# BrainBasher


**D. Oude Bos**


**Master's Thesis**


Human Media Interaction
EEMCS Faculty
University of Twente

University of Twente
*Enschede - The Netherlands*

# BrainBasher

*A Multi-Modal BCI Game for Research and Demonstration*

Danny Oude Bos

Enschede, August 22, 2008

***Master's Thesis***

*Human Media Interaction*

*Faculty EEMCS*

*University of Twente*

***Graduation Committee***

*Dr. Mannes Poel (first supervisor)*

*Prof.dr.ir. Anton Nijholt (chair)*

*Dr. Dirk Heylen*

*Christian Mühl MSc*

*Ir. Boris Reuderink*

# Abstract

Brain-controlled games have generally been developed to test some brain-computer interfacing (BCI) paradigm or for demonstration purposes, without much thought about the user experience.

A simple BCI game has been developed to compare the user experience resulting from BCI versus keyboard input. The user study shows that BCI makes the game more difficult, and more challenging. This results in a more immersive and richer experience. The game has also been compared to a standard clinical design (without the elements of a clear goal, feedback, and playful design). The game interface is more pleasing and the experience more immersive. The subjects also performed significantly better.

BCI as an input modality for games enhances certain aspects of the user experience. The elements introduced by games also have their influence on the use of BCI. It is time to take BCI seriously, and research the interlocking effects of combining this paradigm with that of games.

# Samenvatting

Hersengestuurde spellen zijn over het algemeen ontwikkeld om een of ander hersen-computer-interface (BCI) paradigma te testen of ter demonstratie, zonder veel aandacht voor de gebruikerservaring.

Een simpel BCI-spel is ontwikkeld om de gebruikerservaring van BCI- met toetsenbordinvoer te vergelijken. De gebruikersstudie laat zien dat BCI het spel moeilijker maakt, en meer uitdagend. Het resultaat is een meer absorberende en rijkere ervaring. Het spel is ook vergeleken met een standaard klinisch ontwerp (zonder de elementen van een duidelijk doel, feedback, en speels ontwerp). De interface van het spel is meer aantrekkelijk en de ervaring meer absorberend. De proefpersonen deden het ook significant beter.

BCI als invoermodaliteit voor spellen verbetert zekere onderdelen van de gebruikerservaring. De elementen die worden toegevoegd door spellen hebben ook hun invloed op het gebruik van BCI. Het is tijd om BCI serieus te nemen, en de gecombineerde effecten van de samenvoeging van dit paradigma met dat van spellen te onderzoeken.

# Preface

> "Well" said Pooh, "what I like best – " and then he had to stop and think. Because although Eating Honey was a very good thing to do, there was a moment just before you began to eat it which was better than when you were, but he didn't know what it was called.
>
> — WINNIE THE POOH

Although I'm not sure when exactly I first started to think about brain-computer interfacing, those first thoughts probably included words like "awesome", "science fiction", and "I want to play!".

Sometime in 2006, I decided to actually go for it, and adjusted my master program to include courses that would support this goal. The first subject was signals and transformations, a very interesting math course which introduced me to Fourier transforms. I must admit that I have not yet used the formulas I've learned then, but the basic ideas of sampling and the different ways of looking at signals did help with understanding some methods used in BCI.

The second course was neurophysiology, which was very different from what I was used to from my computer science background. Apart from the general concepts of the brain, the nerve system, and neurons, suddenly I had to go way back to try to remember what I had learned years ago in high school in biology and chemistry class. Fortunately the professor, Enrico Marani, was (and still is) a very animated man who would not let your attention slip for one second.

How I got through the third and final course of neurotechnology, I still don't really know. As the course was intended for master students from electrical engineering or biomedical technology, I was in way over my head. But by practicing on a lot of old exams, and perhaps because the professor thought I'd probably never get around to developing brain implants anyway, I did pass the final test.

Looking back, the most valuable course was one that was already part of the human media interaction master: machine learning. If you have any experience in the BCI field, you know that it is used everywhere, from detection of artifacts to identification of brain activity, from learning to better understand the brain to detection of abnormalities.

In 2006 I had already decided to have my master thesis research be in the area of brain-computer interfacing (BCI), but I had no idea yet of the specifics. Around the time I started my internship at the Music Mind Machine group in Nijmegen (to implement an artifact detection method for their online BCI system), at the University of Twente the first students started with their own research in the BCI field. The main focus at that time was already imaginary movement, and although one of those students (Dirkjan Bussink) did have the intention of developing a game, the combined requirements of both analysis and application proved too much work. This is kind of where I picked up, with a tremendous amount of help from Boris Reuderink who took up the work required for the brain activity analysis and classification. Without this combined effort, it would have taken a lot longer to get where we are now.

Most people probably won't recognize it, as it has been majorly simplified, but the idea for the game has actually been derived from music games. Dance Dance Revolution, Pop'n Music, Donkey Konga, Drum Mania, Guitaroo Man, Guitar Hero – I love them all. Of course it will take some time before BCI is developed enough to provide the user with enough sense of control to include all the music game aspects of action, timing, and duration. But I'm looking forward to the day.

As any report, this is just a superficial reflection of all the work and discussions that actually took place. Like Dirkjan, I hope it may spark other people's interest in BCI, and provide inspiration for continuing research in this area.

Danny Oude Bos

Enschede, August 22, 2008

One can't complain. I have my friends. Someone spoke to me only yesterday.

*Eeyore*, WINNIE THE POOH

# Acknowledgements

There are many people I owe thanks to for helping to bring this project to completion.

First of all, I'd like to thank my significant other, *Martijn Plass*, for his support and advice, and for bearing with me even during the more stressful times. From his point of view as a game developer, he provided valuable insights into game development and evaluation.

Then there is of course my graduation committee: *Mannes Poel*, *Anton Nijholt*, *Dirk Heylen*, *Boris Reuderink*, and *Christian Mühl*. I owe them all a lot for their advice on many levels. With three of them I had a more regular contact, I'd like to thank them specifically. Mannes Poel's solid guidance kept me on the right track during the process. Boris Reuderink implemented the underlying BCI pipeline – without him, there would have been no demonstration at ICT Delta, and perhaps even no practical evaluation of the software. The design and implementation of the EEG analysis code is all his. Christian Mḧl for his support and suggestions. His background in answering the most difficult questions made him also for my purposes a valuable source of wisdom and astonishment ;)

There are more people who I'd like to thank: *Corona Zschüsschen*, illustrator and designer, and a dear friend of mine, for the design of the imagery for the game. Without her the application would not have looked this good – with all its consequences for the user experience. *Besty van Dijk* for providing helpful advice on the user evaluation protocol and questionnaires. *Karolien Poels* from the Game Experience Lab in Eindhoven for sharing the Game Experience Questionnaire with us (and thanks again Christian for arranging this). The enthusiastic *test subjects* (whom I promised to keep anonymous) for bearing with me through the experiments. Their participation has been vital for this research. And *George Michael* for creating music that works great for keeping my thoughts on thesis writing.

But perhaps even most important: I'd like to thank *friends and family* for their continuing support.

Finally, we gratefully acknowledge the support of the *BrainGain Smart Mix Programme* of the Dutch Ministry of Economic Affairs and the Dutch Ministry of Education, Culture and Science.

# Contents

# List of Figures

# List of Tables

# Chapter 1

“When you wake up in the morning, Pooh,” said Piglet at last, “what’s the first thing you say to yourself?”
“What’s for breakfast?” said Pooh. “What do you say, Piglet?”
“I say, I wonder what’s going to happen exciting today?” said Piglet.
Pooh nodded thoughtfully. “It’s the same thing,” he said.

WINNIE THE POOH

# Introduction

The Human Media Interaction (HMI) group at the University of Twente has fairly recently (in 2007) started conducting research in the area of brain-computer interaction (BCI). Within this research, brain activity is analyzed to retrieve information which can be used as input signals for, for example, computer applications.

The research described in this thesis is a continuation of an earlier attempt to create a game that is controlled by specific brain activity – which we will henceforth refer to as brain actions [3].

The added value of combining games and BCI is two-fold. Although BCI research has long been dedicated to the medical domain [19, 9, 47], there is a lot of potential for use with healthy subjects. Gamers especially are often early adopters of new paradigms, in their quest for novelty and challenges [28]. Because the focus is only recently shifting towards this user group, there is a lot to look into and a lot of questions that need to be answered [30, 28].

On the other hand, the game approach may also aid science. It can be expected that test subjects for BCI experiments will be able to stay motivated and focused for longer periods if tests can be presented in a game format [20, 11, 12, 43] However, researchers fear making the feedback more complex which could distract the test subject from the basic experiment and ambiguate the results [41, 18, 3]. This has kept researchers from addressing the value of game elements like feedback and scoring.

This thesis addresses some of these opportunities and issues by developing and evaluating BrainBasher, a BCI game controlled with movement imagery of the left and right index fingers.

## 1.1 Motivation

Some of the main motivational reasons have already been partially outlined above. This section will go a little deeper into those and other reasons behind the motivation.

### 1.1.1 Continuation of Existing Research Directions

In 2007, Dirkjan Bussink started working on the first BCI game within the Human Media Interaction group at our university [3]. His original motivation was to make a beginning in exploring possibilities for using BCI for the general public. Although his original intent was to create a BCI game, in the end his work had to be limited to the setup of a working online classification system. Our project picks up where he left off, by focusing on the game application, instead of the underlying system.

Another incentive is the six-year BrainGain project that kicked off last year as well. Our HMI group participates by doing BCI research focused on applications for healthy users. There are a number of issues that will be looked into, like user experience, using brain signals for control in game environments, and designing interfaces and game environments [29]. This proposal fits perfectly within the presented scope.

Besides, a game to demonstrate BCI research results could be very useful for promotion within and without the university. With this system, theories can also be tested and demonstrated to work in practice.

### 1.1.2 Research Motivation

According to Leeb, motivated subjects perform much better than unmotivated ones [20]. Attention decrease and fatigue are common problems with BCI experiments that could be addressed by keeping the user interested and motivated with an entertaining game experience. Even for users for which BCI fills a functional need, games are necessary says Graimann: "Present-day BCIs seldom provide accurate feedback within an interesting and graphically appealing training environment. Specially designed computer games that provide both a motivational environment and appropriate feedback which facilitates effective learning may be necessary to motivate the users for the long training periods necessary in BCI rehabilitation and neurofeedback therapy applications" [11].

A paper by Malone describes a very interesting research into how game elements can be used to improve the user experience of normal applications [23]. Multiple versions of a simple darts game were played, each one adding another game element: the first version as non-interactive, the second added performance feedback, then scoring, constructive feedback, extrinsic fantasy, music, graphic representation, and finally intrinsic fantasy were added. The total time played was taken as the relevant measure of appeal of the game. Although there were some differences in the influences of these added elements between boys and girls, generally one can say that each feature increased the average total playing time.

Currently, most BCI research is still aimed at restoring communication and movement capabilities of paralyzed patients. As a result of this lack of interest in BCI for the general population, very little has been done to look at the potential added value of BCI and its influence on the user experience in games in particular. However, as Vaughan states: "Gamers comprise a large and rapidly growing population; they tend to be enthusiastic about trying new technologies and are likely to embrace brain signal control. They might even be enthusiastic subjects for experiments developing new control channels." [45].

Online systems are necessary to tackle real-time issues. Unfortunately, real-time studies are on the decline because more and more archival data sets have become available, according to a recent report on international BCI research [2].

Finally, the game that is proposed decouples BCI inputs from the traditional analogies (e.g. left hand movement imagery moves the cursor to the left, or rising EEG activity lets a ball float up), opening up the view for more inventive use of brain activity.

## 1.2 Objectives

The questions that this research tries to answer are derived from recurring elements within the motivation section:

**How does controlling a computer game with the brain influence the user experience** compared to conventional input methods like a keyboard?

Because of the novelty of BCI that situation could be more entertaining for the users. On the other hand it could also be a source of frustration when the interface is not completely reliable. The keyboard input could be perceived as unchallenging when the same level definitions are used for both situations.

**How does using game elements (e.g. a clear goal, feedback) within a BCI experiment influence the user experience and performance** compared to a clinical minimal design like the simple visualization used by Bussink [3]?

The user experience and performance (resulting from the interplay between user and system) are intrinsically connected. The potentially distracting game elements could reduce the user's focus and hence reduce the performance [41, 18]. If the user is more focused and motivated as a result of the game elements, this could result in a performance increase [20, 11, 12, 43]. At the other half of the equation, a better performance could give the user a sense of being good at it, increasing the experienced fun. If the user performs badly, they will feel bad. And what if the user becomes agitated by the game? This could again reduce the performance.

The focus for this research is on the game development and user experience evaluation. Boris Reuderink has implemented the preprocessing, feature selection, and classification steps required for the brain activity analysis. As EEG analysis is a vital part of the system, details about them are included in the design chapter, Chapter 3. However apart from the user experience evaluation, no explicit experiments have been conducted by me personally to validate the chosen EEG analysis approach.

## 1.3 Approach

The following methodology is used to achieve the objectives described in the previous section. The approach is broken down into four global steps:

1. Literature research
2. Prototype design and implementation
3. User evaluation
4. Heuristic evaluation

Details on the planned actions for each of these steps are provided next.

**Literature Research** To gain insight into the current situation in BCI gaming and the applications used in BCI research, a short literature research was conducted to obtain answers to the following questions.

- What BCI games are currently used in research?
- What BCI games are commercially available?

The literature review can be read in Chapter 2.

**Prototype Design and Implementation** Designing the game is one of the most important steps towards a working BCI game application. The right design will avoid problems later on, and also save time when adjustments do have to be made. The system that supports the application is just as important, or maybe even more so, as it is the determining factor in the amount of control the user of the application will have (apart from the control the user has on their own brain actions).

Each of the elements of the system is detailed in Chapter 3. Details on the development of the application can be found in Appendix A.

**User Evaluation** For the user evaluation, an experiment protocol has been defined plus questionnaires have been drafted that ask all the questions needed to find answers to the research questions. The details can be found in Chapter 4, which also contains a description of the results and the analysis.

**Heuristic Evaluation** As a user-independent evaluation, a heuristic analysis of the game is performed. This analysis may provide insight into the suitability of the application as a game and what can be improved in subsequent versions. See Chapter 5 for the methods and results.

## 1.4 Reading Suggestions

The sectioning of the report follows the approach defined above. First the results of the literature research will be shown and discussed in Chapter 2. Next, Chapter 3 details the BrainBasher prototype. Design documents can be found in Appendix A The user evaluation chapter is followed by the description of the heuristic evaluation in Chapters 4 and 5. And as usual, the report ends with results and conclusions.

Depending on your personal interest, certain sections can be skipped. The Related Work chapter may help to understand some design decisions in the chapter that follows and in Appendix A. If this understanding is not considered relevant, this chapter can be disregarded.

The chapter describing the design of the application and the underlying system is mainly interesting for those who want to know the inner workings of the BCI pipeline. It also contains a comprehensive account of the BrainBasher game application. Some terms are introduced and explained here that will be used in subsequent chapters.

The actual research is described in the User and Heuristic Evaluation chapters. The latter will contain a certain amount of references to the User Experience Evaluation as it helps to find answers to certain heuristic guidelines.

But if you are only interested in the results it is possible to skip straight through to the Conclusions and Recommendations. Of course the fastest route is to just read the Summary.

Before beginning a Hunt, it is wise to ask someone what you are looking for before you begin looking for it.

WINNIE THE POOH, POOH'S LITTLE INSTRUCTION BOOK

# Chapter 2

# Related Work

This chapter gives an overview of BCI games that have already been developed both for research and commercial applications. It provides some insight into the current state of research and development, and into some general issues.

The line between games and other applications is not always an easy one to draw. Features that were taken into account are:

1. Is a similar type of application sold as a game?
2. Do the researchers refer to it as a game?
3. Does it not necessarily provide a real-world function?

## 2.1 BCI Games in Research

Most applications in BCI research have been designed to help disabled people. They help perform functions these particular users have lost, like communication [9, 47], and movement [19]. Another target group is people who want to change their mental state so they can function normally. The goal of neurofeedback applications for this group is usually to increase focus or to reduce stress [13, 22].

Some of the games below belong to this functional group, while others have been designed as proof of usefulness of certain BCI input paradigms. The games have been subdivided by their input method, to provide some kind of structure.

### 2.1.1 Movement Imagery

This section shows games that use the typical brain signals that occur when the user imagines to perform a certain movement, also called Movement Imagery (MI).

Last year, Dirkjan Bussink already started the work on a BCI game for the Human Media Interaction department at the University of Twente [3]. The game is based on the 4-class stimulus application used by Graz [39]: a simple cross is shown of which each of the four directions can highlight to indicate a certain action. From north to west: tongue, right hand, feet, and left hand MI. For the game this was extended to analyze the brainwaves immediately after the stimulus and inform the user on the classification result. A score is maintained on how well the user did.

Mu activity over the two hemispheres of the brain can be used to control left (low mu) or right (high mu) movement in a 3D video game. Pineda *et al.* developed a first person shooter that is controlled this way [35].

For the game Jump and Run, first the optimal MI for the player is determined, being either the left hand, the right hand, or feet. The game itself consists of a ball that automatically rolls from left to right. Randomly, hills occur over which the ball has to jump. This ball is controlled by the user, and the height of the ball (for jumping) by the perceived strength of the brain activation caused by the MI. Apart from timing, the game also uses the dimension of duration: hills could be wide, so the user had to keep up the ball for three full seconds [26].

The Berlin Brain-Computer Interface also uses imaginary movement of the left and right hand mapped to left and right inputs. Users have already played a variety of familiar games with this system, like brain-pacman, and brain-pong. Krepki *et al.* describe brain-driver and brain-tetris (includes feet imagery for rotation) to be in development [17]. The development of such a range of games to control with BCI is an interesting step towards applications for healthy users.

### 2.1.2 Visually Evoked Potentials

Visually Evoked Potentials (VEPs) are event-related potentials (ERPs) that are evoked by visual stimuli. A subgroup of this brain activity is Steady-State Visually Evoked Potentials (SSVEPs): when an image is flashed at a certain frequency, this modulation frequency can be detected over the visual cortex. This type of brain activity is not elicited by the user directly (as with MI), but by the action of looking at specific stimuli.

One of the earlier games, or perhaps even the first brain-game, is Vidal's maze which uses visually evoked potentials (VEPs) as input [46]. The user is shown a maze which they have to get out of. During stimulus times a checkerboard, tilted 45 degrees, is shown over the maze and flashed briefly a number of times. Depending on where the user wants to move, he/she looks at one of the target points at the corners of the checkerboard at the top, right, bottom, or left.

Steady-state visually evoked responses (SSVEPs) have also been used to let the user roll a flight simulator to the left (low SSVEP amplitude) or right (high SSVEP amplitude) hands-free [24]. The goal was to reach commanded roll positions as quickly as possible. As feedback, the simulator display contained a horizontal bar showing the currently detected SSVEP amplitude.

Lalor *et al.* developed an SSVEP-based tight-rope walker game in a 3D environment called MindBalance [18]. An animated character balances on a rope with a stick. On each end of the stick there is a checkerboard flag. When the character stumbles to one side, the player focuses on the flag on the opposite side to return to balance.

### 2.1.3 Mental State

Mental State is a very broad category which is home to emotions and general brain activity paradigms. In contrast to the other games described, three of the games in this category are multiplayer or include the option to play it with others.

Brainball is probably one of the more renowned BCI games currently available. Two players control one ball on the table through their state of relaxation [13]. The more relaxed you are compared to your opponent, the more the ball will move away from you. The goal is to score a goal by getting the ball to the other side. It is also possible to play this game in cooperation mode: try to keep the ball in the center, together. The state of relaxation is determined based on the beta and alpha waves ratio. A commercial equivalent is available, called Mindball - more about that further on.

A game developed by Strehl *et al.* [43] is aimed at treating people with attention-deficit/hyperactivity disorder by letting them learn to control Slow Cortical Potentials (SCPs). SCPs are slow event-related shifts in the EEG, which can be self-regulated to influence excitation thresholds of large groups of neurons. On the screen a ball moves from left to right. There is a rectangle at the top and one at the bottom, corresponding with a negative and positive SCP respectively. The game indicates the goal target by highlighting the rectangle. When a negative SCP shift is detected the ball moves up and vice versa. The objective is to hit the right target. When this happens, a smiling face is shown as additional confirmation.

Brainathlon is another competitive neurofeedback game, developed by Palke [32]. It consists of three minigames that reward brain activity in configurable frequency ranges. It can be played single- and two-player. The goal of the first course is to rise a ball above a certain threshold which corresponds to reaching high amplitude activity within a specified frequency range. Course 2 shows a square that has to be highlighted for a certain duration. The square lights up when a certain amplitude within the specified frequency band is achieved. During the final course a red ball is balanced on top of a black line. The balance depends on the ratio between two configurable frequency bands. The goal is let the ball roll off to the right.

Inspired by MindBalance, Shim *et al.* again use the analogy of a tight-rope walker for this balance game [41]. This time the balance is controlled by left vs. right hemisphere brain activity, which is also visualized with meters in the bottom of the screen.

Another relaxation game has been developed in which a simulated ball is controlled by the user's level of mental relaxation. Somewhat similar to Brainball, relaxation moves the ball to the right, stress to the left [22]. It can be played in both single-player and two-player mode. The raw EEG and some other amplitudes are also shown for feedback.

## 2.2 Commercial BCI Games

Most companies that focus on BCI products make very little of what they are actually doing public. The following information is mostly gained from the companies' websites. Most of the older companies sell products which are useful to assist or diminish certain ailments. The more recent companies currently seem to be more concerned with developing proper hardware, but they often also provide some demo software.

It never made it to an official release, but the Atari Mindlink was the earliest attempt to bring 'the mind' as an input modality into the world of video games. The input was not based on EEG but on electromyography (EMG): the headband measured muscle activity on the user's forehead. Mindlink was planned for release in 1984, with a breakout variant and a mind-reading game [1]. The project was cancelled because of performance issues and user-reported headaches [2].

Interactive Productline developed a small range of commercial products based on the experimental Brainball game described earlier. Mindball is mainly sold to museums and research centers [3].

The system designed by S.M.A.R.T. Brain Games can be used in combination with any normal game as it influences the efficacy of the controller. If the user does not maintain the desired brain state (relaxed and focused), the game control decreases. Their main target group is children with attention deficit disorders [4].

G.tec mainly targets paralyzed patients, and is known for the research conducted in collaboration with Graz. Their website features a two-player pong game based on left and right hand MI, and a P300 speller implementation [5].

EmSense focuses on game development companies providing them with a way to analyze the cognitive and emotional response of gamers to their product. This gives developers the means to "identify the most exciting features and optimize the thrill of the game". Their main activity has been to "conduct thousands of tests on video games and tv commercials" [6].

Another BCI company that focus on the games industry directly is Emotiv. With the accompanying wireless dry-electrode headset, the Emotiv system can detect expressions, (actual) gestures and emotions. Of course, no information is

[1] http://www.atariprotos.com/2600/software/mindmaze/mindmaze.htm
[2] http://www.atarimuseum.com/videogames/consoles/2600/mindlink.html
[3] http://www.mindball.se
[4] http://www.smartbraingames.com
[5] http://www.gtec.at/products/g.BCIsys/bci.htm
[6] http://www.emsense.com

provided on how they do it. The website currently features impressive demonstrations of some of their demo software, including a three-dimensional world with which can be interacted by using all of the brain actions that can be detected with the Emotiv system. A very interesting initiative is the Emotiv Development Kit, which enables game developers to create games using Emotiv technology [7]. The shipping of limited edition Emotiv head sets is said to begin near the end of 2008.

Neurosky develops products for manufacturers and developers. With one electrode on the forehead, the system detects attention and meditation which in their demos are used to push or pull, and float objects respectively. Like Emotiv, they also have their own head-set ThinkGear™ with active dry electrodes plus a signal processing library that translates the brain activity into logical control signals, which seems to focus on emotion recognition [8]. The headset is not sold to the general public.

## 2.3 Conclusions

Looking at all these articles, a number of things become apparent. Often the choice for a game application in research is made to keep the user motivated and focused [43, 32, 41]. The possible added value of the game element is widely known and accepted.

However, researchers are afraid to add extra information to the feedback to the user because it could be potentially distracting [18, 41, 3]. Although some applications have been designed that provide a more immersive experience (i.e. provide more information than is necessary to perform the BCI experiment itself), no actual comparative research has been conducted.

Most research applications that are called games are not games in a more specific interpretation of the word as often goals are not explicitly defined, and no scoring system is implemented [35, 22]. Also no special effort is made to create an engaging and entertaining experience for the user (for example with user experience evaluations). For our research it is important to not only think about what is important from a research perspective, but also to take into account the user experience.

The type of user input is independent of the game itself. Balancing games have been designed for both the mental state and SSVEPs [41, 18]. The maze game which was implemented with VEPs [46] could just as well have been played with 4-state MI [3]. In the case of MI it is possible to chose an intuitive analogy, like matching movement to the left with left-hand MI. However, especially when the input is not as directly linked to real-world experience, maintaining a link with reality is not possible and some arbitrary metaphor is chosen [43, 32, 22].

Most commercial BCI companies are not focused on developing games themselves but rather to provide game studios with the opportunity to use this new

[7] http://www.emotiv.com
[8] http://www.neurosky.com

means of interaction in their software. The first commercial BCI game for the general public still has to be released - not accounting for neurofeedback applications.

> Pooh looked at his two paws. He knew that one of them was the right, and he knew that when you had decided which one of them was the right, then the other was the left, but he never could remember how to begin.
>
> — WINNIE THE POOH

# Chapter 3

# BrainBasher

Based on the motivation and related work, a game has been designed. This game, BrainBasher, and the underlying system are explained in this chapter.

The first section assembles the features that were deemed important as a reaction to the issues mentioned in other research. Second, the resulting application is described in detail. The final section describes the BCI pipeline that supports the application.

## 3.1 Requirements

In the previous sections, motivation and related work specifically, some issues have been raised that need to be addressed in the BrainBasher design. As the application is a game, it is also necessary to look at the necessary game elements to incorporate.

### 3.1.1 Game Elements

An article by Malone on designing user interface indicates a number of elements, taken from computer games, that can make an application more fun [23]. Elements that have been selected for BrainBasher are:

- **A clear goal**: the user knows what to aim for;
- **Performance feedback**: the user knows how well they are doing. This also facilitates user learning and gives the user a sense of control;
- **A variable difficulty level**: it is possible to define different levels of difficulty or to adjust the difficulty outside of the game;
- **Multiple level goals**: the game keeps track of the achieved scores;
- **Emotionally appealing fantasies**: the interface is graphically appealing.

