As illustrated in below figures 7.2. The URL of the game is attached to appendix C.

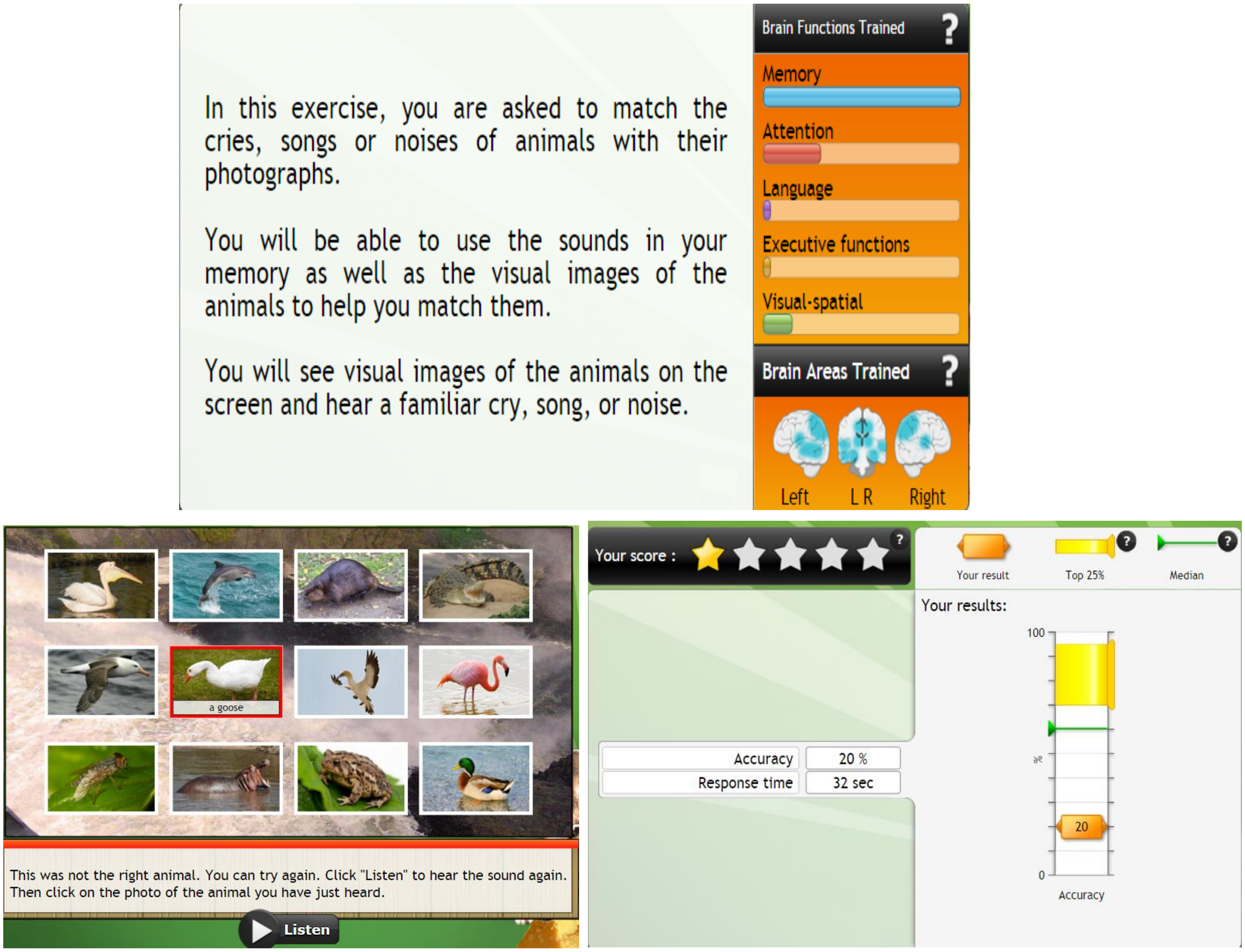


Figure 7.2: Brain Game Application

While individuals were interacting with the game the EEG data was recorded and these recorded data was used to train the Artificial Neural Network.

7.2.3 Evaluating the Neural Network

The 20% of the gathered training data was used to evaluate the Neural Network. The gathered data yielded in high attention level confirming the validity of the gathered data.

