USING BRAIN-COMPUTER INTERFACES IN AN INTERACTIVE MULTIMEDIA APPLICATION

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ABSTRACT
The paper describes experiences from implementing a simple snake game, which can be controlled by the user's brainwaves using the NeuroSky mindset. The NeuroSky mindset is an inexpensive Brain-Computer Interface (BCI) device allowing developers to process EEG signals that can be used to control a computer. The BCI opens for new ways for humans to interact with computers, and can be used for many purposes such as aids for people with physical disabilities. A major challenge with inexpensive Brain-Computer Interfaces like the NeuroSky mindset is to discover which patterns of the brain signals that are sufficient accurate and reliable to be used to control a game, as well as can be used as real-time input of interactive multimedia applications. Our prototype incorporates all parts of a functioning BCI system, which includes acquiring the EEG signals, processing and classifying the EEG signals, and using the signal classification to control a game. The paper share experiences from implementing a BCI controlled game as well as results of testing the game on users. Our experiments found that in our prototype, the user can control the snake game using EEG signals with above 90% accuracy. Our solution differentiates from other appliances of the NeuroSky mindset that it does not require any mental pre-training for the user.

KEY WORDS

Multimedia Systems, Graphical User Interfaces, Brain-Computer Interface, Real Time Systems, Game Technology.

1. Introduction

Research and development of Brain-Computer Interfaces (BCIs) have mainly focused on applications in a medical context, typically helping paralyzed or disabled patients to interact with the external world by mapping brain signals to human cognitive and/or sensory-motor functions [1]. Neurofeedback has successfully been used in detection and treatment of people with AD/HD [2]. The BCI research community has recognized systems that make BCIs 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. BCI devices have also become affordable and available that makes it important to explore various usages of such devices, and how they can be integrated with multimedia applications. BCI development is not longer constrained to making software for patients or for treatment, and there is a shift towards software for people with ordinary health. Especially, game developers are seeing the potential of using BCIs to enhance the game experience through new gameplay and new ways of interacting with games. By introducing BCI to entertainment, developers are motivated to make more user-friendly, faster, cheaper and public available BCI-systems. The targeted group of users are not forced to utilize BCI systems, and thus need to be motivated for doing so apart for the coolness factor of controlling a computer with the mind.

NeuroSky is a company with the slogan "Bio Sensors for Everyone", which in late 2009 released an EEG device named NeuroSky mindset at a low price aimed at the consumer market. The product shipped with software development tools, and a brainwave-sensing headset consisting of loudspeakers, a microphone and one brain wave sensor. The headset is worn like regular headphones where the brain wave sensor is placed on the users forehead. In addition the mindset has 3 sensors on the left ear, which are used as a reference for the brain wave signal on the forehead. The mindset has a microchip which pre-processes the EEG signal and transmits the data to the computer via Bluetooth.

This paper reports from an experimental project where the goal was to develop and evaluate a brain-controlled interactive multimedia application to discover the opportunities and limitations of low-cost consumer BCI-devices such as the NeuroSky mindset. The research questions we wanted to find answers to were:

RQ1: How well does one static sensor on the forehead performs compared to 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 brainwaves is possible to use in a neural network?

RQ4: What kind of user experience does a brain-controlled interactive multimedia application provide?

RQ5: How little practice and training time is it possible to get away with before starting to use the system without affecting the performance of the BCI-system?

The rest of the paper is organized as follows: Section 2, presents related works, Section 3 gives an overview of the BCI multimedia system we developed, Section 4 describes our experiments, and Section 5 concludes the paper.

2. Related Works

NASA and Sony developed a Playstation controller that was used to train pilots to be more alert and attentive during a flight. Correct brain patterns were rewarded with a more responsive game controller and vice versa. A study was conducted where a group of children with ADHD were treated, half of them used traditional neurofeedback training and the other half used the Playstation video game with neurofeedback. Both groups improved equally, but the children playing the game enjoyed their training more, and their parents generally reported to notice a higher level of improvement than the parents from the other group [3].

intendiX is a personal EEG-based spelling system [4]. The user is wearing a cap with several electrodes and is 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. This is enough to pin down the letter that you want to spell when focusing on it. The system does this at a fairly high speed and it should be possible to spell at a rate of 5 to 10 character a minute after 10 minutes of usage. However, it puts a lot of strain on the user using the system as they are continuously receiving stimuli [5].