- **Use familiar metaphors**: the interface uses standard elements, and should be consistent.
- **Optimal level of informational complexity**: information is presented visually and in a consistent manner.
- **Well-formed knowledge structures**: new information is shown when relevant.

### 3.1.2 Eye on the Research

While the game elements are very important, we should not lose track of the research goals and the ways the application should support them.

The game should be relatively simple. The focus of the user should be on playing the game, spending as little time as possible on learning it. It should be visually clean, but provide extra feedback information for the user which adds to the game experience. The number of potential distractions within the application are controlled. Another reason to keep the interface clean and clear, is to make it useful for demonstration purposes.

The type of user input should theoretically be independent of the game itself. First of all, it should be replaceable by keyboard, so the two situations of BCI versus keyboard input can be compared. Secondly, it should be possible to play the game with any brain actions we'd like to test (apart from the actions that will be used for this prototype evaluation) in order to facilitate future research. The number of different actions should be variable, as well as the brain actions themselves. This is also a means of varying the difficulty level of the game itself.

It should not depend on traditional analogies (e.g. left hand movement imagery moves the cursor to the left, or rising EEG activity lets a ball float up).

### 3.1.3 Usable for BCI

Because of the use of the BCI input modality, there are some extra issues that need to be remembered.

The interface should be carefully designed, so the brain actions are derived from the brain action and not from some visual or auditory stimulus.

The BCI system should be online, with real-time feedback. This is mainly a requirement for the BCI pipeline, but the game should support and use it as well.

To be able to recognize the defined brain actions, a classifier is needed which can discern them. This classifier needs to be trained first, on relatively clean data. This requires a training session, with breaks in between to keep the rest of the data as clean as possible. For optimal recognition, the user should be advised to keep the data that is to be analyzed by the classifier clean by avoiding noise in the form of eye and muscle artifacts. An optimal stimulus (showing of the brain action symbol) duration should be selected for during the training session, and also to select an optimal window length for the classifier.

For the game to be usable with different types of classifiers, it should be classifier independent. This can be done by placing no requirements on the analysis software, except for the classification results that are passed on in an appropriate format to the application itself.

## 3.2 Design

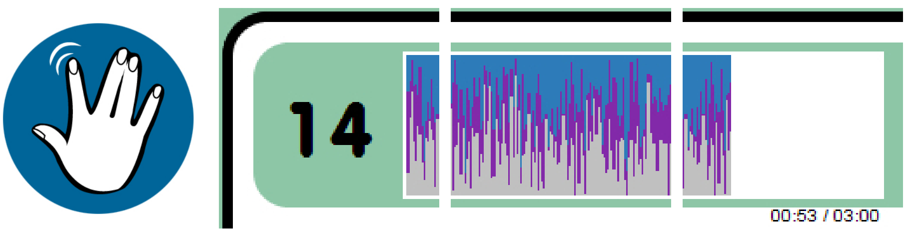
These requirements have been translated into a design for the game BrainBasher that is outlined next. First is described how specific game elements have been merged in the application. The second subsection is about the three different session modi that have been developed to experience the game. The selected brain actions, and why they work, are described at the end.

For more details about the development of this part of the software, refer to Appendix A. There you can find the domain analysis, task analysis, requirements, and the rationale for certain design decisions that have been noted for this application.

### 3.2.1 Creating the Game

The game elements from the Requirements section have been used to ensure this application will be experienced as a game by the user.

**Goal** The target is to 'hit' as many symbols (get the brain actions recognized by the system) as possible within the allotted time.



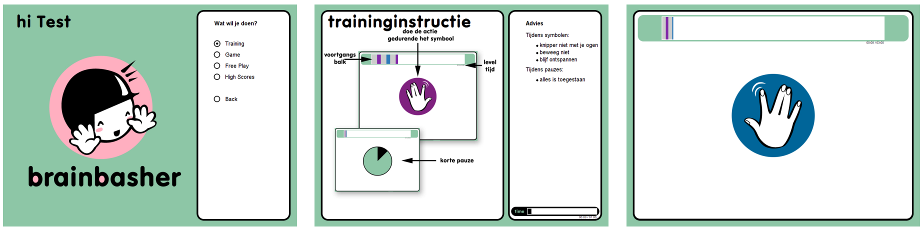

**(a)** *Stimulus symbol, right hand* **(b)** *Score* **(c)** *Confidence levels, in progress bar* **(d)** *Progress bar, with duration*

**Figure 3.1:** ***The four feedback mechanisms.*** *Feedback is provided on the progress towards the goal. The progress bar and score indicate the progress towards a high score at the end of the session. The confidence bar and stimulus are indications of how close the user is to getting the current brain action to be detected by the system.*

**Feedback** Feedback is given in the form of a score which is the count of 'symbols hit' this session, and in the form of a progress bar which besides showing the lapse of time also shows the levels of brain actions the system is detecting in the form of a confidence bar. The confidence bar shows moment by moment the confidence levels for each of the brain action classes. The interpretation is quite intuitive: the more dominant the color of the action you try to perform is, the closer you are to get the action to be detected. The colors used in the bar match the colors of the symbols shown in the center of the screen. 'Rest' is indicated in gray. The stimuli symbols themselves also double as feedback. For example, when the system recognizes the correct brain action from the user, the next symbol is shown. This change of stimulus is a signal to the user that the previous action has been recognized.

**Variable Difficulty** Sessions can be defined to use specific brain actions, to have a certain duration, and to use a specific threshold level for action detection. All these settings together influence the difficulty level of a session.

**Interface** The graphical interface has been designed by Corona Zschüsschen (designer and illustrator), with as main goals to make it fun, simple, and appealing. The interface uses standard elements which recur throughout the application. There is a menu view which can show an explanation or just imagery on the left and the menu items to the right. An information view shows the main text or imagery on the left, and some optional advice to the right. And finally there is the view that is used during sessions which shows the symbol stimuli and the various feedback elements.

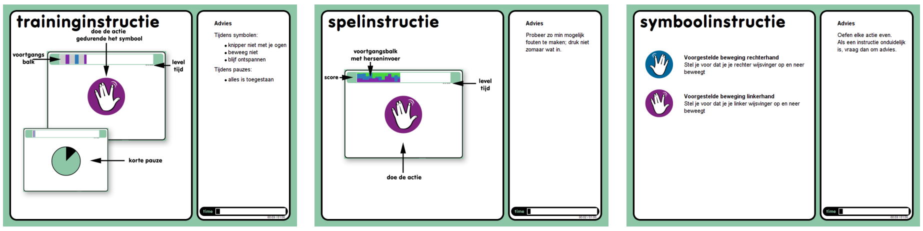



**(a)** *Menu view: main menu* **(b)** *Info view: training instruction* **(c)** *Session view: training session*

**Figure 3.2:** ***The three application views*** *all using similar design features.*

For this prototype it has been decided not to add the element of sound (in the form of sound effects or background music), as it would add another variable with its own effects on the research results. As a drawback, this decision probably makes the game less immersive.

**Information** The most relevant information during the game for the user is shown on the session and symbol instruction screens. The first explains what the user has to do during this specific type of session. The second shows the different symbols and describes the brain actions that are indicated by them.




**(a)** *Training instruction* **(b)** *Game instruction* **(c)** *Symbol instruction*

**Figure 3.3:** ***The three instruction windows.*** *The first two are session instruction screens. The third explains the symbols used.*

### 3.2.2 Session Modi

The BrainBasher application consists of three different modi. The user will first be subject to one or more training sessions in *training mode*. After this the classifiers are trained so the game can be played in *game mode*. Finally there is *free play* in which the user can play around a little to learn how the system reacts to certain inputs.

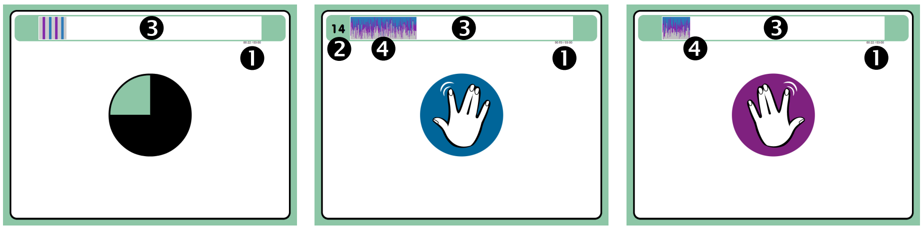
**Training Modus** During a training session, stimuli (symbols) and break periods are alternated. During the stimulus the user performs the indicated brain action (imaginary movement of the left or right index finger). The user is instructed to stay relaxed, not to move, and not to blink or move the eyes. This is to prevent noise in the recorded EEG. The breaks inbetween are added to give the user literally a break from the potentially stressful stimuli periods. One can only go for so long without blinking.

The result is a set of relatively clean data for all the brain action classes, plus data from the break periods which can be used to train a class to indicate that no brain action is being performed. It is possible to do multiple training sessions, to gather more data to train the classifiers with. This should improve the classification performance.

**Game Modus** The goal of the game is to try to get a high score, which is done by 'hitting' the shown symbols as quickly as possible by performing the suggested brain action. When the system recognizes the action, it increases the score and moves on to the next stimulus. Again, the user is given the advice to refrain from moving and blinking when they are trying to perform the brain action. Otherwise the noise in the EEG recording can keep the action from being recognized by the analysis software.

After the game is over, a high score list is shown so the user knows how they did compared to other players or compared to a previous game of their own.

**Free Play Modus** In free play, the application shows the actions recognized by the system. The user can try different variations of input and learn how the



**(a)** *Training mode, showing break* **(b)** *Game mode, showing right hand symbol* **(c)** *Free play mode, showing left hand symbol*

**Figure 3.4:** ***The three application modi.*** *Apart from the symbol stimuli there is the following additional feedback: (1) total and passed time for the current session, (2) the current score, (3) a progress bar, and (4) the confidence levels for the brain actions (in the progress bar).*

system reacts to those.

It also gives a very different sense of the performance of the system. In game mode you only get direct feedback (via the symbols) when the system recognizes the action *correctly*. In this free play mode however, the user gets to see everything the system recognizes, also when it is incorrect.

### 3.2.3 Movement Imagery

For the brain actions, it was decided to go for imaginary movement of the left and right index fingers (and the left-over 'rest' class). But how is it that we can detect these movements?

In the human brain there are specific areas that are involved in movement, be it executed or imagined. The frontal cortex, which is responsible for planning, sends its decision to do something to the premotor cortex. The premotor cortex (located just in front of the primary motor cortex) decides what muscles should be contracted to create the requirement movement. This information is then sent to the primary motor cortex which finally activates specific muscles [1].

The primary motor and sensory cortices (the anterior and posterior central gyri in Figure 3.5 in red and yellow respectively) contain representations of the body, so specific locations within these areas send (motor) or receive (sensory) information from specific body parts. The way this so-called homunculus (mini human) is positioned within these zones can be seen in Figure 3.6. The hands, which are very good at feeling and making complex movements, cover relatively large regions.

The brain consists of two hemispheres where the right hemisphere controls and receives sensory information from the left side of the body, and the left hemisphere from the right. In the case of hand movements, this means that to move the right hand the left hemisphere is activated, and vice versa.

[1]http://thebrain.mcgill.ca/flash/d/d_06/d_06_cr/d_06_cr_mou/d_06_cr_mou.html

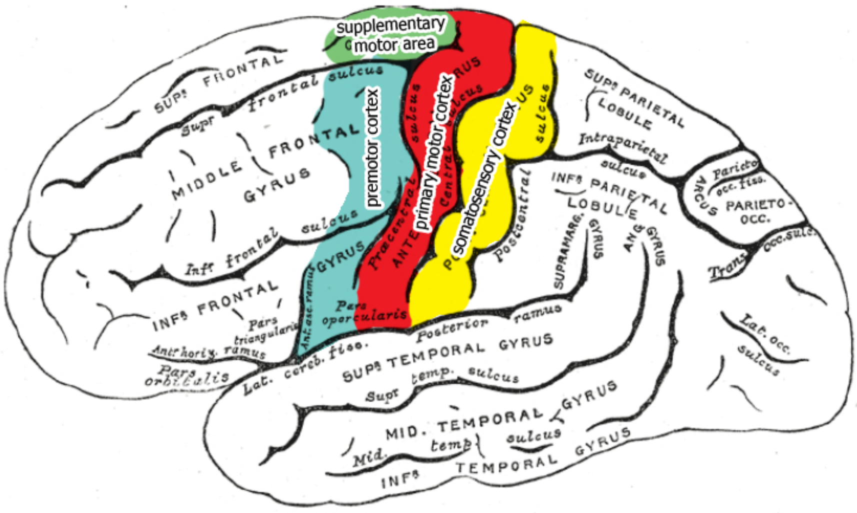



**Figure 3.5:** ***The brain according to Gray's Anatomy*** *with the primary motor cortex in red, the secondary motor areas blue and green, and the sensory cortex in yellow. The frontal cortex is on the left in this picture.*

As Pfurtscheller and Neuper state: "Motor imagery can modify the neuronal activity in the primary sensorimotor areas in a very similar way as observable with a real executed movement" [33]. For imagination of the movement the areas involved in planning and preparing will be activated just as they would for movement execution. Differences between the two cases are caused by the fact that the actual execution of the motion is inhibited for the motor imagery. Research at Graz has shown that "the most prominent EEG changes were localized over the corresponding primary sensorimotor cortex" [33]. Applying this information to the EEG electrode montage we use (see Figure 3.8), the most relevant electrodes are likely to be C3 and C4, for right hand and left hand movement (imagery) respectively. Brain activity may also be seen in the posterior parietal lobe (right behind the somatosensory cortex, around electrodes P3 and P4) as it is involved in the evaluation of motor performance, both for executed and imagined movement [5].

Although actual movement could also have been chosen as brain action, the use of imaginary movement clearly shows that the control signals are derived from the brain. This also gives the user a more distinct sense of what it is like to command a computer with the brain instead of with a keyboard.

There are multiple ways to imagine a movement: kinesthetic, visual first-person, and visual third-person. With kinesthetic motor imagery, the subject imagines how it would feel to make the movement. In the case of visual hand movements, one visualizes the movement of their own hand (first-person) or the hand of another (third-person). Neuper's findings suggest that kinesthetic motor imagery is easier to detect than visual motor imagery [27].

Somewhat related to this, there is also a difference between true imaginary movements and quasi movements. In contrast with the first, the latter is exe-

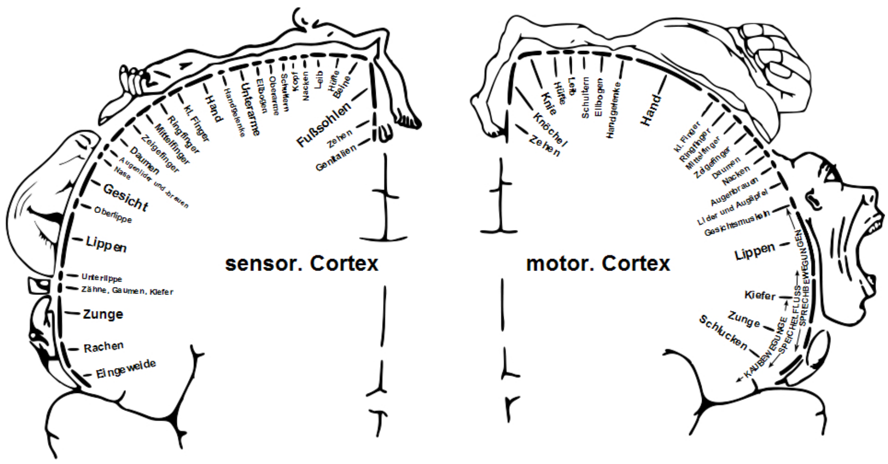



**Figure 3.6:** ***Sensor and motor homunculi*** *showing how specific parts of the body are represented in these brain areas. From Neurology for the Speech-Language Pathologist by Love, R. J. & W. G. Webb, 1992, p19.*

cuted with the intention of movement. The subject is trained by first making the movement and then reducing it until no muscle activity is detected with electromyography (EMG). Training the subject to be able to do this takes 10 to 20 minutes [31]. Nikulin *et al.* reported that detection of quasi movements results in significantly less errors compared to conventional motor imagery [31].

Although the instruction provided to the user during the experiments were focused on kinesthetic movement imagery, the subjects were encouraged to perform the action in a way they felt most comfortable with. Consistency in the brain actions was considered more important than the exact type, as there was little time for practice.

The third class ‘rest’ has been introduced so the system can indicate when it thinks the user is not performing either of the movement imagery tasks. As training data, the resting periods during the training sessions were used. As a side effect, the rest class should get dominant of many muscle and eye artifacts are detected. This is caused by the fact that these resting periods are when the user is allowed to blink and move contrary to the stimuli periods.

## 3.3 BCI Pipeline

For the BrainBasher application to know what the user is thinking, a whole underlying system is required, which records and analyses the brain waves for the predefined brain actions. This is called the BCI pipeline.

A schematic view of the total system is shown in Figure 3.7. The user interacts with the system by executing brain actions and by keyboard. Brain activity is acquired with an EEG setup. EEG Analysis consists of preprocessing, feature extraction and classification. The result is passed on to the application, which is the BrainBasher game described earlier.

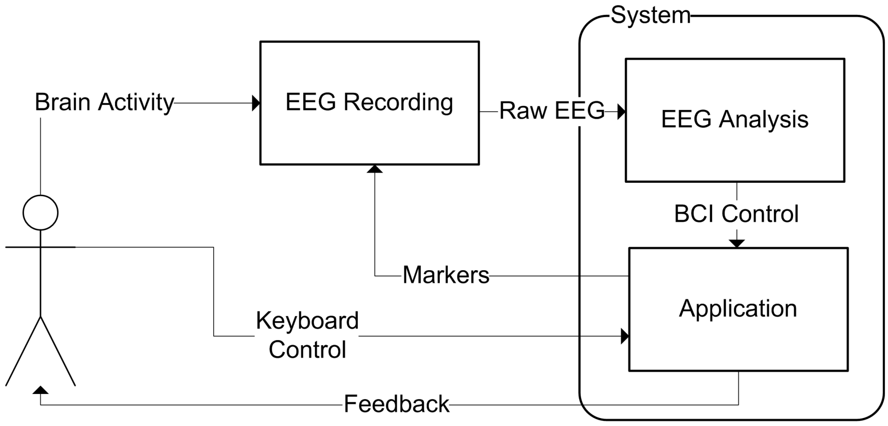



**Figure 3.7:** ***BrainBasher System Overview*** *showing the components that interact within the BCI pipeline.*

The next sections will move a little deeper into each step of this BCI pipeline.

### 3.3.1 User Input

While the user is hooked up to the system with an EEG cap, they can perform 'brain actions' which can be recognized from recorded brain activity. The user can also communicate with the system by providing keyboard commands. This is for example used to navigate through menus within the application.

### 3.3.2 Data Acquisition

The brain activity is recorded with a BioSemi EEG system of 32 electrodes (see Figure 3.8 for the montage), at a sample frequency of 256Hz (giving 256 samples per second). The data is passed on to the computer via USB, and then processed by ActiView which sends the data over TCP to the analysis software which runs on a separate computer.

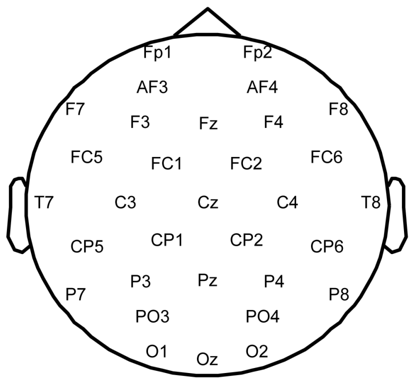



**Figure 3.8:** ***BioSemi Montage*** *for 32 Electrodes.*

EEG measures voltage differences caused by brain activity. As the electrodes are on the outside of the head, the cortical activity that is measured is distorted and attenuated by the tissue and bone in between the electrodes on the head and the cortex. Because of this EEG is not a very precise measurement, spatially.

Nevertheless, EEG has so many advantages that it is still a popular choice for BCI systems. It is fast (high temporal resolution), relatively cheap, and portable. And last but not least: as EEG is non-invasive–it does not require an implant. All these features make the threshold for use fairly low, compared to alternative methods.

### 3.3.3 Preprocessing

Preprocessing, feature extraction and classification are all part of the analysis, which is performed in Matlab. Matlab is very suitable for these tasks because of its strong matrix calculation abilities and the many libraries that are available (like PR Tools [8], EEGLab [6], and FieldTrip).

During the preprocessing step the common average reference is removed, and the data is bandpassed to 8–30Hz as used in Ramoser *et al.* [38]. This range encloses both the alpha (8–13Hz, includes mu rhythm) and beta (13–30Hz) frequency bands, where the event-related synchronizations (ERSs) and desynchronizations (ERDs) were reported to be most prominent [34].

In the training phase, the EEG data is split according to the markers that are added to the data stream by the application. In the experiment situation described in the next chapter, the two training sessions of three minutes each yield the following data set: 72 three-second windows for the rest class, 36 two-second windows for left MI, and again 36 for right MI.

In the classification phase, the incoming data is divided into two-second windows (being 512 samples), with a step size of half a second. As a result, the delay between the user input and the feedback provided by the software is at least two seconds, not including processing delays. Independent of this delay feedback is updated every half second, because of the step size and the processing speed that is fast enough to keep up.

### 3.3.4 Feature Extraction

The Common Spatial Patterns (CSP) method was used to extract features that allow for optimal discrimination of two classes. "The method used to design such spatial filters is based on the simultaneous diagonalization of two covariance matrices" [38]. These features are based on the variance found within the analyzed blocks of data. "A higher variance ... correlates to the ERD/ERS events that should occur" [3].

The CSP process results in a transformation matrix of which the first spatial filters indicate what electrode channels show the most variance for the first class, and the last spatial filters for the second class. Based on a calculated cross validation error rate, a decision is made to either use 2, 4 or 6 spatial filters or transformed channels.

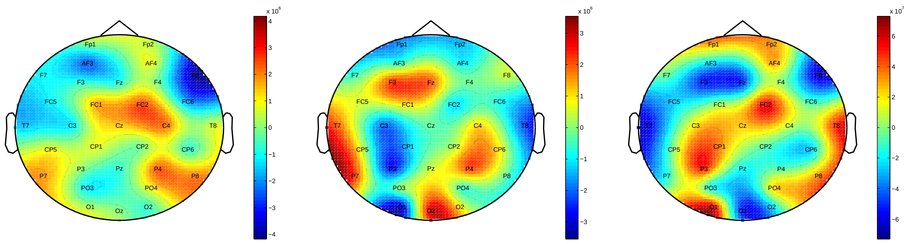
As CSP is used to find features to discriminate between two classes, this process was repeated three times, to test each combination of two for the three classes: rest, left hand movement imagery (MI) and right hand MI. This calculation of the optimal CSP matrices is done based on the training data, directly after the training session is over.

The main advantage of this method that it automatically selects the most-discriminating spatial features for the two classes that are to be separated. As a result the user can theoretically use any brain action they want (as long as it is recognizable within the set frequency range of 8–30Hz), and the analysis will adjust automatically.

Figure 3.9 shows an example of the two most important spatial filters for subject 2 as obtained with CSP to discriminate between left and right MI. The opposition of the channels C3 and C4 are clearly shown in this particular case.

### 3.3.5 Classification

Linear classification methods are generally recommended for EEG classification because of the simplicity and robustness to noise [25].



**(a)** *CSP filter 1* **(b)** *CSP filter 2* **(c)** *Applied LDA*

**Figure 3.9:** ***CSP and LDA scalp maps.*** *The first two scalp maps show the two most relevant spatial filters to discriminate between left and right MI for subject 2, obtained with CSP. The final scalp map shows the result of $csp * lda$, so the filters are weighted according to the transformation values from the LDA classifier.*

Linear Discriminant Analysis (LDA) is such a linear method. LDA is normally used for dimensionality reduction as the data is projected onto a new plane that maximizes the between-class distance and minimizes the within-class distance [1]. LDA assumes the data follows a Gaussian distribution. Krepki has shown in his thesis that this can indeed be assumed for the variances of the C3 and C4 electrode channels [16].

The result of the transformation for the two spatial filters of subject 2 shown as an example in Figure 3.9 can be seen in Figure 3.9c. The LDA classifier assigned the (rounded) weights of 13.7 and -18.3 to the two filters. So where the CSP algorithm is used to detect the locations that show the highest variety for the two classes to discern, it is the LDA which determines the importance of each spatial filter. In this case, the application of the LDA values reduces the opposition between C3 and C4 seen in the CSP filters, which is unexpected based on the neurological theory elaborated in Section 3.2.3.

| Subject | aa | al | av | aw | ay |
|---|---|---|---|---|---|
| Accuracy | 70.54% | 100.00% | 59.18% | 73.21% | 66.67% |

**Table 3.1:** ***BCI Competition III MI data set results*** *using CSP and LDA.*

The classifier trained after the training sessions based on the then obtained data. Classification results, in the form of confidence values for each class, are sent via TCP to application. This is done for each combination of two of the three classes of rest, left MI, and right MI.

To validate this method of using CSP plus LDA for MI classification, it was applied to the BCI competition III MI dataset. The accuracy scores obtained are listed in Table 3.1.

The weighted accuracy for the competition ranking would be 69.40% which would put this method in 5th place of the 15 participating methods.

### 3.3.6 Application

The BrainBasher game receives keyboard input from the user and BCI confidence values via TCP from the classifier.

Based on these inputs and the internal state of the application, it returns appropriate feedback to the user, as has already been described in the Design section in this chapter. It is the application which decides whether a brain action is actually detected, based on the threshold settings from the definition of the current session. Currently this is expressed in a percentage of all incoming confidence values. When the confidence value of one class exceeds this percentage, the application accepts the action as being performed. For the experiments in this study the threshold level was set to 60%, but this value should be adjusted depending on the number of classes that are being assessed.

BrainBasher also sends markers over the parallel port to the EEG to inform the analysis software of certain events. This way that part of the software knows when to record data for training, when to start the classifier training procedure, or when to start classifying incoming data. It is also informed of what symbols are shown to the user, to label the training data set.