7.2.4 Evaluation setup for Attention Racer

Once the neural network was trained the 10 participants were requested to face the attention span test once again and then wear the NeuroSky EEG headset again and play the attention Racer application twice, one in a very calm environment and second in a noisy environment with background music.

While playing the game the Attention racer calculated the average attention level in calm environment and noisy environment for each participant. The below figure 7.4 illustrates the experiment design.

Figure 7.3: Experimental Design

7.3. Experimental results

The below table 7.2 illustrates the experimental results for the 10 participants in calm and noisy environments.

Participant	Mean Attention level (0-100) Calm Environment	Mean Attention level (0-100) Noisy Environment
Tyronne (Male)	71	32
Lakitha (Male)	88	40

Tharindu (Male)	25	44
Vibeeshan (Male)	77	32
Stephanie (Female)	69	41
Praboda (Male)	32	78
Samangi (Female)	42	66
Ranmalee (Female)	91	68
Uditha (Male)	58	42
Tharika (Female)	68	55

Table 7.2. Attention level in each environment

7.4. Evaluation Result discussion and conclusion

The experiment had a 70% success rate (7 out of 10) obtained mean attention levels as anticipated. 4 of the participants were females thus we can conclude that results were more generalized.

However, we had 3 anomalies (participants 3, 6 and 7) where the mean attention in noisy environment was higher than calm environment. This may have caused in minor errors in EEG data acquisition or artifact removal. Overall the system implementation and evaluation was success gaining a success rate of 70% in attention detection.

7.5. Summary

The chapter elaborated on the evaluation of the attention racer system. The selection of the participants. Data acquisition criteria and experimental design and results were discussed in detail. Finally the conclusion of the observed results were discussed and the conclusions were asserted clearly.

Chapter 8

Conclusion and Future Work

8.1. Introduction

This chapter summarizes the attention racer system. It was hypothesized that human attention can be used as input for game controlling. In order to prove this hypothesis NeuroSky mind wave mobile headset was used for EEG data acquisition and an artificial neural network was utilized for data classification. The report elaborated in detail about the existing systems, approach of the proposed system, design, implementation and finally the evaluation.

8.2. Conclusions

It was hypothesized that human attention can be used as an input parameter to control an aspect of a racing car game. For data acquisition NeuroSky EEG headset was utilized and the EEG data acquisition process was successful. Then Artificial Neural Network was used for data classification. ANN proved to be effective, efficient and most suitable machine learning technique for data classification and it calculated the attention level swiftly in a dynamic environment successfully.

Finally, agent based car game was developed and the users car speed was controlled by human attention level. And this module was also implemented successfully as anticipated.

The evaluation results in chapter 07 proved that system was successful 70% in detecting human attention level.

Thus, in a concluding note overall system development and evaluation was successful.

Following objectives were asserted in the introduction chapter of the thesis and was executed successfully in various stages of the research.

The goal of this project is to gain knowledge of the two domains, Brain-Computer Interfaces, special methods for analyzing brain waves, and AI techniques for Game design. From this research, a prototype software application should be implemented that is able to read brain wave input from an EEG device, classify them, and make them be part of the, or the only, user input to a game. This Objectives was successfully completed.

1. The EEG signals are commonly decomposed into five EEG sub-bands: delta, theta, alpha, beta and gamma. Hence, the research seek to study about these wave forms extensively to extract the human attention factor. This was successfully completed in technology section.

2. Furthermore, Support vector machines, decision trees and artificial neural networks are powerful machine learning techniques that can be used for EEG signal classification. Among these classification techniques, artificial neural network is one of the most popular technique for EEG classification Thus, the research focuses on developing an artificial neural network for EEG attention classification. This was successfully completed in Design and implementation of the system.

3. Moreover, Autonomous Agent and Multi-Agent Systems is the key in game development. Thus the research seek to develop a car racing game on a multi agent frame work using 3D gaming platform. This was also successfully completed in Design and implementation of the system.

Thus, all the above objectives were met in the research as anticipated.

8.3. Limitations and Future Work

There are several limitations in the system that needs to be addressed, Firstly, the NeuroSky headset takes around 5 seconds to detect noise and notify the attention racer system that user has detached the headset form his head.

Secondly, artificial neural network provided some anomalies 3/10 in detecting attention level despite the effort to use accurate EEG data for training.

As future work, multi electrode headsets can be utilized for EEG acquisition in order improve the accuracy of the output.

