NTNU
Norwegian University of
Science and Technology

Classification of EEG Signals in a Brain-Computer Interface System

Erik Andreas Larsen

Master of Science in Computer Science
Submission date: June 2011
Supervisor: Alf Inge Wang, IDI
Co-supervisor: Jørn Hokland, IDI

Norwegian University of Science and Technology
Department of Computer and Information Science

Problem Description

This assignment should include both a theoretical and a practical part. In the theoretical part, current Brain-Computer Interface systems and methods should be researched, to create a state-of-the-art overview of, and to learn about the domain. The focus should be on the emergent commercialization of EEG products on the public market. In this project, a NeuroSky mindset (EEG equipment) is available as a test device.

The practical part should implement a system consisting of three modules. The first module should communicate with the NeuroSky mindset and get EEG signals, the second module should process those signals and make input parameters for the third module, which should be a game that have one or several features controlled by the input parameters. The goal is 1) that users should be able to control a game using their minds, and 2) investigate if low price EEG equipment enables that.

Assignment given: 17. January 2011
Supervisor: Alf Inge Wang, IDI
Co-supervisor: Jørn Hokland, IDI

Abstract

Electroencephalography (EEG) equipment are becoming more available on the public market, which enables more diverse research in a currently narrow field. The Brain-Computer Interface (BCI) community recognize the need for systems that makes BCI more user-friendly, real-time, manageable and suited for people that are not forced to use them, like clinical patients, and those who are disabled. Thus, this project is an effort to seek such improvements, having a newly available market product to experiment with: a single channel brain wave reader. However, it is important to stress that this shift in BCI, from patients to healthy and ordinary users, should ultimately be beneficial for those who really need it, indeed.

The main focus have been building a system which enables usage of the available EEG device, and making a prototype that incorporates all parts of a functioning BCI system. These parts are 1) acquiring the EEG signal 2) process and classify the EEG signal and 3) use the signal classification to control a feature in a game. The solution method in the project uses the NeuroSky mindset for part 1, the Fourier transform and an artificial neural network for classifying brain wave patterns in part 2, and a game of Snake uses the classification results to control the character in part 3.

This report outlines the step-by-step implementation and testing for this system, and the result is a functional prototype that can use user EEG to control the snake in the game with over 90% accuracy. Two mental tasks have been used to separate between turning the snake left or right, baseline (thinking nothing in particular) and mental counting. The solution differentiates from other appliances of the NeuroSky mindset that it does not require any pre-training for the user, and it is only partially real-time.

Preface

This report is the final product to complete my Master of Science degree at the Norwegian University of Science and Technology (NTNU). The project was conducted in the period of January to June 2011, at the Department of Computer and Information Science.

I would like to thank my supervisor, associate professor Alf Inge Wang, for valuable discussions and supporting follow-up throughout the project lifespan and for providing me with the necessary equipment. Also, thanks to my co-supervisor, associate professor Jørn Hokland for giving me this opportunity and for being understanding.

Finally, I would like to thank my fellow students Kjetil Aamodt and Kjetil Valle for their general support, lectures on neural networks and for sharing their thoughts when I asked questions, even though they were just as clueless to the answers as me. And of course Bjørg Ane Sandve for being an enthusiastic test guinea pig.

Trondheim, June 2011,
Erik Andreas Larsen

Contents

List of Figures

List of Tables

1 Introduction : The Big Picture

This chapter introduces the project by elaborating its why, how and what, illustrated in figure 1.1. It presents the project motivation and context. Finally, an overview of the report structure is stated.

1.1 Project Purpose: Why Take BCIs to a new Level?

The purpose of this project is to investigate and explore the possibilities that lies within the domain of Brain-Computer Interfaces, using consumer friendly equipment that have recently become available on the public market. The field of Brain-Computer Interfaces (BCI) is a driving force for utilizing electroencephalography technology (EEG), which is the process of recording brain activity from the scalp using electrodes (See chapter 3). In the past, the main focus have been about developing applications in a medical context, helping paralyzed or disabled patients to interact with the external world (Plass-Oude Bos et al., 2010), by mapping brain signals to human cognitive and/or sensory-motor functions.

Figure 1.1: The golden circle model (Sinek, 2009).

However, BCI development is no longer constrained to just patients or for treatment, there is a shift of focus towards people with ordinary health. Especially gamers are becoming a target group that would likely to be adaptive to use EEG as a new modality; giving them advantages or new experiences in gameplay. It is not just treatment in mind, but entertainment also. This shift could benefit patients, because when EEG technology becomes more available, and the powerful gaming industry gets involved, they can become the same driver for improvements as they are for all silicon-based technology: needing, and thus getting, faster processors and graphic engines so they can create better games.

By taking BCI to the level of entertainment, the motivation for making more user-friendly, faster, cheaper and public available systems will be totally different and become of a much higher priority. The targeted group of users are not forced to utilize BCI systems, and thus needs better reasons for wanting to, other than it is cool to be able to control your computer with the mind. Current systems do not meet such standards, which is further elaborated in the next section and chapter 3. The motivating thought is that approaching this issue from an entertaining point of view could help getting BCIs to such standards faster.

1.2 Project Strategy: How NeuroSky Could Level Up BCIs

NeuroSky is a company with the slogan *"Bio Sensors for Everyone!"*, and in late 2009 they released a EEG device named the NeuroSky mindset at a low cost, aimed at the consumer market (Neurosky, n.d.). Shipped with software development tools, people at home can explore the technology, and integrate it with their own design and systems. What used to be reserved for those who had the big money to pay for such equipment, are now very much available for anyone who are interested, either as a user, a developer, or both. This is great news for accelerating BCI research since more people can contribute. The strategy for this project is to utilize the NeuroSky mindset technology and do just that. But, the mindset only provides the brain wave signal, and to interpret and classify it, an artificial neural network will be used. More on this in chapter 5.

To better understand current BCI, consider an example from neurofeedback training used as a treatment alternative for persons with AD/HD. Neurofeedback, also called biofeedback, is a treatment where EEG equipment is used to present real-time records of brain activity. This enables you to train yourself, for instance to become more concentrated or relaxed, by altering your brain wave patterns over time. Feedback about your concentration level is for instance given as a graph, illustrated in figure 1.2.

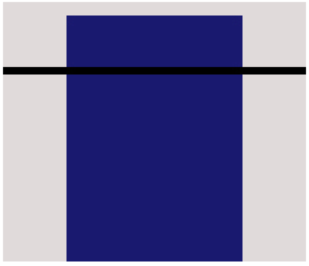

Figure 1.2: Feedback using a blue bar graph.

The subjects task is usually to keep the bar above a certain threshold, indicated here by the horizontal black line. Typically one training sessions like this last for about 45-60 minutes and needs to be repeated to get the wanted effect, variating from 25-50 times depending on the patient (Heinrich, Gevensleven, & Strehl, 2007). This can easily get boring or frustrating for a patient with AD/HD, or anyone else for that matter. Now it is possible to change that.

1.3 Project Results: What a NeuroSky BCI System Could Become

The goal of this project is to gain knowledge of the two domains, i.e Brain-Computer Interfaces, especially methods for analyzing brain waves, and the NeuroSky EEG equipment. 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.

A simple example scenario is as follows: A user is wearing the NeuroSky mindset that forwards brain wave signals to the software application. In order to get general information about the users brain wave pattern, a series of mental task scenarios must be executed by the user. This information will then be used to train a classification system so it can learn to recognize and thus map different brain patterns to actions. The user can then start a game, and the classification system will continuously analyze the incoming brain waves and map them to the appropriate actions and thus control some feature(s) of the running game.

1.3.1 Medical Verification Disclaimer

This project is experimental. The primary objective is to achieve a proof of concept by using the available technologies and following the strategy of the project. Although the medical aspect and clinical value are discussed and argumented for, it is for motivation only. It is outside the scope of this project to verify its medical and clinical utility or its plausibility. However, the possibility for the project of having such value needs to be put into consideration and kept in mind throughout the duration of this project.

1.4 Report Outline

This section describes the remaining chapters and the report structure. The goals and objectives of the project have been introduced in this chapter.

Chapter 2 describes the related work and background for this project and identifies the most important research questions and method of approach.

Chapter 3 explains how the EEG technology works, and the different brain activity patterns that are the foundation for EEG analysis.

Chapter 4 elaborates the Brain-Computer Interface technology, how far it has developed, what it is currently used for and a few underlying methods.

Chapter 5 introduces the main system design and equipment that was available for realizing and implementing it. The different components and their relations to each other are explained.

Chapter 6 reviews the result of using the implemented system for basic eye-blink classification. It describes the method used, and analyses the results in a discussion.

Chapter 7 reviews the result of using the implemented system for mental task classification, which is counting. It describes the method used, and analyses the results in a discussion.

Chapter 8 reviews the result of using the implemented system for controlling a game (a classical Snake-game) according to the project goal. It describes the method used, and analyses the results in a discussion.

Chapter 9 summarize and concludes the project in perspective of the big picture and the research questions from chapter 2. It also makes suggestions for further work.

2 Research Questions and Methods

This chapter explains the background for this project, and identifies the main research questions and methods to bring clarity and define the projects focus, based on lessons learned from earlier efforts and new anticipations.

2.1 Previous Work - How This Project Came Into Being

This project builds upon two previous projects, described below. The latter is the final work of the course TDT4500 - Intelligent Systems Specialization Project, executed autumn 2010, and is the first part of my Master of Science degree.

2.1.1 Playstation Controlled by Brain Waves

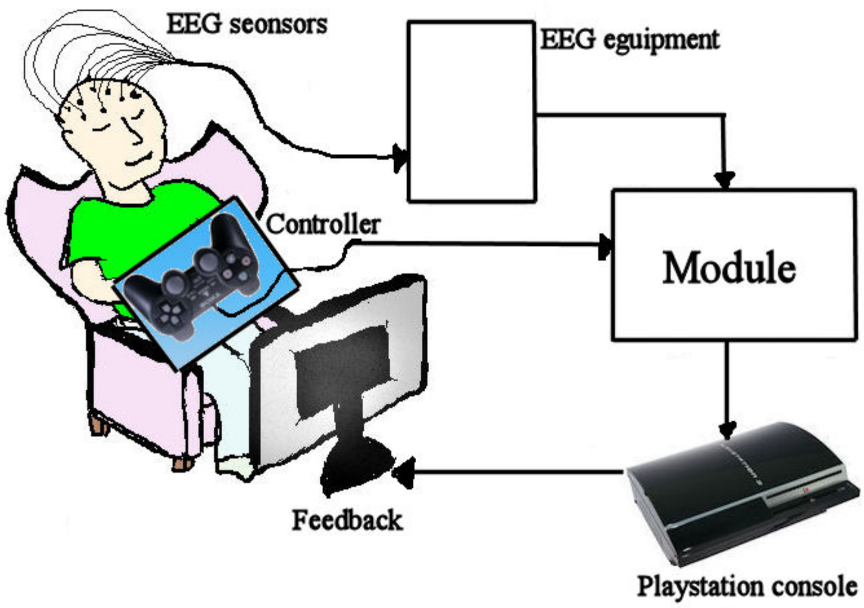

Figure 2.1: System Design: component overview. Sensors reads brain activity and sends signal to the EEG amplifier equipment. The EEG signal is sent to the module, that overrides the Playstation controller. Feedback is given on the screen.

The goal of this project was to meet some of the challenges that people with Attention Deficit and Hyperactive Disorder (AD/HD) have regarding the use of neurofeedback as a treatment option (Pointed out in section 1.2). The electroencephalography laboratory (EEGlab) at the Department of Psychology at NTNU, BUP (outpatients clinic for children) and St.Olavs Hospital, have a co-operative venture where neurofeedback is used when there is suspicion of such disorder or learning disabilities in children. They were interested in exploring a different approach to the usage of this technology; making neurofeedback training more attractive, reducing the training and equipment expenses and making it more fun and available to the public. The proposed method was to combine neurofeedback training with playing video games on a Playstation.

The result was a system with the ability to use clinical approved EEG equipment to control the acceleration of a racing car in a video game, both on PC and Playstation, see figure 2.1. In conclusion, this made it possible to consider a more entertaining way of performing neurotherapy and prompted for a field study to map the potential for further investment (Larsen, 2010).

2.1.2 Helicopter Controlled by Brain Waves

The playstation project builds on work done by Andersen, Juvik, Kjellen, and Storstein (2009), as part of a multidisciplinary course at NTNU. On initiative from Egil Tjåland and in cooperation with Stig Hollup at Department of Psychology, their assignment was to steer a radio controlled helicopter using the principles of neurofeedback. With their solution they were able to adjust the speed of the rotor using the level of concentration in a test person, and lift it off the ground. They developed an application that interfaced EEG software with the radio controller software of the helicopter.

2.2 Project Focus Based on Experience and new Expectations

Figure 2.2: Traditional cap with a grid of electrodes vs. new type, single electrode headset (NeuroSky).

A major limitation in the playstation and the helicopter project was that the EEG signal from the equipment was unavailable as raw and unaltered data. The only information that was available was a modified number from the accompanying software that represented the users concentration level, ranging from 1 to 15. Also, the EEG equipment used, from the Russian company Mitsar (Mitsar, 2008), is expensive. But, the second major limitation is the electrodes needs to be manually placed in a cap, similar to the ones to the left in figure 2.2, but with only two electrodes. Conductive gel was need to be used between the electrodes and scalp surface, and took some time to set up.

The NeuroSky mindset eliminates those limitations by making raw EEG data available and by using a dry sensor which comes pre-attached to the headset. Those are major advantages regarding system development and usability, but there is also drawbacks attached. There is only one electrode, that is statically placed on the forehead. Observable at the tip of the arm to the right, in figure 2.2. Comparing the traditional cap and the NeuroSky mindset, the traditional cap looks like it gives a lot more accurate measurements.

2.2.1 Research Questions

Table 2.1 shows the few superior research questions pre to implementing and experimenting. They are kept open-wide as much details are unknown in advance, but expected to emerge throughout the project.

Table 2.1: Superior research questions

Tag	Description
RQ1:	Can one static sensor on the forehead make up for a grid of sensors placed across the scalp?
RQ2:	What are the advantages and limitations of the NeuroSky mindset?
RQ3:	What kind of classification of brain waves will it be possible to make using a neural network? And if possible, how stable is this classification?
RQ4:	How satisfying or useful will a resulting and working BCI system be for the user?
RQ5:	How little practice and training time is it possible to get away with without affecting the performance of the BCI system?

2.2.2 Research Method

The approach will follow an iterative, empirical trial-and-error model. Uncertainty about what that will work with regards to EEG classification, in a real-time environment makes this reasonable. This also makes it difficulty to break down the goal into easy-to-follow steps, pre-experimenting. The research questions will be a priority, but any findings and interesting experiences should be investigated further and reported. Thus, this research will be an floating process from start to finish, and background information will be inserted were it is relevant and discovered; not only in chapter 3 and 4. This is done to improve readability.

3 EEG Technology: Why and How it Works

This chapter explains how EEG technology works, and the different brain activity patterns that are a foundation for EEG analysis. Followed by some words on the practical applications of it. First, a quick distinction: EEG is about the brain waves themselves, and BCI are more the entire system of interpreting these in a computer fashion.

3.1 EEG Background and Why Brain Activity Can Be Measured

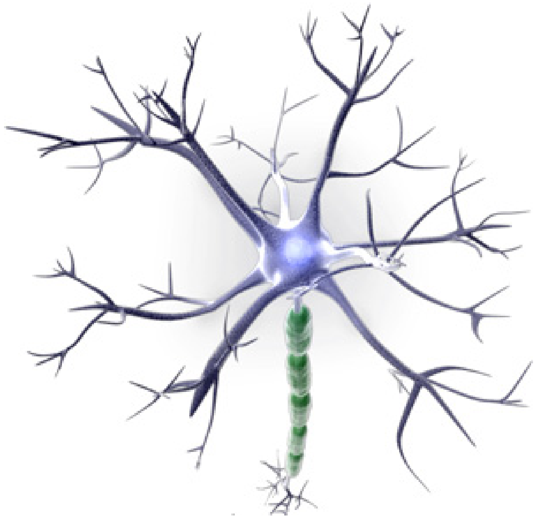

Figure 3.1: Artistic illustration of a single neuron and its synapses.

The brain have always fascinated humans, and particularly a German scientist named Hans Berger, who discover electroencephalography (EEG) about 80 years ago. After this, new methods for exploring it have been found and we can categorize them into two main groups. Invasive and non-invasive. An invasive approach requires physical implants of electrodes in humans or animals, making it possible to measure single neurons or very local field potentials. A non-invasive approach makes use of, for instance, magnetic resonance imaging (MRI) and EEG technology to make measurements. Both gives different perspectives and enables us to look inside the brain and to observe what happens (Kropotov, 2009). In EEG, brain-related electrical potentials are recorded from the scalp. Pairs of conductive electrodes (see figure 4.2) made of silver, for example, are used to read this electricity. The difference in voltage between the electrodes are measured, and since the signal is weak (30-100μV) it has to be amplified. 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**.