### 3.3.7 Hardware and Software

The application software, the data acquisition software, and the data analysis software were all run on separate computers. This is to prevent potential problems because of the required processing power to perform all of these tasks.

BrainBasher was run on the so-called 'Presentation PC' with: a 2x3.20GHz Pentium 4, and 1GB RAM, running Windows XP and using Java 1.6 for the game application. The specifications of the 'Recording PC' is exactly the same. The recording application was Actiview 6.05 (Lores) set on a 256Hz sample frequency. The 'Analysis PC' had a 2x2.13GHz dual processor and 2GB RAM, running Ubuntu Linux 7.10. The analysis was performed in Matlab 7.5.0.338, using the toolkit PRTools 4.0. The data was transfered between the computers using TCP.

When you are a Bear of Very Little Brain, and you Think of Things, you sometimes find that a Thing which seemed very Thingish inside you is quite different when it gets out into the open and has other people looking at it.

WINNIE THE POOH

# Chapter 4

# User Experience Evaluation

To look at the influence of game elements on BCI and the influence of BCI in games, a user evaluation has been conducted using BrainBasher of which the design is detailed in the previous chapter.

This chapter describes the details of the subjects, the experimental protocol, and the obtained results. In the discussion section, a tentative explanation for the observations is given. The conclusions contain a succinct summary of the interpreted results.

## 4.1 Methods

The goal was to compare the effects on the user experience of using BCI input compared to conventional keyboard input, and of using a more complex interface with game elements versus a more clean, clinical design.

### 4.1.1 Subjects

The game was evaluated with fifteen subjects, all right-handed, of which eight were male and seven female. The average age was 29 years, with a minimum of 15 and maximum of 55. Average finished education level was equivalent to senior secondary vocational education ('MBO'), ranging from an elementary school education to MSc. Current education or job level was on average equivalent to higher professional education ('HBO', BSc). Almost half of the subjects used visual aids in the form of contact lenses or glasses. On average, they work with a computer about 5.6 hours a day (one hour minimum to seven hours maximum), of which 2.2 hours (with a five hours maximum) are spent on video games.

### 4.1.2 Three Versions and Two Experiment Groups

Three versions of the game were played: the original BCI-controlled version, one controlled by keyboard, and a cross version reduced to look like a clinical experiment. These versions are hereafter referred to as Original, Keyboard, and Cross.

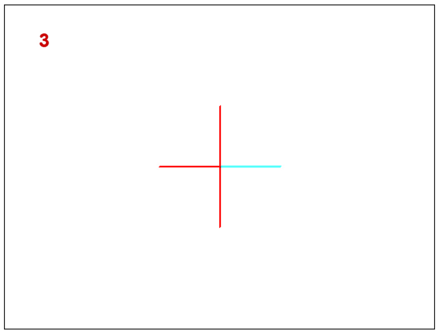



**Figure 4.1:** ***Cross version*** *with a more clinical look and less distractions, but also less feedback.*

Where in Original a left or right hand was shown, the Cross symbols were a cross with the left or right side highlighted. The resulting screen is shown in Figure 4.1). The background is normally black, but turned white here to make it more visible in print.

To limit the influence of the possible effects of user learning and fatigue, two experiment groups were defined (A and B) for which the order of the versions differed. These two groups will be compared to check whether such an influence indeed is showing in the results.

| **Original version** | **Cross version** |
|---|---|
| Indication of symbol, break, and session durations. | No indication of time. |
| A more appealing theme. | Less distractions. |
| Brain activity feedback. | No feedback except for score. |
| Hand symbols had multiple characteristics: form, colour, movement indication. | Simple cross easier to interpret for most subjects. |

**Table 4.1:** ***Comparison of Original and Cross*** *- their advantages and disadvantages.*

### 4.1.3 Test Protocol

For subjects in group A (eight of the fifteen), the order of each step of the experiment was as follows: preparation, Keyboard, Original, Cross, closing. For group B Original and Cross were swapped, resulting in the following order: preparation, Keyboard, Cross, Original, closing. The steps are now described in more detail.

#### Preparation

1. Subject reads consent form (see Appendix B).

2. Subject and researcher fill in the subject information from (Appendix C). This form contains questions about the subject's background and current state.
3. The EEG cap is mounted on the subject's head following the BioSemi manual.
4. Meanwhile the subject can read the game explanation sheet (Appendix D).

**Keyboard**

5. The subject plays the Keyboard version consisting of one three-minute game session.
6. The user experience form for Keyboard is filled in (Appendix E, first form).

Keyboard is controlled with the left ctrl-key to replace the imaginary left index finger movement, and the right ctrl-key for the right index finger. If the keys are pressed with the index fingers, this can already train the subject in knowing what it feels like to make the movement that will later be imagined.

Independent of the experiment group, the first version of the game is always the one with keyboard input. This way the subject can familiarize themselves with the application. The effects of user learning are of no concern as this is a very different input modality.

The user experience forms are based on the Game Experience Questionnaire (GEQ) developed by the Game Experience Lab of Eindhoven University [14]. More details about this questionnaire are to be found in the next section.

**Original**

7. The brain actions are explained and practiced for a short while.
8. The subject plays the Original version: two three-minute training sessions (resulting in 144 sample periods for the resting class, and 36 periods for each MI class), one three-minute game session, and finally one three-minute free play session.
9. The user experience form for Original is filled in (Appendix E, second form).

The subject is explained how to do kinesthetic movement imagery, but is left free to do it the way they felt most comfortable. Some subjects mentioned they felt their fingers making very tiny movements, even when they tried to inhibit it. They were instructed to really focus on keeping the movements imaginary. Most subjects were probably on the line between imaginary and quasi movement. Again, the subjects were encouraged to adopt a strategy that felt most comfortable to them. For details about different types of movement imagery, refer to Section 3.2.3.

#### Cross

10. The subject plays the Cross version: again two three-minute training sessions (to obtain 144 sample periods for the rest class, and 36 for left and right MI each), one three-minute game, and one three-minute free play session.
11. The user experience form for Cross is filled in (Appendix E, third form).

#### Closing

12. The subject is 'unplugged' from the system and the cap is removed.
13. The user experience form about the experience after the experiment is filled in (Appendix E, fourth and final form).
14. Some informal questions are asked to get a more detailed image of the experience of the subject. This conversation also gives the subject the opportunity to tell things that were not asked on the forms.
15. The subject is given the opportunity to shower or just wash the conductive gel (to improve the electrode connection to the head) off.
16. A small gift is presented to the subject as a thank you for undergoing the experiment.

During the experiment, the researcher stayed in the room with the subject at all times. The researcher was mainly a quiet observer, and the person to be addressed in case of problems or questions.

Between sessions, subjects could pause for however long they wanted. Food and drinks were offered to keep the subject comfortable. These breaks were also used to check whether all electrodes were still well-connected and to correct any problems.

### 4.1.4 Measurements

To obtain results to evaluate in order to answer the questions at the core of this research, a number of measurements are collected during the experiments.

#### Game Experience Questionnaire

The goal of the GEQ forms is to determine the self-reported game experience of the user for seven components: immersion, flow, competence, positive and negative affect, annoyance, and challenge [14]. Table 4.2 shows the elements of each component, giving a more precise indication of their meaning. A good game will score high on flow and positive affect. Low scores should be found for negative affect and annoyance. Competence and challenge are two sides that should be balanced for an optimal situation. The user must feel to be able to do what is asked of them, while at the same time it is not so easy that the task becomes uninteresting. It has to be a challenge, but not so difficult that it seems insurmountable.

| GEQ Component | Elements |
|---|---|
| Competence | Proficient, confident, was good at it, successful, fast at reaching the game's targets. |
| Immersion | Pleasing design, impressive, rich experience. |
| Flow | Absorbed, forgot everything around, lost track of time, concentrated, lost connection with outside world. |
| Annoyance | Annoyed, irritable, frustrated. |
| Challenge | Difficult, pressured, challenged, time pressure, effort. |
| Negative affect | Bad mood, distracted, tiresome, bored. |
| Positive affect | Content, fun, happy, felt good, enjoyable. |

**Table 4.2:** ***GEQ Components*** *and their elements as included in the questionnaire.*

Some questions considering immersion have been left out of the questionnaire as they were not applicable to BrainBasher in its current state, like "I felt like I could explore the game world", and "I felt imaginative".

The actual game experience evaluation forms can be found in Appendix E.

#### Game Score

The scores the test subjects obtained during game sessions are used as a measure of performance. This performance measure is not solely depending on the subject, but also on the suitability of the EEG analysis and classification methods.

#### Classifier Plots and Error Rates

To see how well the classifiers were trained, the multiplication values for the electrodes can be plotted as a scalp map showing what areas the classifier considers the most relevant areas on the head for discriminating the different classes. These values are the result of the Common Spatial Patterns (CSP, see Section 3.3.4) matrices multiplied with the Linear Discriminant Analysis (LDA, see Section 3.3.5)) transformation matrix.

In order to determine the number of CSP filters that are used by the classifier, the analysis software performs a cross validation test for 2, 4 and 6 filters, and then choses the number which resulted in the lowest error rate. These error rates can also provide insight into how well the classifier is expected to perform.

## 4.2 Results

The results of this evaluation are split up in four subsections. The first two are relevant to the research questions considering the added value of BCI input and the possible advantages of using game elements in BCI research. The third subsection compares the results for the two experiment groups, to see if there are any significant differences. In the final subsection we take a look at the classifier plots in a try to explain why some subjects seems to have a high amount of control while others display practically no control whatsoever. The described t-test results are all based on independent-samples t-tests.

### 4.2.1 BCI Input Compared to Keyboard

The values for each of the components can be viewed in Figure 4.2. The scores for Original and Cross are scaled with a factor 1/10; the scores for Keyboard with 1/100.

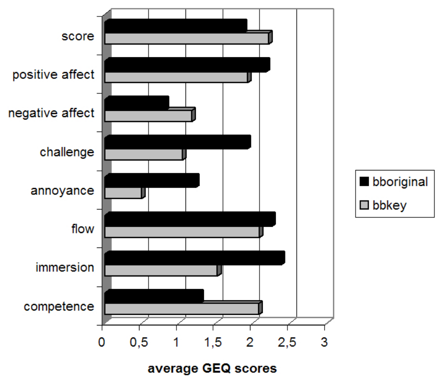
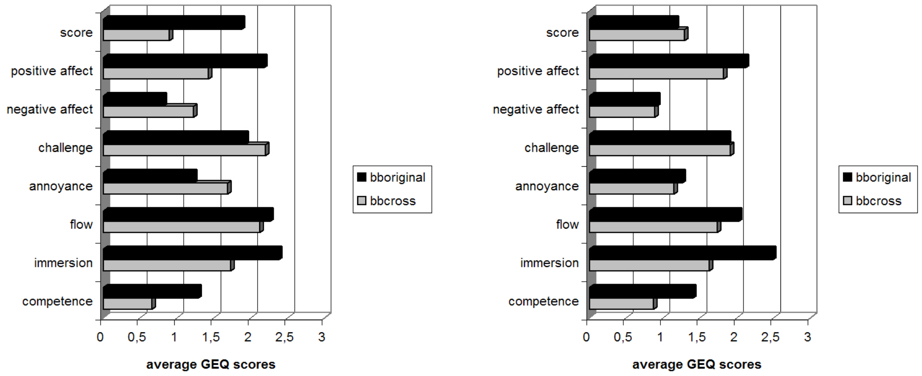



**Figure 4.2:** ***GEQ scores for Original and Keyboard***

Subjects felt significantly more competent ($t(29) = 2.17$, $p < 0.05$) at the keyboard-controlled game. Although they were more annoyed ($t(29) = 2.07$, $p < 0.05$) with Original and it was a lot more difficult ($t(29) = 5.22$, $p < 0.001$), they noted also many positive experiences: it was considered less tiresome ($t(29) = 2.12$, $p < 0.05$), more challenging ($t(29) = 3.26$, $p < 0.01$), a richer experience ($t(29) = 4.85$, $p < 0.001$) and more immersive ($t(29) = 2.99$, $p < 0.01$) than just bashing keys.

### 4.2.2 Game Compared to Experiment

The scores obtained for Original are higher than the scores for Cross. Higher scores result in a more positive experience as the subject feels more competent. To eliminate this influence, sessions with Original have been paired up with Cross sessions in which similar scores have been obtained. Sessions which could not easily be paired score-wise with a session of the other version type have been left out. The new data set contains {Original, Cross}x9 sessions (from the total {Keyboard, Original, Cross}x16), similar experiment group and gender ratios for Original and Cross. Over this new set with a similar score average, again the GEQ component values were determined. The results of the original data set and this new normalized data set are shown in Figure 4.3. The scores for Original and Cross are 1:10; the scores for Keyboard 1:100.




**(a)** ***Primary GEQ scores*** **(b)** ***Normalized GEQ scores****, with similar game score values*

**Figure 4.3:** ***GEQ scores for Original and Cross****.*

There is still a small insignificant ($p = 0.886$) difference between the average scores of the two groups ($M = 11.67$, $M = 12.89$). Even though the scores have been normalized, this incongruency exists as a result of still trying to use as much data as possible. If the scores would have been kept strictly equal, there would have been less variety within the score values themselves. Besides, there would have been less data to perform the statistical analysis on.

Original has a more enjoyable design ($t(16) = 2.67$, $p < 0.05$), and achieves a higher sense of immersion ($t(16) = 2.69$, $p < 0.05$) than Cross. Furthermore, a trend towards higher concentration ($t(16) = 1.79$, $p < 0.10$) and a richer experience ($t(16) = 1.91$, $p < 0.10$) for Original compared to Cross can be observed.

### 4.2.3 Experiment groups A and B

Subject group A first got to play the original BCI version, and then the simplified cross. Group B had it the other way around. The reason for these two groups was to eliminate possible effects of user learning and fatigue.

Overall, group A reported higher immersion ($t(45) = 2.58$, $p < 0.5$), and flow ($t(45) = 1.84$, $p < 0.10$), but also a higher negative affect($t(45) = 1.93$, $p < 0.10$).

When looking at A and B in the results for Original and Cross separately, the following differences are noteworthy. It was more enjoyable to play original as first session, than as second ($t(13) = 3.03$, $p < 0.01$). Original also generated more flow when it was played first ($t(13) = 2.33$, $p < 0.05$). Cross was evaluated as a richer experience when it was played second ($t(14) = 3.86$, $p < 0.01$). Also higher immersion was reported for that case ($t(14) = 2.1$, $p < 0.05$).

The fact that the average game score when playing Cross second is a little lower than when playing Cross as third, could be an effect of user learning. User fatigue could be the cause of the average score for Original being lower when

| Version | Group | Mean | StD |
|---|---|---|---|
| **Cross** | **both** | 8.94 | 14.93 |
| | **A** | 9.75 | 20.01 |
| | **B** | 8.13 | 08.71 |
| **Original** | **both** | 18.69 | 17.42 |
| | **A** | 20.00 | 19.08 |
| | **B** | 17.38 | 16.79 |

**Table 4.3:** ***Average scores for Cross and Original*** *separate for experiment groups A and B.*

it is played as third. But from the scores (see Table 4.3) it can be said that there is no significant difference between A and B within Cross ($p = 0.84$) nor within Original ($p = 0.77$). So statically it does not matter whether the session came second or third for the score. There is however a trend towards a difference between the scores for Cross and Original themselves ($t(30) = 1.70$, $p = 0.10$).

### 4.2.4 Classifier Plots and Error Rates

To get an idea of how well the classifiers were actually trained, the multiplication values are plotted on a head, showing the electrode positions. If the positions with extreme values match the locations expected based on the neurological knowledge about movement imagery (see Section 3.2.3), it conforms to our expectations.

The CSP features provide an indication of where the best discrimination between the two classes can be found. Two, four, or six spatial filters with one value for each electrode signal are returned based on a cross-validation error rate. The LDA transformation vector consists of two, four, or six values depending on the number of spatial filters. When this is applied to the transformed channels from the CSP, the result is one multiplication value per channel. These values are plotted on the top-view of a head.

What classifiers look like which result in high game scores compared to classifiers related to low game scores can be seen in Figure 4.4. As there are many scalp maps (three for the classification, for two game versions, for each subject), two individuals were selected for comparison. The first two rows show classifier scalp maps for subject 5B who obtained relatively low scores during the game session. The second set of rows belong to subject 6B who achieved relatively high game scores. Please note that the classifier plots selected here are specific samples. There are considerable differences between the classifier plots for each individual. For a closer look, one can refer to Appendix F which contains all the classifier plots for all subjects.

The cross validation error rates mentioned below are based on five runs for each dataset in which different samples have been randomly chosen. The average standard deviation is only 1.04% within the same dataset. Looking at the cross validation error rates only, the average values were 20.93% for rest versus left MI, 21.51% for rest versus right, and 43.61% for left versus right MI, for the optimal number of CSP filters which was on average 4.23. Within these two-class combinations, the average standard deviation was 7.86%.

The classifier scalp maps in the very first row have been obtained from the classifiers which were trained on the data from the two training sessions in the Cross version. In the game, the subject only achieved a score of 1. This is also reflected by the cross validation error rates which are 29.78% for rest vs. left MI, 34.54% for rest vs. right MI, and 37.07% for left vs. right MI. The second row shows the classifiers obtained from the training sessions in Original. The cross validation error rates are 20.76%, 19.40%, and 55.83% (from left to right). Again, the game score was 1.

The third row shows the scalp maps for the Cross version with noted error rates of 21.15%, 12.29%, and 20.94% (left to right), which are low numbers compared to the rest. The subject achieved a score of 26 in the game. For Original (depicted in the final row) the error rates are 15.27%, 16.62% and 42.45%, and the game score was 21.

## 4.3 Discussion

This section attempts to explain and interpret the results observed as described above. It also mentions some potential issues caused by the methodology. The order is kept the same as in the Results section. First BCI is compared to using the conventional keyboard. Then Original is compared to Cross to see the influence of using game elements versus a clinical experiment design. The third subsection explores the differences between the two experiment groups A and B, and looks at other indications of user learning and user fatigue. Finally, the classifier plots are analyzed in order to explain the results achieved by the test subjects from a classification point of view.

### 4.3.1 BCI Input Compared to Keyboard

The results of comparing keyboard input with BCI input are not surprising. Subjects felt more competent when using the keyboard for the simple reason that they had a lot of practice with this input device. On average, the subjects used a PC for over 5 hours on a daily basis, using keyboard and mouse. On the other hand, they had no training with using movement imagery for control, naturally resulting in a more difficult and challenging situation which is less tiresome but also likely to cause more annoyance when things go wrong.

The level of immersion was determined by questions about the design, and how rich and impressive the experience was. The only difference for these two cases is the input method, which apparently have a large influence on the experience. It is also possible that the experience was positively influenced by the challenge the novel input method posed. In that case, there is probably some aspect of flow that is influencing the immersion score, as a result from a better balance between challenge and user skill.

Fatigue could theoretically be an issue, as the keyboard version is always played first and Original is second or sometimes even third in row. However there is no clear influence seen in the obtained results, and as the assignment is very simple with keyboard, the mental strain is minimal. Besides, the duration for keyboard version is just three minutes, where the other versions take at least twelve with four three-minute sessions.

For comparing the Original and Cross versions, the scores were normalized to better compare the GEQ values. One could argue that for Keyboard and Original the scores should be normalized as well as the scores for Keyboard are a lot higher. Unfortunately, these scores cannot be so easily compared, as with keyboard control the scores are in a very different range. Some ratio could be determined (for example the 1:10 ratio that is used in Figure 4.2), but its correctness would be uncertain.

Finally, there is one more issue that could have influenced the performance with the BCI version of the game: the pink elephant effect. When a person is instructed not to think of a pink elephant, they cannot help but think of this elephant. In the same way, it could be the case that as the subjects were instructed not to blink and not to move, the results could be opposite.

### 4.3.2 Game Compared to Experiment

Numerous issues are relevant to the comparison of Original and Cross. Why did Cross obtain lower game scores? Was the normalization of the game scores valid and necessary? What uncertainties have been introduced with movement imagery and with the GEQ?

The results from the comparison of the GEQ values contain no surprises. The design for Original was purposely made to be more enjoyable than Cross. That it is also experienced as such is confirmed by the user experience. The recorded richer experience could be a direct result, which in turn may have caused the higher immersion and concentration levels.

#### Cross Lower Game Scores than Original

The game scores are significantly lower for Cross than for Original. This is somewhat expected, because the Cross version provides a lot less feedback to the user. This makes the subject more insecure about how they are doing and what they can do to improve inhibiting user learning. Unfortunately there are some other issues that could have negatively influenced the scores as well.

Another issue with the Cross version, which was unfortunately noted quite late in the experiments period, is that, as there is no transition animation, it is not possible to see if you hit the symbol if it is followed by a symbol of exactly the same class (except for in the change of score). This could be very discouraging to the subjects, with perhaps as a result lower scores.

Because of a flaw in the implementation of the game application, Cross had a tendency for a shorter window length (on average 28 samples shorter than the intended 512 samples which would be the result of exactly 2 seconds at 256Hz sample frequency) than the Original version (which was on average 8 samples longer than the intended 512). This is another likely cause for lower Cross scores, as the classifier just had less data. When subjects scored badly, usually the resting class was very dominant. As an action needed to get at least 60% confidence, the brain actions never got through in those cases. So perhaps the problem is not always in the differentiation between the two brain action classes, but also in the differentiation of a brain action and the resting class.

The main reason why Cross could result in higher game scores is the lack of distracting feedback stimuli. Interestingly, some subjects reported to tune out additional information presented in Original (like the score and progress bar) when the brain action required their full attention. This reduces the relative positive effects of the lack of stimuli in Cross.

But apart from the lack of distractions, there are other reasons why Cross could have performed better. Most subjects found the cross symbols to be easier to interpret than the hand symbols of the original version. They explained they could directly match the position of the highlight to the hand to be moved. The hand symbols were recognized by the color and by the shape, but an additional interpretation step was necessary to link this to the actual action.

Secondly, with the Cross variation, the subject probably is looking to the center of the screen and then the side to the left or right of the cross is highlighted. It is difficult to avoid eye movement reflexes that may be triggered by this stimulus. The artifacts in the EEG caused by this eye movement could theoretically be used by the classifier to detect the 'brain activity' as it would match the markers during the training sessions. Only one Cross classifier for left versus right MI showed a clear opposition of Fp1 and Fp2 (the electrodes near the left and right eye) in the scalp plot. Although the cross validation error rate was 37,07%, the end result was a low game score of 0. The same effect can occur with the hand symbols, for example when the subject focuses on the position of the thumbs which will be on the left half of the screen for the right hand and the right side for the left hand. If it is important that the application is really controlled by brain activity only, one has to be very careful in designing the stimuli, or perhaps even separate the stimuli periods from the brain activity recording periods to prevent effects like these from having any chance of occurring.

### Score Normalization

Whether taking matching scores from both Original and Cross is a valid way of normalization is unsure. Other parameters may have been skewed out of proportion by this action.

Although intuitively, the score normalization was a necessary action, which is also reflected by a more equal rating in certain GEQ components, a comparison of GEQ ratings with the game scores showed no significant correlations.

For Original, the subjects noted a more enjoyable design which is probably also related to the other significant differences with Cross: a higher sense of immersion, higher concentration, and a richer experience.

#### Movement Imagery Strategies

Some additional uncertainty is caused by the inconsistency in the movement imagery strategies used between and within users. The subject was instructed in kinesthetic movement imagery, but was really free to perform the movement imagery in the way most natural to them. This may have influenced the results, as some methods are easier to detect from brain activity than others.

Fast movement or slow movement, and abrupt movement or fluid movement... "What is better?" some subjects asked. They were instructed to at least make an ongoing movement, so the related brain activity would keep triggering. I was informed that fast, abrupt movement would be easier to detect than slow, fluid movement [1], but have found no literature yet to confirm this.

Dividing the training into two sessions is in some ways an advantage. The subjects had to concentrate for shorter periods, so the task was less draining. Secondly, the subject could ask questions after the first session. Often questions were indeed asked, mostly about the exact nature of the expected movement imagery. As a result, this advantage also comes with a downside: there could be a lack of consistency in the data if the subject decided to change their method.

#### Game Evaluation Questionnaire

The user experience forms were filled in after each version, which means that they contain combined information for training, game, as well as free play. These three session types are experienced very differently, so separate forms for each session could have found different answers. It was decided not to do this, as it would have resulted in at least four extra forms of two pages each, and they already have to read through and fill in eleven pages without those.

Another issue with the GEQ forms is that the labels for the answering scale are not perceived as linear. "Niet" ("not") was experienced as a full negative, whereas the next step up "een beetje" ("a little") is already positive. As the values for each of the questions within one component are averaged, this could skew the results somewhat. However, as most of the subjects already had some experience with such answering scales which usually are linear, they probably interpreted this scale as linear in spite of the labeling.

Something that should be noted, although they did not seem to have significantly influenced the results of these experiments, is that the subject information form did not include questions about caffeinated soft drinks. Questions about coffee and green tea were part of the form, and their potential influence on the results of brain experiments are evident.

[1] Private communication with Jeroen Geuze, PhD student in cognitive neuroscience.

### 4.3.3 Experiment Groups A and B

Why does A report a higher immersion and flow, but also a significantly higher negative affect? The first session they get is easier than the first session for group B. Perhaps this raises confidence and therefore motivates subjects toward a higher immersion and flow. The negative affect could then be the result of being severely disappointed at their performance during the second session which is the cross variation.

There could also be another reason for these differences. An indication of this is the fact that also significant differences have been detected for the Keyboard version, which was played first by both groups: higher immersion ($t(14) = 2.31$, $p < 0.05$) and losing connection with the outside world ($t(14) = 2.18$, $p < 0.05$), richer ($t(14) = 3.00$, $p < 0.01$) and more impressive ($t(14) = 2.43$, $p < 0.05$) experience, more difficult ($t(14) = 2.26$, $p < 0.05$), and more distracted ($t(14) = 3.46$, $p < 0.01$) are all experiences that were significantly higher for experiment group A. Although a direct connection is not clear, perhaps it is related to the circumstance that on average group A has finished a higher education ($t(14) = 2.50$, $p < 0.05$ where 0 is no education at all, 5 is a university degree) than group B. Or, as our subject groups are not that large, this occurrence is just a result of chance.