Kellies et al. experimented with severely epileptic patients that were going to have the seizure-stricken parts of their brain removed [6]. The operation required that parts of the skull were opened, and then microelectrodes were installed on the surface to help narrow down the area that needed to be removed. The researchers exploited this by placing the microelectrodes directly on to the Face-Motor Cortex and Wernicke's area that are crucial for speech. Scientists matched the right word, from a string of 10 words, to the corresponding EEG signals between 28 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 to matched words out loud.

An earlier study by Wolpaw and Macfarland used the amplitude or the power levels for vertical movement, and the difference between the power levels for horizontal movement to allow the user to select from four icons, one at each corner of the screen [7].

There are also examples of games utilize BCIs such as Adventures of NeuroBoy where the player can move, levitate, push, pull and burn things using the player's mind, and Mindball where the mind is used to control the speed of a ball. For the former game, attention and meditation values decide what is happening in game, and increased meditation value will lift objects and increased attention will burn objects. For the latter game, the drowsiness and relaxation band powers are used to control the speed of the ball. One example of a game that only uses the NeuroSky attention value is the MainBlaster game where a Nintendo Wiimote is used to target objects on the screen, and when maximum attention value is reach, the target explodes [8].

In [9], the main approaches for utilizing BCI in games and entertainment are outlined. There are two main approaches described: 1) control by affective state, where the cognitive activity is measured to allow detection of what the user is experiencing during a specific task; and 2) issuing commands using brain signals. The most interesting in the article is the discussion about using the BCI to monitor the mental state of the player to dynamically change the gameplay to adapt to the players state of mind.

3. BCI Multimedia System Description

The goal of our interactive BCI multimedia system was to use brain signal input to provide computer interaction. This process can be viewed as a process of four steps as shown in Figure 1.

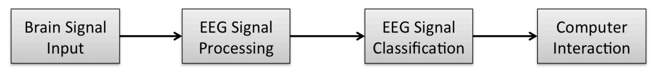

Figure 1. The BCI process flow

Our interactive BCI multimedia system was developed according to the process flow in Figure 1 for the Windows platform in C# using the .Net framework. An overview of our BCI system is shown in Figure 2.

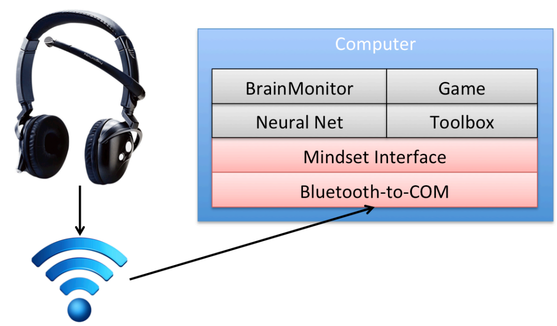

Figure 2. BCI system overview

Our BCI system consists of six parts where the Bluetooth interface and the Mindset Interface are provided by NeuroSky. The Mindset interface consists of libraries that handles the connection, disconnection, and receives a container with data consisting of raw data which is updated every 10 milliseconds and the rest of the data updated every second. The rest of the data consists of signal strength, various bands (Delta, Theta, Alpha1, Alpha2, Beta1, Beta2, and Gamma), attention value, mediation value and eye blink signal.

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

The *Neural Net* component is based on a solution available at [10]. A network setup screen was written to enable easy modification of the following parameters: Maximum training cycles, learning rate, number of nodes in the hidden layer, adjustment of input type to the network, and the activation function in each layer.

The *BrainMonitor* is the main component that provides an event-handler and a graphical user interface that consists of Mindset Control where the user can configure the connection and view the data container, a real-time raw EEG record, sample view, scenario buttons, neural network training, parameter settings, neural network testing and sample control buttons.