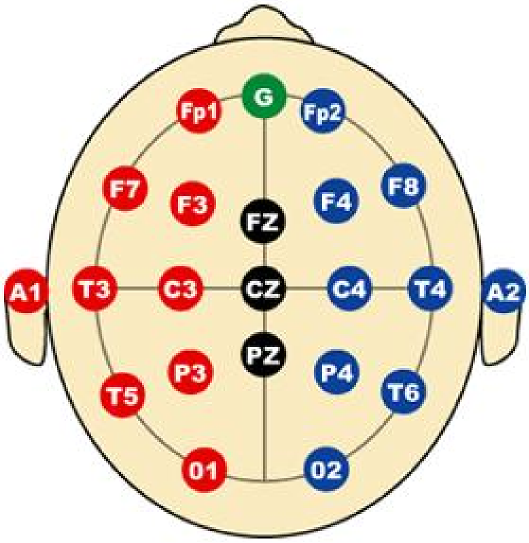

Figure 3.2: The 1020 System - Standardized placement of electrodes on scalp for EEG measurements (Immara, n.d).

3.2 Identifying Different Brain Activity Patterns

Returning to Berger, he found that different electrical frequencies could be linked to actions and different stages of consciouses. This was done by observing subjects performing different task, like solving mathematical problems, while recording their EEG. Figure 3.8 shows the most used frequency bands, and their relations, of the human brain wave activity.

Figure 3.3: Gamma wave.

Gamma waves are in the frequency range of 31Hz and up. It is thought that it reflects the mechanism of consciousness. Beta and gamma waves together have been associated with attention, perception, and cognition (Rangaswamy et al., 2002).

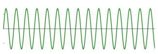

Figure 3.4: Beta wave.

Beta waves are in the frequency range of 12 and 30 Hz, but are often divided into β_1 and β_2 to get a more specific range. The waves are small and fast, associated with focused concentration and best defined in central and frontal areas. When resisting or suppressing movement, or solving a math task, there is an increase of beta activity (Y. Zhang, Chen, Bressler, & Ding, 2009). In one study by Rangaswamy et al. (2002), significantly increased beta power was found in all of the 307 alcohol-dependent subjects, measured across the whole scalp. This leads to an hyperexcitable state which consumption of alcohol temporarily alleviates.

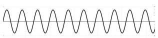

Figure 3.5: Alpha wave.

Alpha waves, ranging from 7.5 to 12 Hz, are slower and associated with relaxation and disengagement. Thinking of something peaceful with eyes closed should give an increase of alpha activity. Most profound in the back of the head (o1 and o2, figure 3.2) and in the frontal lobe. Several studies have found a significantly rise in alpha power after smoking marijuana (Lukas, Mendelson, & Benedikt, 1995).

Figure 3.6: Theta wave.

Theta waves, ranging from 3.5 to 7.5 Hz, are linked to inefficiency, daydreaming, and the very lowest waves of theta represent the fine line between being awake or in a sleep state. Theta arises from emotional stress, especially frustration or disappointment (L. Zhang, He, Miao, & Yang, 2005). It has also been associated with access to unconscious material, creative inspiration and deep meditation. High levels of theta are considered abnormal in adults, and is, for instance, much related to AD/HD (Heinrich, Gevensleven, & Strehl, 2007).

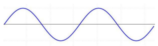

Figure 3.7: Delta wave.

Delta waves, ranging from 0.5 to 3.5 Hz, are the slowest waves and occurs when sleeping (Hammond, 2006). If these waves occur in the awake state, it thought to indicate physical defects in the brain. Movement can make artificial delta waves, but with an instant analysis (just observing raw EEG records), this can be verified or unconfirmed.

MU is associated with motor activities, and is also found in the alpha wave frequency range, but where the maximum amplitude is recorded over motor cortex. So it basically triggers when there is an actual movement or there is an intent to move (Bernier, Dawson, Webb, & Murias, 2007).

All these wave-groups occur in different parts of the brain in varying degree.

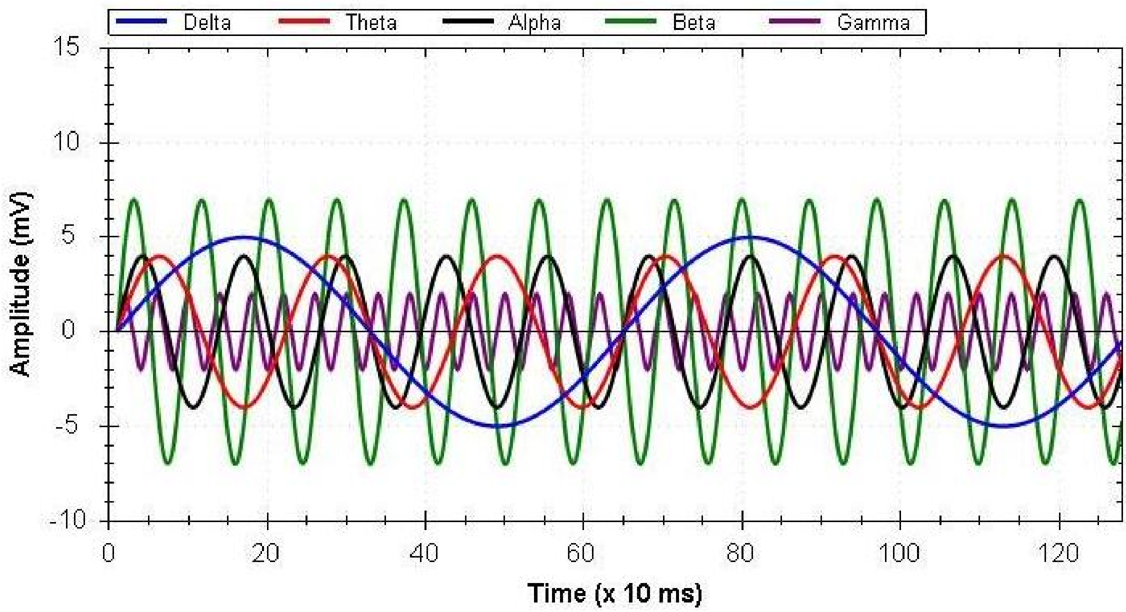

Figure 3.8: The 5 main frequency bands and their relation to each other.

3.3 Practical Application of EEG Technology

The most used application of EEG is to observe and study records manually, to search for, or to understand, brain damage and various disorders, like for instance epilepsy (Sundaram, Sadler, Young, & Pillay, 1999). Empirical research and case studies throughout the decades have led to functional brain maps, see figure 3.9, that combined with electrodes placed according to the 10-20 system (see figure 3.2) makes activity in these areas observable. Indeed, EEG is a tool used in hospitals for declaring patients brains to be dead, when no activity is monitored.

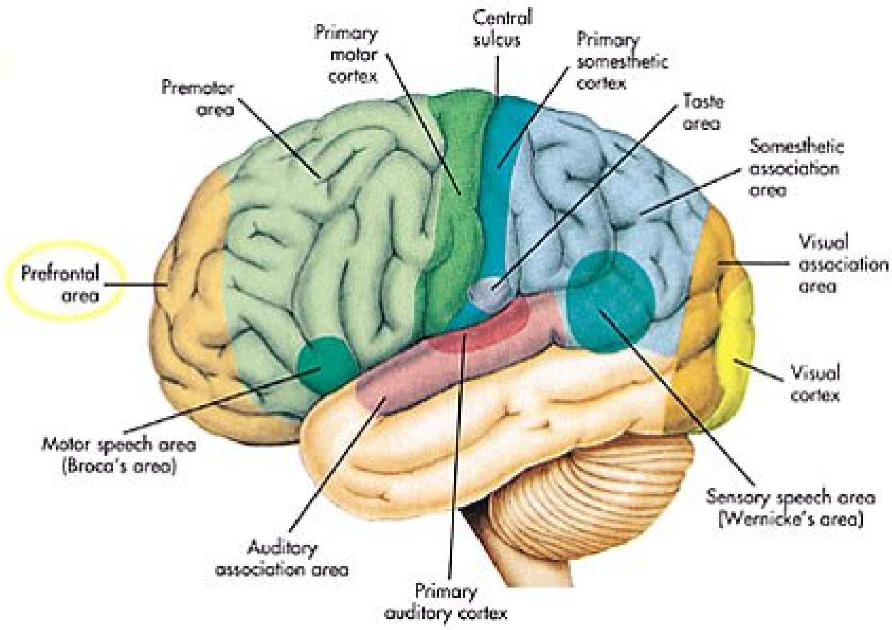

Figure 3.9: Basic functional brain map (Universe-review.ca, n.d.).

The study of brain waves and how they relate to different mental states, have led to number of alternative methods and beliefs on how to manipulate these waves. For instance, in order to become e.g more relaxed, focused and smarter, you can buy music that plays in specific hertzes that promise to do just that (*Brain Entertainment*, n.d.). A well known advice deduced from this is that you should let your baby listen to Mozart while growing up, having the effects mentioned. Besides this somewhat regarded pseudoscience, there have been a lot of interesting studies of mental states and how they are effected, summarized for instance in Braverman (1990). A area that have been researched in a great amount is the relation of drugs, medication and EEG. And according to his article, an increase of alpha activity is found when taking antidepressants, and addictive drugs like morphine, heroin and marijuana. It has also been identified that drug users often lack a natural amount of occurring alpha waves, and thus it can explain why they become addicts. Alcoholics have been found to have an excess of occurring beta waves, and that this can inhibit their ability to relax. Alcohol research shows that its use increases the amplitude of the slow waves frequencies and decrease the fast waves. Thus, it suggests that alcohol becomes the quick remedy to become relaxed.

Further, Braverman talk about "how brain waves symbolizes the various parts of our consciousness, and that if we get the knowledge and treatment to change them, we can get closer to get our very balanced brain waves, or happiness". One way to get knowledge is to use ERP, described below, and one way to conduct treatment is a method called neurofeedback, further described in section 3.3.2.

3.3.1 Event Related Potentials (ERP)

Exposure to external stimuli, such as a tone or light flash, can generate responses in the EEG wave, as shown in figure 3.10. Internal stimuli, like skipping an expected stimulus can also generate a response. In both cases this is called Event Related Potentials (ERP), or Evoked Potential (EP). What this means exactly is that there is an observable amplitude peak (potential) that occurs at a definite latency time after the specific stimuli. The most used is the P300, were the peak comes 300 ms after the event. In chapter 4 we will see BCI systems applying this. In diagnostic appliance, however, P300 is used to map the external stimuli to brain activity in specific areas. For example, if exposed to a tone, there should be a reaction in the EEG close to the auditory processing area (See figure 3.9).

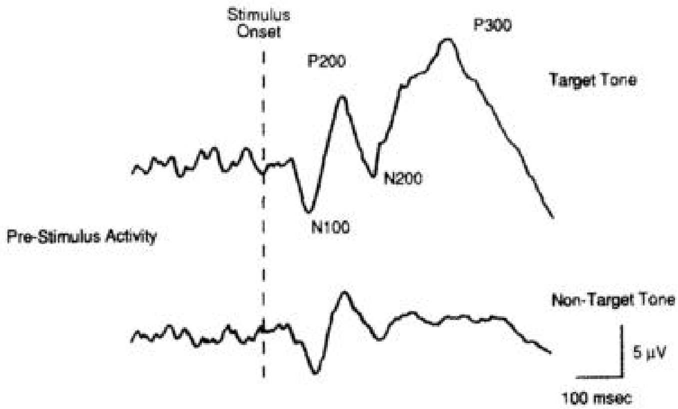

Figure 3.10: "Sample-evoked response potential in response to a target (70 dB. 2 kHz) and nontarget (70 dB, 1 kHz) tone. The P300 wave is clearly seen only after presentation of the target tone." (Lukas et al., 1990).

3.3.2 Neurofeedback Training and how it Can be Used to Treat AD/HD

AD/HD is a common diagnostics that EEG helps to detect. Traditionally, an increase of beta activity and a decrease of theta activity is wanted to reduce inattention (Kropotov et al., 2007). Studies of AD/HD treatment using neurofeedback have been criticized for being small in scale, and for not providing enough statistical power. But recently, in addition to these small scaled studies, larger studies have been conducted that concludes in favor of such treatment (Gevensleben et al., 2009) (Sherlin et al., 2010) (Heinrich et al., 2007) (Masterpasqua & Healey, 2003). People with AD/HD tend to have more slow waves in general, and when they are present in the frontal lobe, the forehead, it becomes difficult to manage attention, behavior and impulse control.

The principle of altering brain waves is shown in figure 3.11, and is an example of an BCI. Self-regulative abilities to do this comes by getting real-time visual and/or auditory feedback, and is like operant conditioning. With frequent training, long termed effect is possible (Hammond, 2006). Electrodes on the scalp picks up the electrical activity, the signals are weak so they go into an amplifier that boosts them before it is sent to a software on a computer. There the signal gets interpreted and processed into feedback to the user. Dividing the signal into the frequency bands can be done by applying a Fourier transform (further explained in section 4.3). Their factors can then be used to calculate a ratio, for instance Beta/Theta (Leins, Goth, Hinterberger, Klinger, & Strehl, 2007). This ratio can be used to determine the hight of a bar graph (Figure 1.2) and displayed on a monitor. Feedback is obtained.

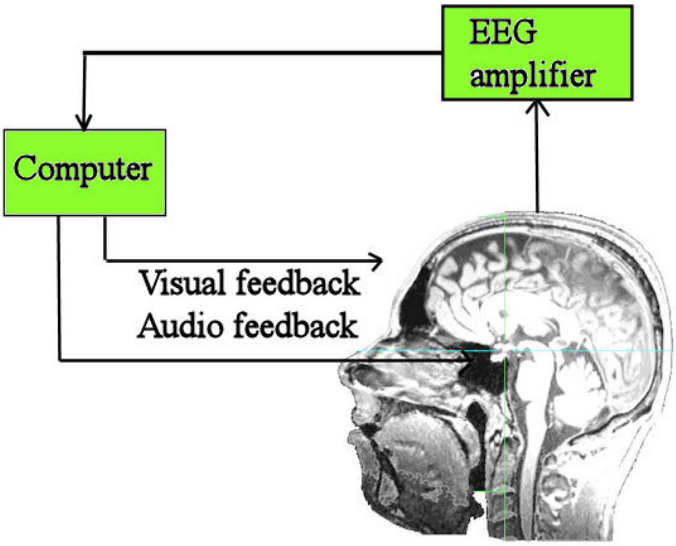

Figure 3.11: Neurofeedback principle. MR scanning is of the author's own head. Electrodes are attached to the scalp. The amplifier reads the electricity registered, amplifies this and issues a analog-to-digital converter which sends EEG data to the computer. The computer process the data and display it for the patient. The feedback can be used to verify correct behaviour.

3.3.3 Meditation - Selfconducting "Neurofeedback" From Within

Not everyone seems to need visual feedback in order to alter their brain waves. Studies of experienced mediators, using EEG, shows remarkable capabilities to affect their frequency power while meditating, and keep a stable frequency for the entire time (Stigsby, Rodenberg, & Moth, 1981). In one study, 20 normal people showed increased fast Theta and slow Beta frequencies, predominantly in the frontal area, by applying a Zen meditation task(Takahashia et al., 2005). It requires no previous training because it focuses on breath control. This gives an interesting perspective on neurofeedback and brain waves in general.

4 Brain-Computer Interfaces

This chapter explains Brain-Computer Interfaces and reviews some of the available products and systems on the market today. Current methods and potentials in the technology are identified.

4.1 What is a Brain-Computer Interface?

Wolpaw (2010) put it this way:

> Brain-computer interface is a method of communication based on neural activity generated by the brain and is independent of its normal output pathways of peripheral nerves and muscles. The goal of BCI is not to determine a person's intent by eavesdropping on brain activity, but rather to provide a new channel of output for the brain that requires voluntary adaptive control by the user.

Further, it is identified four different application areas of BCI, some which have been mentioned in chapter 3 already:

1. **Bioengineering applications:** Devices with assisting purposes for disabled people.

2. **Human subject monitoring:** Research and detection of sleep disorders, neurological diseases, attention monitoring, and/or overall "mental state".

3. **Neuroscience research:** real-time methods for correlating observable behavior with recorded neural signals.

4. **Human-Machine Interaction:** Interface devices between humans, computers or machines.

In this project we are concerned with item 4, and all steps in the common BCI process flow shown in figure 4.1.

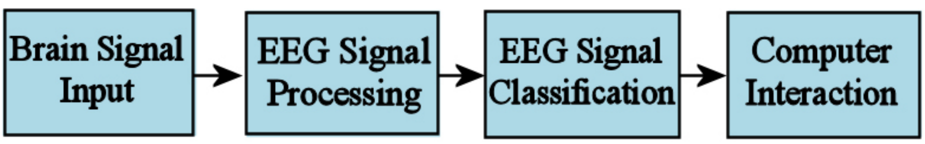

Figure 4.1: Brain-Computer Interface process flow.