Although the game scores for Original and for Cross did not differ significantly between the experiment groups, something else does show the effects of user fatigue. When comparing the alertness level before the experiment ($m = 2.63$ on a scale to 4) and afterwards ($m = 1.93$ of 4), there is a trend towards a lower alertness to the end ($t(29) = 1.94$, $p < 0.10$)

The effects of user learning could have been demonstrated by one of the test subjects, as he as the only person has played the game multiple times – even one whole day as a demonstration – before the experiment. Yet, this subject did not achieve a high score. He was ranked third for Cross and fourth for Original (out of fifteen). If the older scores would have been stored with timestamps, this could have been very insightful considering user learning and user fatigue. Unfortunately, this is not the case.

### 4.3.4 Classifier Plots and Error Rates

Referring back to Figure 4.4, the scalp maps in the first row belong to a subject who only achieved a score of 1 in the game session with this version of the application. The first two plots are not really clear in what exactly they are discriminating on. Based on the third scalp map, no clear distinction between C3 and C4 is possible. However, P3 and P4 have clear opposite values. Apparently just this feature is not enough to score points in the game.

The second row shows the classifiers obtained from the training sessions in Original. Where the C3 and C4 were marked as opposites for the resting class detection scalp maps in the top row, here they are mapped to the same sign. Perhaps this is the reason why the performance is a little better, based on the cross validation error rates. But for this session too, the subject only achieved a score of 1. This could have been caused by the classifier for left versus right MI, which has a very high error rate. The scalp map for this classifier again shows C3 and C4 in similar value ranges, and even P3 and P4 are assigned the same signs.

The next two rows show the classifiers for subject 6B, who obtained relatively high scores in the game sessions. The first row shows the scalp maps for the Cross version, with low error rates compared to the rest. The subject achieved a score of 26 in the game. For Original the game score was 21. One difference with the low-scoring classifiers in the top two rows is the highlighting of the area near the eyes, which could mean it discriminates between rest and movement imagery partially on eye movement, which is only allowed during the rest periods. The classifier for left versus right for Cross shows a nice division between the area around C3 and C4. This coincides with the relatively low cross validation error rate. The left vs. right classifier for Original does not achieve such a high performance, and C3 and C4 do not show the same extremes. P3 and P4 do have opposite signs, but this seems not good enough for a good discernment of the two classes.

It becomes clear that the interpretation of these scalp maps are not always straightforward. Apart from the areas of interest around the eyes and neck, and near C3, C4, P3 and P4, other things seem to be happening on which the classifier tries to discern the classes. For lack of neurophysiological knowledge, it is not easy to identify what is going on.

Although it would have been interesting to see what the classifier algorithm considers the most relevant features on average, this could not be done easily and hence was not done at all. The first problem is the difference in electrode channel multiplication values which can be in the order of $10^5$, but also $10^6$ or even $10^7$. These differences could be solved by applying some normalization function to the electrode values. Unfortunately, there is another reason why these maps could not be averaged: the measured EEG is just an outward measurement of the occurring brain activity. It is not an accurate indication of the positions of the sources that generate these voltage differences. Because of this, taking an average would result in a scalp map with no true meaning.

The cross validation error rates were higher than expected based on the results obtained on the BCI Competition III data set. Although that data set did not include a resting class, the error rate obtained with BrainBasher (43.61%) is a lot higher than can be derived from the competition accuracy of 69.40%. Also, with an accuracy of about 79% for detecting the resting class versus movement imagery within BrainBasher, and then another chance of about 56% of identifying left or right correctly, the resulting performance would be below chance level.

It is important to note the importance of the accuracy of detecting the resting class. When the confidence value for 'rest' is high enough, it will detect the rest action only, and hence block any movement imagery actions. An indication that this is actually occurring is visible in the cross validation error versus game score plot in Figure 4.5. Although the correlations are not very strong, the expected relation to be witnessed is: the lower the error rate, the higher the score. The only case where this relation does not show – where even the opposite is happening – is for left versus right MI. This means that if the cross validation error rate is some indication of how well the classifier is expected to perform, the end result is determined by the detection of the rest class, and not by a correct classification of left or right MI.

There are a number of reasons why the classifier training could go wrong. The test subject may not execute the task in the way instructed, or may not consistently be using the same imagery method. Noise in the EEG can also prevent the CSP method from focusing on the right positions.

## 4.4 Conclusions

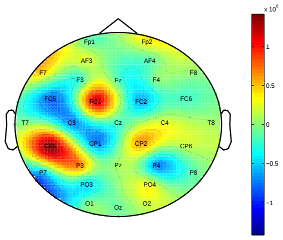
As can be expected for such a simple game, the Keyboard version was considered easy, and quite tiresome. BCI input resulted in a more challenging, more immersive, and richer experience. It made it harder to play as well. Overall, the BCI version did not result in a significantly higher positive affect.

The more engaging design and the extra stimuli presented to the subjects in the Original version resulted in more immersion compared to the Cross game. Subjects also enjoyed the design more. The game scores for the Cross version were significantly lower, which are most probably caused by the lack of user feedback, and the unintendedly shorter window sizes. Also, a high level of inconsistency between used movement imagery strategies is expected. Not only will they have been different between subjects, but within one experiment some players also have switched methods. The influence of this fact on the results is unknown.

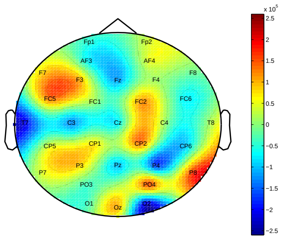
BCI as input modality can certainly add to the game experience, and vice versa: the effects game elements can have on subject motivation during clinical experiments should not be ignored.

No significant signs of user learning or fatigue have been detected for the experiment groups A and B. However, the level of alertness showed a trend to be lower after the experiment than at the beginning.

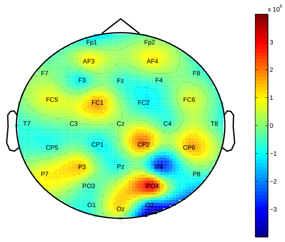
When looking at the scalp maps which show the electrode locations relevant for the classification, often a clear division between C3 and C4 can be found for well-performing subjects, where this feature is less easy to discern for others. The accuracy in detection of the resting class is also important for the resulting game score, because it can block any movement imagery classes from being detected. When the confidence value for the rest class is above a certain level, the values for left and right MI will never get high enough to pass the threshold. There are also locations highlighted in the scalp maps which do not directly make sense based on our current neurophysiological knowledge.



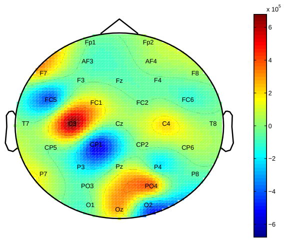
**(a)** *5B Cross, rest vs. left*



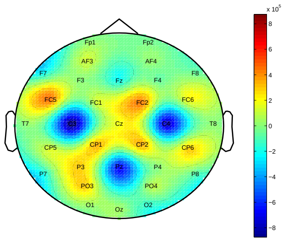
**(b)** *5B Cross, rest vs. right*



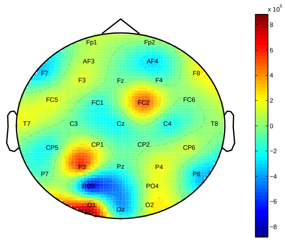
**(c)** *5B Cross, left vs. right*



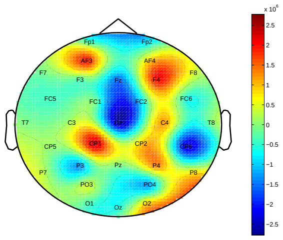
**(d)** *5B Original, rest vs. left*



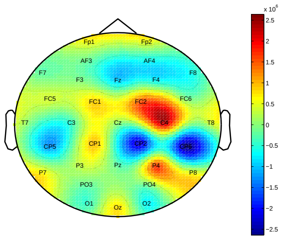
**(e)** *5B Original, rest vs. right*



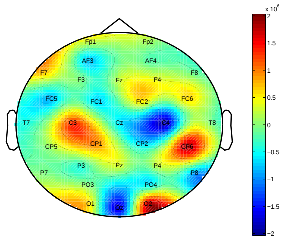
**(f)** *5B Original, left vs. right*



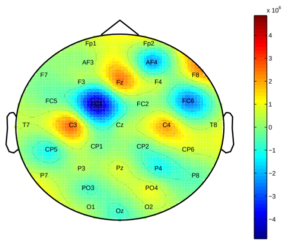
**(g)** *6B Cross, rest vs. left*



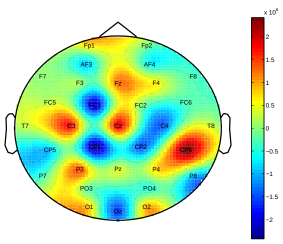
**(h)** *6B Cross, rest vs. right*



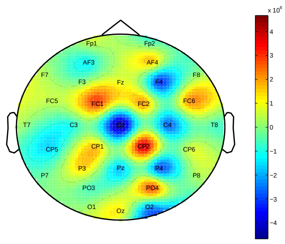
**(i)** *6B Cross, left vs. right*



**(j)** *6B Original, rest vs. left*



**(k)** *6B Original, rest vs. right*



**(l)** *6B Original, left vs. right*

**Figure 4.4:** ***Classifier plot comparison*** *for low game scores (the upper two rows) versus high scores (the lower two rows), separate for Cross and Original.*

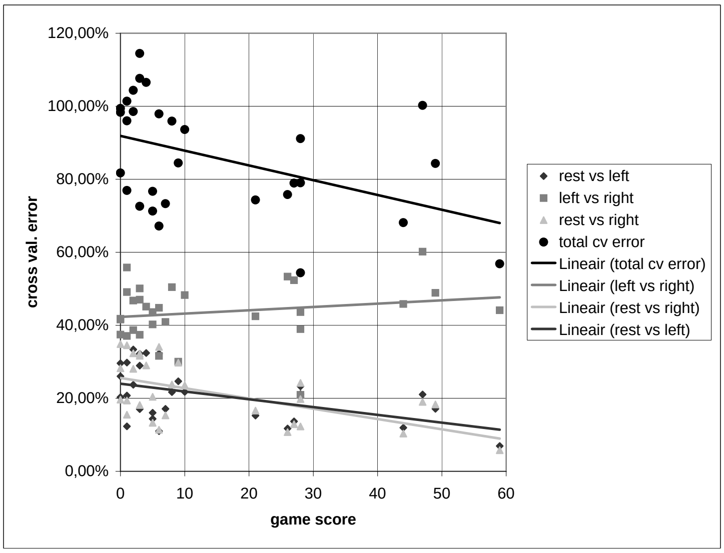



**Figure 4.5:** ***Error rate versus game score plot*** *showing the relations between the average cross validation error rates and the scores obtained during the game sessions. Each dot corresponds to one session.*

It is more fun to talk with someone who doesn't use long, difficult words but rather short, easy words like "What about lunch?"

WINNIE THE POOH

# Chapter 5

# Heuristic Evaluation

This chapter describes the heuristic evaluation that has been performed to identify potential problems (and their solutions) with BrainBasher. This is especially vital for future research with this application.

Heuristics are guidelines that can aid developers during the design process, but also function as an evaluation tool. Compared to user studies, an expert evaluation based on heuristics is a fast and cheap method to identify problems. On the other hand, some issues just cannot be identified easily without observing potential users interacting with the system. This is resolved by the user experience evaluation described in the previous chapter.

Over the years, the guidelines for usability have been almost perfected, while heuristics for games specifically have only gotten attention the last couple of years[10, 7]. Some attempts have been made to create lists that address most issues [7, 44, 23, 15, 10], but it seems difficult to discern general principles that are relevant for multiple or preferably all game genres.

The two most promising sets of heuristics for evaluating the game experience are the Heuristic Evaluation for Playability (HEP) heuristics developed by Desurvire *et al.* and the GameFlow model from Sweetser and Wyeth [7, 44].

The HEP heuristics are grouped into four categories: game play, game story, mechanics, and usability. They were verified by using them during the development of a Flash game and comparing the issues detected with HEP with those derived from user testing [7].

The guidelines described as part of GameFlow are divided in eight components related to the eight elements that constitute flow experiences. Flow was first introduced by Mihaly Csikszentmihalyi to explain the feeling of enjoyment from performing some activity [4]. The main characteristics of an activity that would increase the chance of experiencing flow are according to Csikszentmihalyi: (1) clear goals, (2) concentration and focus, (3) a loss of self-consciousness, (4) an altered sense of time, (5) direct and immediate feedback, (6) a balance between ability and challenge , (7) a sense of personal control over the activity, and (8) merging of action and awareness [1]. As the goal of games is to create an enjoyable experience [37, 44, 4], the use of flow characteristics in an attempt to create games that result in a flow experience is a very logical step.

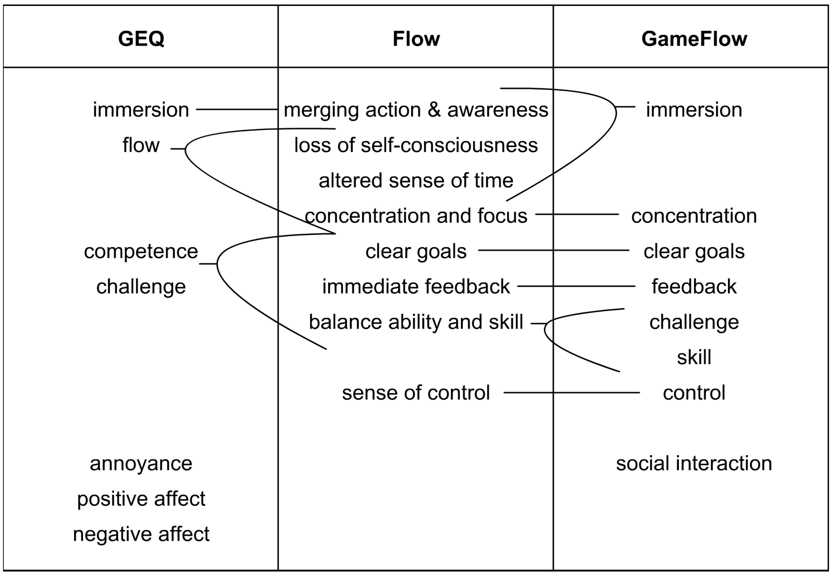



**Figure 5.1:** ***Terminology overview*** *showing the relations between the words used in Flow, GameFlow and GEQ.*

The categories in GameFlow seem to match somewhat with the GEQ components from the user experience questionnaire. The GEQ components are: immersion, flow, competence, positive and negative affect, annoyance, and challenge. The similar and overlapping terminology of the three different models may be confusing. Figure 5.1 shows how the words in these different contexts relate to each other.

Neither of these sets of guidelines have been tested on a large scale, and both advise to include user studies to identify problems that cannot be seen with a simple guideline evaluation. The authors of GameFlow warn against using the guidelines as an evaluation tool for game developers, although they say it can be useful for reviewing and identifying issues related to player enjoyment. Similarly, HEP is stated as most useful during design and preliminary prototyping phases.

Because of the similarities with the GEQ components, and because its guidelines are less genre-specific than the HEP heuristics, it was decided to use the GameFlow model to evaluate BrainBasher heuristically.

Where an expert review of the application on its own did not suffice to provide an insight into a specific heuristic, observations and GEQ results from the user experience evaluation have been taken into account.

[1] `http://en.wikipedia.org/wiki/Flow_(psychology)`

## 5.1 Concentration

One of the most important elements to increase the chance of experiencing flow is concentration. “Games should require concentration and the player should be able to concentrate on the game” [44].

**HCo1.** *The game should provide a lot of stimuli from different sources.*

In the case of BrainBasher, there are multiple stimuli situated on different locations on the screen. The number of stimuli and the use of different feedback modalities is still limited. This is done on purpose, as this statement is in direct opposite with the guidelines for developing clinical BCI experiments which aim to keep the application as clean as possible.

For the purpose of this specific research, the difference between the clinical Cross version and the Original game should not be so large that the situations are not comparable any more. Nevertheless, for future work it could be very interesting to add the feedback modality of sound in the form of background music and sound effects.

**HCo2.** *The game must provide stimuli that are worth attending to.*

All the presented stimuli are relevant to some point.

**HCo3.** *The game should quickly grab the user’s attention and maintain their focus throughout the game.*

Based on the reports from test subjects themselves and their answers in the GEQs, users experience a high sense of immersion and focus while playing BrainBasher. This could be a direct side effect from controlling the game with the brain. Focus is essentially a requirement to provide the necessary input for the application.

**HCo4.** *The user should not be burdened with tasks that do not feel important.*

The BrainBasher game is so simple, that it does not include any superfluous tasks.

**HCo5.** *The game should have a high workload, while still being appropriate for the user’s perceptual, cognitive, and memory limits.*

Users reported to tune out stimuli that were not of prime importance. For example, when they try to perform a brain action, they ignore the score and session duration feedback. This could be a sign that using the brain to control a game results in a much higher workload than using conventional methods of input like a mouse or keyboard. Perhaps because the game is very simple, this did not seem to cause any problems.

**HCo6.** *The user should not be distracted from tasks that they want or need to concentrate on.*

Because of the simplicity of the game and the limited amount of stimuli, this posed no problem. Users reported to be able to ignore irrelevant information easily.

## 5.2 Challenge

To experience flow in the definition of Csikszentmihalyi requires a fine balance between the abilities of the player and the challenge provided by the game. With insufficient challenge, the player will be bored, but if the tasks are too difficult it becomes overwhelming [4].

**HCh1.** *Challenges in the game must match the user's skill levels.*

As the perceived effort of controlling a game with brain activity is not much researched yet, it is difficult to say anything about whether the challenge of doing so is a good match of the skill levels of potential users. It is also a skill that most people have not yet trained at all.

The subjects reported the following during the user experience evaluation experiments: They all found it a difficult task, even when they got relatively high scores during the game session. Most users felt uncertain whether they were doing the right thing, as they had never done anything like this before and they would have liked more feedback so they could learn to do it right. Given the fact that all the sessions for one version together only take twelve minutes, they were also given little time to learn and adjust.

**HCh2.** *The game should provide different levels of challenge for different users.*

It is possible to define different levels of challenge and provide these sessions of different levels to the user, but during the experiments each subject got to play exactly the same game.

**HCh3.** *The level of challenge should increase as the user progresses through the game and increases their skill level.*

The game is currently not in such a state of development that there has been created a storyline for the user to follow. However, this is an interesting option for future work, especially if the influences of user learning and user fatigue are also going to be researched.

**HCh4.** *The game should provide new challenges at an appropriate pace*

At the moment, the game is very simple, and constant. There are only two brain actions the user can perform. If the system is going to be extended in the future to support more brain actions, then it could be very useful to keep this guideline in mind and introduce them gradually.

## 5.3 Player Skills

The development of the skills of the player should be supported by the game in an inconspicuous way. Preferably no explicit help is needed at all, and the player will learn while playing the game itself, which should be motivating to continue playing.

**HSk1.** *The game should increase the user's skills at an appropriate pace as they progress through the game.*

For the experiments, the subjects only played for a very short time (just two times three minutes in game mode with BCI), so for this specific use this guideline is not that applicable.

The game does support level design which makes it possible to gradually increase difficulty until the user attains full mastery. Even when the game is easily controlled by the player, there is still the challenge of being faster than others or beating your own score by becoming even faster.

**HSk2.** *The user should be able to start playing a game without reading the manual.*

The application shows information about the current session mode and shows the meaning of the symbols that will be shown before starting the actual session. It has not been tested whether this information is sufficient for the user to play the game with no additional guidance whatsoever.

The subjects from the experiment did get to read one A4 leaflet containing some additional explanation of how the game works.

**HSk3.** *Learning the game should not be boring, but be part of the fun.*

Learning to play the game is actually the main goal, as a higher score will be the result of a better proficiency. Secondly, as this is a very novel means of interacting with a game, every user will start with very little knowledge and experience, so especially in the beginning it is all about learning.

**HSk4.** *The game should include online help so users don't need to exit the game.*

As already mentioned before, the application always explains the current session mode, and the symbols that will be used. No other online help is provided.

Whether this is sufficient information is something that should be tested. During the experiments users got an additional leaflet to read, and could ask questions about things they did not completely understand. The question is also how much information is really required for the user to perform well, considering new input modality.

**HSk5.** *The user should be taught to play the game through tutorials or initial levels that feel like playing the game.*

The training mode was deliberately designed to look a lot like the other two session modes. Even though the training session is mainly required so the system can start recognizing the brain actions, it is also a means for the user to learn to play.

For the experiments it was chosen to start each run with a version of the game controlled by keyboard. This provided another learning opportunity, while still playing the game plus acquiring interesting information for the user evaluation of the game.

Adding a separate tutorial is an option, but does not seem necessary at this moment.

**HSk6.** *The user should be rewarded appropriately for their effort and skill development.*

The skill system is very simple, easy to understand, and directly reflects the user's skill and effort. Unfortunately the two cannot be separated as both effort and skill are primarily relevant for the user's success at providing brain activity the system able to recognize as brain actions.

**HSk7.** *The game interface and mechanics should be easy to learn and use.*

Common interface elements have been used in the forms of menus, progress bars, scoring, and the symbols have also been designed to reflect the intended brain action.

The subjects from the experiment seemed to work quite intuitively with the interface. It could be interesting to research what symbols would be easiest to recognize and interpret correctly. Most subjects reported that the cross symbols were easier as they could be interpreted on position. A few people preferred the hand symbols as they were a better representation of what was asked of them. The hands also provided multiple distinctions in color and form, where the crosses differed only in the aspect of what side was highlighted. This was both seen as an advantage and as a disadvantage.

## 5.4 Control

The player should feel in control, and at the same time should be warded against errors by means of recovery.

**HCl1.** *The user should feel a sense of control over the game interface and input devices.*

**HCl2.** *The user should feel a sense of control over their characters or units and their movements and interactions in the game world.*

The sense of control over actions in the game is directly related to the sense of control over the input devices, as the brain actions are the game actions.

The experiment subjects were asked two questions on this subject to rate their sense of control over the brain actions, and their sense of proficiency. Their answers to these questions were quite similar: the sense of control and proficiency for Cross were 0.69 and 0.75 (of 4), and for Original 1.53 and 1.40 (of 4). For comparison, the sense of proficiency for the keyboard version was 2.31 of 4.

This difference between Original and Cross is also reflected in the scores obtained for these two versions, but even when looking at the GEQ values for the normalized scores (Figure 4.3b) proficiency for Cross was rated much lower than Original with 0.89 versus 1.44. So somehow the sense of proficiency not only depends on how well the users did, but also on something related to the design which is very likely the amount of feedback.

Based on informal talks with the subjects, most users did not feel as much in control of the recognized brain actions as they wanted to be. There are many ways to improve on this, both on the user side (improved feedback, improved interface and information, user learning) and the system side (artifact detection, feature selection, classification, online learning).

**HCl3.** *The user should feel a sense of control and impact onto the game world (like their actions matter and they are shaping the game world).*

The game world was kept very simple. The means of impact on this world is by performing brain actions which if correct increase the score. The question of the sense of control is then reduced to the guidelines listed above.

**HCl4.** *The user should feel a sense of control over the actions that they take and the strategies that they use and that they are free to play the game the way they want to (not simply discovering actions and strategies planned by the game developers)*

The game itself is so simple that there were the only points at which different strategies were reported.

As mentioned in the design chapter, there are multiple strategies (visual or kinesthetic, imaginary or quasi movement, and also: fast or slow, smooth or abrupt) for performing the brain actions, some of which are easier to detect than others. Because of the analysis methods used, the classifier was very open to the use of different strategies.

It is also possible to apply different strategies to determining what action to perform. For example, instead of just interpreting the symbol and performing the appropriate action, one subject just focused on the symbol changing to something else. As there were only two options, the change meant he had to switch hands.

**HCl5.** *The user should feel a sense of control over the game shell (starting, stopping, saving, etc).*

No special attention was paid to this during the experiments, but no problems were reported.

**HCl6.** *The user should not be able to make errors that are detrimental to the game and should be supported in recovering from errors.*

There was nothing the user could do to make such errors. If the analyzing system is stopped, then the classifier for that subject is lost, but this action can currently only be performed by the researcher, as it is not accessible from the game application. If in the future more actions are available to the user, this guideline should be kept in mind.

## 5.5 Clear Goals

The player should know what the goals are to be able to derive what they should do.

**HGo1.** *(Intermediate) goals should be clear and presented at appropriate times.*

An explanation of each session mode is provided before the session starts. The goals of each mode could perhaps be shown more explicitly in these explanation, as the explanation currently is more focused on the interface elements.

The main goal of getting a high score can be split up in intermediate goals of getting the brain action recognized by the system repeatedly. This goal is mentioned in the game session mode explanation.

The experiment subjects were also informed of the goals in an informative leaflet, plus they could ask questions to the researcher present. In the questionnaires the subjects rated their understanding of the goal of the game as 3.45 out of 4. Their understanding of what they had to do was slightly lower with 3.1 for Cross and 3.4 for Original, but these values are still very close to the maximum of 4. Based on these numbers it can be said that most users did understand the goal and what to do to attain it.

**HGo2.** *Overriding goals should be clear and presented early.*

There were no overriding goals.

## 5.6 Feedback

The amount of feedback is the main difference between the Original and clinical Cross versions of the game that the subjects played during the experiments. Feedback is vital for the player in knowing their current state and progress. Without feedback, the user cannot adjust their own actions and thus learn to improve.

**HFb1.** *The user should receive feedback on progress toward their goals.*

The confidence bar shows the user how well they performing the brain actions in such a way that it is recognized correctly by the system. It shows the advancement in this intermediate goal. The progress bar including session duration provides feedback on the progression towards the end of the level or session. The score is an indication of the progress towards getting a high score.

**HFb2.** *The user should receive immediate feedback on their actions.*

The most direct form of feedback is the confidence bar which provides an indication of how strongly each brain action is recognized in the analyzed brain activity. And then there is also feedback in the form of the score increase and symbol switching when an action has been recognized correctly.

There are also some other feedback elements in other parts of the interface. In menu view, the options are shown and the currently selected option is marked. In information view, a timer bar shows exactly how much time there was still left before the application automatically continues on to the next screen.

**HFb3.** *The user should always know their status or score.*

In game mode, the score is always on screen in the left top corner. The status of their currently detected brain actions is shown in the confidence bar.

## 5.7 Immersion

Immersion in the terminology of GameFlow is related to merging action and awareness, loss of self-consciousness, and altered sense of time as described by Csikszentmihalyi.