Furthermore, mediation, eye blink cognitive features can be used to control more aspects of the game for instance eye blink for acceleration of the car or for braking etc...

8.4. Summary

The chapter summarized about the report and discussed about the evaluation results, and how successful the research was. The limitation of the system was highlighted along with future work. In a concluding not the overall system and research was a success.

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Appendices

Appendix A:

NeuroSky Mindwave Mobile Protocols

A.1 Introduction

This section elaborates on NeuroSky EEG headset and its communication protocols

A.2 Technical Spec

The Mindwave Mobile safely measures and outputs the EEG power spectrums (alpha waves, beta waves, etc), NeuroSky eSense meters (attention and meditation) and eye blinks. The device consists of a headset, an ear-clip, and a sensor arm. The headset's reference and ground electrodes are on the ear clip and the EEG electrode is on the sensor arm, resting on the forehead above the eye (FP1 position). It uses a single AAA battery with 8 hours of battery life.

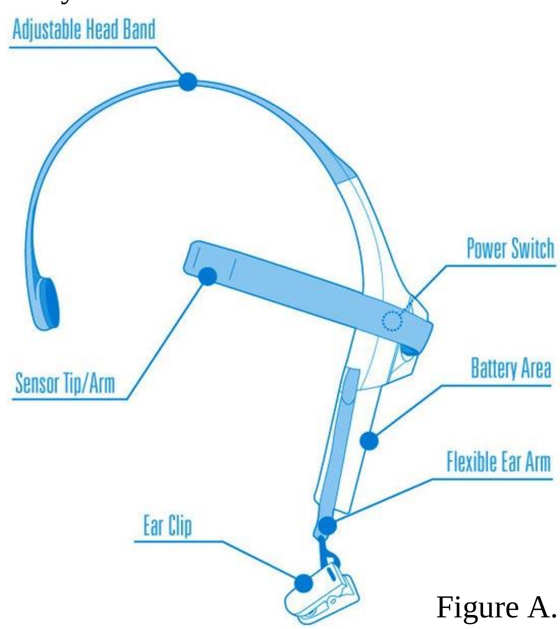

Figure A.1: NeuroSky Headset [38]

A.3 Headset Measures

- Raw-Brainwaves
- Processing and output of EEG power spectrums (Alpha, Beta, etc.)
- Processing and output of NeuroSky proprietary eSense meter for Attention, Meditation, and other future meters
- EEG/ECG signal quality analysis (can be used to detect poor contact and whether the device is off the head)

A.4 EEG Data types

The below table illustrates different types of outputs from NeuroSky headset.

Key	Description	Data Type
Time	TimeStamps of packet received	double
Raw	Raw EEG data	short
EegPowerDelta	Delta Power	uint
EegPowerTheta	Theta Power	uint
EegPowerAlpha1	Low Alpha Power	uint
EegPowerAlpha2	High Alpha Power	uint
EegPowerBeta1	Low Beta Power	uint
EegPowerBeta2	High Beta Power	uint
EegPowerGamma1	Low Gamma Power	uint
EegPowerGamma2	High Gamma Power	uint
Attention	Attention eSense	double
Meditation	Meditation eSense	double
PoorSignal	Poor Signal	double
BlinkStrength	Strength of detected blink. The Blink Strength ranges from 1 (small blink) to 255 (large blink). Unless a blink occurred, nothing will be returned. Blinks are only calculated if PoorSignal is less than 51.	uint

Table A.1: NeuroSky Headset Outputs [38]

A.5 .NET SDK

The below table A2 shows the API reference for .NET.

void Connect(string portName)	Attempts to open a connection with the port name specified by portName.
void ConnectScan()	Attempts to open a connection to the first Device seen by the Connector.
void ConnectScan(string portName)	Same as ConnectScan but scans the port specified by portName first.
void Discount()	Closes all open connections.
void Disconnect(Connection connection)	Close a specific connection specified by Connection.
void Disconnect(Device device)	Close a specific device specified by Device.
void Send(string portName, byte[byteToSend)	Send an array of bytes to a specific port.

Table A.2: NeuroSky Headset API Reference table

Appendix B:

Attention Racer System

B.1 Introduction

This chapter elaborates regarding the attention racer system implementation.

B.2 Main Screen of the application

The Figure B.1 illustrates the main screen for attention racer system. Composed of EEG data acquisition module, neural network module and racing game surface.