The *Game* component contains samples screens and the game logic and visualization for the snake game.

4. Experiments With BCI For Interaction

This section describes the set-up and results from experimentation using a BCI in a multimedia application for interaction carried out in three phases.

4.1 Phase 1: EEG Eye-Blink Classification set-up

Our first test evaluated how well EEG Eye-Blink could be classified using neural networks. The software configuration for this test was written to generate new sample objects that added themselves as observers of the mindset data stream, and filled up an array of raw EEG data until it reached the set sample size. This size was set to 128 data points, making each sample 1280 milliseconds to complete. By observing the real-time EEG record in the BrainMonitor program, it was evident that an eye blink gave a major fluctuation in the EEG signal. This made eye blink a perfect candidate as a classifier, and also indicated that eye blink could be useful for controlling an interactive multimedia application. The baseline was 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 3 shows a screenshot of the sample screen for the scenario program.

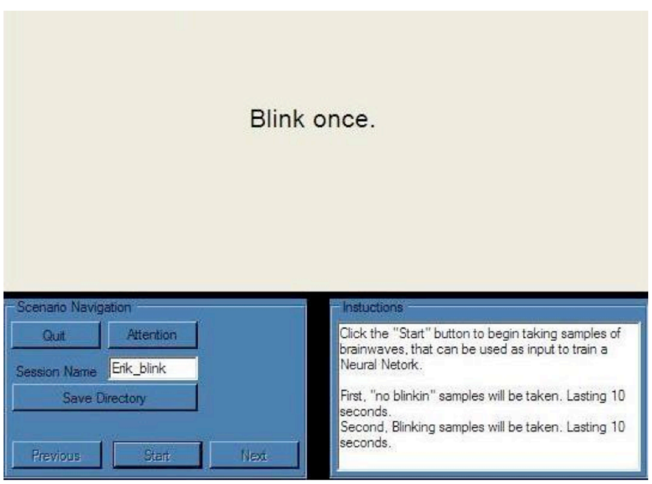

Figure 3. Sampling screen for the Eye-Blink classification

The test scenario was split into two parts. Part one gathered five samples from the baseline task, and part two gathered five samples from the blink task. All samples were saved to disk so the could be used later. The collection of samples from each part in a scenario is called a *set*.

The neural network architecture for this task consisted of five inputs related to the five power bands of a sample: delta, theta, alpha, beta, and gamma. These bands were obtained by conducting Fast Fourier Transform (FFT) on the raw EEG data, and then dividing them into buckets according to their frequency range. Each band value was scaled with respect to the highest frequency in each individual sample, ensuring that all values were in the interval between 0 and 1. Because there were only two features, one output node was sufficient, where all the baseline samples were trained to have the value 0 and the blink samples were trained to have the value 1. The learning rate was set to 0.25, learning cycles to 5000 and number of hidden nodes to 3. The activation function for the input layer was linear and sigmoid was used both for the hidden and the output layer.

4.2 Phase 1: EEG Eye-Blink Classification Results

We wanted two different tests to evaluate how effective eye blink was as a user input. The first test was just as described in previous section, while we introduced noise in the second test by tapping on the forehead. The classification results from test one is shown in Table 1.

Table 1. The classification results from eye blink experiment

Scenario Task	Set 1	Set 2	Set 3	Set 4	Set 5	Average
Baseline (Eyes closed)	0.82	0.96	0.94	0.97	0.96	0.93
Eye blink	0.01	0.01	0	0.01	0.03	0.01

The results showed that eye blink worked very well as an input and our system was able to classify eye blink correctly at an average of 99%. Although noise was expected from the headset, we did not anticipate that it would be very sensible to movements. Because of this, it was decided to conduct all baseline experiments and sampling with eyes open without any movement of head and body. The disadvantage of this approach is that it becomes very tiresome for the eyes. Indeed, this noise issue and the fact that the only electrode on the mindset is placed in the forehead brings up the question whether the blinking disturb the only input signal to make it unreliable? Figure 4 shows a plot of how attention and meditation levels were influenced by eye blink.