The following guidelines cannot really be evaluated without asking users how they feel while playing the game. The GEQ scores will be used to determine how well they are being adhered to. Without a comparison the GEQ values do not have much meaning. For the sake of interpretation, we will say that an average score of lower than 1.5 out of 4 is sufficiently low to say that it does not fulfill this statement. If the statement posed in the GEQ obtained a score of 2.5 out of 4, the average user is said to agree. For those GEQ values in between, the result is said to be uncertain.

**HIm1.** *The user should become less aware of their surroundings.*

The GEQ contained two related statements: about forgetting the environment, and being away from the outside world, with scores of 2.33 and 2.00 respectively. As these scores are below 2.5, this could perhaps be improved on somehow.

**HIm2.** *The user should become less self-aware and less worried about everyday life or self.*

The GEQ did not contain questions about self-awareness, but perhaps one could say that the more absorbed and concentrated the user is, the less self-aware they will probably be as well. The users did note that they were not really thinking about other things when playing the game (score 1.00), which means indirectly that they were not worrying about every life or self.

**HIm3.** *The user should experience an altered sense of time.*

The experiment subjects did not really lose their sense of time (score 1.33). This could be an indication that perhaps more should be done to increase the sense of immersion.

**HIm4.** *The user should feel emotionally involved in the game.*

**HIm5.** *The user should feel viscerally involved in the game.*

There were no specific GEQ questions considering the emotional and visceral involvement of the user. Two GEQ statements that are related to these heuristic consider absorption and concentration, which yielded values of 2.67 and 2.93. Based on this, this guideline is adhered to. The general sense of immersion was rated 2.38.

## 5.8 Social Interaction

The issue of social interaction is more important for multi-player games, than for the simple single-player game BrainBasher is at the moment. Yet, even for single-player games interaction can motivate users.

**HSo1.** *The game should support competition and cooperation between users.*

Although the game is currently implemented as a single player game only, social interaction and competition has been added in the form of high score lists.

**HSo2.** *The game should support social interaction between users (chat, etc).*

Social interaction in the form of chat could be interesting if the game would be extended to include multi-player options.

**HSo3.** *The game should support social communities inside and outside the game.*

For a small research application as this, social communities are not really relevant.

## 5.9 Conclusions

The game experience heuristics helped detect some issues and provided some new ideas. This section summarizes the previous section.

Based on the guidelines, the following ideas for improvement of the current application are proposed. The addition of auditory stimuli (background music, sound effects) may increase the level of concentration of the user on the game. Different kinds of feedback can provide more information on what the user can do to improve the recognizability of their brain actions may make it easier to learn and perform this task. Goals of each mode may be included more explicitly in the session mode explanations. The level of control by the user can be improved in many ways, both on the user and the system side: improved feedback, improved interface and information, user learning, artifact detection, improved feature selection and classification.

Some of the issues the heuristics point at could not properly be evaluated simply because of lack of knowledge. The influence of using BCI input on the workload is something that may need to be researched, in order to balance the total workload of the game. Whether the game itself already provides sufficient information to the user so no external help is required should be evaluated. For the performance of the user, it is important that the symbols are easy to recognize and interpret. For this reason, a variety of symbols should be evaluated to find the optimal visualizations. The sense of immersion can still be improved. Research into this subject may generate new ideas.

Finally, there were some items that could be relevant for future versions of the game application. If the application is in the future extended to support more brain actions, they should be introduced to the user gradually. If the application is ever extended to include multi-player modes, social interaction between players can be encouraged by e.g. providing a chat feature.

> "I don't see much sense in that" said Rabbit. "No," said Pooh humbly, "there isn't. But there was going to be when I began it. It's just that something happened to it along the way."
>
> WINNIE THE POOH

# Chapter 6

# Conclusions and Recommendations

To bring the thesis to completion, the most important deductions from the previous chapters are summarized here. The user experience evaluation provided the answers to the main research questions. The main goal of the heuristic evaluation was to discover points for improvement, which have been added to the Future Work section.

## 6.1 Conclusions

To move directly to the main questions this research was to answer:

**How does controlling a computer game with the brain influence the user experience** compared to conventional input methods like a keyboard?

The keyboard-controlled game was considered easy, and tiresome even. As expected, BCI control was perceived as more difficult, but also more challenging, more immersive, and resulted in a richer experience.

**How does using game elements (e.g. a clear goal, feedback) within a BCI experiment influence the user experience and performance** compared to a clinical minimal design like the simple visualization used by Bussink [3]?

The version which included the game elements achieved more immersion and the design was more pleasing than the clinical experiment variety. The obtained game scores were also significantly higher, but this may also have been caused by an unintended technical issue causing the stimulus durations of the game variety to be longer than the clinical variation.

It can be concluded that the novel input modality of BCI can certainly improve the game experience. The same is true for adding game elements to more clinical designs: the effects this can have on subject motivation should not be neglected.

## 6.2 Discussion

This section describes some of the most important issues that have been mentioned in the earlier chapters. Some concern the answers to the research questions. Others are also relevant for the general use of BCI as an input modality.

The lower game scores attained with the clinical experiment design are most likely caused by the lack of user feedback and the inadvertently shorter window sizes.

Another issue that may have impacted the game scores in general is the expected high level of inconsistency between used movement imagery strategies. Not only will they have been different between subjects, but within one experiment some players also have switched methods. The exact influence of this fact on the results is yet unknown.

Although user learning and user fatigue were reckoned with in the chosen methods, no significant signs of either were detected. There is a trend towards a lower alertness at the end of the experiments however.

As a final issue, even with the neurophysiological research done for this study, it is difficult to interpret the classifier scalp maps in Chapter 4. Extreme values around C3, C4, P3, and P4 for movement imagery detection do seem to be a valid indication of effectiveness however. For the rest class, some plots mark the area around the eyes, but others which still get an acceptable error rate do not. More research into what brain activations can be expected for the different kinds of MI, and what brain activations are recorded in practice, could help in understanding what is happening, and also in validating the feature selection and extraction processes.

## 6.3 Recommendations

This research has shown that BCI input for controlling games can have a positive impact on the game experience. But this is only the beginning. Many possibilities of use of BCI still have to be researched, or even be invented. Also the effects of using this input modality need to be examined more closely, e.g. its influence on the cognitive load of the user, user learning, and user fatigue.

One must be careful not to train on the visual or auditory stimulus used to indicate certain brain actions. To provide an example from this research, the cross symbol could have induced an eye movement artifact which could be used by the automatic classifier to discriminate between classes. Careful consideration has to be taken to avoid issues like this, which can be done by being very careful with the stimulus designs, or perhaps even better: by not using the brain activity from the period in which the stimulus is just being shown.

The EEG cap is not considered comfortable. Subjects reported it to increase an already existing headache – but this may also be related to the high levels of concentration required for BCI control. For the user a cap like Emotiv's would probably a lot more pleasant. On the other hand, from a research point of view the accompanying reduction of the amount of EEG channels may be unacceptable.

Even with the uncomfortable cap, the conductive gel, and the long experiments, at the moment user motivation does not seem to be a problem with BCI research like this. For now, the novelty factor is sufficient to attract interested subjects. In the future, other incentives may be required.

## 6.4 Future Work

The ideas described in this section are partially based on the issues detected with the game experience heuristics, but much of it are ideas generated from just working with the system and from communication with fellow researchers. The most urgent future work is to fix the high priority problems within the system. See Appendix G.

Presented here are many ideas sorted in three main categories. The system improvements mainly consider the pipeline used to analyze the brain activity. The second category provides some ideas for new features which could be implemented in a newer version of the application. But perhaps the most relevant list of ideas are the issues and questions listed in the Research category.

#### System Improvements

The ideas for improvement mentioned here mostly concern the analysis and classification of the brain signals into actions.

The classification performance may be enhanced by somehow providing the classifiers with cleaner training data. Artifact filtering or detection is a way to achieve this. If an artifact is detected, the stimulus could be shown a second time, or the data cleaned with a filter could be used.

Another possibility is detection and removal of outliers in the training data set. The subject could also provide feedback about whether they thought a trial went well, or not so well. In the latter case, the data can be discarded, and perhaps the trial should be redone. It may also have a positive effect to ignore the first number of windows of a training set, as the user is still learning to perform the action correctly.

Automatic detection of bad channels (for example based on high offsets) could also improve the data quality. The bad channels can be left out, or repopulated with interpolated data based on the other signals around the bad electrode. Based on neurophysiological knowledge, it is possible to improve on the feature selection step, for example by pre-selecting a set of channels suspected to be most relevant for movement imagery, like C3, C4, P3, and P4.

The performance can also be improved by letting the classifiers learn when the system is online and running as well. It may even be possible to eliminate training altogether, which would improve the experience for the user by removing tedious training sessions and the ability to provide feedback about their brain actions early on. Finally, performing a comparison of different analysis methods would it possible to select the most optimal combination.

The delay through the whole system - from stimulus to feedback about that stimulus - is a very important measurement that is yet unknown in our case. It is important to know the delay and to pinpoint any bottlenecks, as the total system delay plays a part in the possible speed as a communication channel, but also because the delay in the feedback to the user about their actions should be minimal for optimal user learning.

Some other features that could be useful are the following. The ability to rerun the experiment offline as if it is online facilitates running tests without the need of actual subjects. Besides, it could be useful to rerun an experiment in an online manner to analyse certain events more closely. It is also important to encourage collaboration with other research groups in the Netherlands. This could be done by porting the current system to the BrainStream platform which is used by the Music Mind Machine group of Radboud University as well as the F.C. Donders centre.

#### New Application Features

Some features that could be added to the applications are noted in this section.

Some ways to insert more variation in the game play and create more ways to control a system are the use of timing and duration. Timing requires a brain action to be performed at (or about) a specific moment. Duration is created by performing the brain action for a specific length of time.

In similar games, often the next action to be performed (after the one that is currently demanded) is already shown on screen somewhere, so the user can anticipate which potentially increases their performance. This action preview feature introduces new questions: would it also increase the performance with brain actions? Or would this additional feedback and the resulting change in brain activity actually decrease the performance?

Developing a multiplayer version of the game could be interesting as it would add the factor of user interaction by playing together or against each other.

Again, collaboration can be encouraged by porting the game to work with the GipBrain system which has been developed at the Radboud University. The system makes it possible to create single- and multiplayer games which run in a web browser. As the only input the system requires are the actions to be performed, it is totally independent of the actual BCI pipeline. The downside of GipBrain is that the application itself will be in the form of a Java applet, with all its limitations.

#### Research

Many ideas for future research have been generated over the time of this study.

First there is the factor of brain action input. There are many different types of brain actions one could use, outside the field of movement imagery as well. A comparison of different types of brain actions could show what actions are easier to perform than others and what combinations of actions are easier to get identified by the system.

Within the area of movement imagery actions, a comparison different methods of execution could show what works best for most people. Think about imaginary, quasi, and actual movement, but also the speed and abruptness of the movement (the MMM group in Nijmegen uses sound increasing and decreasing in pitch to indicate the exact timing of the finger movement to the subject). Another issue is: how does the brain activity change when the movement becomes an automated procedure? And what is the influence of this on the detectability of the action?

Different brain action classes (movement imagery, cognitive state, or elicited brain activity like SSVEP) can be used in a mixed manner, or even combined where multiple actions have to be performed at the same time. When does it become too complex for the subject, or the classification system, to handle? As a reminder: the different actions should be introduced gradually to the user.

Alternatively, brain actions can also be mixed or combined with other input modalities, like keyboard and BCI. For example, mouse and/or keyboard could be used to move through a virtual world, and brain actions could be used to perform special 'magical' actions.

The stimuli and feedback features are also a potential area of research. A variety of stimulus symbols could be evaluated to find visualizations that result in an optimal performance by the user. The symbols should be easy to recognize and interpret. In case of animated symbols (like actually showing the hand movement to be made) one has to be wary of mirror neurons.

The addition of auditory stimuli (sound effects, background music) could increase the level of concentration of the user. Does it also improve the recognizability of the BCI input?

Different kinds of feedback could be added to provide more information on what the user can do to improve the recognizability of their brain actions. This may make it easier to learn to perform the task, and may also improve the performance itself. One could think of, for example, adding feedback about detected eye and/or muscle artifacts, or feedback about activity measured at electrode locations that should get activated based on neurophysiological knowledge about the brain actions.

Then there are some effects resulting from the interplay between user and application that may prove to be very relevant for the achieved performance. First there is the effect of user learning which is is defined by the performance improvement caused by user adaptation to the BCI system without the system adjusting to the user. Preferably, the system would adapt itself to the user as well, creating a very complex system which makes it very difficult to trace performance improvements to their origin.

User fatigue may decrease the performance when working with the system over a long period of time. Using BCI input may be cause user fatigue to set in earlier than when using conventional input methods. BCI may also be more susceptible to problems caused by user fatigue as it uses brain activity directly. These issues are important to research as it could seriously limit the use of BCI as a method for control for the general population.

Something very much related to this, is the issue of workload. BCI control may require more cognitive resources as it uses the brain activity itself. For efficiency, the total workload of all the tasks the user is working on needs to be balanced. The influence of BCI on the workload is therefore a relevant issue to research and consider in the design of BCI applications.

Inter- and intra-subject generalization are two other issues that are very relevant for the practical use of BCI. If it is possible to generalize between subjects, classifiers trained on one subject could also work for another. This is an important step in the possibility of starting out with a general classifier which would already be able to somewhat detect intended brain actions without the user having to undergo extensive training first. The possibility to generalize for one subject over time is also required for such a general classifier to be possible. But even when using personalized classifiers, the question of what the expiration date of a certain BCI classifier would be is significant. The less repetitive training is required, the easier and more pleasant it is for the user to actually make use of this input method.

The heuristic evaluation indicated that the sense of immersion with BrainBasher may still be improved. Literature research could be done to generate ideas which could then be implemented and tested in practice. User experience monitoring (which is also part of BrainGain) could help in determining weak points in the user experience which could subsequently be improved.

Another way of addressing the user experience is to go at it from a totally different way. Instead of the development of an application for BCI, BCI input could be used in an already existing application; a game which is already primed to achieve an optimal user experience. This can also be combined with the idea of combining multiple input methods: conventional methods of control could be used to navigate through the game, and spell casting etc. could be performed by brain.

Most BCI research is based on relatively little data, which provides a very shaky basis for research results. A great method to collect a lot of data from many different subjects could be the organization of a BrainBasher competition in which participants compete to demonstrate how well they are in control of their own brain.

As can be expected with such a relatively new area of research, the work that can be done seems endless.

# Bibliography


[1] E. Alpaydin. *Introduction To Machine Learning*. MIT Press, 2004. 23

[2] T.W. Berger, J.K. Chapin, G.A. Gerhardt, D.J McFarland, J.C. Principe, W.V. Soussou, D.M. Taylor, and P.A. Tresco. International Assessment of Research and Development in Brain-Computer Interfaces. Technical report, World Technology Evaluation Center, Inc., 2007. 3

[3] D. Bussink. Towards the first hmi bci game. Master's thesis, Human Media Interactio n Department, Faculty EWI, University of Twente, 2008. 1, 2, 3, 8, 11, 22, 57, 137

[4] J. Chen. Flow in games (and everything else). *Communications of the ACM*, 50(4):31–34, 2007. 45, 46, 48

[5] D.J. Crammond. Motor imagery: never in your wildest dream. *Trends in Neurosciences*, 20(2):54–57, 1997. 19

[6] A. Delorme and S. Makeig. EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods*, 134(1):9–21, 2004. 22

[7] H. Desurvire, M. Caplan, and J.A. Toth. Using heuristics to evaluate the playability of games. *Conference on Human Factors in Computing Systems*, pages 1509–1512, 2004. 45

[8] R. P. W. Duin. Prtools version 3.0: A matlab toolbox for pattern recognition. In *Proc. of SPIE*, page 1331, 2000. 22

[9] L.A. Farwell and E. Donchin. Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials. *Electroencephalography and clinical neurophysiology*, 70(6):510–523, 1988. 1, 7

[10] M.A. Federoff. *HEURISTICS AND USABILITY GUIDELINES FOR THE CREATION AND EVALUATION OF FUN IN VIDEO GAMES*. PhD thesis, Indiana University, 2002. 45

[11] B. Graimann, B. Allison, and A. Gräser. New Applications for Non-invasive Brain-Computer Interfaces and the Need for Engaging Training Environments. *BRAINPLAY 07 Brain-Computer Interfaces and Games Workshop at ACE (Advances in Computer Entertainment)*, 2007. 1, 2, 3

[12] C. Guger, G. Edlinger, W. Harkam, I. Niedermayer, G. Pfurtscheller, G.T. OEG, and A. Graz. How many people are able to operate an EEG-based

brain-computer interface (BCI)? *Neural Systems and Rehabilitation Engineering, IEEE Transactions on [see also IEEE Trans. on Rehabilitation Engineering]*, 11(2):145–147, 2003. 1, 3

[13] S.I. Hjelm and C. Browall. Brainball–using brain activity for cool competition. *Proceedings of NordiCHI*, 2000. 7, 9

[14] W. IJsselsteijn, Y. de Kort, K. Poels, A. Jurgelionis, and F. Bellotti. Characterising and Measuring User Experiences in Digital Games. *International Conference on Advances in Computer Entertainment Technology, June*, 2007. 29, 30, 115

[15] H. Korhonen and E.M.I. Koivisto. Playability heuristics for mobile games. *Proceedings of the 8th conference on Human-computer interaction with mobile devices and services*, pages 9–16, 2006. 45

[16] R. Krepki. Brain-Computer Interfaces: Design and Implementation of an Online BCI System of the Control in Gaming Applications and Virtual Limbs. *Doctoral Dissertation, Technische Universität, Berlin, Germany*, 2004. 23

[17] R. Krepki, B. Blankertz, G. Curio, and K.R. Müller. The Berlin Brain-Computer Interface (BBCI)–towards a new communication channel for online control in gaming applications. *Multimedia Tools and Applications*, 33(1):73–90, 2007. 8

[18] E.C. Lalor, S.P. Kelly, C. Finucane, R. Burke, R. Smith, R.B. Reilly, and G. McDarby. Steady-State VEP-Based Brain-Computer Interface Control in an Immersive 3D Gaming Environment. *EURASIP Journal on Applied Signal Processing*, 2005(19):3156–3164, 2005. 1, 3, 9, 11

[19] R. Leeb. Self-Paced (Asynchronous) BCI Control of a Wheelchair in Virtual Environments: A Case Study with a Tetraplegic. *Computational Intelligence and Neuroscience*, 2007:1–8, 2007. 1, 7

[20] R. Leeb, F. Lee, C. Keinrath, R. Scherer, H. Bischof, and G. Pfurtscheller. Brain–Computer Communication: Motivation, Aim, and Impact of Exploring a Virtual Apartment. *Neural Systems and Rehabilitation Engineering, IEEE Transactions on [see also IEEE Trans. on Rehabilitation Engineering]*, 15(4):473–482, 2007. 1, 2, 3

[21] T.C. Lethbridge and R. Laganière. *Object-oriented Software Engineering: Practical Software Development Using UML and Java*. McGraw-Hill, 2001. 77, 87, 89, 96

[22] T.A. Lin and L.R. John. Quantifying Mental Relaxation with EEG for use in Computer Games. *International Conference on Internet Computing*, pages 409–415, 2006. 7, 10, 11

[23] T.W. Malone. Heuristics for designing enjoyable user interfaces: Lessons from computer games. *Proceedings of the 1982 conference on Human factors in computing systems*, pages 63–68, 1982. 2, 13, 45

[24] M. Middendorf, G. McMillan, G. Calhoun, and K.S. Jones. Brain-computer interfaces based on the steady-state visual-evokedresponse. *Rehabilitation*

*Engineering, IEEE Transactions on [see also IEEE Trans. on Neural Systems and Rehabilitation]*, 8(2):211–214, 2000. 8

[25] K.R. Muller, CW Anderson, and GE Birch. Linear and nonlinear methods for brain-computer interfaces. *Neural Systems and Rehabilitation Engineering, IEEE Transactions on [see also IEEE Trans. on Rehabilitation Engineering]*, 11(2):165–169, 2003. 23

[26] G. Müller-Putz, R. Scherer, and G. Pfurtscheller. Game-like Training to Learn Single Switch Operated Neuroprosthetic Control. *BRAINPLAY 07 Brain-Computer Interfaces and Games Workshop at ACE (Advances in Computer Entertainment)*, 2007. 8

[27] C. Neuper, R. Scherer, M. Reiner, and G. Pfurtscheller. Imagery of motor actions: Differential effects of kinesthetic and visual–motor mode of imagery in single-trial EEG. *Cognitive Brain Research*, 25(3):668–677, 2005. 19

[28] A. Nijholt, D. Tan, G. Pfurtscheller, C. Brunner, J.R. Millán, B. Allison, B. Graimann, F. Popescu, B. Blankertz, and K.R. Müller. Brain-Computer Interfacing for Intelligent Systems. *IEEE Intell. Systems*, 23(3):72–79, 2008. 1

[29] A. Nijholt, J. van Erp, and D. K. J. Heylen. Braingain: Bci for hci and games. In S. J. Nasuto and F. Hwang, editors, *Symposium Brain Computer Interfaces and Human Computer Interaction: A Convergence of Ideas at the AISB 2008 Convention "Communication, Interaction and Social Intelligence", Aberdeen, UK*, pages 32–35, Brighton, UK, April 2008. The Society for the Study of Artificial Intelligence and Simulation of Behaviour. 2

[30] Anton Nijholt, Desney Tan, Brendan Allison, Jose del R. Milan, and Bernhard Graimann. Brain-computer interfaces for hci and games. In *CHI '08: CHI '08 extended abstracts on Human factors in computing systems*, pages 3925–3928, New York, NY, USA, 2008. ACM. 1

[31] V.V. Nikulin, F.U. Hohlefeld, A.M. Jacobs, and G. Curio. Quasi-movements: A novel motor–cognitive phenomenon. *Neuropsychologia*, 2007. 20

[32] A. Palke. *Brainathlon: Enhancing Brainwave Control Through Brain-controlled Game Play*. PhD thesis, Mills College, 2004. 9, 11

[33] G. Pfurtscheller and C. Neuper. Motor imagery and direct brain-computer communication. *Proceedings of the IEEE*, 89(7):1123–1134, 2001. 19

[34] G. Pfurtscheller, C. Neuper, D. Flotzinger, and M. Pregenzer. EEG-based discrimination between imagination of right and left hand movement. *Electroencephalography and Clinical Neurophysiology*, 103(6):642–651, 1997. 22

[35] J.A. Pineda, D.S. Silverman, A. Vankov, and J. Hestenes. Learning to control brain rhythms: making a brain-computer interface possible. *Neural Systems and Rehabilitation Engineering, IEEE Transactions on [see also IEEE Trans. on Rehabilitation Engineering]*, 11(2):181–184, 2003. 8, 11

[36] J. Preece, Y. Rogers, and H. Sharp. *Interaction design: beyond human-computer interaction*. Wiley, 2002. 71, 77, 87, 89, 91, 95

[37] R. Ragulayan, D. Gunn, and R. Romero. A Gameplay-Centered Design Framework for Human Factors in Games. *International Encyclopedia Of Ergonomics And Human Factors*, 2006. 46

[38] H. Ramoser, J. Muller-Gerking, and G. Pfurtscheller. Optimal spatial filtering of single trial EEG during imagined handmovement. *Rehabilitation Engineering, IEEE Transactions on [see also IEEE Trans. on Neural Systems and Rehabilitation]*, 8(4):441–446, 2000. 22

[39] A. Schlögl, F. Lee, H. Bischof, and G. Pfurtscheller. Communication: Characterization of four-class motor imagery EEG data for the BCI-competition 2005. *Journal of Neural Engineering*, 2(4):L14–L22, 2005. 8

[40] Terrence J. Sejnowski, Guido Dornhege, José del R. Millán, Thilo Hinterberger, Dennis J. McFarland, and Klaus-Robert Müller. *Toward Brain-Computer Interfacing (Neural Information Processing)*. The MIT Press, 2007. 91

[41] Beom-Soo Shim, Sung-Wook Lee, and Jeong-Hoon Shin. Implementation of a 3-dimensional game for developing balanced brainwave. *Software Engineering Research, Management & Applications, 2007. SERA 2007. 5th ACIS International Conference on*, pages 751–758, 2007. 1, 3, 9, 11

[42] S. Shipp, M. Blanton, and S. Zeki. A visuo-somatomotor pathway through superior parietal cortex in the macaque monkey: cortical connections of areas V6 and V6A. *European Journal of Neuroscience*, 10(10):3171–3193, 1998. 134

[43] U. Strehl, U. Leins, G. Goth, C. Klinger, T. Hinterberger, and N. Birbaumer. Self-regulation of Slow Cortical Potentials: A New Treatment for Children With Attention-Deficit/Hyperactivity Disorder. *Pediatrics*, 2006. 1, 3, 9, 11

[44] P. Sweetser and P. Wyeth. GameFlow: a model for evaluating player enjoyment in games. *Computers in Entertainment (CIE)*, 3(3):3–3, 2005. 45, 46, 47

[45] T.M. Vaughan. Guest editorial brain-computer interface technology: a review of the second international meeting. *Neural Systems and Rehabilitation Engineering, IEEE Transactions on [see also IEEE Trans. on Rehabilitation Engineering]*, 11(2):94–109, 2003. 3

[46] J.J. Vidal. Real-time detection of brain events in EEG. *Proceedings of the IEEE*, 65(5):633–641, 1977. 8, 11

[47] S.A. Wills and D.J.C. MacKay. DASHER An Efficient Writing System for Brain–Computer Interfaces? *Neural Systems and Rehabilitation Engineering, IEEE Transactions on*, 14(2):244, 2006. 1, 7

# Appendix A

# Prototype Development

## A.1 Domain Analysis

To come to a well-formulated understanding of the background and the problem, a domain analysis has been conducted.

### A.1.1 Domain Description

This research combines two domains: the field of BCI research, and gaming.

Most BCI research has focused on paralyzed patients. Game-like experiments have been devised, but where never a goal in itself. Read section 2.1 for details.

The gaming industry is doing very well, and has been doing very well for a large number of years now. Some BCI-related companies are already offering headsets and software libraries to help the gaming industry to the next level, i.e. incorporate brain activity as an additional modality to improve the game experience. The first commercial BCI game has yet to be released for the general market. Refer to section 2.2 to read more about this.

### A.1.2 Users

Four types of users have been identified.