Figure B.1: Attention Racer Game Screen

B.3 EEG Data Acquisition Screen

The below screen Figure B.2 illustrates the EEG data gathering screen. This is used to acquire and save EEG attention data.

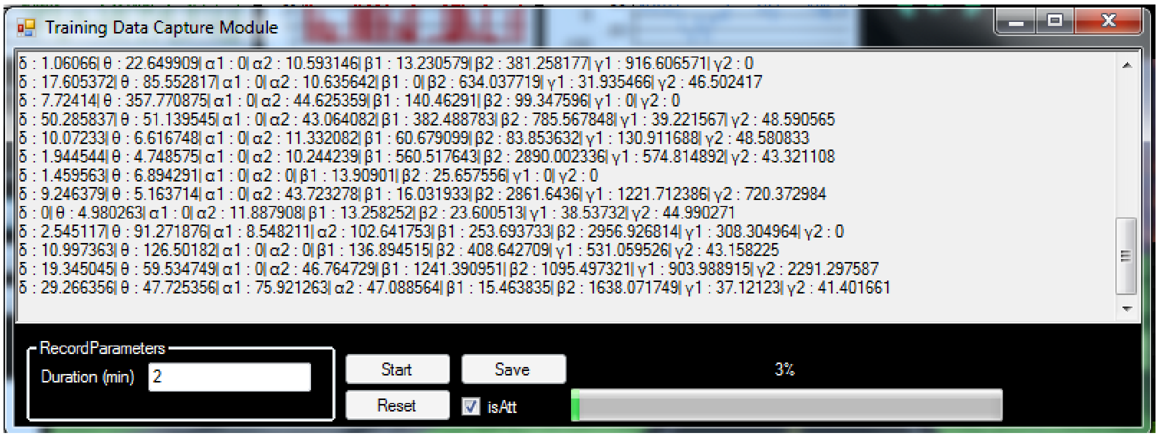

Figure B.2: EEG data gathering screen

B.4 Artificial neural network training screen

The blow Figure B.3 illustrates artificial neural network training module that is been utilized for ANN training.

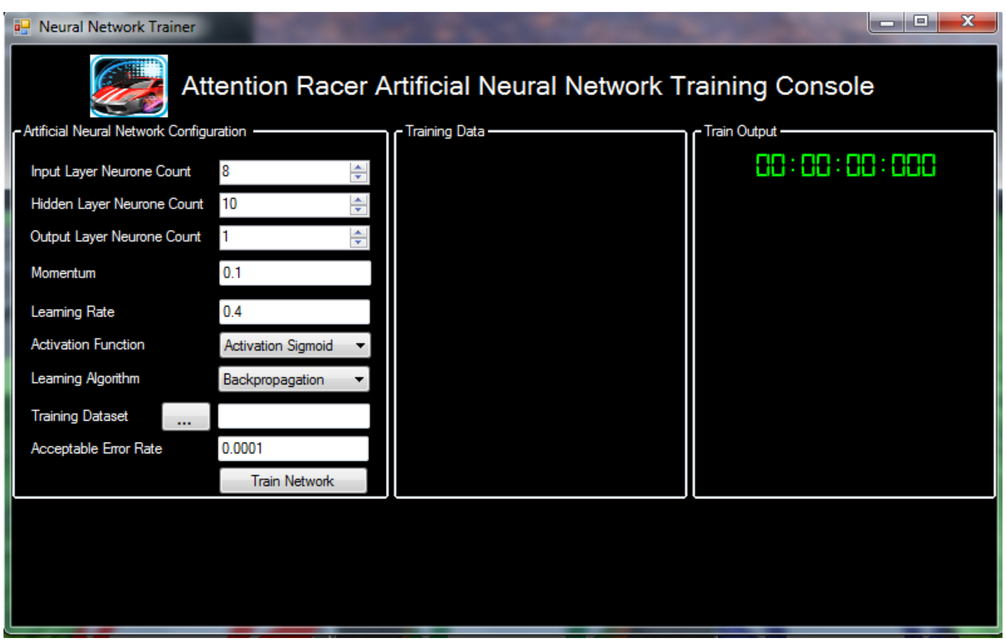

Figure B.3: Artificial neural network training screen

B.5 Console Logger

The below figure displays the console logger of the attention racer system which logs all the messages.