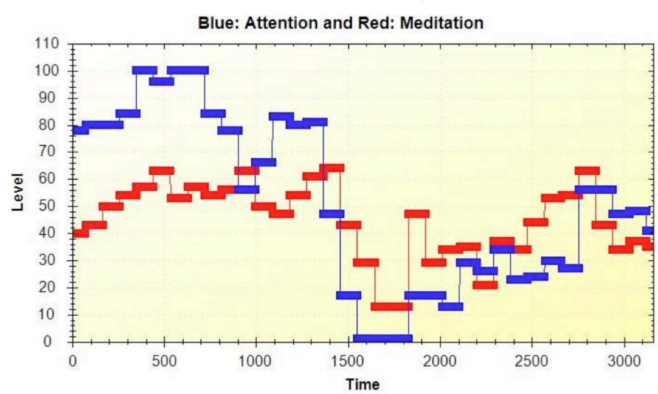

Figure 4. Attention and mediation levels for baseline and blink task

Figure 4 clearly shows that the NeuroSky algorithms that calculate attention and meditation were influenced by eye blinking. During the baseline part, the average attention and meditation level were approximately between 80-100 and 50-60, respectively. When the blink part started, both these levels dropped drastically, especially attention. This was counter-intuitive, because when 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 was that whenever there was an absence of blink, the attention level went to the top, and that the same level was 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 were 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 [11, 12]. However, the fact remained that the results indicated that persons using the mindset should not blink during sampling. This was not ideal when considering making use of it in a real-time system and for longer periods, like in gaming.

When comparing the power spectrum for baseline and eye blink, the difference was evident. Blink gave 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 the gamma decreased, that would be a blink signature. The amount of change from pre-values could indicate strength. This indicated that for BCIs like NeuroSky, no neural network was 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. Our system should be able to classify more than muscle movement.

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 was safe to assume that this was 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 difference between band powers of the single sample and the set was evident.

The drawback with this approach was that it now took 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 major limitation.

4.3 Phase 2: EEG Mental Task Classification Set-up

In phase 2, we carried out three experimental tasks to get better insight into how BCI can be used for interactive multimedia applications.

The *first* experimental task was to see if it was possible to characterize the mental state of thinking about and visualizing movement. Such a mental state would be useful to control a game e.g. to say that a character should start to move. This is a mental task that is common to use in EEG experiments [13]. 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 trails, there were no consistent findings that proved to be classifiable. This lead to the *second* experimental task in this phase.

The *second* experimental task was that visually invoked movement could help change the mental state of the test person faster and more consistently. By combining motion intention and Event Related Potentials (ERP), it could be possible that the P300 effect would have an impact on the band powers. ERP describes the phenomena that external stimuli such as a tone or a light flash can generate responses in the EEG wave. The P300 effect means that the observable amplitude peak occurs 300ms after an event. A new test scenario screen was implemented and the screenshot is shown in Figure 5. The test scenario screen had a cartoon game character that moved an arm up and down repetitively towards the forehead. The test person was instructed to do the same, and follow the rhythm of the motion – to receive and respond to external stimuli.