**Player** The direct user of the game is the person who will actually play it. The main goal of the *player* will be to have fun playing a novel game with BCI input. This user is necessary for both demonstration of the system and conducting research.

**Audience** The *audience* consists of a number of people watching a person play the game. This user will want to see the system in action and enjoy doing so. This *audience* will only be there during demonstrations.

**Researcher** The person conducting research can use the game to test implementations with a *player*, and to gather data from this *player* for further research. The *researcher* wants a platform which can be adapted easily for different kinds of BCI-related research. The system should be able to provide results like classification performances, and make it possible to run a simulation offline afterwards to test adjustments to the implementation. For this user it is also important to be able to demonstrate the results of the research. During demonstrations, the *researcher* does not necessarily have to be present.

**Institution** The *institution* to which the *researcher* is linked is a stakeholder for which this software could improve the efficiency of the research and provide a means to demonstrate research results to the outside.

The *researcher* is part of developing the game as this user defines the classifiers to support a certain research question. The implementation can be tested and finetuned with *players*. When the result is stable enough, the research can be demonstrated by the *institution* (possibly represented by the *researcher* him- or herself) to an *audience*, with again a *player* to show the game.

### A.1.3 Environment

The general setup necessary to play consists of: an EEG cap, a system to record the brain activity, and a screen in front of the player. A keyboard could be necessary during some steps, which could be controlled by a *researcher* (perhaps with a separate screen showing a copy of the visuals for the *player*), or the *player* themselves. Obviously, a computer will be necessary to capture and process the data and run the application.

In the HMI experiment room, there is a BioSemi setup available with 32 electrodes. The data is captured, amplified, and sent to the recording PC via USB. On the PC Actiview is used to record the data to disk. Actiview can also retransmit the data via TCP.

It is possible to add extra computers to the system for example to divide the EEG capture, processing and application over separate computers. This could be preferable to minimize delays if a lot of processing time is required which would otherwise slow down the whole system.

The presence of numerous electrical appliances within range of the setup could introduce nonphysiological artefacts in the recorded signal. Hopefully, most of its influence can be filtered out with a simple 50Hz notch filter. For MI the problem will be minimal as its feature extraction zooms in on low frequencies.

### A.1.4 Tasks and Procedures

The actors defined in the user section are: player, audience, researcher, and institution. The only two actors that interact with the system directly are the player and the researcher.

Here the main tasks identified for these actors are listed. For a detailed analysis of these tasks and the corresponding user-machine interactions, see section A.2.

**Player**

- *Create a new profile*: when a person has never played before, there is no data available yet. The *player* should create a new profile so this data can be stored for future use.
- *Select an existing profile*: if a person has played before, the corresponding profile can be selected so the already trained classifiers can be used to identify BCI actions.
- *Train:* for the user to be able to play, first classifiers need to be trained to detect the necessary BCI actions. This is done with a training session.
- *Play:* the essence of the game: letting the user play.
- *Free play:* a mode in which the *player* is not constraint by expected actions, but can freely test and play to get a feel for the interaction.
- *View high scores:* to encourage the competitive edge a game can bring, a high score list is an essential tool. The *player* will want to know how he or she performed compared to other *players*.
- *Update training*: even if personal classifiers are already available, the identification of BCI actions may worsen over time as too many factors change. With a short training session the *player* should be able to update the already existing classifiers to increase performance.
- *Clear training:* if the existing personal classifiers have a very low accuracy, the *player* can decide to clear the existing data and retrain from scratch without losing the rest of the data linked to the profile.

**Researcher**

- *Hook in a classifier:* the *researcher* must be able to tell the system to use a particular classifier implementation to conduct the research.
- *Define an experiment:* for collecting data, the *researcher* must have full control over the definition of a training experiment. For demonstration purposes, the *researcher* must also be able to define what actions can be used in a game experiment.
- *Collect data:* to learn what has happened and possibly improve the classifier, data needs to be collected for offline analysis.
- *Analyze data:* analysis of the collected data provides research results.
- *Demonstrate results:* if a sufficiently working classifiers have been implemented, a working prototype with these classifiers can be demonstrated.
- *Unhook a classifier*: as classifiers may be replaced, it must also be possible to unhook a hooked-in implementation.

### A.1.5 Competing Software

The conclusions drawn based on the literature research can be found in section 2.3. The two issues most important for the design of this application:

- The game should be usable for a variety of BCI research situations. All of the existing games rely heavily on a specific number of inputs, or input dimention, because they have been developed to test a particular BCI paradigm. This game should have a variable number of inputs.

- The game should be engaging and entertaining. The user interface must be graphically appealing.

### A.1.6 Similarities Across Domains and Organizations

This game is originally designed for the human media interaction group at the University of Twente. Their main goal within BCI research is to develop applications for the general population, while most institutions target paralyzed patients. To make this application of interest for these other groups, the direct interaction with the application by movement (i.e. typing and key presses) must be limited to actions that the researcher can perform for the player without influencing the experiment.

While for other research institutions it may be more important to obtain clean data, for this group the entertainment factor is also of high importance. Although this could also result in cleaner data because of the increased focus from a motivated user, it is also possible that the added information will distract the user. This is an issue that has to be looked into.

### A.1.7 Problem Definition

This project tries to address a wide variety of problems. To narrow the scope, this section will define the type of game that will be developed.

During the game, a symbol will be shown to the user, which represents an action which can be detected with the BCI system. When the action is detected the next target symbol appears in the center. There are a number of design decisions on what information to show, how, where, and when, so for now this global description will have to do.

As for the training session, each of the input symbols will be shown a number of times for a fixed duration. The EEG recorded during these time windows can be used to train classifiers.

This type of game was chosen for a number of reasons. The concept has proven to be appealing to a wide variety of users in games like Donkey Konga™(Nintendo©) and Dance Dance Revolution™(Konami©). Any brain activity that can be controlled by the user and detected from EEG can be used as an input for the game. Besides, the number of different types of input is unconstraint.

## A.2 Task Analysis

As mentioned in only two actors come in direct contact with the application: the *player* and the *researcher*. The identified main tasks for these two types of users are described and analyzed in detail in this section. Scenarios provide a storyline description of each of these tasks, followed by an essential use case to define the interaction with the system (as defined and explained in [36]).

### A.2.1 Player

For each of these scenarios, the player is already hooked up to the system with the EEGcap, and the necessary software applications started. The *player* is called Pete.

**Task 1. Create Profile** As Pete has never played this game before, he does not have a profile yet. In the start screen he chooses to create a new profile and enters his name to label it he knows which is his for next time. The system moves Pete to training mode, because classifiers need to be trained before Pete can actually play the game.

For the use case, refer to Table A.1.

| User Intention | System Responsibility |
|---|---|
| Create a new profile | |
| | Ask for a name |
| Enter name | |
| | Create profile and use it |
| | Forward the user to training |

**Table A.1:** *Use case: player - task 1. create profile*

**Task 2. Select Profile** Next time Pete wants to play, he can select his profile from the list.

For the use case, refer to Table A.2.

| User Intention | System Responsibility |
|---|---|
| Select profile | |
| | Use selected profile |
| | Forward the user to menu |

**Table A.2:** *Use case: player - task 2. select profile*

**Task 3. Training** Pete wants to play the game, but before he can play a training session is necessary to train the classifiers. Therefore Pete is forced to do a training session first.

As Pete has never trained before, he chooses to do the complete training.

An instructional screen informs the player on what is going to happen (symbols will be shown representing actions, intertweened with resting periods; explanation of what symbols belong to what actions), some advice (stay relaxed, no blinking or movement during stimuli periods; during break periods anything is allowed as long as the cap stays on and no apparel is harmed), and what the symbols mean that he's going to see during the training session.

When the training begins, a symbol is shown in the center of the screen. Pete remembers the corresponding action (maybe from the instructional screen, but hopefully because of a well-chosen representation), in this case: imaginary movement of the left hand. As long as the symbol is shown, Pete keeps imagining the movement.

Then a short break starts. Pete can see how much time he has, and knows from the instruction screen that this is the time to move, blink, and get comfortable.

When the break is over a new symbol is shown. This process is repeated until the time-progress bar is full.

Pete sees a screen that tells him to wait a moment while the classifiers are training. Then the screen changes to show the training session is over, and Pete goes back to the menu.

The use case can be found in Table A.3.

| **User Intention** | **System Responsibility** |
|---|---|
| Start training | |
| | Show list of available training sessions |
| Choose training session | |
| | Inform player on the procedure, give advice, explain symbols |
| *Repeat* | |
| | Show symbol |
| Perform indicated action | |
| | Show resting period |
| *Until all symbols have been shown* | |
| | Show classifiers busy training |
| | Show training session is over |
| OK | |
| | Bring player back to menu |

**Table A.3:** *Use case: player - task 3. training*

**Task 4. Playing** Pete is happy to finally select the option to play the game from the menu.

A list of available games appears on the screen. Pete chooses the one with imaginary movement.

Again an instructional screen shows what is going to happen (symbols, try to 'hit' them) and some advice (stay relaxed, don't blink during actions). Also, the meanings of the symbols that can be encountered in this level of the game are explained.

A symbol is shown in the center of the screen. Pete again remembers the corresponding action and tries to perform it as well as he can. If the BCI action is detected by the system, the game moves on showing the next symbol.

When all the symbols have been processed or when the level time has expired, Pete moves on to the next level.

After all levels have been played, Pete can see his personal results, and his ranking in the high scores.

Pete returns to the menu.

For the use case, see Table A.4.

| **User Intention** | | **System Responsibility** |
|---|---|---|
| Start game | | |
| | | Show available game sessions |
| Choose game session | | |
| | | Inform player on the procedure, give advice |
| | *Repeat (game)* | |
| | | explain level symbols |
| | *Repeat (level)* | |
| | | Show symbol |
| Perform indicated action | | |
| | | Detect action |
| | *Until level over* | |
| | *Until game over* | |
| | | Show results |
| OK | | |
| | | Bring player back to menu |

**Table A.4:** *Use case: player - task 4. playing*

**Task 5. Free Play** Pete wants to test how well the application recognizes the BCI actions and practice a bit without the time pressure of the game. He goes to free play mode.

Pete selects a free play session which can differ in the specific actions that can be detected.

An instruction screen shows what actions can currently be recognized, with their corresponding symbols, and also gives some advise to increase the chance of correct identification.

Now Pete sees a blank screen (except for the progress bar) and tries a couple of actions. When the system detects an action, the symbol is shown in the center of the screen.

After a couple of minutes Pete has seen enough, goes back to the menu.

The use case is defined in Table A.5.

| **User Intention** | **System Responsibility** |
|---|---|
| Start free play | |
| | Show list of available sessions |
| Choose free play session | |
| | Inform player on the procedure, give advice, explain symbols |
| *Repeat* | |
| Perform action | |
| | Show detected action |
| *Until player wants to stop* | |
| Stop | |
| | Bring player back to menu |

**Table A.5:** *Use case: player - task 5. free play*

**Task 6. View High Scores** Pete's friend Roger enters the room, and Pete wants to show off his great scores. From the menu, Pete commands the application to show the current high scores. The application shows the list.

For the use case, see Table A.6.

| **User Intention** | **System Responsibility** |
|---|---|
| View high scores | |
| | Show high scores |
| OK | |
| | Bring player back to menu |

**Table A.6:** *Use case: player - task 6. view high scores*

**Task 7. Update Training** Pete has the idea that the system is not detecting his imaginary movement actions as well as it used to. He decides to do a training session to update the classifiers.

For a specification of the interaction after choosing the action from the menu, see Table A.3..

**Task 8. Clear Training** Pete notices the action detection is doing really bad, and decides to start over with clean classifiers. This action sets the classifiers to default, and forces Pete to do a training session.

For a specification of the interaction after choosing the action from the menu, refer to Table A.3.

### A.2.2 Researcher

*Researcher* Roger also uses the system for a number of tasks, which are described in this section.

Again, the focus is on the interaction with the system, not on related tasks. The implementation of the classifiers, and hooking up the *player* to the system (for research, data collection, and demonstration) are not described. As it turns out, most of the tasks of the researcher will not include direct interaction with the system, so use cases are not necessary. However, all the described actions are vital to conduct research with the platform, which is why they are still important to describe and to keep in mind while designing the system.

**Task 1. Hook in a classifier** Roger has been working on this classifier in Matlab. Finally it is ready to be tested in practice.

He adds the training and classification function references to the lists the Matlab wrapper (which is part of the system) uses to pass on the EEG data to all classifiers that are hooked in to the system. Roger will also provide a definition of the data windows (also known as *epochs*).

Because the information the Matlab wrapper will need can be formatted quite easily, there will probably no actual system interaction and therefore no use case. This information can very well be defined in text files (or ini files) which the Matlab wrapper can then read in.

**Task 2. Define an experiment** To test the classifier, Roger wants to define an experiment.

As his classifier will separate left hand movement imagery from right hand movement imagery, Roger lets the experiment consist of left hand and right hand stimuli (symbols). He decides to provide a specific order so each of his testers (*players*) will be subject to exactly the same experiment. He also defines how long the symbols are shown (stimulus duration), and the length of the breaks inbetween (interval duration), according to what he thinks will provide the best data or results. All this information is stored as a training experiment definition file which can be used in training mode within the game application.

For demonstration purposes, Roger also wants to define a game experiment, consisting of a duration and what actions can be used.

This task does not require direct interaction with the Matlab wrapper nor with the game application. However, this task is vital for the research and therefore need to be defined. It would be possible to device a small program to generate the experiment definition file based on a number of parameters provided by the *researcher*.

**Task 3. Collect data** During the experiments Roger needs to collect potentially relevant data. He can then use this data to perform analysis and perhaps improve on his current classifier implementation.

The EEG data itself is stored by Actiview (if storing is activated). This data will also contain the markers indicating events in the game application like entering a certain mode (training, game, free play), or showing a certain symbol. From this data, many things can be derived, for example: how long it took the *player* to hit certain symbols (from the time the symbol is shown to the time the next appears).

The Matlab wrapper can maintain logs on training parameters, in training mode. In game mode, the Matlab wrapper can also record any classification results based on incoming EEG data.

This task is vital for the research, but no use case can be made for the *researcher* as no interaction with the system is necessary. For a definition of the *player* interaction, see Table A.3.

**Task 4. Perform analysis** Roger analyzes the collected data just as he normally would – in Matlab.

Again there is no interaction with the system, and therefore no use case.

**Task 5. Demonstrate results** This task already described in the player task analysis.

Roger tells the *audience* a bit about the system first, encourages *audience* participation by letting the *player* do a free play session after a quick game demonstration, and answers questions from the *audience* at the end.

Refer to the *player* use cases for training, playing, and free play in Tables A.3, A.4, and A.5 respectively.

**Task 6. Unhook a classifier** During some experiments Roger wants to use other classifier implementations. To unhook a classifier, he just removes the trainer and classifier functions from the lists described in task 1.

## A.3 Requirements

Based on the domain analysis, task analysis, and discussion over a paper prototype, a number of functional and non-functional requirements were identified. This section describes them.

To define the requirements a slimmed-down version of the Volere requirements specification template was used, maintaining the pure essentials [36]:

- *ID:* some type-number identification so the requirements can easily be referred to.
- *Description:* a short description of the intention of the requirement.
- *Rationale:* the reasoning as to why this requirement is really necessary.
- *Fit Criterion:* a measure to decide when the solution meets the requirement.

### A.3.1 Project Constraints

In consultation with the committee the following project constraints were highlighted:

- The goal should be to design a BCI application to demonstrate research work.
- The BCI application should be a game.
- The application should run on a PC.
- The application should be implemented in Java.

### A.3.2 Functional Requirements

Functional requirements define what the system should do [36, 21]. These requirements have been derived mainly from the scenarios and use cases described in section A.2. System tests are used to test these requirements during a later stage of development.

**System Requirements** The system requirements are referred to by Preece as 'functional requirements' as well [36]. To eliminate this double use of terminology, these 'functional functional requirements' are referred to as system requirements. This section focuses on the system functionality for the users and services to other systems [21].

| System-01 | Profile Creation |
|---|---|
| Description | The player should be able to create a new profile. |
| Rationale | If a player has never played before, a new profile will have to be created in which player statistics and other information can be saved. |
| Fit Criterion | The player can create a new profile to play. |

| **System-02** | **Profile Selection** |
|---|---|
| Description | The player should be able to use an existing profile. |
| Rationale | If a player has already played before, he should be able to use the original profile with his original classifiers and statistics. |
| Fit Criterion | The player can select an already existing profile to play with. |

| **System-03** | **Training Mode** |
|---|---|
| Description | The player should be able to enter a training mode. |
| Rationale | If a player has never played before or has played a long time ago, a training session is necessary to (re)train the classifiers. |
| Fit Criterion | The player do a training session to (re)train the classifiers. |

| **System-04** | **Training Resting Periods** |
|---|---|
| Description | During the training session, there should be resting periods inbetween symbols. |
| Rationale | To record clean data, the player tries to stay relaxed, and not move or blink. To relieve the user of some stress, during these breaks the player is allowed to do these things. |
| Fit Criterion | The training mode should include resting periods inbetween symbols. |

| **System-05** | **Training Session Selection** |
|---|---|
| Description | The player should be able to select among a variety of training sessions. |
| Rationale | The first reason is that if the player only enters the training mode for a quick update of the classifiers, a short training session may be sufficient. Secondly, the training mode is the mode in which the session can be controlled most precise. This makes it the most interesting mode for gathering data for the researcher. For this it would be handy for the researcher to be able to specify a number of different training sessions, when can then be accessed from within the application. |
| Fit Criterion | The player can select from among a number of training sessions in training mode. |
| Related | Sys-06 |

| **System-06** | **Training Session Definition** |
|---|---|
| Description | The researcher should be able to define a training session. |
| Rationale | Training mode is the most interesting mode for gathering research data (see description Sys-05). It would be handy for the researcher to be able to specify a number of different training sessions. Besides, to keep the researcher in control, it shoulld be possible to define the exact ordering of the symbols. If full control on symbol ordering is not important, and preknowledge or boredom of the player is to be avoided, a method of defining a training session with random ordering would be useful. |
| Fit Criterion | (1) The researcher can define a training session in specifics (the symbols, the order, the symbol duration, the break duration), or (2) with random ordering (the symbols, the number of repetitions or a list to be randomized, the symbol duration, the break duration). |
| Related | Sys-05 |

| **System-07** | **Training Session Definition(s) Required for Training** |
|---|---|
| Description | The player should not be able to enter training mode if no training session definitions are available. |
| Rationale | If the researcher has not yet defined a training session yet, there is nothing for the player to train. |
| Fit Criterion | If there are no training session definitions, training mode is unavailable. |

| **System-08** | **Training Update** |
|---|---|
| Description | The player should be able to update existing classifiers connected to the profile. |
| Rationale | If the player hasn't been connected to the game for a period, the trained classifiers will be outdated. It may not be necessary to start from scratch however. If a short training session can be used to update the classifiers, this could save time. |
| Fit Criterion | The player can do a training session to update the classifiers. |

| **System-09** | **Training Clear** |
|---|---|
| Description | The player should be able to clear existing classifiers connected to the profile. |
| Rationale | If the player hasn't been connected to the game for a period, the trained classifiers will be outdated. The change may be so large that the best solution is to start with a clean set of classifiers. Creation of a new profile will also cause the personal statistics to be lost. Instead, to clear the classifiers followed by a training session would be a better option. |
| Fit Criterion | The player can clear his training variables for the classifiers. |

| **System-10** | **Game Mode** |
|---|---|
| Description | The player should be able to enter a game mode. |
| Rationale | The mode that will be used to test the game experience, and to demonstrate the system to an audience, is the game mode. |
| Fit Criterion | The player can do a game session. |

| **System-11** | **Game Session Selection** |
|---|---|
| Description | The player should be able to select from among a variety of game sessions. |
| Rationale | Both for experimental and demonstrational purposes it could be handy to be able to select from among a number of sessions. This could also be used to let the player ease in the game by starting with easier sessions, and to keep the game interesting if it is played by the same person often. |
| Fit Criterion | The player can select from among a number of game sessions in game mode. |
| Related | Sys-10 |

| **System-12** | **Game Session Definition** |
|---|---|
| Description | The player or researcher should be able to define a game session. |
| Rationale | Game mode is both interesting for the game experience as well as for demonstration. It could also have some interesting research purposes. To make use of these functions fully, it has to be possible to define different game sessions. To keep the game interesting, a random ordering of symbols could be used. For demonstration or research purposes, it should also be possible to define the exact ordering of the symbols as they occur in the session. |
| Fit Criterion | (1) The player or researcher can define a game session with random ordering (the symbols, the duration - for each level), or (2) with a specific order (the symbols, the ordering, the duration - for each level). |
| Related | Sys-09 |

| **System-13** | **Game Levels** |
|---|---|
| Description | A game session should have the possibility to consist of a number of levels. |
| Rationale | Unlike training sessions, game session definitions provide a lower amount of control for the researcher. In order to be able to ease a player into it, levels can be made increasingly difficult for example by increasing the available symbols for each level, or increasing the duration. Game levels can also be used to bring variety into one game session and hence to improve the user experience. |
| Fit Criterion | If a game can be defined consisting of a number of levels each of which has a specific duration and symbols. |

| **System-14** | **Game Session Definition(s) Required for Game Mode** |
|---|---|
| Description | The player should not be able to enter game mode if no game session definitions are available. |
| Rationale | If the researcher has not yet defined a game session yet, there is nothing for the player to play. |
| Fit Criterion | If there are no game session definitions, game mode is unavailable. |

| **System-15** | **Game Results** |
|---|---|
| Description | At the end of a game, the user should be shown the results. |
| Rationale | If the player is to be motivated by the game experience, to achieve a certain goal, then the results of the game session should be shown at the end of the session. |
| Fit Criterion | The player is shown the results (both personal and compared to other players) at the end of a game session. |

| **System-16** | **Free Play Mode** |
|---|---|
| Description | The player should be able to enter a free play mode. |
| Rationale | To test the current performance of the classifiers in a quick experimental way to see if an update training is necessary, a free play mode could be useful. To encourage participation of the audience during a demonstration, free play mode could also be a way to react to requests. |
| Fit Criterion | The player can do a free play session. |

| **System-17** | **Free Play Session Selection** |
|---|---|
| Description | The player should be able to select from among a variety of free play sessions. |
| Rationale | For test purposes it would be handy to be able to define the inputs that can be used. For demonstration purposes, a set duraction could also be useful. |
| Fit Criterion | The player can select from among a number of free play sessions in free play mode. |
| Related | Sys-10 |

| **System-18** | **Free Play Session Definition** |
|---|---|
| Description | The player or researcher should be able to define a free play session. |
| Rationale | For the same reason a free play session selection is required: for test and demonstration purposes. |
| Fit Criterion | (1) The player or researcher can define a free play session (input symbols, duration). |
| Related | Sys-09 |

| **System-19** | **High Scores View** |
|---|---|
| Description | The player should be able to view the high scores. |
| Rationale | It is motivating for the player to know how others do. By viewing the overall high scores the player gets a feel for what he/she could aim for, and what his/her performance is compared to others. |
| Fit Criterion | The player can view the overall high scores. |

| System-20 | Trained Classifiers Required for Game & Free Play. |
|---|---|
| Description | Before a player can enter the game or free play modes, the classifiers need to be trained first. |
| Rationale | If the classifiers have not been trained, the detected BCI input the game application receives will be of no value. So before a mode can be entered in which this detection input is vital for its playability, the classifiers need to be trained in training mode. |
| Fit Criterion | Game and Free Play only become available if the classifiers have been trained - after a training session has been done (when a new profile is created or the classifiers for a profile have been cleared). |

| System-21 | Optional User Learning |
|---|---|
| Description | In game and free play modes, the player should be able to see how close he is to getting the action correctly detected to make user learning a possibility. |
| Rationale | In order for the player to learn from interacting with the system, he needs to know what the system is 'seeing'. This way, the player can adjust his actions or methods to achieve better results. There may be reasons for the researcher not wanting to incorporate user learning this explicitely in his experiments. For this reason, this feature should be able to be turned off. |
| Fit Criterion | (1) In game and free play, the player can see what the system is perceiving about the action the player is trying to perform. (2) The researcher can turn off this form feedback. |

Although the player may perceive the system as simple as seen in Figure A.1a or perhaps even have a more expanded system view as depicted in Figure A.1b , the researcher is aware of the dichitomy between application and EEG analysis as shown in Figure A.1c.

The view in Figure A.1c will be used to describe the necessary inputs and ouputs. The EEG recording software (ActiView) and the user are considered external components. Although the EEG analysis software and the application are both part of the system that is designed in this project, there is an explicit separation between the two which makes it necessary to define the inputs and outputs between these two components as well.

Storing of the EEG recordings with the application markers is done by Actiview, and is therefore not included in the data requirements for this system.