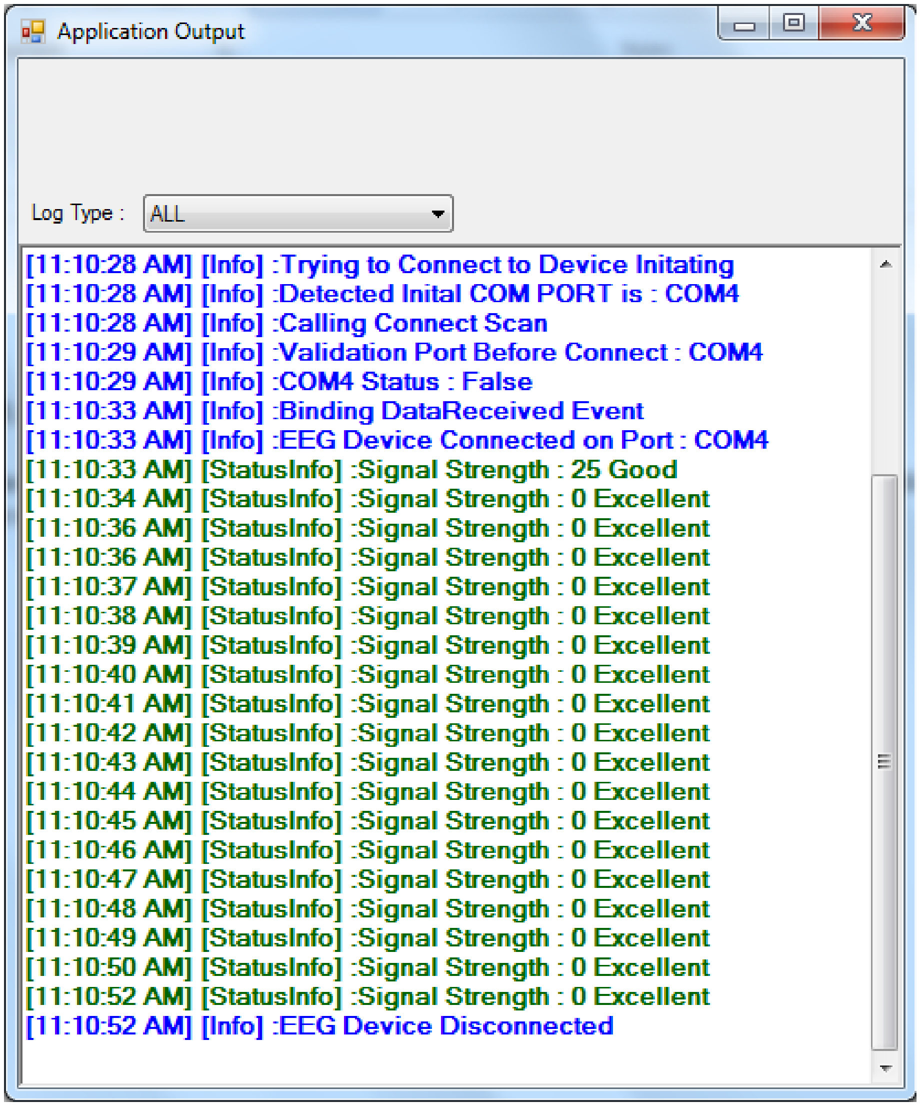

Figure B.4: Console Logger of Attention Racer

Appendix C:

Attention Span Test and Brain Game

C.1 Introduction

This chapter elaborates the details about attention span test and brain game used in evaluation phase.

C.2 Attention Span Test

The attention Span test questioner can be obtained from the below link.

http://psychologytoday.tests.psychtests.com/bin/transfer?req=MTF8MzM2MXwxMTEx
NTMyNHwwfDE=&refempt=

10 questions will be asked in 5 minutes and participants in evaluation are supposed to answer them. Once the test is completed marks will be calculated and participants above 75% attention span level is selected for evaluation. Sample questioner is listed below.

Attention Span Test

10 questions, 5 min.