4.1.1 Five Central Factors of BCI Design

Lotte, Congedo, Lécuyer, Lamarche, and Arnaldi (2007) have identified a few features that are common, and critical, to BCI design, that are listed here:

1. **noise and outliers**: BCI features are noisy or contain outliers because EEG signals have a poor signal-to-noise ratio;
2. **high dimensionality: in BCI systems, feature vectors are often of high dimensionality. Indeed, several features are generally extracted from several channels and from several time segments before being concatenated into a single feature vector;**
3. **time information:** BCI features should contain time information as brain activity patterns are generally related to specific time variations of EEG;
4. **non-stationarity:** BCI features are non-stationary since EEG signals may rapidly vary over time and more especially over sessions;
5. **small training sets:** the training sets are relatively small, since the training process is time consuming and demanding for the subjects.

Item 2 is highlighted because the NeuroSky EEG device used for this project is a single channel device. This reduces complexity for processing, but it also reduces signal accuracy, because there is only a single source of input. All of the referenced studies that are presented in the next section used 4 electrodes and most of them even more.

4.2 State of the Art BCI and Existing Systems

In chapter 1, it is mentioned that there is a focus shift from patients to gamers, and that this focus could benefit patients also. This is further illustrated here by using NASA and Sony as an example: NASA have been using neurofeedback to train their pilots to be more alert and attentive during a flight (NASA patent, dated 1994). Together with Sony, they used this technology to develop a specialized Playstation controller that would react to brain patterns. Correct brain patterns were rewarded with a more responsive controller and vice versa. A study was conducted were a group of children with ADHD was treated using neurofeedback. One half of the group trained using traditional neurofeedback, and the other half used the Playstation video game. Both groups improved about equally, but the group playing the video game enjoyed their training more, and their parents generally reported to notice more improvement than the parents from the other group (Reuderink, 2008a). Treatment can be made more appealing, fun and still give the wanted results.

4.2.1 Available Products on the Market: Healty People

When describing some of the products on the market it gives a good insight to the potential that lies in neurofeedback. The NASA and Sony feedback system differs from the traditional neurofeedback in that the feedback and reward are not explicit on the display, but implicit in the how the subject is able to control a task using brain waves.

- **"Yt Mer" (Perform More):** By expanding the target group, more efforts will be made to make the technology available, user friendly, entertaining and affordable. But this is only started. In 2010, the first "BrainWave Optimization" company was established in Norway (Berg, 2010). "Yt Mer" is an organization that is offering neurofeedback training to customers so that they can achieve higher performance, lower stress levels, better sleep patterns and increased well-being. It is very expensive, thus it is mostly targeting larger firms and enterprises.

- **Emotiv:** Their motto is "You think, therefore you can" (Emotiv, n.d.). Emotiv claims that you can use thoughts, feelings and emotions to control your computer. The accompanying software comes with a machine learning algorithm that learns how your brain visualizes, for example push and pull of objects, from the EEG measurements. This can be mapped to computer controls. Their neuroheadset consists of 14 sensors, includes a gyroscope and is priced 299 US dollars. The headset is high-tech and a comparison with a traditional EEG hair net is shown in figure 4.2.

However, the Emotiv EPOC Neuroheadset is only available for purchase to US customers. This is because there is not enough testing of the headset to achieve CE marking that makes it possible to sell in Europe and other countries, including Norway. Software Development Kits (SDKs) can be bought however, it includes a beta-headset to use at ones own risk and software to develop applications for it.

Figure 4.2: What the EPOC neuroheadset looks like.

4.2.2 Available Products on the Market: AD/HD Diagnose

- **Play Attention:** A company named Unique Logic and Technology (UL&T) develops neurofeedback technology that targets children and people with AD/HD and general attention problems. They focus on in-home training, using a computer and special made programs and games. Even though training is done home, they have specialists and professionals available that ensures that the system, and training, is correctly set up and executed by the user. The EEG equipment is a helmet (looks like a bicycle helmet) that is based on the NASA patent with sensors in it. Their system is not just for home use, it is used in over 450 schools districts in the US, in hospitals and psychologist's offices also.

- **SmartBrain:** SmartBrain Technologies, in co-operation with NASA, have made neurofeedback available for use with Playstation and Xbox (SmartBrain, n.d.). This makes it possible to apply it to thousands of different games, though the controlling feature is always the same. Their system includes a special made controller and does not require a computer to operate. The controller becomes more responsive when the user is concentrated and is basically the market product of the NASA study mentioned in section 4.2. Two versions are for sale: a personal and a professionally supervised. The personal edition costs approximately 600 US dollars and comes with three training presets. In general, they reward decrease of the slow brain patterns of alpha and theta brain waves and increase in faster brain waves (beta). The professionally supervised edition makes it possible to adjust the parameters individually to fit the user needs.

4.2.3 Available Products on the Market: Other Dysfunction

- **Spelling With the Brain:** intendiX is a personal EEG-based spelling system (G.tec, 2009), utilizing the P300 principle (see section 3.3.1). The user is wearing a cap with several electrodes and presented with a matrix containing all the letters of the alphabet. The rows and columns are then flashed quickly and randomly, and whenever the system flashes a row or column, it registers your reaction according to P300. This is enough to pin down the letter than you want to spell, when focusing on it. The system does this at a fairly high speed, and to quote intendiX: "This requires some training but most subjects can use *intendiX*® after only 10 minutes with a reasonable performance: A spelling rate of 5 to 10 characters per minute can be achieved by the majority of healthy users at their first trial." Still, as (Blankertz et al., 2006) pointed out, it is strainful for the users of evoked potential BCIs, because their are continuously receiving stimuli. However, it really opens up a way for patients to communicate, or issue commands on the computer.

- **Mind Speech:** Kellis et al. (2010) experimented with severely-epileptic patients that were going to have the seizure-stricken parts of their brain removed. This operation requires that part of the skull is opened, and then microelectrodes are installed on the surface to help narrow down the area that needs to be removed. The researchers exploited this by putting microelectrodes directly on to the Face-Motor Cortex and Wernicke's area (highlighted in figure 3.9) that are crucial for speech. Scientists matched the right word, from a string of 10 words, to the corresponding EEG signal between 28 percent and 48 percent of the time, which is better than chance. This could in the future make it possible for disabled people to communicate, using a speech synthesizer to read the matched words out loud.

- **Mind Cursor:** A earlier study by Wolpaw and Mcfarland (1994), uses the principle of MU (see section 3.2), the amplitude, or power levels for vertical movement, and the difference between the power levels for horizontal movement. This allowed the user to select from four icons, one at each corner of the screen. Using MU for movement is common, because it maps well to intentional movement.

4.2.4 Games on the Market and What all the Products Have in Common

The two game examples below is very common properties to apply in BCI games. As with most games available today, they rely on attention and concentration values. It seems it is the most reliable or easiest property to calculate, especially when readings from the forehead is used.

- **Adventures of Neuroboy:** NeuroSky have their own demo game that comes with the mindset. You are a character that can move in a world and levitate, push, pull and burn things with you mind. Attention and meditation values calculated in the mindset decides how this happen. Increased meditation value will lift objects, and increased attention will for instance burn things.
- **Mindball:** You wear a headband that reads brain waves, like the NeuroSky mindset, from the forehead. Theta and alpha (drowsiness and relaxation) band powers are used to control the speed of a ball. It is used to move a ball from A to B in competition with an opponent. The one who is more concentrated pushed the ball towards the other, and wins.

An example of a game that only uses the NeuroSky attention value is the MindBlaster game (Peek, 2010a). Using a Nintendo Wiimote, targets on the screen are locked in, and when maximum attention value is reach, the target explodes. Other projects involve driving a remote controlled toy vehicle. These examples makes it less interesting to apply the attention value from the mindset directly.

Another thing that these games have in common is that it reflects the brain waves in almost real-time, so it is like neurofeedback. If you do not concentrate, the car will not move. So it may require a lot of training to be able to drive smoothly, or to levitate an object and so forth. This can be demotivating because one never gets to the play part, but is stuck struggling with brain wave control. One could easily get bored, or just giving up. Thus, this is a good reason for lowering the need for training, and make games more easy to play.

4.3 BCI Development: EEG Analysis, FFT and Band Powers

The Fourier Transformation and extraction of band powers is by far the most applied method for signal processing and analysis (Lotte et al., 2007). The algorithm is based on discrete Fourier transform (DFT) equation 4.1, and by applying that to the EEG signal it makes it possible to separate the EEG rhythms (see section 3.2). Definition of the DFT:

$$X_k = \sum_{n=0}^{N-1} x_n e^{-i2k\pi \frac{n}{N}} \qquad k = 0, \ldots, N-1 \tag{4.1}$$

and the inverse of it:

$$x_n = \frac{1}{N} \sum_{n=0}^{N-1} X_k e^{i2k\pi \frac{n}{N}} \tag{4.2}$$

The performance of the DTF is $O(N^2)$, but there is a more efficient algorithm called fast Fourier Transform (FFT), that can compute the same result in only $O(NlogN)$. This is a great improvement and one of the reasons why FFT is the favorable method of analyzing EEG signals, and other waves like sound.

4.4 Five Different Approaches for Classifying EEG Signals

There are five categories that covers the most used algorithms in BCI classification systems, and they are: linear classifiers, nonlinear Bayesian classifiers, nearest neighbor classifiers, neural networks, and a combination of classifiers (Lotte et al., 2007). In all categories there have been achieved good BCI results, except for the nearest neighbor classifiers, which seems to not handle dimensionality very well. However, neural networks are the most popular in BCI research, and is the chosen method to classify in this project also.

4.4.1 Neural Networks: Multilayer Perceptron

Multilayer perceptron means that the neural network consists of an input layer, possibly and minimum one hidden layer, and one output layer, as shown in figure 4.3. The output of each node in one layer connects to the input of the next layer, but not within the same layer.

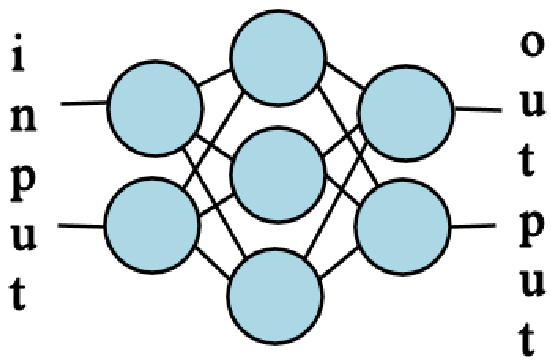

Figure 4.3: Neural network: 2 input neurons, 3 hidden layer neurons and 2 output neurons. Neurons are also referred to as **nodes**, and the lines between the nodes are called **synapses**.

The inspiration comes from the network of neurons in the human brain, but very much a simplified version of it. The great strength with neural networks is that they are flexible and almost universal approximators, giving the right setup: Neural networks needs to be trained before it can be used. In case of supervised learning, training sets with sample input and the corresponding output are given to the network, and then an algorithm adjust the weights of the synapses so that it can map valid input to correct output. A very common algorithm for this use is the backpropagation algorithm. In that case, the neurons look like the one in figure 4.4.

Except from the input nodes, all other nodes will have their input determined by the sum of all the incoming synapses. This becomes input to the **activation function** in the nodes (corresponds to the action potential in biological neurons, see section 3.1), which determine the nodes output: if it ”fires” nor not.

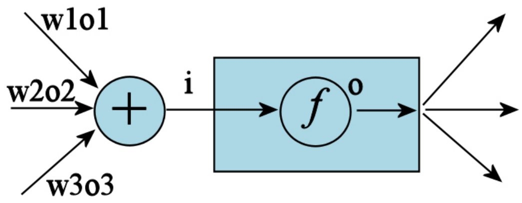

Figure 4.4: Neuron in a feed-forward propagation network. f is the activation function.

4.4.2 Backprogagation Algorithm

To understand neural networks better, and how the backpropagation works, the algorithm is given in pseudocode below. For more details, please refer to Dario and Mattiussi (2008) and NeuronDotNet (n.d.-a).

Initialize the weights in the network
while stopping criterion has reached **do**
  for all example e ∈ training set **do**
    O = actual, output(network, e); propagate forward
    T = wanted output for e
    Calculate error (T - O) at each neuron in the output layer
    Compute Mean Squared Error value; propagate backward
    Compute $delta_{weightupdate}$ for all weights
    Update all the weights in the network such that the sum-squared value of error is minimized.
  end for
end while

The Mean Squared Error (MSE) value is calculated using equation 4.3. This value reflects the effectiveness of the training done so far. The stopping criterion could either be when the MSE has reached an acceptable limit, or when the number of training cycles is attained.

$$\hat{\theta} = E[(\hat{\theta}(X) - \theta)^2] \tag{4.3}$$

There are several types of activation function commonly used, these are:

- **Sigmoid Activation Function:** $y = 1/(1 + Exp(-x))$
- **Linear Activation Function:** $y = x$
- **Logarithmic Activation Function:** $y = Log(1 + |x|)$
- **Sine Activation Function:** $y = Sin(x)$
- **Tanh Activation Function:** $y = Tanh(x)$

5 Solution Design: System Implementation

This chapter describes the overall final system implementation. Some details are left for chapter 6, 7 and 8, as they are more relevant there.

5.1 System Overview, Environment and Components

Figure 5.1 shows an overview of the main components in the system design. The system flow is described below, followed by a component specification. The entire project is written in the Visual Studio 2010 environment, using C# as programming language. A HP tx2020ed laptop with Windows XP SP3 have been used.

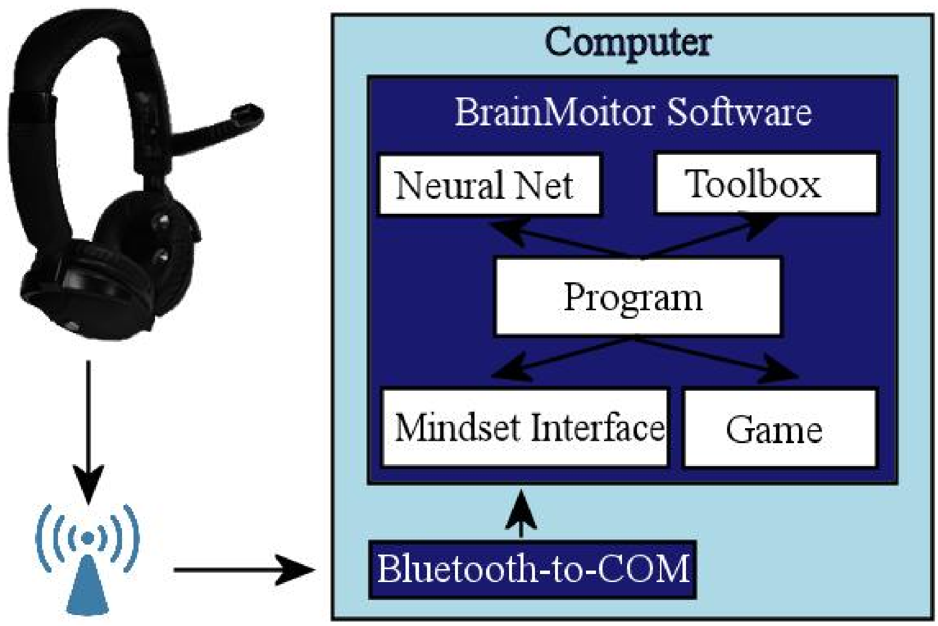

Figure 5.1: System Design: component overview. NeuroSky mindset and the computer program main parts.

Comparing these components with the BCI process flow in figure 4.1, we see that **Mindset**, **Bluetooth-to-COM**, and **Mindset Interface**, corresponds to ”brain signal input”; **toolbox** corresponds to ”EEG signal processing”; **Neural Network** corresponds to ”EEG signal classification” and **Game** corresponds to ”computer interaction”.

NeuroSky mindset: The easy to apply EEG device, that is wearable like regular headphones. It has one dry sensor that can be placed on the forehead, left side (approximately equal to Fp1 in the 10-20 system, figure 3.2). And 3 dry sensors on the left ear, for reference. It has a microchip which pre-process the EEG signal, and transmits that data via bluetooth. The output data is presented in table 5.1. The processing algorithms are not an open protocol, but it does a FFT on the signal which gives the band powers. However, these powers are scaled and filtered and thus only relative to each other (NeuroSky, 2010). Also, the mindset have speakers, like a headset, and a microphone, so it can be used for multiple tasks.