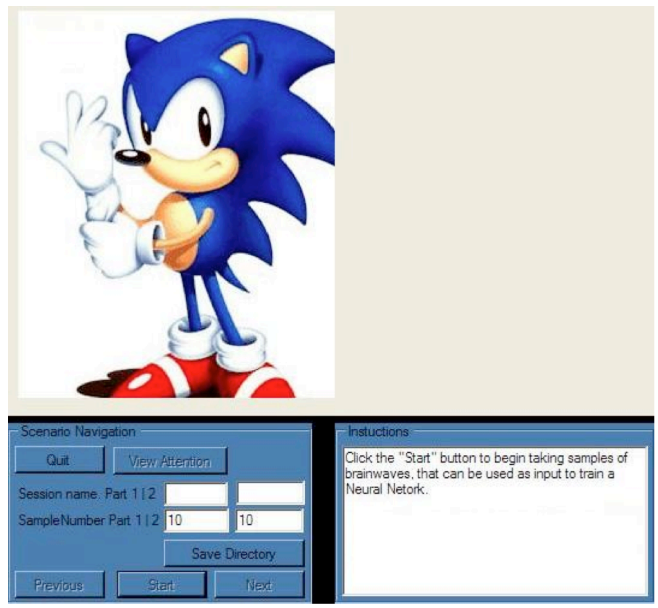

Figure 5. Sampling screen with visual movement

Again, recording and sampling were done with eyes open during the whole session. The scenario was split into 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 and gamma); 5 band powers (5 inputs to the network) and meditation and attention values (7 inputs to the network); and specific band powers (delta, theta, alpha1, alpha2, beta1, beta2, gamma1, gamma2) (8 inputs to the network). Numerous trails and tests were conducted, but no results were found indicating that this was a usable approach toward for classifying a mental state. However, from the classification results it became clear that using meditation and attention values as additional inputs to the neural network in addition to the 5 band powers only made things worse.

The *third* experimental task consisted of the mental task of visual counting, which has been used successfully in other research such as in a study of [14]. This task also matches the functionality of the frontal lobe, as it is related to mathematics and problem solving. This experimental task was conducted in two variations: one with eyes open and one with eyes closed. The task was carried out in two parts. In the first part, 20 baseline samples were recorded. In the second part, 20 visual counting samples were recorded. The 20 samples from each part were used to generate 1 training-set per feature, averaged and normalized (scaled to the maximum value of 1.0). The experimental task with eyes open gave some results, but they were not satisfying. Our assumption was that by doing the same experimental task with eyes close would increase the difference in band powers, as when eyes are closed the perception process is halted in the brain, as there are no visual inputs. This is also supported in literature where in a study by Zhang et al. it was recorded a major alpha waves increase for 20 EEG subjects when eyes were closed opposed to eyes open [15].

Table 2 shows the results from using counting as input both with eyes open and eyes closed. The results from eyes open are taken from the best among the sessions that were conducted where 4 of 5 sets were correct both with baseline and count. For eyes open, we achieved an average of 3 correct classifications out of 5. In one session only 1 of 5 was correctly classified. With eyes closed, the results were improved as shown in the table where 5 out of 5 sets were correctly classified. We found also an increase of alpha activity and decrease of all other waves when eyes were closed.

Table 2. Results from counting with eyes open vs. eyes closed.

Scenario Task	Set 1	Set 2	Set 3	Set 4	Set 5	Average
Eyes open						
Baseline	0.93	0.95	0.95	0.8	0.87	0.9
Counting	0.01	0.07	0.06	0.09	0.94	0.23
Eyes closed						
Baseline	0.93	0.74	0.93	0.95	0.98	0.91
Counting	0.11	0.3	0.06	0.05	0.18	0.14

4.4 Phase 2: EEG Mental Task Classification Set-up Results

The results from phase 2 indicate the possibility to classify baseline and mental count states with a probability greater than 90%. This result is achieved when combining sampling with eyes open and eyes closed. Experiments with eyes open had a correct classification about 60%. There were some exceptions with an average of 20% and some that made it above 90%. To summarize, we found that the classifications using counting provided unstable results. There can be a number of reasons for this: One electrode is not sufficient to get the information, the chosen tasks was not suitable with regards to the location of the electrode, the band frequencies were not the best choice for signal analysis in this context, and/or neural networks were not the most suitable classification method in this context.

Most EEG studies uses 4 electrodes or more placed at some distance from the forehead. This is an indication that perhaps one electrode is just not enough. Also this might indicate that it is more difficult to find a function or task that can be directed towards the electrode location. Our results also revealed that the classifications work much better with eyes closed. For an interactive multimedia application this is not ideal, as the user should respond to events on the screen. Having the baseline task done with eyes closed may not be ideal for gameplay, but it gives a very good opportunity to rest the eyes. As the results from phase 1 shows, blinking the eyes cause a major disturbance on the EEG signals. This means that the ideal mode of input is not to blink the eyes during interaction with the multimedia system. In practice, a BCI-based game that cannot solve this problem in another way, need to include sessions were the user can rest her or his eyes which at the same time can be used to get the baseline.