1 2

1. Do you get distracted easily (e.g. by background noise, other people's conversations, etc.)?

- ○ Yes
- ○ Sometimes

- ○ No

2. How often are you late for work or an appointment?

- ○ Quite often
- ○ Often
- ○ Sometimes
- ○ Rarely
- ○ Almost never

3. How often do you catch yourself daydreaming at work?

- ○ Quite often
- ○ Often
- ○ Sometimes
- ○ Rarely
- ○ Almost never

4. Do you jump from task to task because you just can't seem to focus long enough to finish one completely?

- ○ Yes
- ○ Sometimes
- ○ No

5. How do you deal with boring, repetitive tasks?

- ○ I'm fine with them; I have very little trouble getting them done.
- ○ I don't mind them, but I may end up needing a break from time to time.
- ○ I can't stand them - they bore me out of my skull.

6. You're on the phone with a friend just as your favorite TV show starts. How difficult would it be for you to pay attention to the conversation?

- ○ Extremely difficult
- ○ Very difficult
- ○ Somewhat difficult
- ○ Slightly difficult
- ○ Not at all difficult

7. When reading a book or magazine, how often do you find yourself re-reading the same paragraph or skipping ahead?

- ○ Quite often
- ○ Often
- ○ Sometimes
- ○ Rarely
- ○ Almost never

8. Do you have a knack for noticing details (e.g. typos in a document)?

- ○ Yes
- ○ No

9. Do you lose your patience easily?

- ○ Yes
- ○ Sometimes
- ○ No

10. How often do you interrupt people during conversations?

- Quite often
- Often
- Sometimes
- Rarely
- Almost never

C.3 Brain game Design for attention data Acquisition

Brain game "The Squeaking Mouse" was developed by AARP systems and URL for the game can be found in below link.

http://braingames1.aarp.org/the_squeaking_mouse.html

The participants were requested to wear the NeuroSky Headset mobile and interact with this game for EEG data Acquisition. Below figure illustrates the game Screens.

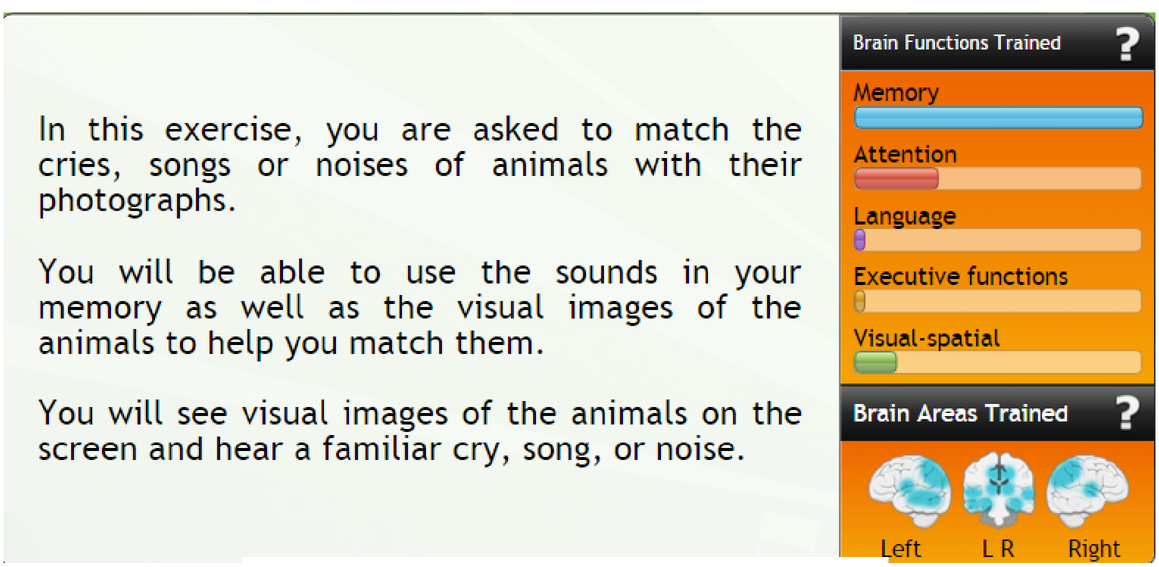

Figure C.1: The Squeaking Mouse Intro Screen

The below screen allows the user to perform required configurations to the system.