Table 5.1: NeuroSky output protocol

Output	Description
Raw Data	Returns raw EEG data, sampled at 1HZ
Signal	Returns poor signal level, 0 is good signal, 200 is off-head state.
Delta	The "delta band" of EEG (0.5 - 2.75Hz).
Theta	The "theta band" of EEG (3.5 - 6.75Hz).
Alpha 1	The "low alpha" band of EEG (7.5 - 9.25Hz).
Alpha 2	The "high alpha" band of EEG (10 - 11.75Hz).
Beta 1	The "low beta" band of EEG (13 - 16.75Hz).
Beta 2	The "high beta" band of EEG (18 - 29.75Hz).
Gamma 1	The "low gamma" band of EEG (31 - 39.75Hz).
Gamma 2	The "mid gamma" band of EEG (41 - 49.75Hz).
Attention	Returns the eSense Attention integer value, between 0 and 100
Meditation	Returns the eSense Meditation integer value, between 0 and 100
Blink	Returns an integer value between 0-255, indicating the blink strength.

Note: Even though band power data are available from the mindset, having total control of that process using only the raw data is part of understanding BCI.

Mindset Interface

Mindset interface: There are libraries available for almost every platform and programming language, that interfaces the bluetooth communication with the mindset and computer. In this project, a .NET wrapper from Peek (2010b) was used. It handles connection, disconnection, and receives a container with all the output data in table 5.1 every 10 milliseconds (raw data) and every second (all other output).

Bluetooth-Com

Bluetooth: A bluetooth device is included in the mindset package. The device software converts the bluetooth connection to a COM-port, which makes application and device communication much easier.

Program

The Program is the main thread, event-handler and is named **BrainMonitor**. It has a graphical user interface, viewable in figure 5.2, that both displays and give users control of all the implemented features.

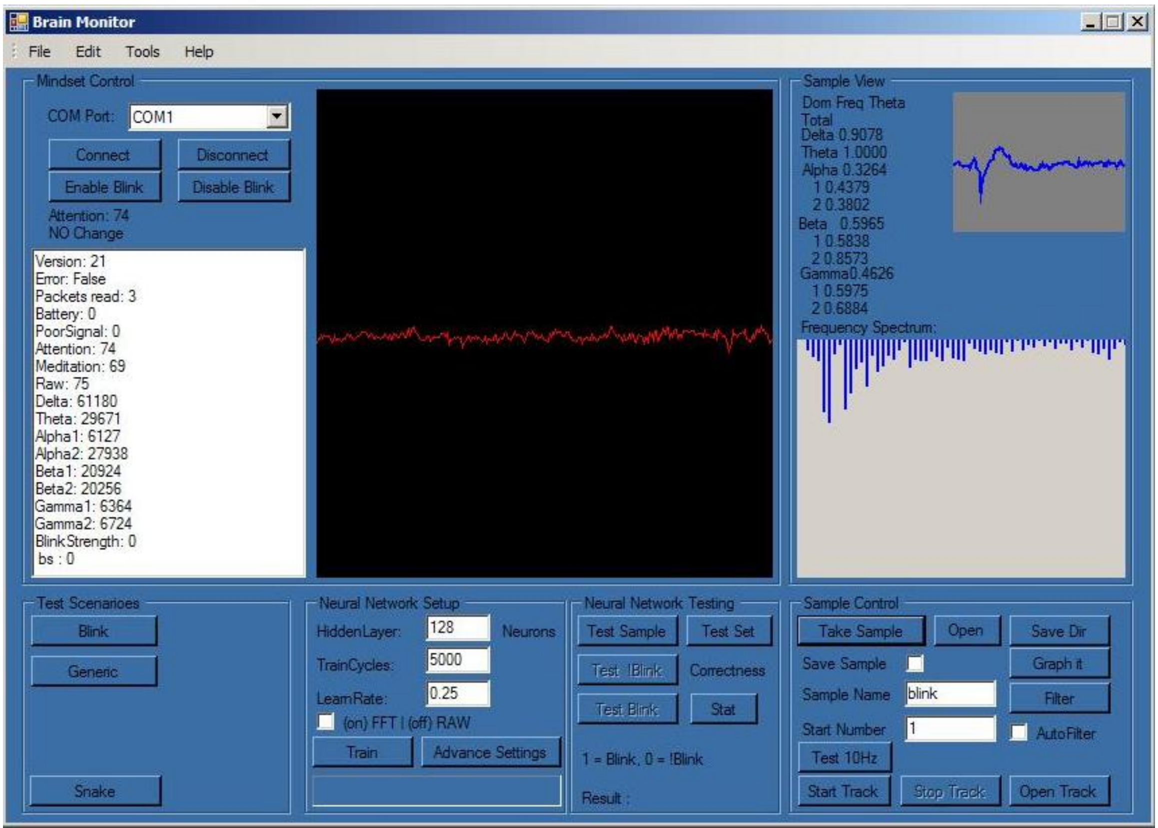

Figure 5.2: Screenshot of BrainMonitor Graphical Interface. Upper left: Mindset Control for connection, and mindset container view. At the top, middle screen: real-time raw EEG record. Upper right: Sample view 2^7 spatial points and the Fourier Transformation and band power. From bottom left to right: Scenario buttons, Neural Network training and parameter setting, Neural Network testing, and Sample control buttons.

The "Take sample" button in the sample control panel in figure 5.2 is particularly useful for taking a live sample from the incoming EEG signal. Doing this, all data about the sample is displayed in the sample view. It can be named, saved to disk and retrieved later. Also, if a neural network is trained and ready to receive input, the current live sample can be tested with that network. This is a great help to quickly generate and test EEG samples.

Toolbox

The toolbox contains mainly the Fourier Transform algorithm. The algorithm was verified with a 10Hz sine wave using the function $F(t) = \sin(2\pi 10t)$, giving a spectrum that only have a power bar at 10Hz. Further, it contains the disk operator that can read and write samples to disk so that sessions can be saved and re-opened. Plotting of data in graphs for presentation is also handled.

Neural Net

The neural network is built on a solution available at NeuronDotNet (n.d.-b), and is an implementation of the sort explained in 4.4.1. A network setup screen was written to enable easy modification of parameters, these are: Maximum training cycles, learning rate, number of nodes in the hidden layer, adjustment of input type to the network (details in chapter 6,7,8), and the activation function in each layer; sigmoid activation, linear activation, logarithmic activation, sine activation and tanh activation.

Game

The game was one of the reasons for choosing Visual Studio and C#, in addition to the available mindset library. The first idea was to find an open source XNA game, preferably a role playing game, to which the EEG could control some feature in a dialog; feeling angry or tense could make the main character only able to select bad options, for instance. However, this was omitted later in the project, and a version of the classical game Snake was implemented instead. This is covered in more detail in chapter 8.

5.2 Implementation Steps Overview and Test Procedure

The following chapters, 6, 7 and 8, are a chronological approximation of the ongoing implementation and testing done in the project. Basically, step 1 is were part one, two and three in the BCI process flow (see figure 4.1) are realized and tested. Step 2 is were part two and three are further improved to accomplish more complex classification, and step 3 is the final implementation and realization of step 4 and the complete BCI system test.

Most testing is done by the author himself, unless specified otherwise. It was decided to not test on many people, mainly to save time and to keep consistency since experiments kept changing parameters. But, the interest for trying the EEG equipment among fellow students was unquestionable. Several hundred test scenarios were conducted in total, across several different experiments. Thus, only the most representative test results are included here, to ensure fruitful discussions and present the projects achievements.

6 Step One: EEG Eye-Blink Classification

Describes the first approach towards reaching the project goals. The method that leads to the results is explained, the results presented, analyzed and followed by a discussion about the methods benefits, disadvantages and lessons learned.

6.1 Method, System Setup and Neural Network Architecture

The first step was to 1) be able to connect to the NeuroSky mindset, 2) sample the incoming raw EEG data, 3) use these samples to train a neural network, and then 4) test the correctness. The game part was to be left out for later, as it would depend on the neural network to be able to correctly classify brain waves. In this section, each sub-step is described.

6.1.1 1: Connecting with the NeuroSky mindset

This worked flawlessly. The library that handles the communication with the bluetooth device did the job.

6.1.2 2: Sample the Incoming Raw EEG Data

The program is written to generate new sample objects that will add themselves as observers of the mindset datastream (following the observer pattern), and fill up an array of raw EEG data until it reaches the set sample size. This size was set to 128 data points, so each sample takes 1280 milliseconds to complete (data is updated every 10ms). There are two simple reasons for this: FFT analysis needs a frame that is of a reasonable length, or else it will be difficult to do any accurate analysis (Wolpaw, 2010). And, the FFT algorithm in the program needs an input array were the size of it is a power of two.

By observing the real-time EEG record in the BrainMonitor program (see figure 5.1), it was evident, but not surprisingly, that an eye blink gave a major fluctuation in the EEG signal. Thus, it was decided to make this a first classification feature for the neural network; correctness of the neural networks output would be easily verified, since analyzing the sample by observation would tell if it should be classified as a blink or not. The other feature would be the **baseline:** thinking of nothing in particular, keeping the eyes open. To gather a collection of EEG samples to be used for network training, a scenario program was written that would do this automatically while giving task instructions. Figure 6.1 shows the test scenario screen used.

Additionally, it was observed that the mindset was very sensitive to movement and noise, and this is dealt with in section 6.2.2.

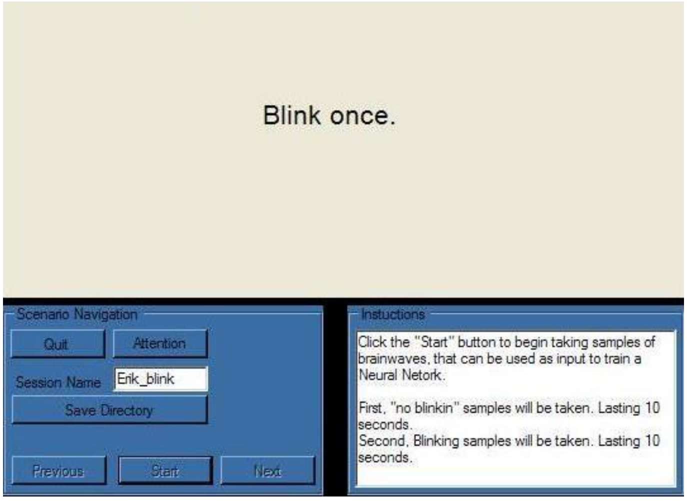

Figure 6.1: Sampling Screen: Middle: live instructions; bottom right: overall test instructions; bottom left: test control, session save directory and name. When the subject should blink, the "blink" string was flashed on the screen.

The test scenario was split in two parts, giving instructions to the user on the screen. Part one gathered samples from the baseline task, 5 in total, and part two gathered samples from the blink task, 5 in total. All the samples (with name, number, raw EEG and FFT data) are saved to disk so they can be recalled later. The collection of samples from each part in a scenario is called a **set**.

6.1.3 3: Neural Network Architecture and Training Setup

Figure 6.2 shows the architecture of the neural network. The input string to the network was the five power bands of a sample: delta, theta, alpha, beta and gamma. These were obtained by conducting FFT on the raw EEG data, and then dividing them into buckets according to their frequency range. Each band value is scaled with respect to the highest frequency in each individual sample, ensuring that all values are in the interval between 0 and 1.

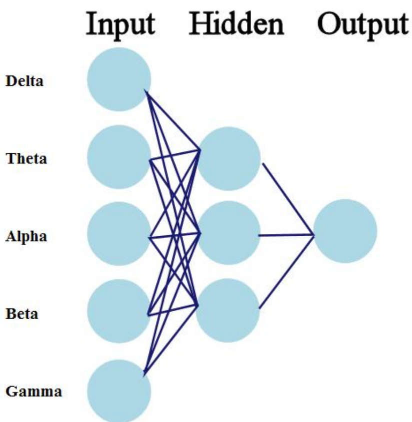

Figure 6.2: Neural network architecture 1: 5 input nodes, 3 hidden nodes, 1 output node.

Because there are only two features, 1 output node is sufficient, and all baseline samples were trained to have 0 as the output value, and all blink samples were trained to have 1 as the output value. The network was trained with 1 set of each sample feature (5 blink samples, and 5 baseline samples).
Network parameters: learning rate was set to 0.25, learning cycles to 5000 and number of hidden nodes to 3. Activation function for the input layer was linear, and sigmoid was used for both hidden and output layer. Variations of these parameters were tested, but it did not have any great impact on the results.

6.1.4 4: Test of the Neural Network

The network can be tested using a single sample, or a collection of samples (which was used in this experiment). In the latter case, the correctness of the set is calculated with the basic average equation 6.1, which sums the result from each individual input sample in the set and divide it on the total number of samples. An experiment consists of 5 scenarios taken in one single session (no headset removal). Result values above 0.5 is regarded as a 1, and values below 0.5 is regarded as a 0.

$$A = \frac{1}{N}\sum_{i=1}^{N} a_i \tag{6.1}$$

6.2 Test Results and Findings

This section show results from two test experiments, the first experiment is the one described above in the previous section. Second experiment is a noise test scenario, where movement of the head and touching is done and recorded, in order to get a viewpoint on that. Noise is also referred to as artifacts, in the text.

6.2.1 Experiment One: Baseline vs. Blink

Figure 6.3, 6.4, 6.5, 6.6, and 6.7 are graphical presentation of input samples, from both the baseline and blink task as specified.

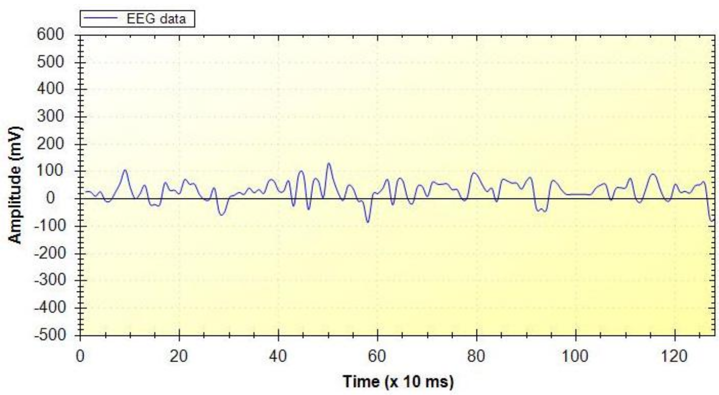

Figure 6.3: Displays the raw EEG record of a baseline sample. Frequency spectrum of it is showed in figure 6.4.

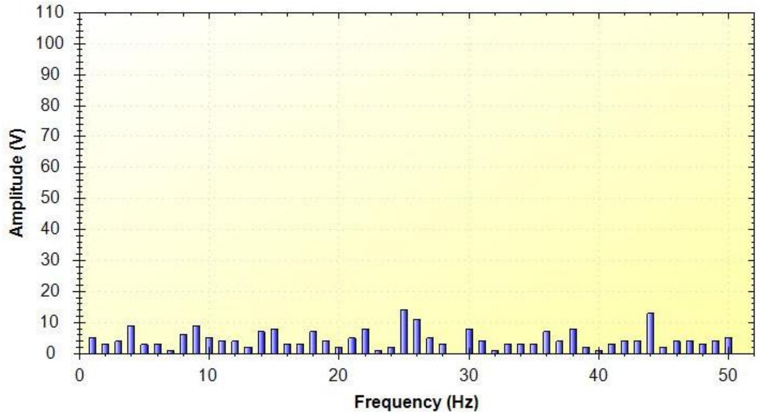

Figure 6.4: Displays the frequency spectrum of baseline sample in figure 6.3.

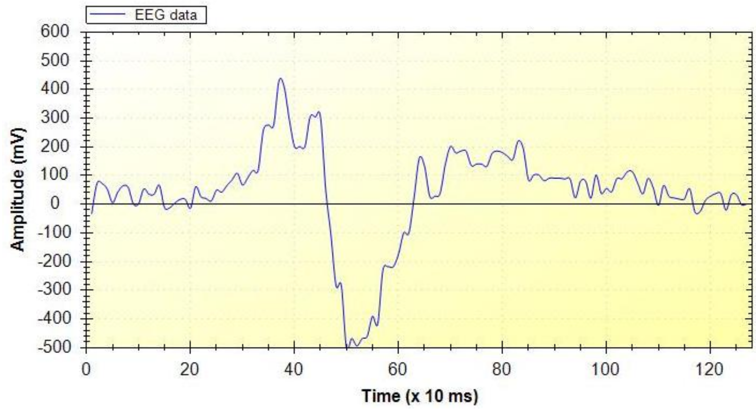

Figure 6.5: Displays the raw EEG record of a blink sample. Frequency spectrum of it is showed in figure 6.6.

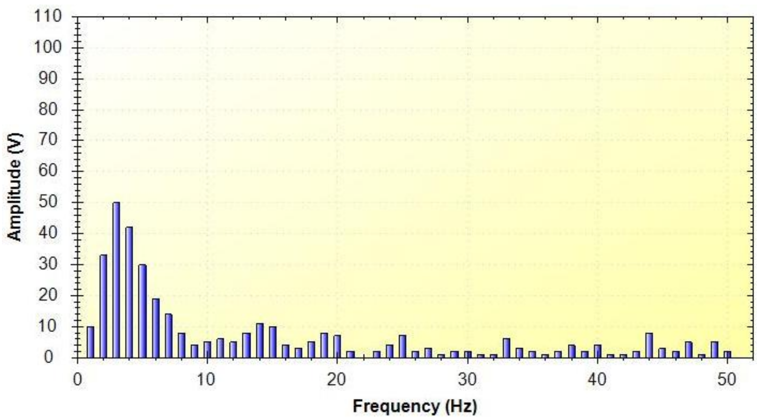

Figure 6.6: Displays the frequency spectrum of blink sample in figure 6.5.