Mentally visualizing movement has been much used in other EEG experiments with very good classification ratings [16]. We did not get any recognizable classifications for visual movement in our projects. Most likely, the location of the electrode can explain this result. Unfortunately, we could not verify this explanation by moving the electrode since it is unmovable and can only be placed on the forehead. To look for other explanations, we experimented with using the attention and meditation levels as extra input to the neural network. However, these levels did not vary sufficiently to be used for classification.

Our results also showed that EEG signals could vary even for the same person, showing that EEG signals are non-stationary. This indicated that new neural networks should be trained with fresh input for every session.

4.5 Phase 3: Controlling a Game with EEG

Based on the results from phase 1 and 2, the focus of phase 3 was to experiment with a real-time interactive multimedia application. We chose to implement a version of the well-known game snake, where the user controls a snake that moves forward, to the left or to the right. The goal is to locate and eat apples, which makes the snake longer, and to survive without crashing into its tale.

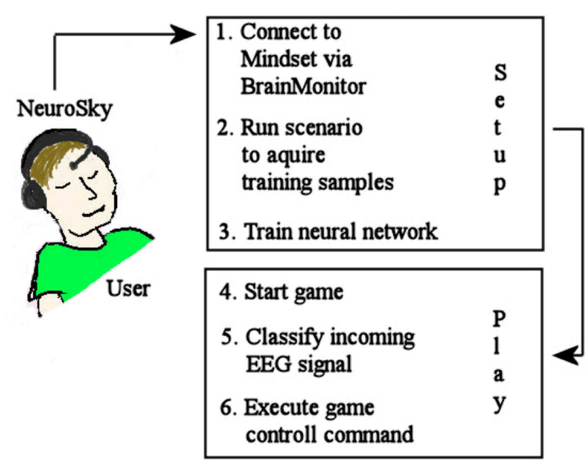

Figure 6. Overview of control flow of the snake game

An illustration of the control flow of the application is shown in Figure 6. First the user connects the Mindset to the BrainMonitor software. The second step is to provide the application with training samples that will later be used to classify user input. In step three, the neural network is trained and when this step is completed, the user can start the game (step four). The game loop consists of classifying incoming EEG signals (step five) and executing game control commands (step six) to change direction of the snake.

The first three steps are required to initialize the game and train the neural network, while the last three steps represent the game itself.

A challenge when using BCI to interact with a multimedia application in real-time is of course that it takes time to classify incoming EEG-signals. This makes it challenging to provide real-time behavior. We chose to solve this problem with an hybrid-approach which lets the user get real-time responses to user input as well as the game gets the proper time to collect samples for classification. It takes 20 seconds to do a proper classification. In our Snake game, the snake moves slowly forward without any input from the user. If the user wants to change the direction of the snake, the user needs to blink her or his eyes. An eye blink can be recognized almost in real-time and only introduce a short latency. After the eye blink, the game will go into sampling mode to find whether the player wants to change the direction of the snake to the left or to the right. The system waits 1.5 seconds before going into sampling mode to avoid contamination of the blink artifact. The snake stops its movement during the sampling mode. To get the best classification, the user should close her or his eyes during sampling mode. The user will know that the sampling is over when the game plays a "ding" sound. The snake will turn to the left if baseline is detected (no particular mental state) and to the right if mental counting is detected. The state diagram of the snake control is shown in Figure 7.