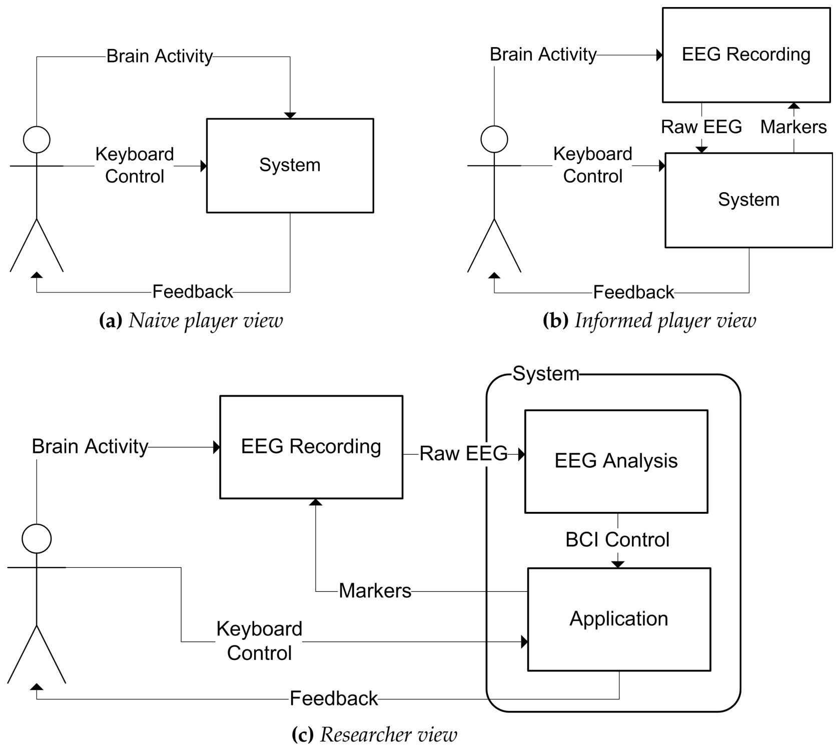



**Figure A.1:** *System views.*

| System-22 | EEG Analysis Initialization |
|---|---|
| Description | The EEG Analysis subsystem should read in classifier specifications on startup. |
| Rationale | The researcher should be able to define what functions the EEG Analysis subsystem calls for training classifiers and using them for classification. He also defines the windows of EEG data that will be the input for the functions. For the system to be able to use this information, it first has to read it in. |
| Fit Criterion | The EEG Analysis subsystem reads in the classifier functions and window definitions on initilization. |

| System-23 | EEG Analysis Inputs |
|---|---|
| Description | The EEG Analysis subsystem should receive marked EEG data. |
| Rationale | The part of the system that analysis the brain activity recordings requires the EEG signals that have been recorded combined with the markers that have been added to the EEG recording by the application. The EEG is the data that this subsystem analyzes. The markers are necessary for the analysis because they indicate certain events like the showing of specific symbols. This information has to be available to train the classifiers. Secondly the game application will add markers when a certain mode is entered so the analysis component knows whether it should train the classifiers or provide classification results to the application. |
| Fit Criterion | The EEG Analysis subsystem receives EEG data with application markers. |

| System-24 | EEG Analysis Process |
|---|---|
| Description | The EEG Analysis subsystem should process incoming brain activity signals to detect BCI actions. |
| Rationale | The goal of the EEG Analysis subsystem is to analyze brain activity and detect BCI actions performed by the player. It will need feature extraction and classification algorithms to do this. These algorithms will be provided by the researcher (see System-22). |
| Fit Criterion | The EEG Analysis subsystem analyzes incoming EEG recordings for BCI actions. |

| **System-25** | **EEG Analysis Outputs** |
|---|---|
| Description | The EEG Analysis subsystem should inform the application of detected BCI actions. |
| Rationale | The goal of the EEG Analysis subsystem is to analyze brain activity and detect BCI actions performed by the player. These actions are then used as input for the game application. Therefore, the EEG Analysis system has to output the detected actions. To reflect the fact that the detection is never 100% certain, the subsystem should send confidence values. |
| Fit Criterion | The EEG Analysis subsystem sends detected BCI actions as confidence values to the application. |

| **System-26** | **EEG Analysis Logging** |
|---|---|
| Description | The EEG Analysis subsystem should log certain information for the researcher's analysis. |
| Rationale | For analysis afterwards, information like classification results and the classifier parameters as result of training is vital for the researcher. |
| Fit Criterion | The EEG Analysis subsystem logs data for the researcher: (1) classification results (timestamped), and (2) classifier parameters after training. |

| **System-27** | **Game Application Initialization** |
|---|---|
| Description | On startup, the game application should read in profile information and session definitions. |
| Rationale | The game needs to load a variety of information in order to run properly: (1) User profiles, with information on the available classifiers and their personal statistics to build the high scores screen; (2) Training session definitions, for training session selection; (3) Game session definitions, for game session selection; (4) Free play session definitions, for free play session selection. |
| Fit Criterion | The game application loads (1) profile information, and (2)-(4) session definitions for training, game, and free play modes. |

| **System-28** | **Game Application Inputs** |
|---|---|
| Description | The application should receive BCI and keyboard inputs. |
| Rationale | The goal of the application is to play a game using BCI inputs. These inputs are received from the EEG Analysis subsystem in the form of confidence values, as classification is not an absolute process. This means the application has to set a threshold itself to decide when an action is considerd 'performed'. As a backup for when BCI inputs cannot be used (because it is not yet available, or not trustworthy enough for the operation), keyboard input is available. This type of input can be used by the researcher as well as the player, whereas the BCI inputs always come from the player although indirectly. |
| Fit Criterion | The game application receives (1) BCI action confidence values, and (2) keyboard input. |

| **System-29** | **Game Application Processing** |
|---|---|
| Description | The application should process BCI action classification results and update the game state accordingly. |
| Rationale | The incoming confidence values for the different BCI actions need to be processed, deciding what action is currently performed (or no action at all), and using this information to update the game state. |
| Fit Criterion | The game application processes BCI action confidence values to update the game state. |

| **System-30** | **Game Application Outputs** |
|---|---|
| Description | The game application should add markers to the EEG and provide player feedback. |
| Rationale | The game application adds markers to the recorded EEG stream for use by the Analysis subsystem, but its main task is to provide feedback and stimuli to the user on the game status and BCI input. For this it can use a computer screen, plus speakers or head phones for auditory feedback. |
| Fit Criterion | (1) The game application adds markers to the EEG stream, and (2) provides visual and auditory player feedback. |

| **System-31** | **Game Application Logging** |
|---|---|
| Description | The game application should store player information in profiles. |
| Rationale | The game application logs user-specific information in user profiles to create high score tables and for use next run. These profiles consist of user statistics and classifier information. |
| Fit Criterion | The game stores user statistics and classifier information in profiles. |

**Data Requirements** Preece states: "Data requirements capture the type, volatility, size/amount, persistence, accuracy, and value of the amounts of the required data" [36]. Lethbridge adds that it is also about under what conditions what inputs should be accepted [21].

| **Data-1** | **Raw EEG** |
|---|---|
| Description | The EEG format is determined by Actiview, and always accepted by the analysis subsystem. |
| Rationale | EEG is required to train the classifiers and to determine the BCI actions which are used as input for the game application. |
| Fit Criterion | (1) Format: 24-bit voltage values for each of the channels for each sample per data block (defined by Actiview, outside our control); (2) Sending: By Actiview, when the software is active and set to send over TCP; (3) Acceptance: By the EEG Analysis subsystem, whenever there is something to accept to prevent buffer problems; (4) Timing: defined by Actiview - outside our control. |

| **Data-2** | **BCI Action Confidence Values** |
|---|---|
| Description | BCI action values range from 0 to 1 indicating the confidence level. The values are accepted by the application in game and free play mode. |
| Rationale | BCI action values are the necessary BCI input for the game application for use during game and free play sessions. Confidence values provide an indication of how certain the classifiers are about their detection, which could be useful information for the application as well as for user feedback. |
| Fit Criterion | (1) Format: for each available action a real value [0,1] indicating the confidence of detection; (2) Sending: By EEG Analysis when classification results are available, when the player is in game or free play mode; (3) Acceptance: By the application, when the player is in game or free play mode; (4) Timing: depends on the EEG Analysis processing speed. Fast, to provide timely feedback to the player. |

| **Data-3** | **Keyboard Input** |
|---|---|
| Descripion | Keyboard is an alternative input modality for cases when BCI input is not handy or available. |
| Rationale | BCI input will not always be available or usable, so an alternative mode of input has to be available which can be used to abort or pause sessions, make selections, and enter profile names. |
| Fit Criterion | Acceptance: By the application in any mode. |

| **Data-4** | **Application Markers** |
|---|---|
| Description | Application markers are added to the EEG stream: what symbol is shown, what mode is entered. |
| Rationale | For the EEG analysis it is necessary to know what mode the application is in, and for training the classifiers it needs to know what symbols are shown to the player. These markers are added to the EEG so the event is matched to the recorded brain activity time-wise. This method also makes offline analysis more easy as the markers are stored with the EEG data. |
| Fit Criterion | (1) Format: defined by the Biosemi system and cable (yet unknown, probably a 24-bit integer) ; (2) Sending: By application, when a symbol is shown - what symbol is shown, when a mode is entered - what mode is entered. |

| **Data-5** | **Classifier Hook-in Definition** |
|---|---|
| Description | The definitions that describe the hooked in classifiers and windows should be easily readible and editable. |
| Rationale | Developing an interface apart from the application is not part of the project. On the other hand, the researcher must be able to hook in classifiers without too much trouble. |
| Fit Criterion | Format: easily readible and editable without fancy interfaces. |

| **Data-6** | **Session Definition** |
|---|---|
| Description | The definitions that describe (training, game, free play) sessions should be easily readible and editable. |
| Rationale | Developing an interface apart from the application is not part of the project. On the other hand, the researcher must be able to define sessions without too much trouble. |
| Fit Criterion | Format: easily readible and editable without fancy interfaces. |

| **Data-7** | **Session Status** |
|---|---|
| Description | The player should be able to be aware of the current session status. |
| Rationale | In order for the player to be able to play the game, he needs to know his current status and what he is supposed to do. |
| Fit Criterion | 1) During the game, the player needs to know his score, how far along he is, what he is supposed to do. 2) During training, the player needs to know how far along he is, what he is supposed to do. 3) During free play, the player needs to know what the detected actions are, how far along he is. |

### A.3.3 Non-functional Requirements

Constraints on the design of the system and its development are defined as non-functional requirements [36, 21].

The non-functional requirements are divided into a number of types according to [36]:

- *Environmental requirements:* constraints caused by the environment in which the system will be used.
- *User requirements:* the characteristics of the user groups.
- *Usability requirements:* effectiveness, efficiency, sarefty, utility, learnability, and memorability.
- *User experience requirements:* satisfying, enjoyable, fun, entertaining, helpful, motivating, aesthetically pleasing, supportive of creativity, rewarding, and emotionally fulfilling.

To include the software engineering point of view, one section is added to this list:

- *Software quality requirements:* maintainability and reusability (usability, efficiency, and reliability are already included elsewhere) [21].

The same method for describing these requirements is used as for the functional requirements earlier:

- *ID:* a means to refer to the requirement.
- *Description:* a general description of the requirement.
- *Rationale:* The reason for the necessity of the requirement.
- *Fit criterion:* defines when the requirement is met.

**Environmental Requirements** The circumstances in which the system will operate can pose additional requirements to the product [36, 21]. The system will mainly be used in a laboratory setting (for research) or in a demonstration setting.

| **Environment-1** | **Head Gear** |
|---|---|
| Description | The player will be required to wear some kind of headgear to measure the brain activity. |
| Rationale | To record brain activity, some kind of apparel is necessary. For this purpose, the HMI group has Biosemi caps available at the HMI group with 32 electrodes. |
| Fit criterion | The player wears head gear that can measure brain activity. |

| **Environment-2** | **Audio-independent Interaction** |
|---|---|
| Description | The *player* should not necessarily need to hear the audio feedback the application provides. |
| Rationale | When the system is used for demonstration, it is possible that the presenter is talking while the application is running, or that people from the audience are asking questions. Depending on the situation, the environment could already be noisy to start with. |
| Fit Criterion | The *player* can play the game just as well without hearing the audio feedback. |

| **Environment-3** | **Actiview for EEG Recording** |
|---|---|
| Description | Actiview is used for EEG recording. |
| Rationale | The software that is used for EEG recording has its own ways of doing things and passing on data. The brainbasher system will have to adjust to that so both packages can work together. |
| Fit Criterion | Communication is adapted to work with Actiview for EEG recording. |

| **Environment-4** | **Matlab for EEG Analysis** |
|---|---|
| Description | Matlab is used for EEG analysis. |
| Rationale | Matlab is used internationally by practically all research groups that work on BCI. For this reason Matlab will be used for the EEG analysis subsystem. Besides, Matlab is probably also the most suitable application for the job. |
| Fit Criterion | Communication is adapted to work with Matlab for EEG Analysis. |

| **Environment-5** | **Java for Application Development** |
|---|---|
| Description | Java is used for application development. |
| Rationale | As one of the mandated requirements, Java is the chosen language to develop the application with. Its platform independence could also be of high value. |
| Fit Criterion | Communication is adapted to work with the Java application. |

| **Environment-6** | **TCP for Inter-Subsystem Communication** |
|---|---|
| Description | Inter-subsystem communication should be able to take place over a network to support distributed processing. |
| Rationale | The hardware requirements of the computers this all has to run on are not explicitly defined. The hardware can be upgraded and a computer network can be setup for distributed processing if it shows to be necessary. However, to make this possible, the software must support it. |
| Fit Criterion | Communication between subsystems (EEG Recording, EEG Analysis, Game) happens via TCP. |

| **Environment-7** | **Screen Visible** |
|---|---|
| Description | The screen should be visible to users who interact with the system directly. |
| Rationale | Visual feedback is the main method of communication to the player, so the screen should be clearly visible. Secondly, it another user (researcher) is in charge of the keyboard, the screen should be visible for him/her as well, for the same reason. |
| Fit Criterion | The visual feedback should be visible by screen by all users who can provide input, e.g. the player, and optionally the researcher for keyboard control. |

**User Requirements** This part describes the different types of users of the system and captures their abilities and skills in user profiles [36].

| **User-1** | **Player Profile** |
|---|---|
| Task Description | Plays the game |
| Hardware Experience | Possibly novice |
| Software Experience | Possibly novice |
| Frequency of Use | Highly irregularly; for experiments, demonstrations, and hopefully even for fun sometimes. |
| Abilities | No seeing problems, not brain-illiterate [40]. |

| **User-2** | **Researcher Profile** |
|---|---|
| Task Description | Defines the classifiers, runs experiments |
| Hardware Experience | EEG setup - expert |
| Software Experience | Actiview - expert, Matlab - expert, Java - possibly novice |
| Frequency of Use | Regularly; when implementing the classifiers, setting up experiments, running experiments. |
| Abilities | No seeing problems, experience with Matlab. |

| **User-3** | **Audience Profile** |
|---|---|
| Task Description | Watches the system being used by player, receives information on the workings of the system. |
| Hardware Experience | Possbily some with EEG setups |
| Software Experience | Possibly some with Actiview, Matlab, and maybe even Java |
| Abilities | No seeing or hearing problems (to receive the explanation of the presenter). |

**Usability Requirements** Preece lists the usability goals as being [36]:

- *Effectiveness:* the user can meet its goals with the system.
- *Efficiency:* the goals can be reached with minimal effort.
- *Safety:* the chance of making mistakes is minimized, and recovery methods are available.
- *Utility:* the system provides an appropriate set of functions.
- *Learnability:* the system is easy to learn to use.

- *Memorability:* it is easy to remember how to use the system.

For this system, the most important usability goals are: learnability, effectiveness, and safety. The player must know what to do, preferably without any extra explanation from the researcher. The system must support the goals of the user, which apart from the game functionality are mostly described as user experience goals which are described just a little further on in this section. Safety is important because the researcher must interfere as little as possible during experiments. Besides, the things that can go wrong during a demonstration must also be minized.

Of secondary importance are: efficiency, utility, and memorability. Although of less importance than the other types of usability, being able to do things efficiently within the application is not to be ignored, as well as providing the right features while not providing too many. Memorability is not as important because the players will be highly irregular users, which makes learnability far more vital.

Effectiveness and utility are already targeted by the functional requirements. To evaluate the opinion of the user on these issues, one could inquire whether he/she felt some functionality was missing, or the opposite: superfluous.

| **Learnability-1** | **Easy Symbol Image Interpretation** |
|---|---|
| Description | The player should have no problems interpreting the image the symbol shows. |
| Rationale | The time the player needs to analyze the visual should be minimal. Therefore the symbols should be clear in what they represent. If the visuals are clear, this also improves how well the player can remember the action that is linked to it. |
| Fit Criterion | The player (90%) can see what the symbols represent, during the explanation of the symbols. |

| **Learnability-2** | **Player Instruction** |
|---|---|
| Description | The player should be instructed at the beginning of a session. |
| Rationale | (1) The player needs to be prepared for what is going to happen - this will have a positive effect on the recorded brain signals. (2) Normally during EEG experiments, test subjects are given a range of instructions for example to avoid artefacts. It should also be possible to provide these kinds of instructions in the application. (3) The player needs to be informed on what actions the symbols represent, to be able to perform the tasks. |
| Fit Criterion | The player is given three types of instruction: (1) process instruction, (2) artefact avoidance, (3) symbol interpretation. |

| **Learnability-3** | **Mode Explanation** |
|---|---|
| Description | The player should be explained what the procedure is for a given mode on entering. |
| Rationale | Before a session in a certain mode begins, the player should receive an explanation of the procedure, what he can expect to see or happen. This is both important for the player experience as well as for obtaining more clear brain signals because the player is less confused. |
| Fit Criterion | Before a session begins, the player receives explanation of what is going to happen. |

| **Learnability-4** | **Symbol Explanation** |
|---|---|
| Description | The player should be shown what actions are represented by what symbols. |
| Rationale | Even though the symbols themselves should already give some indication, a specific description of the action that is linked to the symbol should be provided for the user. This prevents the user from performing very different actions in order to try a certain symbol - which could result in detection problems when a classifier is optimized for one specific interpretation only. It also reduces player confusion. |
| Fit Criterion | The player is presented with an overview of the symbols he can encounter plus a precise description of the action to be performed when this happens. |

| **Safety-1** | **Abort Sessions** |
|---|---|
| Description | The player should be able to abort training, game, and free play sessions. |
| Rationale | If a player (or researcher) accidentily started a session, or wants to stop for some reason, this should be supported by the system. |
| Fit Criterion | When in a session, a player can abort the session, which returns the player back to the menu. |

| **Safety-2** | **Going Back** |
|---|---|
| Description | The player should be able to go back. |
| Rationale | Also when not in a session, the player should have the option to return to where he/she came from if a wrong decision was made. |
| Fit Criterion | The player can return to the previous screen. |

| **Safety-3** | **Confirmation for Dangerous Actions** |
|---|---|
| Description | The player should be asked for confirmation on actions that could result in permanent damage. |
| Rationale | Certain actions, like 'clear classifiers' or 'delete profile' can result in permanent data loss. For such actions the player should always give an extra confirmation. |
| Fit Criterion | The player is asked for confirmation on potentially 'dangerous' actions. |

| **Safety-4** | **Pause During Training** |
|---|---|
| Description | The player or researcher should be able to pause the training session. |
| Rationale | Pausing the training session could be handy for example if the player feels a sneeze coming up, or something else that could drastically influence the EEG recording. The session can move back to the beginning of showing the current symbol. |
| Fit Criterion | During training, the system can be paused. It shows it is paused. When the system is 'depaused' the session returns to the beginning of showing the current symbol. |

| **Safety-5** | **Pause During Game and Free Play** |
|---|---|
| Description | The player or researcher should be able to pause a game or free play session. |
| Rationale | Pausing a game or free play session could be useful during demonstrations, or when something happens that makes it impossible for the player to concentrate on the game itself. |
| Fit Criterion | During game or free play, the system can be paused. It shows it is paused. When the system is 'depaused' the session continues right where it left off. |

| **Safety-6** | **Status Information** |
|---|---|
| Description | The player should be kept informed of what the system is doing, especially if no inputs can be given. |
| Rationale | At the end of the training session, the training of the classifiers may take some time. The player has to be made aware that this is happening. |
| Fit Criterion | The player is informed when the system is unresponsive about why this is so. |

| **Efficiency-1** | **Most-Recently Used Profile Easily Accessible** |
|---|---|
| Description | The profile list should make the most-recently used user profile more easily accessible than older profiles. |
| Rationale | To increase the efficiency of player interaction, the most-recently used player profile should be accessible more easily than older profiles, as it has a higher chance of being used again. |
| Fit Criterion | The most-recently used user profile is more easily accessible than other profiles. |

| **Efficiency-2** | **New Profile Easily Accessible** |
|---|---|
| Description | The profile list should make creating a new profile more accessible than existing profiles. |
| Rationale | To increase the efficiency of player interaction, the option to create a new profile should be more easily accessible than already existing profiles. Especially research situations will almost always require a new profile to be created. |
| Fit Criterion | The option to create a new user profile is more easily accessible than existing profiles. |

| **Memorability-1** | **Easy Symbol Action Interpretation** |
| --- | --- |
| Description | The player should have no problems remembering what actions the symbols represent. |
| Rationale | The time the player needs to remember the action belonging to the symbol should be minimal. Therefore the symbols should be logical in what action they are linked to. The symbols are explained at the beginning of the session, so especially remembering connection with the action it indicates is important. |
| Fit Criterion | The player (90%) can remember what actions the symbols represent after the symbols have been explained, during the session. |

**User Experience Requirements** User experience goals are: satisfying, enjoyable, fun, entertaining, helpful, motivating, aesthetically pleasing, supportive of creativity, rewarding, and emotionally fulfilling [36].

Some of these words seem synonyms on first sight, or at least heavily overlapping. To increase clarity on their individual differences, here is a description of each of these experience goals (based on dictionary and thesaurus research):

- *Satisfying:* fulfilling of functional needs, expectations, desires, or demands.
- *Enjoyable:* giving pleasure.
- *Fun:* being merrily playful.
- *Entertaining:* holding the attention with something amusing or diverting.
- *Helpful:* providing assistance.
- *Motivating:* providing incentive.
- *Aesthetically pleasing:* satisfying the desire for beauty or good taste.
- *Supportive of creativity:* providing means to be original or use the imagination.
- *Rewarding:* providing a valuable or worthwhile experience.
- *Emotionally fulfilling:* satisfying emotional needs.

Based on these descriptions, the most important experience for each type of user are:

- *Player:* enjoyable, fun, entertaining, motivating, and aesthetically pleasing.
- *Researcher:* satisfying, helpful, and supportive of creativity.
- *Audience:* entertaining, fun, and aesthetically pleasing.

These user experience goals are evaluated with enquiries during the user evaluation.

**Software Quality Requirements** Lethbridge focuses on constraints to ensure software quality in the non-functional requirements explanation [21]. These quality requirements focus on usability, efficiency, reliability, maintainability, and reuability.

| **Quality-1** | **BCI Input Response Time** |
|---|---|
| Description | The delay between brain activity and feedback to the user about it should be minimal. |
| Rationale | The longer the delays, the harder it will be for the player to connect the action to the feedback. Long delays make the system slow which can result in irritation, especially if the classifiers have a low accuracy as well which would increase the time to get a correct hit on an action even more. |
| Fit Criterion | The delay between brain activity and feedback to the user about that brain activity should be minimal; 3 seconds at most. |

| **Quality-2** | **Keyboard Input Response Time** |
|---|---|
| Description | The delay between keyboard activity and feedback to the user about it should be minimal. |
| Rationale | The player will expect immediate feedback to keyboard input. |
| Fit Criterion | The reaction to keyboard input is immediate. |

| **Quality-3** | **Classifier Recovery** |
|---|---|
| Description | Classifier parameters should be stored when available to prevent data loss. |
| Rationale | If something goes wrong, the data loss should be minimal. The EEG is already stored by Actiview. The classifier parameters should also be stored, by the EEG Analysis subsystem. This should be done as soon as the parameters are available, to minimze the chance of data loss. |
| Fit Criterion | Classifier parameters are stored when available, and can be recovered. |

| **Quality-4** | **Profile Recovery** |
|---|---|
| Description | Profile updates should be stored immediately to prevent data loss. |
| Rationale | If something goes wrong, the data loss should be minimal. As soon as profile updates are available (after each session), these changes should be stored to disk. |
| Fit Criterion | Profile updates are stored when available. |

| **Quality-5** | **Anticipate Timed Actions** |
|---|---|
| Description | The system should be open to adding timed actions. |
| Rationale | One of the ideas for subsequent releases is to add timed actions which have to be performed within a certain time period. To make this possible, the system should anticipate this possibility. |
| Fit Criterion | It is possible to add the feature of timed actions in a subsequent release. |

| **Quality-6** | **Anticipate Actions with Duration** |
|---|---|
| Description | The system should be open to adding actions with duration. |
| Rationale | One of the ideas for subsequent releases is to add actions which have to be performed for a certain duration. To make this possible, the system should anticipate this possibility. |
| Fit Criterion | It is possible to add the feature of actions with duration in a subsequent release. |

| **Quality-7** | **Anticipate Different Visualizations** |
|---|---|
| Description | The system should be open to using different visualizations or views. |
| Rationale | It should be possible to test different visualizations of the game, or to try to change the game experience by changing the view. |
| Fit Criterion | It is possible to use a different view for a certain state in a subsequent release. |

| **Quality-8** | **Separate Subsystems** |
|---|---|
| Description | The EEG analysis module and the game application should be separate. |
| Rationale | It should be possible to use the EEG analysis with a different application. On the other hand, it should also be possible to use the game application with a different analysis module. |
| Fit Criterion | The EEG analysis module and game application are totally separate entities which can be switched with different implementations. |

| **Quality-9** | **Code Testing** |
|---|---|
| Description | Each class should be tested. |
| Rationale | The inner workings of the application should be thoroughly tested to prevent unexpected problems. |
| Fit Criterion | Each class is tested with JUnit. |

| **Quality-10** | **Requirements Testing** |
|---|---|
| Description | Each requirement should be tested. |
| Rationale | All these requirements have been formulated to ensure a system that fulfills all necessary needs. To make sure this actually is the case, the fit criteria for all these requirements need to be tested. |
| Fit Criterion | The fit critera are evaluated with system tests and user evaluations - whatever is most appropriate. |

## A.4 Software Architecture

Design and architecture is important for developing software that is easy to maintain, extend, and adjust. For this research however the software development was not of prime importance, and the available time was limited. For this reason, the software architecture section here is not very extensive. It only consists of two parts: the state diagrams, and class diagram.

### A.4.1 State Diagrams

From the user point-of-view, the BrainBasher application moves through certain states. The relations between the different states are depicted in the following state diagrams.

To keep the state transitions clear, the state diagram is split up in five parts. Figure A.2 shows everything up until the selection from the main menu. From there, each of the choices are elaborated in their own state diagrams: training in Figure A.3, game in Figure A.4, free play in Figure A.5, and high scores in Figure A.6. The other menu options are still listed in the diagram to remind the reader that those options are also possible selections from the menu state.

Currently, after the player has created a new profile, they are not forced to do a training session. However, this feature is recommended, as no brain actions can be detected without training data for the classifiers.

### A.4.2 Class Diagram

Figure A.7 shows a general overview of the relations between the main classes in the BrainBasher package.

The Model-View-Controller architecture has been used often, which is also visible by the Views observing Models and Sessions. The MainController is responsible for passing on inputs to the correct models and views, and for performing the necessary state transitions.

Some of the classes that are not mentioned are for example the Symbol class which is used in training and game sessions to represent the brain action series to be performed during the session. There is also a SpriteView with a SymbolSpriteModel to support symbol animations in SessionViews. ProgressBarView is used to add a progress bar in SessionViews, but also in InfoViews.