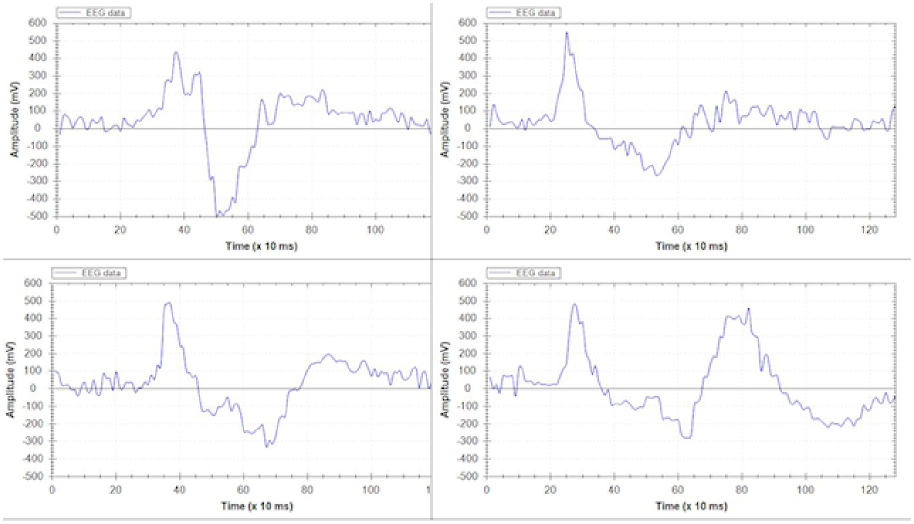

Figure 6.7: 4 of the 5 samples used to generate blink training input for the neural network.

Table 6.1 and 6.2 contains the baseline and blink input used, respectively, for the neural network. Each set equals the sum of band powers for each sample in one scenario run. Set 1 in each table was used to train the network. Table 6.3 is the corresponding output, the classification results, from the neural network.

Table 6.1: Band powers of baseline samples. Eyes open.

Band	Set 1	Set 2	Set 3	Set 4	Set 5	Total (Sum)
Delta	1.78	0.97	1.4	0.64	0.68	5.47
Theta	1.3	0.94	0.98	1.05	1.16	5.43
Alpha	1.42	1.49	1.28	1.1	1.33	6.62
Beta	4.28	4.84	4.62	4.69	5	23.43
Gamma	4.19	4.57	4.87	4.64	4.29	22.57
Sum	12.97	12.81	13.16	12.11	12.46	63.51

Table 6.2: Band powers of blink samples.

Band	Set 1	Set 2	Set 3	Set 4	Set 5	Total (Sum)
Delta	4.94	4.39	4.69	4.74	3.54	22.3
Theta	2.88	3.59	3.98	3.26	3.5	17.21
Alpha	1.62	2.6	2.74	2.26	2.13	11.35
Beta	3.58	4.52	4.18	4.41	4.7	21.4
Gamma	2.83	3.33	4.23	3.67	3.46	17.52
Sum	15.85	18.43	19.82	18.34	17.34	89.77

Table 6.3: Classification result using data sets from table 6.1 and 6.2. Close to 1 = baseline, and close to 0 = blink.

Scenario Task	Set 1	Set 2	Set 3	Set 4	Set 5	Total (Average)
Baseline (Eyes Open)	0.82	0.96	0.94	0.97	0.96	0.93
Blink	0.01	0.01	0	0.01	0.03	0.01

During each scenario, the attention and meditation values, that is calculated by and received from the mindset, were plotten in a graph, and figure 6.8 is an example of this. The plotting is from scenario 4, the first half (Time < 1600) is from the baseline, and second half is the blink set (found in table 6.2 and 6.1).

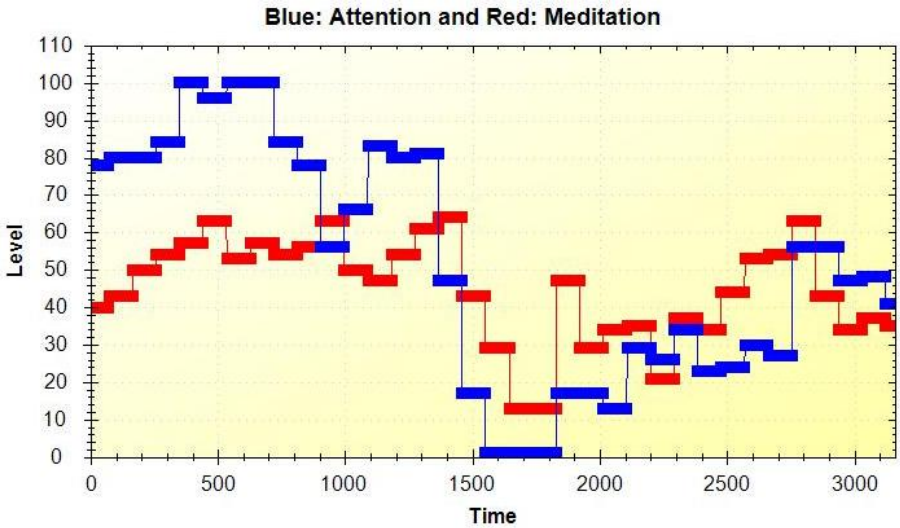

Figure 6.8: Plotting of attention and meditation levels during scenario 1, a shift in both values when going from baseline to blink task is clearly seen.

6.2.2 Experiment Two: Noise Sensitivity

Figure 6.9 shows a noise sample, with the respective frequency spectrum in figure 6.10. When compared to the figures 6.5 and 6.6 of the blink sample, they are quite similar. This sample was taken when the forehead of the test person was tapped with a finger. Other movements like jumping, turning the head, nodding also gave similar noise samples. This particular sample was classified as a blink.

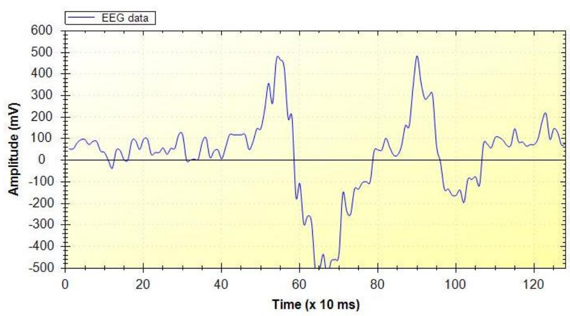

Figure 6.9: Spatial sample of noise : Tapping on the forehead.

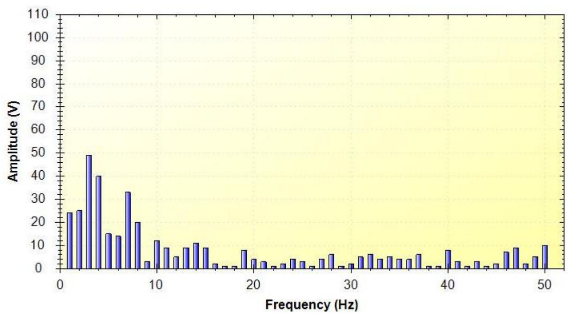

Figure 6.10: Frequency spectrum of noise : Tapping on the forehead.

6.3 Discussion of Results and the Sensitive Electrode

The result from the tests demonstrates that the implementation works as it should, so far. It can connect and communicate with the mindset, sample EEG input, train and test a neural network. Also, the system was able to classify blink correctly, averaging at 99%.

Although noise was expected from the headset, it was still not anticipated that it would be so sensitive to movements. Because of this, it was decided to conduct all baseline experiments and sampling with eyes open, and without any movements of head and body. The disadvantage of this is that it becomes very tiresome for the eyes, on the other hand, the strict rule ease off the need to filter the EEG signal for such artifacts. Indeed, this noise issue and the fact that the only electrode on the mindset is placed in the forehead, brings research question 1 to the table: Does blinking disturb the only input signal too much so that it makes it unreliable?

In figure 6.8, it is clearly seen that the NeuroSky algorithms that calculates attention and meditation are influenced by blinking. During the baseline part, the average attention and meditation level is approximately between 80-100 and 50-60, respectively. When the blink part starts, both these levels drop drastically, especially attention. This is counter-intuitive, because waiting for the blink commands, and respond to them appropriately, should bring the test person to a higher level of alertness and focus, and not make them more inattentive. The blinks in this particular scenario may have been exaggerated and caused major disturbance, but the tendency across all the experiments is that whenever there is an absence of blink, the attention level goes to the top, and that the same level is very difficult to reach even when blinking normally. But would this still be true if the electrode was placed elsewhere on the scalp? This was tried, but it was unsuccessful to get a signal. And because the electrode is static, the options are limited without breaking the mindset. In some studies, placement of frontal electrode is used to control that the samples they take from other electrodes do not contain blink artifacts (Lukas et al., 1995) (Wolpaw et al., 2000). However, the fact remains that the results indicates that persons using the mindset should not blink during sampling. This is not ideal when considering to make use of it in a real-time system and for longer periods, like in gaming.

6.3.1 Simpler Blink Detection

In table 6.1 and 6.2, or when comparing the power spectrum of figure 6.4 and 6.6, the difference between baseline and blink is clear. Blink is a simultaneously high boost of delta (more than 4 times in average), theta and alpha amplitudes, and a decrease in gamma. Blink detection could be done by monitoring, for instance, delta, theta and gamma. If delta and theta values increased simultaneously, and gamma decreased, that would be a blink signature. The amount of change from pre-values could indicate strength. Like that of NeuroSky. No neural network is needed. Finally, blinking could also be detected by using a camera, and it is a muscle movement. Thus, it is not regarded as true brain communication as BCI is defined in chapter 4. The system should be able to classify more than muscle movement.

6.3.2 Critical Discovery: Making Better and More Stable Input Samples

This was actually discovered while trying to classify a mental task in step two. No positive results were found when trying to classify input samples, so changes had to be made. It is mention here, because it led to the fact that lot of test sessions needed to be redone. Further, all results presented in this step, in step 2 and 3, follows this way of generating network input.

Table 6.4

Band	Level
Delta	1
Theta	0.024
Alpha	0.096
Beta	0.079
Gamma	0.677

Table 6.5

Band	Level
Delta	19.38
Theta	6.54
Alpha	3.95
Beta	2.78
Gamma	10.26

Table 6.6

Band	Level
Delta	0.923
Theta	0.311
Alpha	0.188
Beta	0.132
Gamma	0.489

Up to this point in the project, the neural network had been trained and tested with single samples, representing 1280 milliseconds of EEG information each. This was fine when only dealing with blink detection, because that is a very defined and short event (Testing of blink was still redone to ensure consistency in all tests, in all steps). However, when dealing with mental states, it is safe to assume that this is not so, without long practice at least. The discovery was that the samples needed to be reflecting a time period much greater than 1.3 seconds. This was done by taking the average of all the band powers from all samples in a scenario set. The result is shown above. Table 6.4 represent the band powers of a single baseline sample (Scaled with respect to highest frequency). Table 6.5 represents the summation of band powers of 20 baseline samples (taken from the same scenario), and finally, table 6.6 is the average of table 6.5, and represents one sample set, usable for training and testing. The difference between band powers of the single sample and the set is evident.

The drawback is that it now takes approximately 20 seconds to generate input for the network. In a game setting and real-time environment, this is a long time, and it is a limitation.

7 Step Two: EEG Mental Task Classification

7.1 Method, System Setup and Neural Network Architecture

The classification of blink had demonstrated that the system worked and is able to complete the three first step in the BCI process chain (see figure 4.1). However, the system should be able to classify more than just a blink. This section describes three approaches, called experiments, to find that which could be classified as a mental state by the system. For all experiments, testing of the neural network are the same as in step 1, explained in section 6.1.4.

7.1.1 Experiment One: Motion Task Attempt

It was decided that the mental state should be of a simple character, and the first choice then became a **motion task:** thinking about and visualizing movement. This is a mental task that is common to use in EEG experiments (Curran, 2003). Collection of data sets was done by sampling baseline first, followed by visualizing movement: Raising and lowering one arm, both arms, and legs. However, despite all efforts and numerous trials and testing, there were no consistent findings that proved to be classifiable. This led to the second experiment.

7.1.2 Experiment Two: Motion task and ERP Combined Attempt

The idea for this experiment was that visually invoked movement could help change the mental state of the test person faster and more consistent. By combining motion intention and ERP (see section 3.3.1), it could be possible that the P300 effect would have an impact on the band powers. A new test scenario screen was implemented, see figure 7.1, that had a cartoon character doing arm movements: moving an arm up and down repetitively towards the forehead. The test person is instructed to imagine doing the same, and follow the rhythm in the motion; receiving and responding to external stimuli.

Again, recording and sampling were done with eyes open during the whole session. The scenario was split in two parts: sampling motion first and baseline second. As input to the neural network, three types were tried: 5 band powers (delta, theta, alpha, beta, gamma); 5 band powers and meditation and attention values, making it a 7 input network; specific band powers (delta, theta, alpha1, alpha2, beta1, beta2, gamma1, gamma2), making it a 8 input network.

Numerous trials and tests were conducted, but no results were found indicating that this was a usable approach towards being able to classify a mental state. However, from the classification results it became clear that using meditation and attention values as additional input to the neural network, and the specific band powers, were worser options than only using the 5 band powers. This if further discussed in section 7.3.

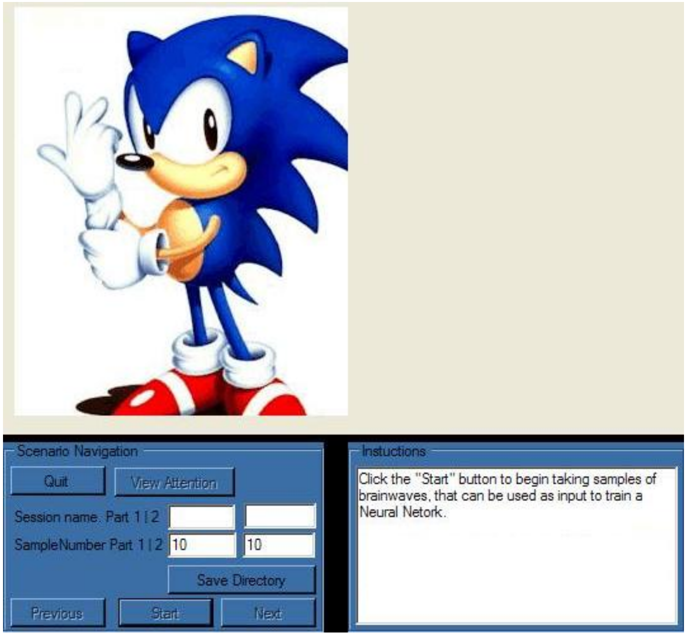

Figure 7.1: Sampling screen: Middle: live instructions; bottom right: overall test instructions; bottom left: test control, session save directory and options.

7.1.3 Experiment Three A: Visual Counting Task - Eyes Open

It was decided to try another mental task: visual counting, which have been used successfully in, for instance, a study by Keirn and Aunon (1990). This also matches the functionality of the frontal lobe, as it is related to mathematics and problem solving. 1 scenario consisted of two parts: in the first part, 20 baseline samples was recorded. In the second part, 20 visual counting samples was recorder. Eyes were open during the entire scenario. The 20 samples from each part was used to generate 1 training set per feature, averaged and scaled to 1, like discussed in section 6.3.2.

7.1.4 Experiment Three B: Visual Counting Task - Eyes Closed

Experiment 3A gave results, but they were not satisfying. This led to a variant where the baseline part of a scenario was conducted with eyes closed, in an attempt to increase the difference in band powers. This should work because if one assumes that when closing your eyes, the perception process is halted in the brain since there are no visual input anymore. Regardless, in a study by L. Zhang et al. (2005) it was recorded a major alpha waves increase in 20 EEG subjects, when their eyes were closed vs. when their eyes were open.

7.1.5 Neural Network Architecture and Setup for Experiment Three

The neural network architecture are the same as in step 1 (see section 6.1.3). Results from experiment two indicated that the 5 input band power gave better performance, so that was used in this setup as well. Network consisted of 1 input layer: 5 input nodes, 1 hidden layer: 3 hidden nodes, 1 output layer, 1 node.

Network parameters setup: learning rate was set to 0.2, learning cycles set to 1000. Activation function for the input layer was linear, sigmoid function for the hidden and the output layer. Variations of these parameters were also tested, but did not have any great impact on the results, like in step 1.

7.2 Test Results and Findings

Only results from experiment three are shown here, experiment one and two are excluded due to the fact that they were unsuccessful attempts.