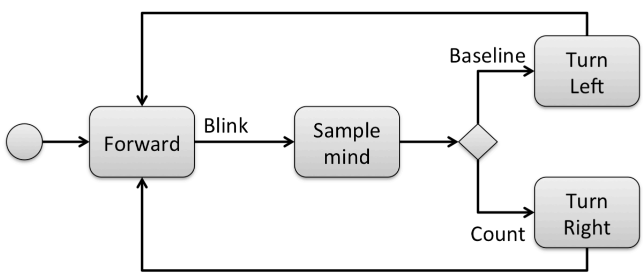

Figure 7. State diagram for controlling the snake

The experimental tests of the game followed the flow described in Figure 6. There were two types of tests: 1) play and 2) control. Both types of tests followed the steps 2 to 6 and the headset was not moved during the tests. For step 2, 20 samples of baseline (eye closed) and 20 samples of mental counting (eyes open) were taken and used to train the network. The network was then tested using the same sets to ensure that they classified correctly. Value close to 1 represented the baseline, while value close 0 represented to mental count.

To avoid a 20 seconds long sample collection while playing, it was reduced to 10 seconds, averaging 10 samples into a single input instead of 20.

4.5.1 Experimental Test One: Play Test

For the first experimental test, the user played the game following the process described in Figure 6 as well as using old data for training the neural network. The purpose was to see if those training sets were usable after disconnecting and relocating the headset. If this approach succeeded, it would be possible to make user profiles that would reduce the time to start a game by bypassing the setup steps. The test stopped when the game was over (snake crashed into its tale). During the test, the following statistics were recorded: number of correct classifications, number of wrong classifications, number of correct blinks, number of missed blinks, number of faulty blinks (the system incorrectly enters sampling mode after the user blinks normally without intention of going into sampling mode), and total game time. Note that the NeuroSky kit produce an amplitude according to the strength of the eye blink which makes it possible to put a threshold to distinguish between a purposeful blink and a normal blink.

4.5.2 Experimental Test Two: Control Test

In this task, the user classified a baseline with eyes open, and a counting task with eyes closed to see how much the state of the eyes affected the results.

4.6 Phase 3: Controlling a Game with EEG Results

The game was played through several sessions and multiple players. The results for the experimental task one (Play Test) where the training sets were not reused are shown in Table 3.

Table 3.Results from experimental task one with fresh training sets

Measure	Average
Playtime	7 min
% of time used to collect samples	46%
Apples eaten	4,5
Accuracy of classification	97%
Correct detected eye blinks	83%
Missed detected eye blinks	13%
Faulty detected eye blinks	6%

As we can see from Table III, the average playing time was 7 minutes where on average 46% of the time was used to collect samples. The average number of apples eaten per game was 4,5 with a range from 3 to 8 apples. The accuracy of the left and right controls was 97%; where as the correctness of detecting eye blinks was 83%. When reusing training sets, no correct classifications were achieved.

For experimental task two (Control Test), with eyes closed the average recognition certainty of the baseline task was 96%, and reduced to 64% when doing mental counting instead. With eyes open, average recognition certainty of the mental counting was 90%, and was reduced to 30% when conducting the baseline task.

Our results from phase 3 clearly show the potential of a BCI system that enables users to play a snake game controlling everything with EEG signals. Correct classification and eye-blink detection in the play tests for the subjects were over 90%. These results were acquired without any pre-mental training of the users that have never used EEG equipment before. Further, the control tests indicated that it was not just the two eye states, open and closed, that affected 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. The subjects of the experiment had a good experience using EEG to control the snake. Compared to the test experiments in phase 2, the game testing was much more relaxed and less strainful for the eyes. This was mainly due to that the system used a blink strength feature that allowed normal blinking to go undetected, and that closed eyes was a key feature for the baseline task. This was a satisfying solution since the game needed to pause to collect samples anyway, and the user was in control of when this would happen. Also, since mouse, keyboard or a game controller is not used, the user can adjust the sitting position more freely. From our findings, we believe that it is important for BCI-games to utilize the sampling phase required for such interfaces to be a part of the game plot and include mental tasks to be a natural part of the story and the game play of the game.