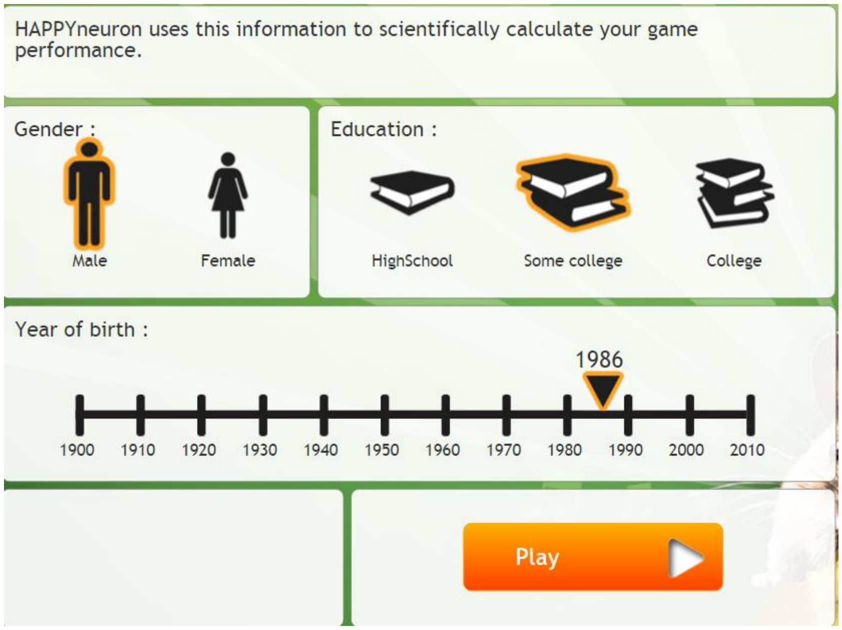

Figure C.2: The Squeaking Mouse Configuration Screen

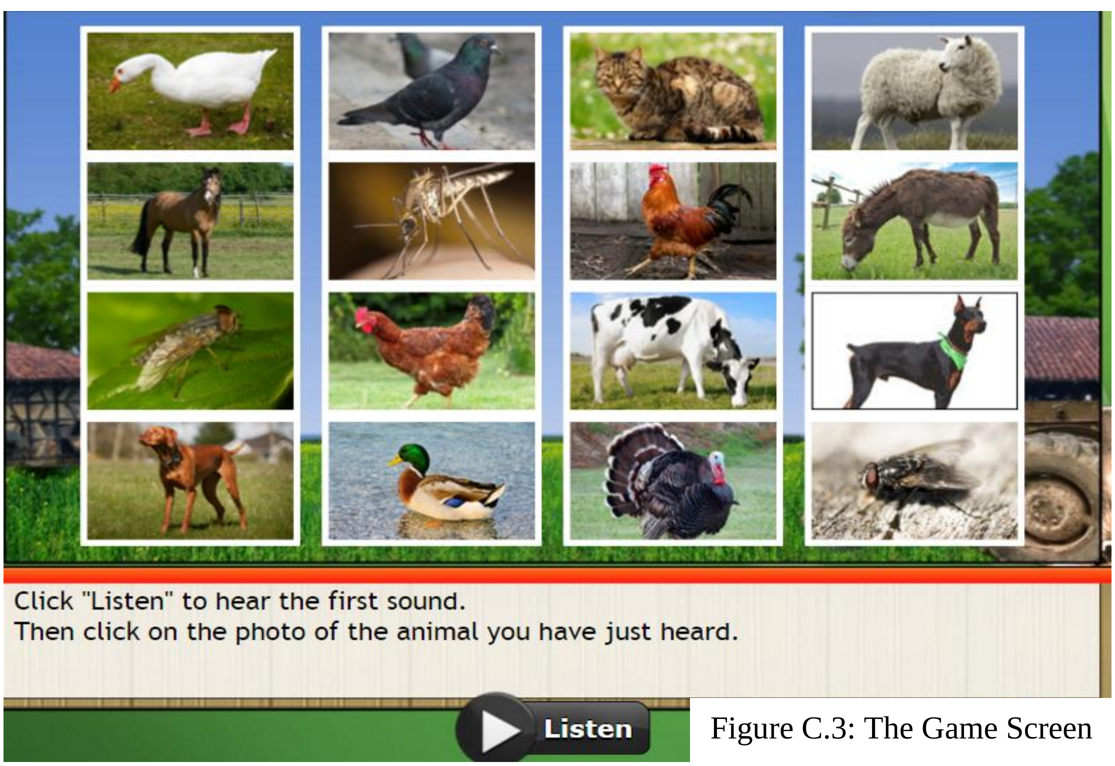

Figure C.3: The Game Screen