7.2.1 Results Experiment Three A: Eyes Open Only

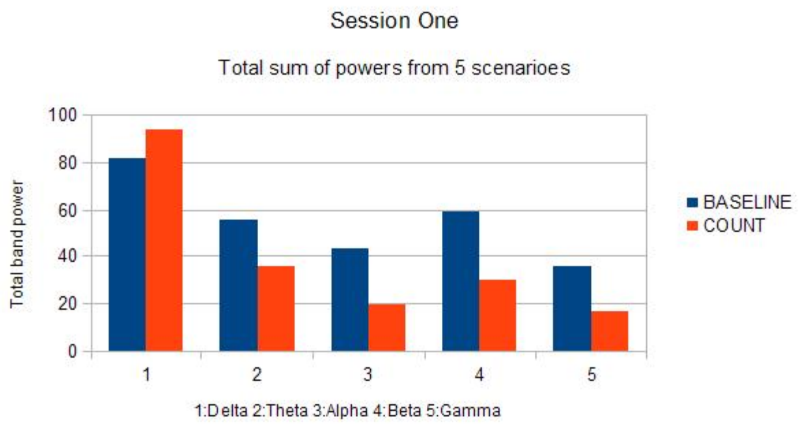

Figure 7.2: Comparing total band power from all 5 sets in session one.

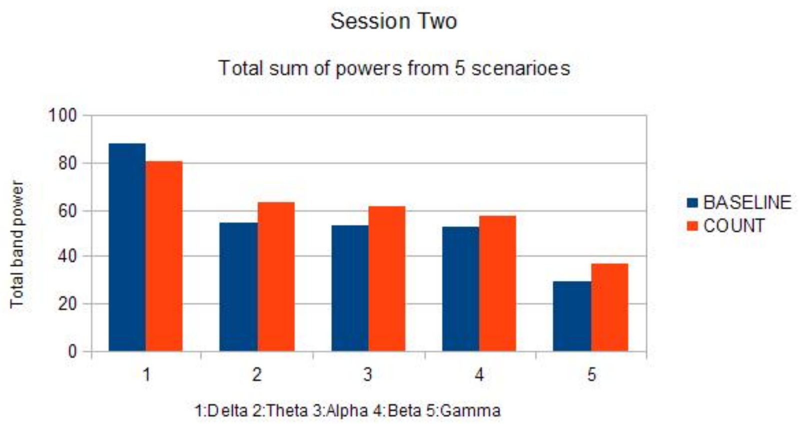

Figure 7.3: Comparing total band power from all 5 sets in the sessino two.

Figure 7.2 and 7.3 show results from two sessions of experiment three. The bars show the total summation of power in each frequency band over all the sets from 5 scenarios. When comparing the two charts, they are the opposite of each other: Blue dominates red in session one, and vice versa in session two.

The results in table 7.1 is the best among the sessions that were conducted, and classified 4 of 5 sets correctly, both baseline and count. 3 correct classifications of 5 possible was the average. In one session, only 1 of 5 was correctly classified, and that was when the neural network was tested with the same set that was trained with.

Table 7.1: Classification result using data sets from figure 7.2

Task	Set 1	Set 2	Set 3	Set 4	Set 5	Total (Average)
Baseline (Eyes Open)	0.93	0.95	0.95	0.8	0.87	0.9
Blink	0.01	0.07	0.06	0.09	0.94	0.23

7.2.2 Results Experiment Three B: Eyes Closed and Eyes Open

Table 7.2: Band powers of baseline. Eyes closed.

Band	Set 1	Set 2	Set 3	Set 4	Set 5	Total (Sum)
Delta	11.1	18.78	17.51	11.14	6.35	64.89
Theta	6.87	7.73	7.41	6.43	6.78	33.22
Alpha	15.64	10.08	14.03	17.47	20.16	77.38
Beta	8.53	6.52	6.22	11.08	8.29	40.64
Gamma	2.88	1.28	1.42	2.35	2.19	10.12
Sum	45.02	44.39	46.59	48.48	43.77	228.25

Table 7.3: Band powers of mental task: Count. Eyes open.

Band	Set 1	Set 2	Set 3	Set 4	Set 5	Total (Sum)
Delta	19.02	19.26	18.32	17.37	14.15	88.12
Theta	10.51	9.23	11.97	11.53	13.88	57.11
Alpha	8.42	5.6	7.5	10.18	13.71	45.42
Beta	8.93	4.32	9.42	12.7	10.73	46.09
Gamma	4.36	1.85	4.88	7.85	5.82	24.76
Sum	51.24	40.25	52.08	59.64	58.3	261.51

Table 7.4: Classification result using data sets from table 7.2 and 7.3.

Task	Set 1	Set 2	Set 3	Set 4	Set 5	Total (Average)
Baseline	0.93	0.74	0.93	0.95	0.98	0.91
Count	0.11	0.3	0.06	0.05	0.18	0.14

As seen in table 7.4, classification scores 5 of 5. Specific detail about the total band power from each set used for baseline and counting, are found in 7.2 and 7.3, respectively. The tables show an increase of alpha activity, and a decrease of all the other waves, when eyes are closed.

Figure 7.4 through 7.7 are input samples used in the session, it illustrates the difficulty to interpret the waves by observation for the untrained eye.

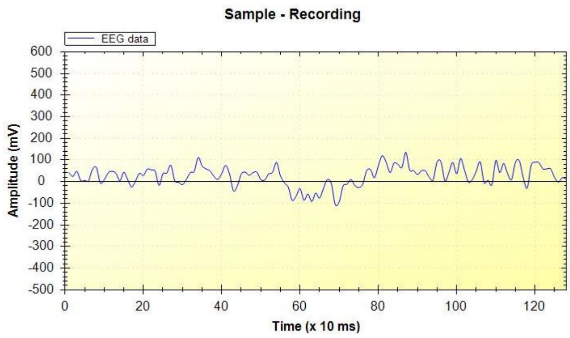

Figure 7.4: Spatial sample of baseline - Eyes closed

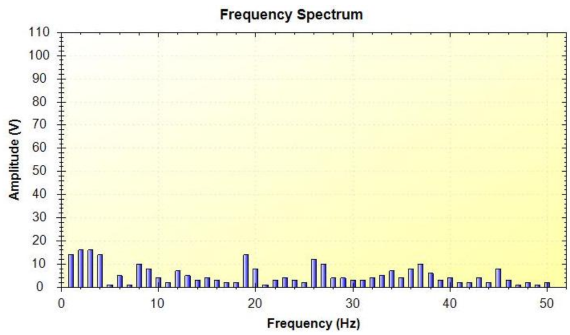

Figure 7.5: Frequency spectrum of baseline - Eyes closed

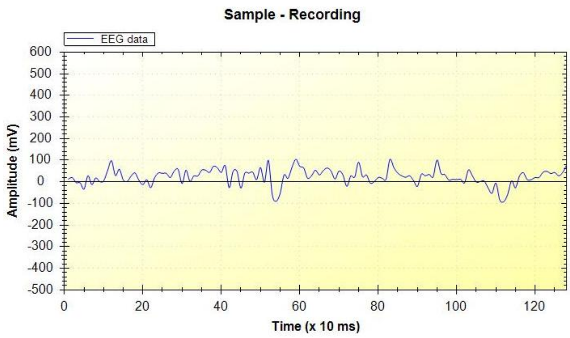

Figure 7.6: Spatial Sample of visual count

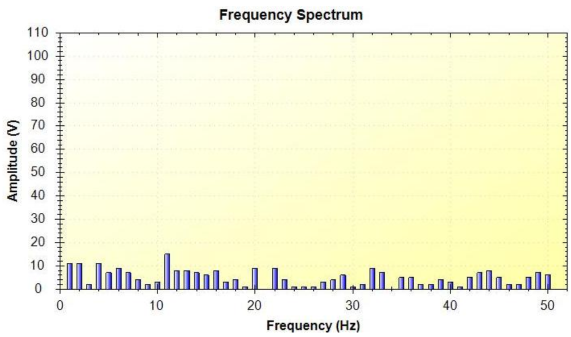

Figure 7.7: Frequency spectrum of visual count sample

7.3 Discussion of Results and How the Eye State is the Key

Results from the experiments indicate the possibility to classify baseline and mental count states, with a probability greater than 90%. This is if using a method that combines sampling with eyes open and eyes closed. Experiments with eyes open only, averaged with about 60% correct classifications. There were some exceptions making only 20% in average, and one that made it above 90%. In summation, these are unstable results. There can be a number of reasons for this, and they are listed below and then discussed:

1. One electrode is not adequate to get the information needed to identify complex though patterns in the mind.
2. The chosen tasks are not suitable with regards to the location of the electrode.
3. The chosen tasks are not suitable with regards to the test person.
4. Band frequencies are not the best choice for signal analysis in this context.
5. It is difficult to control that tasks are carried out correctly by the test person.
6. Neural Network is not the most suitable classification choice in this context.

As mentioned in section 4.1.1, most EEG studies uses 4 electrodes on more, placed at some distance from the forehead (C, P, O groups in the 10-20 system, see figure 3.2). This suggest that perhaps one electrode is just not enough, since this is not common practice. This aside, it can also mean that it is more difficult to find a function or task that can be directed towards the electrode location. There is no way to safeguard that one of several electrodes will record the essential information. Still, results from experiment 3B accords with the conclusion from previous research in L. Zhang et al. (2005). The biggest difference in total sum of band power with eyes closed and eyes open is the alpha wave, as the study suggests. However, in a game scenario, closing the eyes in long periods are not ideal for gameplay, unless something is particularly designed for it. This is also the reason why it took so long before experimenting with the eyes closed. The focus was what would work in a game setting, and not in the system.

Visualizing movement is something that is very much used in EEG experiments. Usually, it gives very good classification ratings in other studies (Lotte et al., 2007), but no results were made when trying it in this project. Again, location of the electrode can be assumed to be the reason for this. However, this can not be verified since the mindset electrode is static. Moving it would require to break the device.

But there could also be other explanations. It is known that EEG patients and test persons can learn to do a mental task, that is recognizable in the system, and then forget how to do them some time later. Some are unable to re-learn it again. It also happens that there are one or several persons in a healthy test population that cannot be recognized for their mental efforts by the system, even though the rest of the group can (Curran, 2003). The EEG of people is very different, so it is possible that the test person in this experiment was not able to do the task, in a manner that affected the EEG in any case. Also, it could be that other persons motion intentions will be detected, but not their mental counting, or perhaps both. As an example of not doing the task correctly, consider the baseline task. Could the instruction to not think about anything in particular, have the opposite effect? That you start to think about not thinking, or you focus to much about not thinking? This is where practice comes into play, being able to regulate mental activity, an issue of EEG that is discussed in section 3.3.2. However, this could explain the variations of results in experiment 3A: High mental activity in both baseline and visualization would give similar band powers. The test person may think he is doing two different task, but in reality he is doing the same.

From this, some experiments were decided to be conducted with the attention and meditation levels as extra input to the neural network. But the levels did not vary enough, for the same reasons discussed in section 6.3: eyes open over time will return a stable, high level attention value. Thus, this did not solve the problem.

Results were also made that suggests that EEG signals can vary even in the same person, as the identifier in section 4.1.1 states: EEG signals are non-stationarity. The results referred to are the two identical sessions with opposite input values in experiment 3A, figure 7.2 and 7.3. The band powers in session one are generally lower than baseline during mental count, but higher in session two. This indicates that new neural networks should be trained with fresh input, for every session.

7.3.1 Baseline Comparison: Eyes open vs Eyes Closed

Having the baseline task done with eyes closed may not be ideal for gameplay, but it gives a very good opportunity to rest them. It is stressed again here, that forcing your eyes not to blink is disturbing in the long run. This is the most negative when it comes to carry out these experiments, but as we have seen, it is the best alternative if one wants to both view the screen and execute commands.

8 Step Three: Controlling a Game with EEG

8.1 Final System, Game Design and Test Conditions

With the results made in step 2 and experiment 3B, it was time for experimenting with real-time classification while playing a game. A version of Snake was implemented. First of all, because it is a very understandable and easy game to play with few controls. Secondly, it is no doubt a classic game that is still popular today, which leads to an assuming third point: that people find this game amusing. Elaboration of the Snake implementation continues in section 8.1.2, explaining the workings of the game loop. Finally, the last test of the entire BCI system is explained, before the results are discussed.

8.1.1 Overview of the Main Parts of the Final System

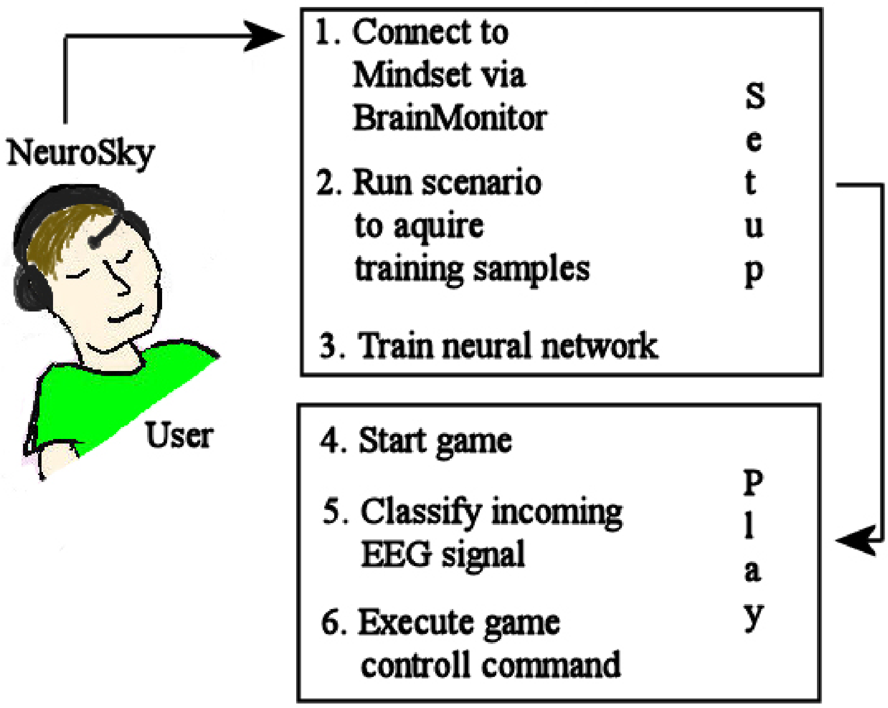

Figure 8.1: Overview of final system flow

Figure 8.1 shows the two parts of the final system and the steps within them. In order to play, the system needs to be initialized with a trained neural network.

This implemented version of Snake has the following gameplay. You start with a single square that you control, and which represents the snake. It can move in three directions: forward, left and right. The goal is to locate and eat apples on a map, making the snake grow in length, and to become as large as possible. Collision with the snake body will end the game, and avoiding this gets more difficult as the snake grows, adding thrill. The map is borderless, meaning that if the snake goes outside the screen, it will re-enter from the border opposite of it. This adds an strategic element, and it can be used to escape from a tight spot, or quickly navigate from one end of the screen, to the other.

The controllable features to choose from, are the three directions of movement. For the sake of having speed in the game, moving forward should be automatic, and whether to turn left or right should be controlled by the user via EEG input. Section 6.3.2 discusses the need for many samples to be able to classify a mental task, and as a result of that, the game can not be real-time; meaning that the game should pause while collecting samples for classification. If it was to be real-time, not only would the user need to know the next action 20 seconds in advance, but it would only be possible to issue a command every 20 seconds. During that time, the snake would continue forward uncontrolled. Unless the snake moves really slow. To have EEG controlling all three directions would also be too slow, for the same reasons. Alternatively, the forward direction could be controlled by the attention level received every second from the mindset. But, for now, moving forward is considered automatic. This is a fair setup to attain speed, since forward is the most used direction in which the snake moves.

The system should have a mechanism to initialize the pause for sample collection. This should be user controlled, and a blink input was chosen. User blink can be detected almost real-time, and since the mindset gives information about the blink strength, it is possible to set a a high threshold that allows regular blinking for the user. This removes the need to play the entire game with open eyes. Also, choosing blink eliminates the need to interact with a keyboard or mouse, making the game totally controlled by EEG. Figure 8.2 is the resulting state diagram for the game control. At game start, snake enters the move forward state. When blink is detected, "sampling mode" is entered. The system waits 1.5 seconds before doing this. If not, the first sample taken would be contaminated with blink artifacts.