In this paragraph a summary of the observations from playing the game is given. If the user was focused, it was easy to handle and control the game. One time, when the snake was in a tight spot and the user had to make a baseline turn (left turn), the excitement led to too much mental activity and was therefor classified as a counting task (the snake died). Further, since the snake rotates, it was not always so obvious what the left and the right side of the snake were. We also noticed some latency from the physical blink to the detection by the system, making it important to time the blinking well. The users reported a mastering feeling when they were able to get the classification results as intended. Further, the users reported that the time used to collect samples did not feel bothersome long.

5. Conclusion

This paper has presented 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 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 snake successfully.

The biggest challenge and what consumed most of the time in the project was not the implementation itself, but doing tests with the use of real-time EEG input. The paper describes three experimental phases along with results that have given insights into how EEG signals work and the challenges of BCI systems. The first phases included to implement all the components of the system and make them communicate with each other, and 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 phase two, were a new method was discovered that required ten times as many samples and thus more 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 improved to above 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 phase 3, where a version of the game Snake was designed and implemented to work with the EEG input. The results from the user tests show that the snake's movements were correctly controlled with accuracy between 90 and 100%.

Regarding the research questions described in Section I, the following conclusions were made based on the results and findings in the project:

RQ1 (*one static sensor compared to grid of sensors*): One electrode on the forehead cannot replace a grid of, or several, electrodes. No papers of previous studies were found where only one electrode had been used. The experience from this study was that mental efforts that are relatively safe to classify with a grid of electrodes did not work with just one. However, there might be other reasons for this than just the single electrode, but our experiences indicate that one sensor is not adequate for classifying various kinds of mental activities.

RQ2 (*advantages and limitations of the NeuroSky mindset*): Having the experience of using both the NeuroSky mindset and traditional EEG equipment, NeuroSky fulfills the expectations. 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 sufficiently to be placed at other places than the forehead. Also, one or two additional sensors would have helped. An alternative headset is the Emotive headset featuring 14 electrodes. It headset is only slightly more expensive. The main limitation of placement of the sensor is that the EEG signals are heavily influenced by eye 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 the NeuroSky mindset's dry sensor.

RQ3 (*what kind of classification of brainwaves is possible using a neural network*): The type of classification achieved using a neural network was that of band power patterns, where the difference between the power bands is of such degree that they are distinguishable, and where the right mental tasks are chosen that will promote this pattern in the users' EEG.

RQ4 (*what kind of user experience does a brain-controlled interactive multimedia application provide*): The resulting BCI system enables an entertaining way for training brainwave control. The test-persons thought is was more fun to play our snake game, than the NeuroBoy software that comes with the NeuroSky mindset.

RQ5 (*how little mental practice and training time is it possible to get away with without affecting the performance of the BCI-system*): It required no mental pre-training to use the resulting system, only 1-2 minutes of preparation time, where EEG samples needed to be taken for the training of the neural network. With these samples, the network learned the difference between the two mental task patterns based on the users current EEG. It was assumed that some pre-training would be needed in order to learn how to do the tasks, but this was not the case.

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 mental pre-training needed in order to play, one just have to focus on the task. In the other games, the parameters that control the attention levels are unknown. If the game reacts 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. Our project has shown that it is possible to provide interactive multimedia systems with a BCI that does not require any mental training before playing the game or must be played with expensive BCI equipment. Our snake game should be ideal for mental training of e.g. kids with AD/HD or for paralyzed patients that want to kill some time.

There are two directions we want to continue our research with our BCI prototype. *Firstly,* we want to further develop the BCI system, improve the game, signal processing and classification procedures, and feature extensions. Improvements we would like to see are implementation of automatic blink strength threshold adjustment, possibility to classify several features, add P300 recognition to assist in classification verification, provide an interface in the BrainMonitor program to existing games, and provide an activator output that can provide physical objects to move to make a more involving experience. Secondly, we would like to do large-scale experimental tests with many users that include EEG surveys and monitoring to verify our results, explore classification possibilities and explore placement possibilities of the mindsets electrode. We would also like to experiment with different kinds of commercial available BCI headsets, to explore how the difference in number and placement of electrodes affect the results and effectiveness of the equipment for usage for interactive multimedia applications.

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