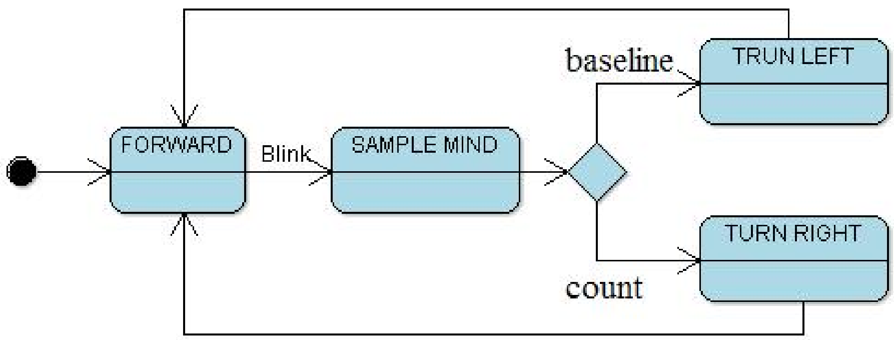

Figure 8.2: Snake control state diagram

Results from classification determines either a ”left turn” or a ”right turn” state, before returning to the forward state again. Since the intended classification experiment is 3B, the baseline task is conducted with eyes closed, so the user needs to be informed when the sample collection is over. This is solved by playing a ”ding” sound when sample mode is entered and exited.

8.1.3 Test Setup, Conditions and Statistics

The testing follows the system flow of figure 8.1. There is two types of tests, 1) **play** and 2) **control.** Sessions in both test types repeats step 2 to 6. The headset is not to be moved during a session. For step 2, 20 samples of baseline (eyes closed) and 20 samples of mental counting (eyes open) were taken and used to train the network. The network is then tested with the same sets, to ensure that they classify correctly: Close to 1 represents baseline, close to 0 represents mental count. Same network setup as in section 6.1.3 still applies.

NOTE: Because 20 seconds seemed like a long time, sample collection while playing was reduced to 10 seconds, averaging 10 samples into a single input instead of 20.

1. Play Test: The user plays the game following the rules. Tests were done where only step 3 to 6 was repeated, using old data to training the neural network. The purpose is to see if those training sets are usable after disconnection and relocation of the headset. In that case, it could indicate that it is possible to make user profiles, to quickly start a game and bypass the last setup steps.

Testing stops when the game is over, or if the user do not want to continue for whatever reason. During the test, statistics of the following is taken:

- **Number of correct classifications:** result is like the test person intended.
- **Number of wrong classifications:** result is not like the test person intended.
- **Number of correct blinks:** System correctly enters sampling mode after user gave a powerful blink to indicate that it should.
- **Number of missed blinks:** System incorrectly do not enter sampling mode after the user gave a powerful blink to indicate that it should.
- **Number of faulty blinks:** System incorrectly enters sampling mode after the user blinked normally, without intention of going into sampling mode.
- **Total game time.**

2. Control test: The user tries to classify a baseline task with eyes open, and a counting task with eyes closed. This is interesting, because it can indicate whether mental efforts affects the results at all, or if it is just controlled by eye states.

8.2 Final Testing, Results and Findings

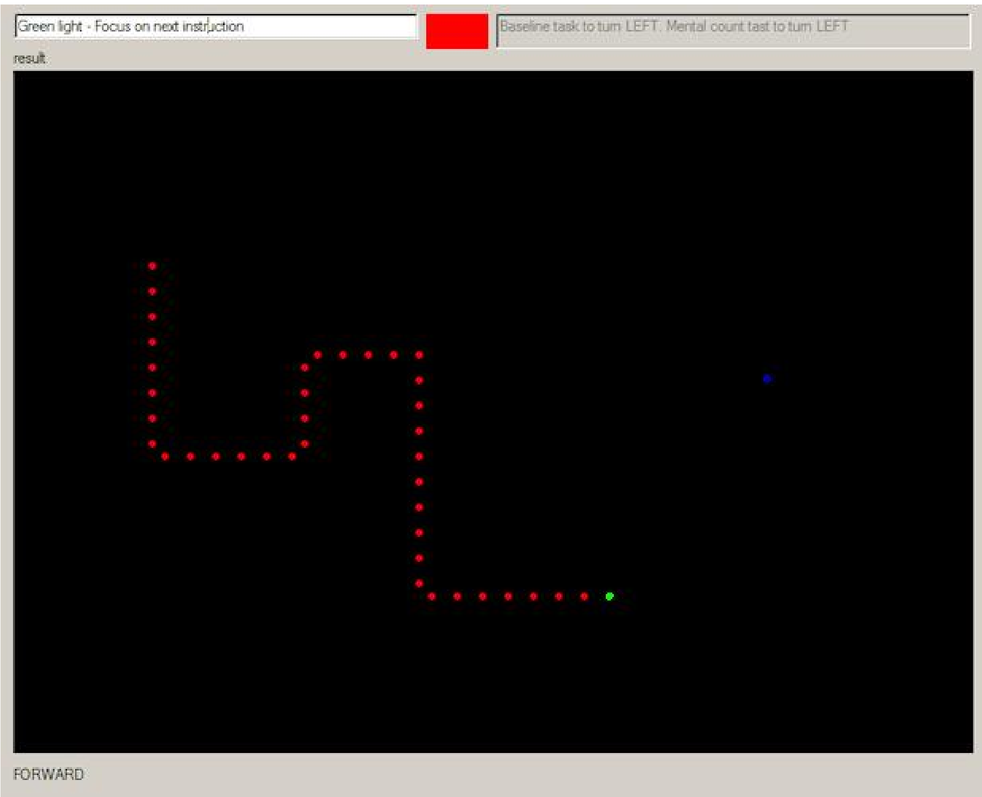

Figure 8.3: Screenshot from the snake-game. Middle top: Box that is colored red when brain waves are NOT recorded, and green when it is recording. Center: Game display: Red dots represents the snake body, green dot is the snake head, and blue dot is an apple. Bottom left: current action.

8.2.1 Play Test Results

Test person one:

Game 1 lasted 7 minutes and 47 seconds, were 61% of that time was used to collect samples. 4 apples were eaten before the game was over (crashed into the end of the tail when growing). The neural network was trained, and had an accuracy of 0.98 when tested with the same sets it was trained with.

Table 8.1: Test results game 1, subject one

Feature	Correct	Miss	Fault	Accuracy
Blink	21	1	2	0.87
Classifications	21	2	-	0.91

Game 2 lasted approximately 6 minutes, were 51% of the time was used to collect samples. 8 apples were eaten before it was game over (The 3 blink misses was the cause of that). The neural network was trained, and had an accuracy of 0.95 when tested with the same sets it was trained with.

Table 8.2: Test results game 2, subject one

Feature	Correct	Miss	Fault	Accuracy
Blink	15	3	1	0.8
Classifications	16	0	-	1.00

Test person two:

Table 8.3: Test results game 1, subject two

Feature	Correct	Miss	Fault	Accuracy
Blink	12	4	2	0.87
Classifications	10	2	-	0.83

Game 1 lasted 9 minutes and 13 seconds, were 34% of that time was used to collect samples. 3 apples were eaten before it was game over. The neural network was trained, and had an accuracy of 0.97 when tested with the same sets it was trained with.

Table 8.4: Test results game 2, subject two

Feature	Correct	Miss	Fault	Accuracy
Blink	10	0	0	1.00
Classifications	10	0	-	1.00

Game 2 lasted approximately 5 minutes, were 38% of the time was used to collect samples. 3 apples were eaten before it was game over. The neural network was trained, and had an accuracy of 0.96 when tested with the same sets it was trained with.

Reusing Training Sets: For both subjects, it was unsuccessful to reuse the training sets. No correct classifications were achieved.

Test person one:

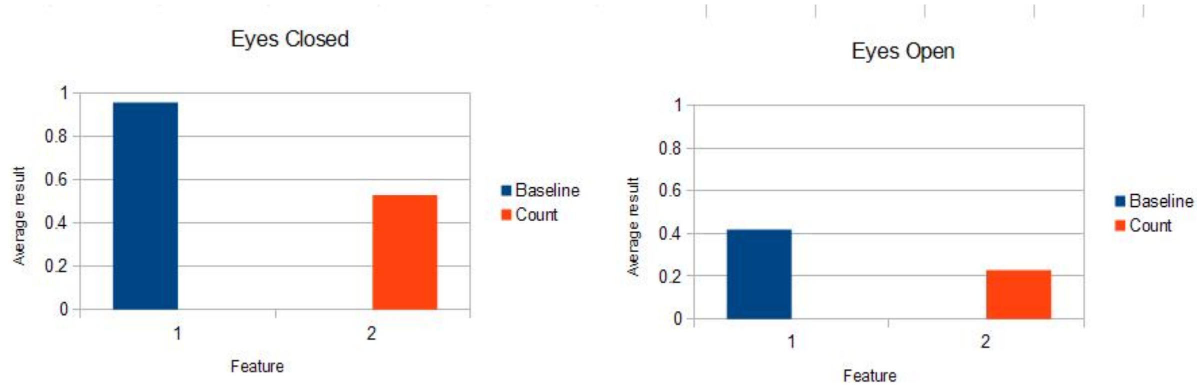

Figure 8.4: Results from control test 1.

In figure 8.4, each bar is the total average from 5 classification results in the control test. With eyes closed, recognition certainty of the baseline task is close to 100%, and gets reduced to about 50% when doing mental counting instead. With eyes open, recognition certainty of mental counting is close to 80% (Close to 0 is classified as counting, thus the probability is calculated by subtracting 1), and reduced to 60% when conducting the baseline task.

Test person two:

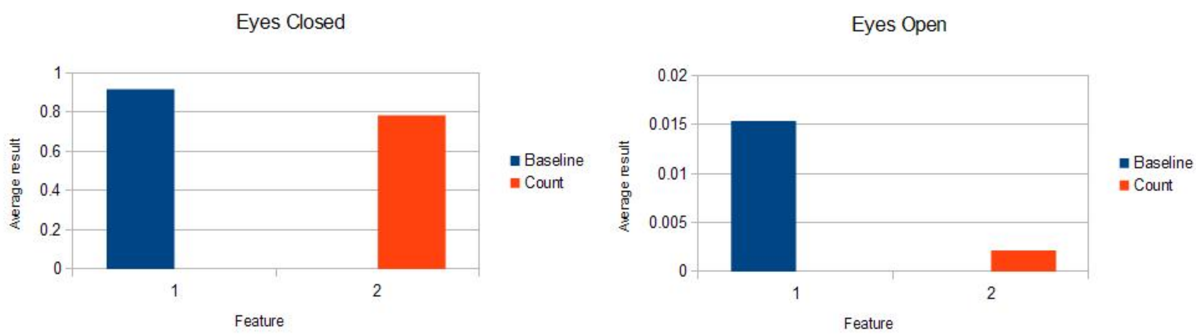

Figure 8.5: Results from control test 2.

In figure 8.5, each bar is the total average from 5 classification results in the control test. With eyes closed, recognition certainty of the baseline task is 91%, and gets reduced to about 78% when doing mental counting instead. With eyes open, recognition certainty of mental counting is close to 99% (Close to 0 is classified as counting, thus the probability is calculated by subtracting 1), and reduced to 0.97% when conducting the baseline task.

8.3 Discussion of Results

The results show a BCI system that enables users to play a game of Snake, controlling everything with EEG signals. Correct classification and eye-blink detection in the play tests for the subjects are over 90%. Also, acquiring this accuracy required no training. This is true for subject two, who had never used EEG equipment before. The author of this project, who is subject one, have had two months of experimenting with it, and can not be regarded as unfamiliar with the device and the classification tasks. However, the results are acceptable as a proof-of-concept for this project, and provides a good platform for which further improvements can increase the accuracy.

Further, the control tests indicates that it is not just the two eye states, open and closed, that affects the EEG signal. With eyes open, it was possible to successfully classify a baseline task when attempted, and likewise, it was possible to identify a count task when eyes were closed. In general, when not doing the mental tasks correctly, the classification probability was lowered with 40% to 50%. This suggests, that perhaps with more experience and practice it will be possible to obtain faster and more accurate brain wave control and thus make the eye state redundant. Still, these states are the key to correct classification in the current system, at least for beginners. It is clear that subject one was more able to alter the waves than subject two, implying that perhaps training made this effect. However, and more importantly, these result indicates that the classification is not controlled by muscle movement.

Figure 8.6: Testing - it is very relaxed.

Both users had good experiences with using EEG to control the snake. Compared to the test experiments in step 2, the game testing was much more relaxed and less strainful for the eyes. This has to do with the blink strength feature that allows normal blinking to go undetected, and that closed eyes is a key feature for the baseline task. This is a satisfying solution since the game needs to pause to collect samples anyway, and the user is in control of when that will happen. Also, since mouse and keyboard are not used, the possibilities of sitting position are many more (Illustrated in figure 8.6).

Observations and notations from playing:

- If focused, it is easy to handle and control the snake.
- One time, when the snake was in a tight spot and it had to make a baseline turn (left turn), the excitement led to too much mental activity, and it was classified as a counting task, and the snake died.
- Since the snake rotates, it is not always so obvious what the left and the right side of the snake is.
- There can be some delay from the physical blink to it is detected by the system. Therefore, the blinking must be timed extra carefully.
- Being able to get the classification results that is intended gave a mastering feeling.
- The borderless map was used a lot to make shortcuts and to escape. It reduces the necessity of having to turn very often. This also speeds up the game.
- Time used to collect samples did not feel long.

9 Conclusion

This report presents results that shows that is it possible to build a Brain-Computer Interface system that allow users to play a game and controlling it with their brain waves. This have been accomplished by using the NeuroSky mindset EEG equipment featuring only one electrode on the forehead. EEG signals from the user are sent to the computer via bluetooth. The signal is then processed and the waves band power is calculated using the Fourier transform. This information is used as input to a neural network that is trained to classify two different mental tasks. Then this classification is used to control the movements (left and right turn) of a character in a custom built PC game, successfully.

The biggest challenge and time-consumption in the project was not the implementation itself, but testing it with the use of real-time EEG input. Three major test steps is outlined with results that have given insights in the workings of EEG and difficulties with BCI systems. The first step was to implement all the components of the system and make them communicate with each other, then enable the system to classify blinks in the incoming EEG signal samples. This was done with a success rate close to 99%. The solution worked, indeed, but was not adequate to classify mental tasks. This was improved in step two, were a new method was discovered that required ten times as many samples and thus effort from the user. Still, it became possible to classify two mental states: baseline (relaxed, calm and not thinking of anything in particular), and mental counting. The first results only gave 60% probability of correct classification, but this was further increased to greater than 90%. This high rate was only attainable when eye states (eyes open and closed) were used actively by the user in addition to the tasks. However, this enabled the realization of step 3, were a version of the game Snake was designed and implemented to work with the EEG input. Results from user tests show that the snakes movements were correctly controlled with an accuracy of 90 to 100%.

Regarding the research questions (see section 2.2.1), the following conclusions are made from the project results and findings:

RQ1: That one electrode in the forehead can replace a grid of, or several, electrodes is highly unlikely. No papers were found of previous studies, were only one electrode have been used. The experience from this study, is that mental efforts that are relatively safe to classify did not work. There can however be other reasons for this than just the single electrode, but at least it suggest that one is not adequate.

RQ2: Having the experience of using both the NeuroSky mindset and traditional EEG equipment, NeuroSky fulfills the expectations as described in the early chapters. More interestingly, the limitation that was most profound with the mindset was the static electrode placement. It can be moved to a certain degree, but not enough to get it away from the forehead. Also, one or two additional sensors would have been great. The Emotive headset, featuring 14 electrodes (see section 4.2.1), would be the recommended choice for this upgrade. It is only slightly more expensive. The connected limitation with placement is that the sensor is heavily influenced by blink. However, the reason the electrode is placed on the forehead, is because people do not have hair there, which is a requirement for this type of dry sensor.

RQ3: The type of classification achieved using a neural network is that of band power patterns. Where the difference between the power bands is of such degree that they are distinguishable, and were the right mental tasks are chosen that will promote this pattern in the users EEG.

RQ4: The resulting BCI system enables an entertaining way for training brain wave control. Both test persons thought is was more fun to play the snake game, than the NeuroBoy software that comes with the NeuroSky mindset. However, more people should test the system to verify that this is truly so.

RQ5: It requires no training to use the resulting system, only 1-2 minutes of preparation time, were EEG samples needs to be taken for the neural network training. With these samples the network learns the difference between the two mental task patterns based on the users current EEG. It was assumed that some training would be needed in order to learn how to do the tasks. This too should be verified by testing the system on more people and get the necessary statistics.

Compared to the games that have used the NeuroSky mindset and the attention value only, this game stand out as more easy to use. It is easier to control the output of mental efforts and thus the accuracy is higher. In a context were the output is binary, the accuracy is additionally higher. The classification (rather than a threshold) takes longer time, so the game is slower. But is works, and it is still fun. Also, there is no training needed in order to play, one just have to focus on the task. In the other games, the parameters than controls the attention levels are unknown. If it is raised by increased beta waves and lower theta waves, one would have to figure out how to manipulate these waves in a trail-and-error style. In neurofeedback therapy, this is perhaps wanted, but if one just want to play, the snake game is much easier. Like a patient that is paralyzed and want to kill some time, and not train brain wave control.

9.1 Further Development and Ideas for the Future

There are two main suggestion for continued work with the system presented in this report. 1) Further development of the program, improving the game, signal processing and classification procedures and feature extensions. 2) Use the current program as a tool for larger scale tests with people, to do EEG surveys and monitoring studies. Most of these suggestions comes from observations made, or questions asked, in the discussion sections of chapter 6, 7 and 8.

1) Further development and improvements of BrainMonitor

- **Implementation of automatic blink strength threshold adjustment:** This would minimize the blink fault error and increase playability. The strength value varies a lot, depending on the electrode placement when the mindset is put on. This can be automatically adjusted by collecting blink strength samples, in an scenario run, from the user when blinking normally. The average value of these samples would then become the threshold.

- **Enable the possibility to classify several features:** One option, using the existing neural setup, is to have several neural networks trained for different recognition task and test EEG samples from the user simultaneously on all of them. Their results are then compared and the network with highest probability wins. Another option is to design a new neural network architecture with all the features wanted in the system represented in the output layer. One output node per feature.

- **Add P300 recognition, to assist in classification verification:** For example, if the user blinks when playing the snake game to signal "sample mode", detecting the P300 signal could verify that this is the wanted move. Instead of looking at band powers to find the P300, the raw incoming EEG data could be spatially analyzed by an algorithm that searches and verifies a peak in the incoming sample.

- **Interface the BrainMonitor program with existing games:** There are many open source games available, that could be interesting to connect with the EEG equipment. The advantage is that a lot of work is already done, like the graphical display and gameplay, so the focus can remain on what and how the EEG function should be. This is further described in the "ideas for the future" section.

- **Interface the BrainMonitor program with hardware:** There exists a library for simple communication with a microcontroller. The same microcontroller that was used in the Playstation project described in section 2.1.1 could be used to integrate it with hardware and make physical objects move, for example.

2) BrainMonitor as a tool

Here are some suggestions of how to utilize the current system as it is:

- **More verifications:** Run tests that run over a period of time, to see if it is possible to improve brain wave control skills using the system. The goal and motivation should be to annihilate the need for the eye states, and rely on mental efforts only.

- **Explore classification possibilities:** Define new experiments to find if there are other mental tasks that are usable for classification in the system. This could be rotation, mental speech or specific memory retrieval.

- **Explore placement possibilities:** Disassemble, if possible, the arm on the mindset that holds the electrode and find alternative placement for it. Conduct test to see if those placements are better suited for solving the classification tasks at hand. The inconvenience is that there can be no hair between the electrode and scalp.

9.1.1 Ideas for the Future - NeuroSky Entertainment

Instead of having the mind directly control features of a game, it could be used as an unconscious influence in the gameplay. For example, in a role playing game, you have a main character, and perhaps a party of followers or helpers. It is common, that throughout the game, your main character gains more experience and get better in a set of skills that will help to conquer challenges later in the game. EEG could be used to add a new dimension to that kind of character building. A continuous analysis of the brain waves could form user models that will be used for influence, with both short- and long-term effects. In the latter case, if you are in general very relaxed or focused, your character might regenerate quicker (if combat is involved), or have more endurance, or get access to special spells of the defensive kind. The opposite would apply for those who are generally restless.

In the external game world, it the player gives signs of drowsiness, the game could introduce unexpected happenings, like an suddenly ambush or develop a creepy atmosphere using mediums like music and lights, whatever is most appropriate. This would be a short-term effect. An other example could be that the dialog could adjust to the users current mood, or how the party of followers engage and act around you. This would create more variation in the game and give them more personality. Additionally, the EEG classifications and algorithms that are to analyze the brain waves do not have to be that accurate. Incorrect results would not hinder the gameplay. And thus it may be a good place to start applying EEG. At least when applying one electrode equipment like the mindset and sampling takes time, indirect influence may be the better way to go.

References

Andersen, K., Juvik, E., Kjellen, E., & Storstein, K. I. B. (2009). *Radio controlled helicopter using neurofeedback.* unpublished.

Andrew T Campbell, Tanzeem Choudhury, Shaohan Hu, Hong Lu, Mashfiqui Rabbi, Rajeev D S Raizada, M. K. M. . (2010). NeuroPhone: Brain-Mobile Phone Interface using a Wireless EEG Headset. *MobiHeld 2*, 3–8. Available from http://www1.cs.dartmouth.edu/reports/TR2010-666.pdf

Berg, K. (2010). *Balanser hjernen og yt mer.* Retrieved from http://www.ytmer.no/.

Bernier, R., Dawson, G., Webb, S., & Murias, M. (2007, August). EEG mu rhythm and imitation impairments in individuals with autism spectrum disorder. *Brain and cognition*, *64*(3), 228–37.

Blankertz, B., Dornhege, G., Krauledat, M., Müller, K.-R., Kunzmann, V., Losch, F., et al. (2006, June). The Berlin Brain-Computer Interface: EEG-based communication without subject training. *IEEE transactions on neural systems and rehabilitation engineering : a publication of the IEEE Engineering in Medicine and Biology Society*, *14*(2), 147–52. Available from http://www.ncbi.nlm.nih.gov/pubmed/16792281

Bos, O., & Reuderink, B. (2008). Brainbasher: a BCI game. *Eindhoven University of Technology*, 36–39. Available from http://doc.utwente.nl/65050/

Brain Entertainment. (n.d.). Available from http://betabrainwave.com/

Braverman, E. (1990). Brain mapping: a short guide to interpretation, philosophy and future. *Journal of Orthomolecular Medicine*, *5*(4), 189–197. Available from http://orthomolecular.org/library/jom/1990/pdf/1990-v05n04-p189.pdf

Curran, E. (2003, April). Learning to control brain activity: A review of the production and control of EEG components for driving brain–computer interface (BCI) systems. *Brain and Cognition*, *51*(3), 326–336. Available from http://linkinghub.elsevier.com/retrieve/pii/S0278262603000368

Dario, F., & Mattiussi, C. (2008). *Bio-Inspired Artificial Intelligence* (R. C. Arkin, Ed.). London, England: MIT press.

Emotiv. (n.d.). *Brain Computer Interface Technology.* Retrieved autumn 2010 from http://www.emotiv.com/.

Fabiani, G. E., McFarland, D. J., Wolpaw, J. R., & Pfurtscheller, G. (2004, September). Conversion of EEG activity into cursor movement by a brain-computer interface (BCI). *IEEE transactions on neural systems and rehabilitation engineering : a publication of the IEEE Engineering in Medicine and Biology Society*, *12*(3), 331–8. Available from http://www.ncbi.nlm.nih.gov/pubmed/15473195

Felzer, T., & Freisleben, B. (2003, December). Analyzing EEG signals using the probability estimating guarded neural classifier. *IEEE transactions on neural systems and rehabilitation engineering : a publication of the IEEE Engineering in Medicine and Biology Society*, *11*(4), 361–71. Available from http://www.ncbi.nlm.nih.gov/pubmed/14960111

Gevensleben, H., Holl, B., Albrecht, B., Vogel, C., Schlamp, D., Kratz, O., et al. (2009). Is neurofeedback an efficacious treatment for ADHD? A randomised controlled clinical trial. *Journal of Child Psychology and Psychiatry, 50:7*, 780–789.

Gilden, L. (2009). *The Role of Language in Human Social Conflict.* Retrieved autumn 2010, from http://www.lifwynnfoundation.org/langrole.htm.

G.tec. (2009). *intendiX - World ' s first personal BCI speller* (Vol. 2011) (No. i). Available from http://www.intendix.com/

Hammond, D. C. (2006). What is Neurofeedback? *Journal of Neurotherapy, 10:4*, 11.

Heinrich, H., Gevensleven, H., & Strehl, U. (2007). Annotation: Neurofeedback - train your brain to train behaviour. *Journal of Child Psychology and Psychiatry, 48:1*, 3–16.

Hiraiwa, A., Shimohara, K., & Tokunaga, Y. (2002). EEG topography recognition by neural networks. *Engineering in Medicine and Biology Magazine, IEEE, 9*(3), 39–42. Available from http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=59211

Hsu, W.-Y., & Sun, Y.-N. (2009, January). EEG-based motor imagery analysis using weighted wavelet transform features. *Journal of neuroscience methods, 176*(2), 310–8. Available from http://www.ncbi.nlm.nih.gov/pubmed/18848844

Immrama. (n.d.). Available from http://www.immrama.org/eeg/electrode.html

Juri D. Kropotov. (2009). *Quantitative EEG, Event-Related Potentials and Neurotherapy.*

Keirn, Z. a., & Aunon, J. I. (1990, December). A new mode of communication between man and his surroundings. *IEEE transactions on bio-medical engineering, 37*(12), 1209–14. Available from http://www.ncbi.nlm.nih.gov/pubmed/2149711

Kellis, S., Miller, K., Thomson, K., Brown, R., House, P., & Greger, B. (2010, September). Decoding spoken words using local field potentials recorded from the cortical surface. *Journal of neural engineering, 7*(5), 10pp. Available from http://www.ncbi.nlm.nih.gov/pubmed/20811093

Kropotov, J. D. (2009). *Quantitative EEG, Event-Related Potentials And Neurotherapy.* 525 B Street, Suite 1900, San Diego, CA 92101-4495, USA: Elsevier Inc.

Kropotov, J. D., Yatsenko, V. A. G., Ponomarev, V. A., Chutko, L. S., Yakovenko, E. A., & Nikishena, I. S. (2007). Changes in EEG Spectrograms, Event-Related Potentials and Event-Related Desynchronization Induced by Relative Beta Training in ADHD Children. *Journal of Neurotherapy, 11:2*, 3–11.

Larsen, E. A. (2010). *Playstation Controlled by Brain Waves* (Tech. Rep.). Trondheim.

Leins, U., Goth, G., Hinterberger, T., Klinger, C., & Strehl, U. (2007). Neurofeedback for Children with ADHD: A Comparison of SCP and Theta/Beta Protocols. *Appl Psychophysiol Biofeedback, 32*, 73–88.

Leuthardt, E. C., Schalk, G., Wolpaw, J. R., Ojemann, J. G., & Moran, D. W. (2004, June). A brain-computer interface using electrocorticographic signals in humans. *Journal of neural engineering, 1*(2), 63–71. Available from http://www.ncbi.nlm.nih.gov/pubmed/15876624

Liu, M., Ji, H., & Zhao, C. (2008, May). Event Related Potentials Extraction from

EEG Using Artificial Neural Network. *2008 Congress on Image and Signal Processing*, 213–215.

Lotte, F., Congedo, M., Lécuyer, a., Lamarche, F., & Arnaldi, B. (2007, June). A review of classification algorithms for EEG-based brain-computer interfaces. *Journal of neural engineering*, *4*(2), R1–R13. Available from http://www.ncbi.nlm.nih.gov/pubmed/17409472

Lukas, S. E., Mendelson, J. H., & Benedikt, R. (1995, February). Electroencephalographic correlates of marihuana-induced euphoria. *Drug and alcohol dependence*, *37*(2), 131–40. Available from http://www.ncbi.nlm.nih.gov/pubmed/7758402

Lukas, S. E., Mendelson, J. H., Kouri, E., Bolduc, M., & Amass, L. (1990). Ethanol-induced alterations in EEG alpha activity and apparent source of the auditory P300 evoked response potential. *Alcohol (Fayetteville, N.Y.)*, *7*(5), 471–7. Available from http://www.ncbi.nlm.nih.gov/pubmed/2222851

Masterpasqua, F., & Healey, K. N. (2003). Neurofeedback in Psychological Practice. *Professional Psychology: Research and Practice*, *34:6*, 652–656.

Mitsar. (2008). *BIOFEEDBACK TRAINER MITSAR-BFB.* pdf available at http://www.mitsar-medical.com/download/promo/Mitsar-BFB_2008.pdf.

Mitsar. (2010). *Mitsar Co. Ltd. Medical equipment for functional diagnostics and neurofeedback.* Retrieved from http://www.mitsar-medical.com/.

Nawrath, M. (n.d.). *Lab3 - Laboratory for Experimental Computer Science.* Retrieved autumn 2010, from http://interface.khm.de/index.php/lab/experiments/arduino-realtime-audio-processing.

NeuronDotNet. (n.d.-a). *Backpropagation Algorithm.* Available from http://neurondotnet.freehostia.com/manual/bpnalgo.html

NeuronDotNet. (n.d.-b). *NeuronDotNet.* Available from http://neurondotnet.freehostia.com/download.html

Neurosky. (n.d.). *Neurosky.* Available from http://www.neurosky.com/

NeuroSky, I. A. (2010). *ThinkGear Socket Protocol* (Tech. Rep.). Available from http://www.neurosky.com/

Peek, B. (2010a). *MindBlaster.* Available from http://channel9.msdn.com/coding4fun/articles/MindBlaster

Peek, B. (2010b). *ThinkGearNET 1.1.* Available from http://thinkgearnet.codeplex.com/

Plass-Oude Bos, D., Reuderink, B., Laar, B. L. A. van de, Gürkök, H., Mühl, C., Poel, M., et al. (2010, October). Human-Computer Interaction for BCI Games: Usability and User Experience. In A. Sourin (Ed.), *Proceedings of the international conference on cyberworlds 2010, singapore* (pp. 277–281). Los Alamitos: IEEE Computer Society Press. http://eprints.eemcs.utwente.nl/18057/.

PlayAttention. (n.d.). *Play Attention.* Retrieved in august 2010 from http://www.playattention.com/.

Rangaswamy, M., Porjesz, B., Chorlian, D. B., Wang, K., Jones, K. a., Bauer, L. O., et al. (2002, October). Beta power in the EEG of alcoholics. *Biological psychiatry*, *52*(8), 831–42. Available from http://www.ncbi.nlm.nih.gov/pubmed/12372655

Reuderink, B. (2008a). Games and Brain-Computer Interfaces: The State of the Art. *Internal Report*. http://www.borisreuderink.nl/files/publications/reuderink2008gbc.pdf.

Reuderink, B. (2008b). Games and brain-computer interfaces: The state of the art. *WP2 BrainGain Deliverable, HMI, University of Twente (September 2008)*, 1–11.

Schalk, G., McFarland, D. J., Hinterberger, T., Birbaumer, N., & Wolpaw, J. R. (2004, June). *BCI2000: a general-purpose brain-computer interface (BCI) system.* (Vol. 51) (No. 6). Available from http://www.ncbi.nlm.nih.gov/pubmed/15188875

Sherlin, Leslie, Arns, Martijn, Lubar, Joel, et al. (2010). A Position Paper on Neurofeedback for the Treatment of ADHD. *Journal of Neurotherapy*, *14:2*, 66–78.

Sinek, S. (2009). *Start With Why.* Retrieved autumn 2010 from http://www.startwithwhy.com/.

SmartBrain. (n.d.). *Biofeedback.* Retrieved december 2010, from http://www.smartbraintech.com/.

Stigsby, B., Rodenberg, J. C., & Moth, H. B. (1981). Electroencephalographic findings during mantra meditation (Transcendental Meditation). A Controlled, Quantitative Study of Experienced Mediators. *Electroencephalography and Chnical Neurophystology,*, *51*, 434–442.

Sundaram, M., Sadler, R. M., Young, G. B., & Pillay, N. (1999). REVIEW ARTICLE EEG in Epilepsy : Current Perspectives. *The Canadian Journal of Neurological Sciences*, *26*(4), 255–262.

Takahashia, T., Murataa, T., Hamadab, T., Omoria, M., Kosakaa, H., Kikuchic, M., et al. (2005). Changes in EEG and autonomic nervous activity during meditation and their association with personality traits. *International Journal of Psychophysiology*, *55*, 199–207.

Universe-review.ca. (n.d.). *A Review of the Universe.* Available from http://universe-review.ca/I10-80-prefrontal.jpg

Wolpaw, J. R. (2010, November). Brain-computer interface research comes of age: traditional assumptions meet emerging realities. *Journal of motor behavior*, *42*(6), 351–3. Available from http://www.ncbi.nlm.nih.gov/pubmed/21278858

Wolpaw, J. R., Editor, G., Birbaumer, N., Heetderks, W. J., Mcfarland, D. J., Peckham, P. H., et al. (2000). Brain – Computer Interface Technology : A Review of the First International Meeting. *IEEE Trans. Rehabil.*, *8*(2), 164–173.

Wolpaw, J. R., & Mcfarland, D. J. (1994). Multichannel EEG-based brain-computer communication. *Electroencephalography and clinical Neurophysiolog*, *90*, 444–449.

Zhang, L., He, W., Miao, X., & Yang, J. (2005, January). Dynamic EEG Analysis via the Variability of Band Relative Intensity Ratio: A Time-Frequency Method. *Conference proceedings : ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Conference*, *3*(1), 2664–7. Available from http://www.ncbi.nlm.nih.gov/pubmed/17282787

Zhang, Y., Chen, Y., Bressler, S. L., & Ding, M. (2009). Response preparation and inhibition: The role of the cortical sensorimotor beta rhythm. *Neuroscience*, *156:1*, 238–246.