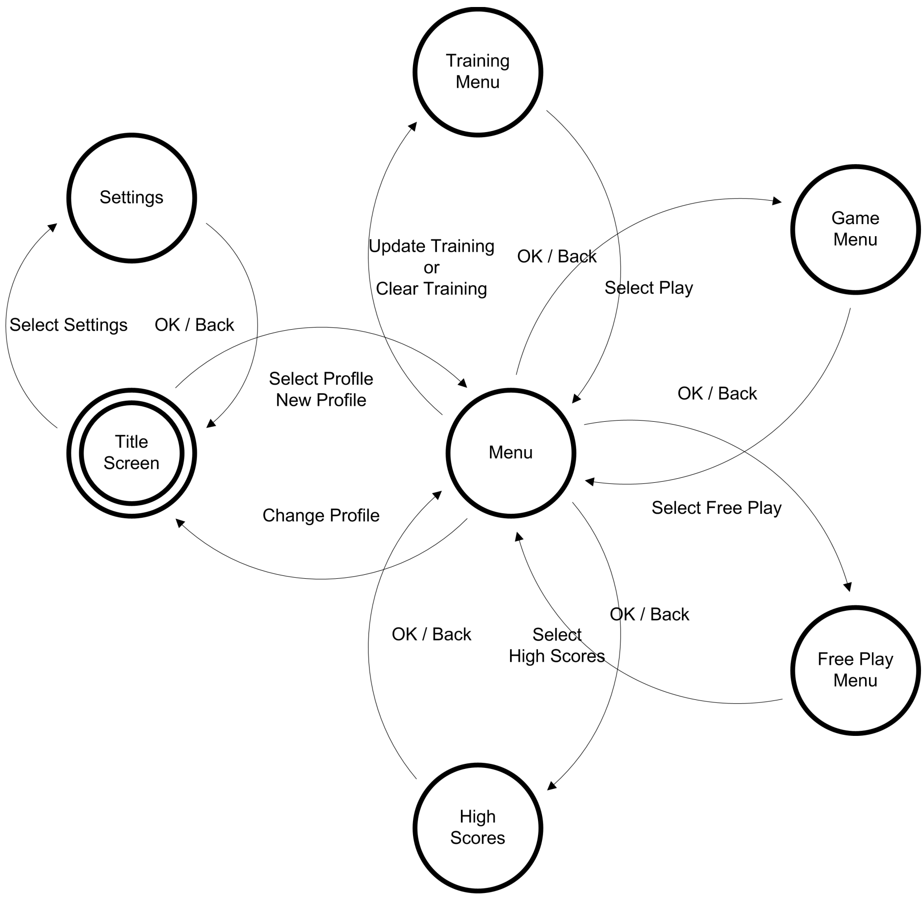



**Figure A.2:** *State diagram - menu*

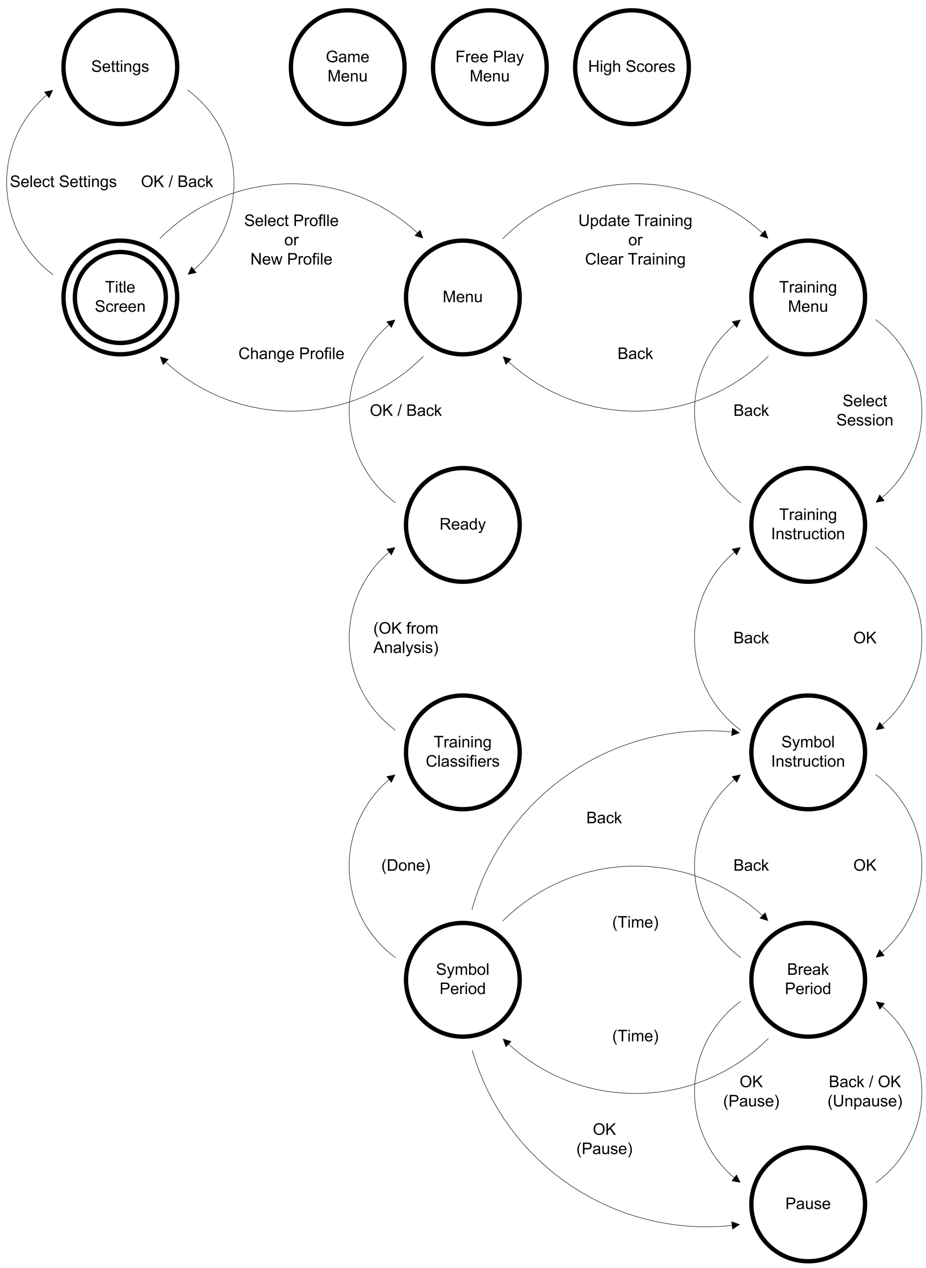



**Figure A.3:** *State diagram - training*

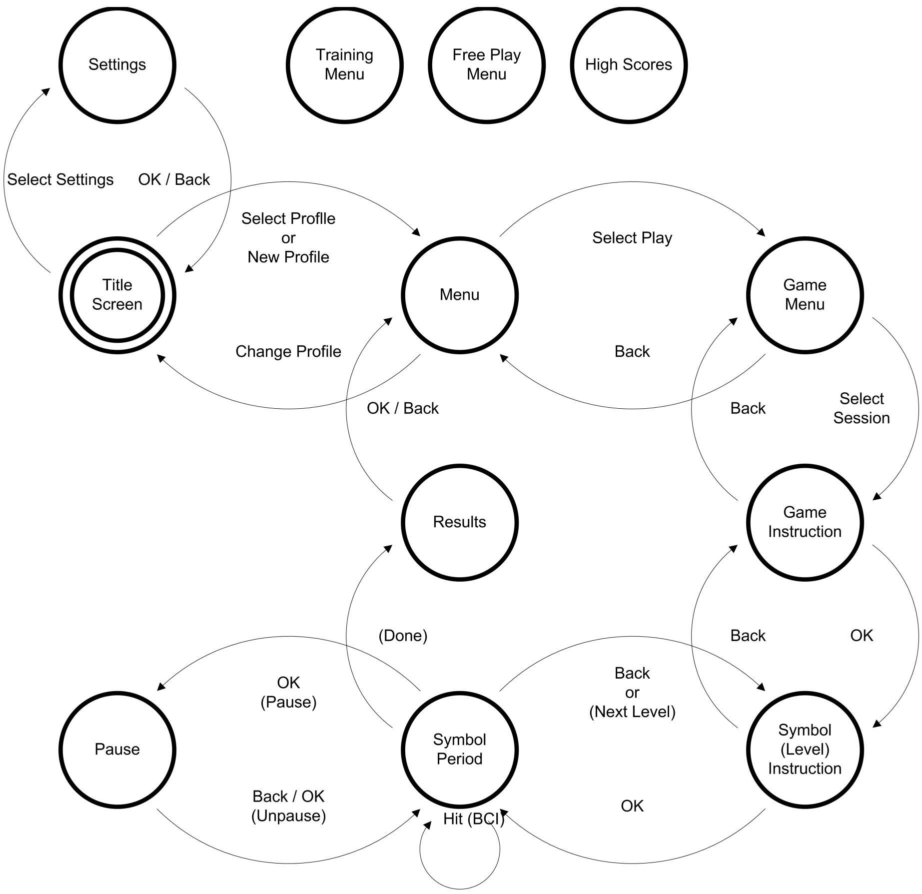



**Figure A.4:** *State diagram - game*

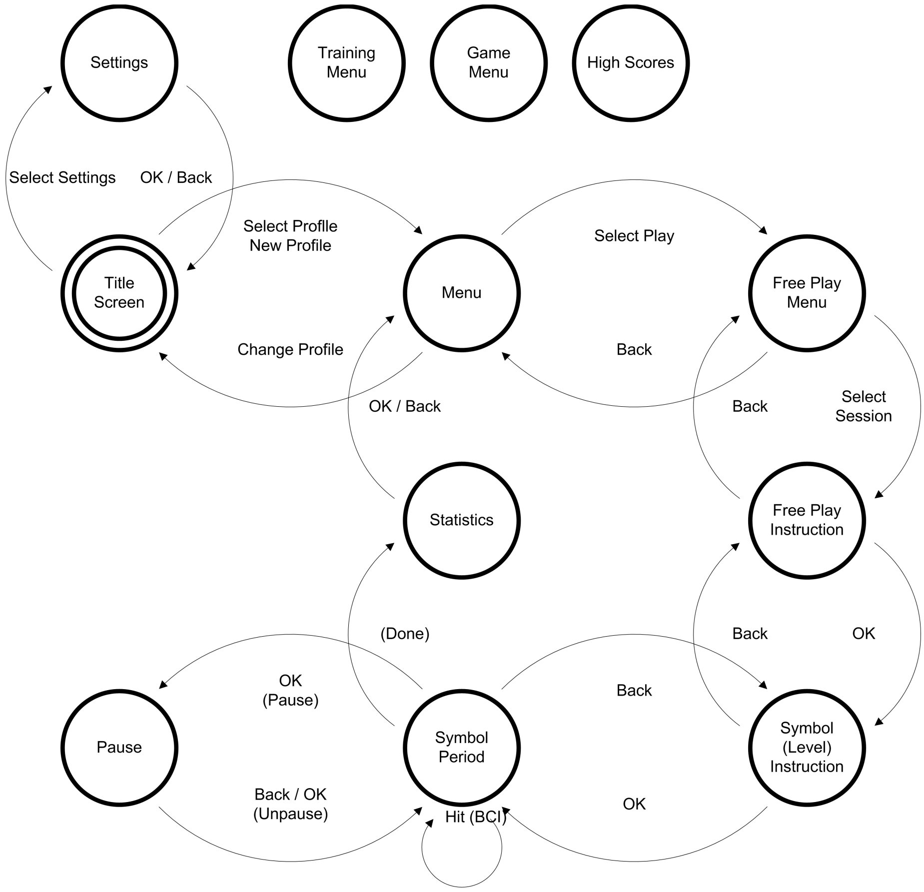



**Figure A.5:** *State diagram - free play*

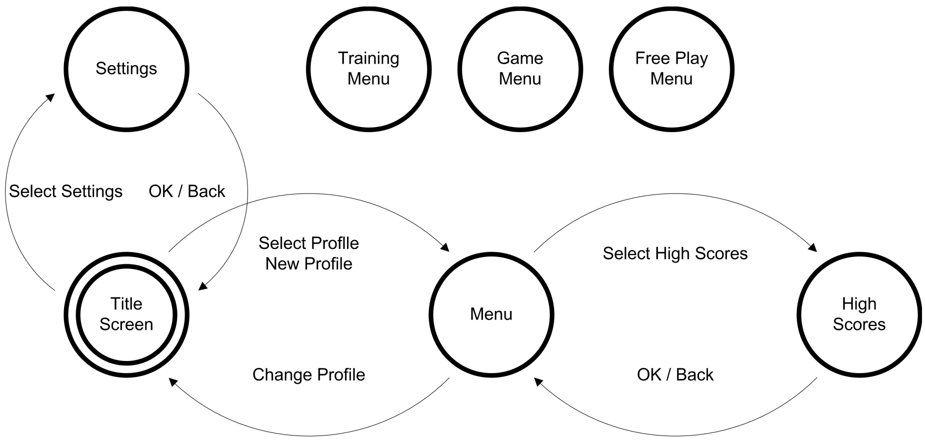



**Figure A.6:** *State diagram - high scores*

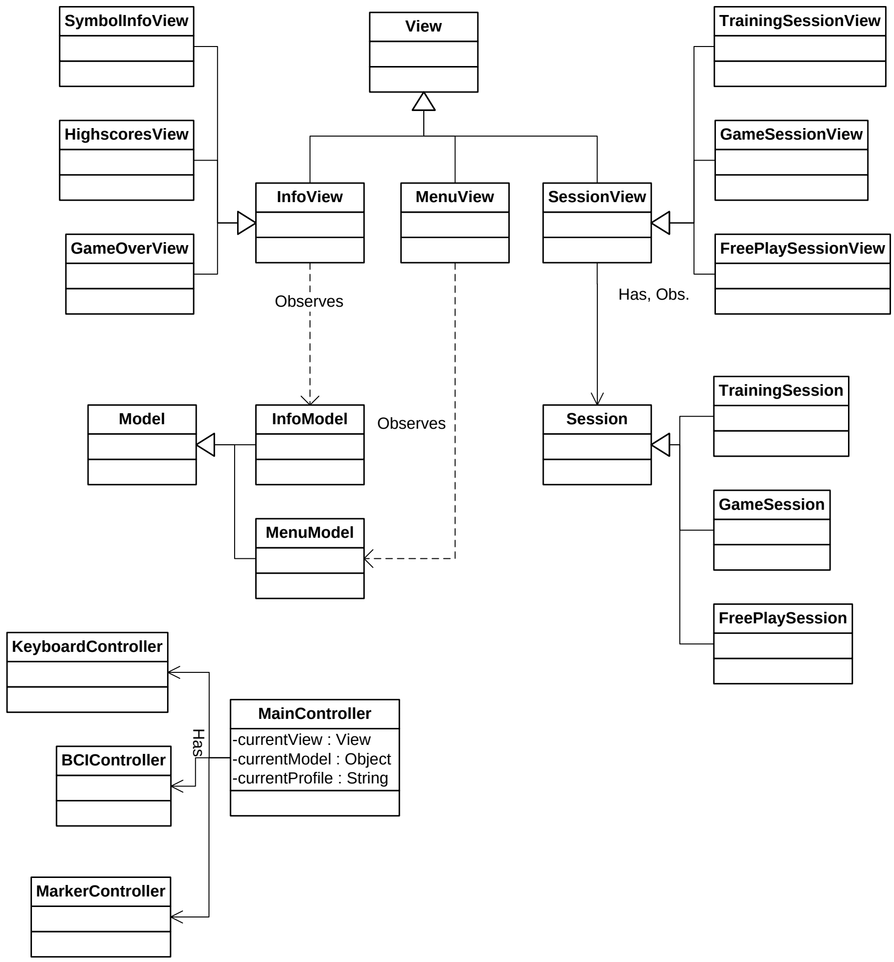



**Figure A.7:** ***Class diagram*** *giving a general overview.*

# Appendix B

# Consent Form (Dutch)

The first task of the subject is to read through and sign the informed consent. This consent form explains the basics of the experiment, informs the subject that their data will remain anonymous in publication and that they can abort the experiment at any time without providing a reason.

The consent form, as all other materials used during the experiment, is stated in Dutch as this is the mother tongue of most of the test subjects.

Naam onderzoeker: ……………………… Deelnemer ID: ……………………

Universiteit Twente
Faculteit Elektrotechniek, Wiskunde en Informatica (EWI)
Leerstoel: Human Media Interaction (HMI)
Postbus 217
7500 AE Enschede

# **Informed Consent** (geïnformeerde toestemming)

Beste deelnemer,

Je hebt aangeboden om mee te doen met dit onderzoek. Dit document bevat wat informatie over je rechten en de procedure van het volgende experiment. Lees alsjeblieft de volgende paragrafen zorgvuldig door.

1) Het doel van het onderzoek

Het doel van dit onderzoek is de gebruikerservaring te bepalen voor verschillende varianten van een spel dat met de hersenen aangestuurd kan worden.

2) De procedure van het onderzoek

In het begin zul je een elektrodecap op krijgen. Je hoofd zal hiervoor worden opgemeten, je hoofdhuid kan wat schoongemaakt worden met alcohol, en een cap zal worden vastgemaakt. In deze cap zitten gaten waarin gel zal worden gespoten en elektrodes zullen worden geklikt. Dit hele proces duurt ongeveer 15-20 minuten.
Het daadwerkelijke experiment zal ongeveer een uur duren. De onderzoeker zal bij je in de ruimte blijven gedurende het experiment en kun je elk moment vragen stellen.
In dit onderzoek zul je drie keer een spel spelen dat je kunt besturen met je hersenen. Elke keer zal het spel net wat anders zijn.
Het spelen bestaat uit drie onderdelen. Eerst krijg je twee korte trainingsessies (training). Daarna een sessie waarin daadwerkelijk het spel wordt gedaan (game), en ten slotte een variant waarin je vrij wat dingen kunt uitproberen (free play). Een sessie duurt 3 minuten. Een normaal spel spelen duurt dus 12 minuten in totaal. Met pauzes tussendoor zal de tijdsduur iets hoger uitkomen.
Tussen de spellen door zal een korte vragenlijst worden ingevuld.
Discussieer het experiment achteraf niet met anderen die mogelijk nog zullen deelnemen. Dit is om te voorkomen dat de resultaten mogelijk worden beïnvloed door voorkennis.

3) Risico’s en bijwerkingen

Dit onderzoek is gebaseerd op de huidige kennis van de hoofdonderzoeker en is veilig en pijnloos voor de deelnemers. Door deel te nemen aan dit onderzoek loop je geen specifieke risico’s, en er zijn geen bijwerkingen bekend. *Echter, omdat dit soort onderzoeken in het algemeen vrij nieuw is, kunnen onbekende bijwerkingen niet worden uitgesloten.*
Belangrijk: laat het de onderzoeker zo snel mogelijk weten als je ziektes hebt of onder medische behandeling staat. Laat het ook meteen weten als je ooit een epileptische aanval hebt gehad of last hebt van oorsuizen. Vragen hierover kun je stellen aan de onderzoeker.

4) Stoppen van het experiment

Je hebt het recht om het experiment op elk moment te stoppen zonder te vertellen waarom. Deelname is volledig vrijwillig en zonder verplichtingen. Er zijn geen nadelen door het stoppen van het onderzoek.
Tijdens het experiment zijn er meerdere pauzemomenten. Zelfs als je zelf een pauze wilt of naar de WC moet, kan dit op elk moment.
Als je op enig moment tijdens het experiment ongemak voelt, laat dat dan direct weten aan de onderzoeker.

5) Privacybescherming

Je privacy wordt gerespecteerd. Persoonlijke gegevens zullen niet worden doorgespeeld aan derden. De verzamelde data wordt anoniem gemaakt door ons en zal alleen in deze anonieme vorm worden gebruikt en gepubliceerd.

6) Verklaring

Door je handtekening onderaan dit formulier te zetten, ga je akkoord met het volgende:

"Ik verklaar hierbij dat de onderzoeker van dit experiment me heeft geïnformeerd over de bovenstaande punten. Ik heb het gelezen en begrepen. Ik ben in overeenstemming met elk van de punten. Hierbij geef ik toestemming dat de data die verkregen wordt met dit onderzoek wordt geanalyseerd voor wetenschappelijke doeleinden en anoniem wordt gebruikt voor publicatie. Ik ben geïnformeerd over mijn rechten als proefpersoon en over de vrijwillige deelname van dit onderzoek."

…………………………………………………………………….
Plaats, datum Handtekening

……………………………………………………………………….
In geval van minderjarige, handtekening van ouder

# Appendix C

# Subject Information Form (Dutch)

The second form the subject gets to see is the subject information form. This sheet is partially filled by the researcher (me) and for the rest by the subject themselves. Some of the questions could be seen as very personal, so to have the subject fill it in in relative privacy will probably result in more accurate answers.

The subject information form, as all other materials used during the experiment, is stated in Dutch as this is the mother tongue of most of the test subjects.

# Informatie Proefpersoon

***Algemene informatie experiment*** *in te vullen door onderzoeker*

*Datum:* ___ - ___ - _______ *Start:* ___ : ___ *Eind:* ___ : ___

*Omschrijving:* ____________________________________________

____________________________________________

____________________________________________

*Software:* ____________________________________________

*Actiview settings:* *Bandpass:* ____ Hz - ____ Hz *Sample frequency:* _____ Hz

*Experiment definitie:* ________________________________________

*Onderzoeker(s):* ________________________________________

***Algemene informatie proefpersoon***

| *in te vullen door proefpersoon* | *in te vullen door onderzoeker* |
|---|---|
| *ID:* ___________________________ | *Hoofd omtrek*: ___ cm *Cap*: _____ |
| *Geslacht:* m / v | *Nasion-inion:* ___ cm *Cz*: ___cm |
| *Leeftijd:* ____ | *Slaap-slaap:* ___ cm *Cz*: ___cm |
| *Dominantie:* linkshandig / rechtshandig | *Haaromschrijving:* ______________ |
| *Opleiding:* _________________________ | *Haarproducten:* ________________ |
| *Beroep:* ___________________________ | |

*Visuele hulpmiddelen:* o contactlenzen o bril o geen

*Alcoholconsumptie:* o dagelijks o wekelijks o maandelijks
o minder dan maandelijks o nooit
Voor experiment: __________________________

*Koffieconsumptie:* o 5+ kopjes per dag o 3-5 kopjes o 1-3 kopjes
o minder dan 1 kopje o nooit
Voor experiment: __________________________

*Zwarte/groene thee: consumptie* o 5+ kopjes per dag o 3-5 kopjes o 1-3 kopjes
o minder dan 1 kopje o nooit
Voor experiment: __________________________

*Tabakconsumptie:* o 2+ pakjes per dag o 1-2 per dag o 1 pakje per dag
o minder dan 1 pakje o af en toe o nooit
Voor experiment: __________________________

*Aantal uren slaap:* per nacht: ___ voor experiment: ___

*Mate van alertheid op dit moment:*
niet alert o o o o o zeer alert

*Medicijnen:* ______________________________

*Aandachts-/neurologische/psychiatrische problemen:*
______________________________

| | | | |
|---|---|---|---|
| *Werken met de PC* | o 6+ uur per dag | o 4-6 uur p.d. | o 2-4 uur p.d. |
| *(niet per se voor beroep)* | o dagelijks, <2 uur | o wekelijks | o maandelijks |
| | o minder dan maandelijks | | o nooit |
| *Computerspellen spelen* | o 6+ uur per dag | o 4-6 uur p.d. | o 2-4 uur p.d. |
| | o dagelijks, < 2 uur | o wekelijks | o maandelijks |
| | o minder dan maandelijks | | o nooit |

***Handigheidstest:***

*Geef aan met welke hand je de volgende taken zou uitvoeren:*

| | |
|---|---|
| *Schrijven* | Links / Rechts |
| *Tekenen* | Links / Rechts |
| *Bal gooien* | Links / Rechts |
| *Knippen* | Links / Rechts |
| *Tanden poetsen* | Links / Rechts |
| *Brood snijden met mes* | Links / Rechts |
| *Eten met een lepel* | Links / Rechts |
| *Een computermuis gebruiken* | Links / Rechts |
| *Een lucifer aansteken* *(de andere hand houdt het doosje vast)* | Links / Rechts |
| *Een pot openmaken* *(de andere hand houdt de pot vast)* | Links / Rechts |

*Met welke hand schrijven:*

| | | | | | |
|---|---|---|---|---|---|
| *Moeder* | L / R / ? | *Zus* | L / R / ? | *Dochter* | L / R / ? |
| *Vader* | L / R / ? | *Broer* | L / R / ? | *Zoon* | L / R / ? |

*Eventuele extra broers/zussen/dochters/zonen:*

| | | | |
|---|---|---|---|
| L / R | L / R | L / R | L / R |
| L / R | L / R | L / R | L / R |

*Opmerkingen:*

______________________________
______________________________
______________________________
______________________________
______________________________
______________________________
______________________________

# Appendix D

# Game Explanation Sheet (Dutch)

While the subject was prepped with the EEG cap, they could read a more detailed explanation of the game they were going to play.

The game explanation, as all other materials used during the experiment, is stated in Dutch as this is the mother tongue of most of the test subjects.

# Speluitleg

Het spel bestaat uit drie onderdelen: *training*, *game*, en *free play*.

Er zijn twee acties om het spel aan te sturen: ingebeelde beweging van de wijsvinger van de linker hand, en ingebeelde beweging van de wijsvinger van de rechter hand.
De onderzoeker zal de beweging voordoen. Doe de beweging na. Probeer vervolgens de beweging in te beelden. Dit kun je doen door het gevoel te hebben dat je bijna de beweging maakt, maar de daadwerkelijke beweging van je hand tegenhoudt net voor het gebeurt. Probeer het eens.

**Training**
De training zal worden opgesplitst in twee korte sessies.
Volg de instructies op het scherm. Tijdens de training krijg je een symbool te zien voor ingebeelde beweging van de linker wijsvinger of voor de rechter wijsvinger. Probeer deze taak zo goed mogelijk uit te voeren zo lang het symbool in beeld is. Probeer gedurende deze periode zo ontspannen mogelijk te blijven, niet te bewegen, en zo min mogelijk met de ogen te knipperen. Tussen twee symbolen door is er altijd een korte pauze waarin je wel gewoon mag bewegen en met je ogen knipperen.
Bovenin het scherm zie je een voortgangsbalk waaraan je kunt zien hoe lang het spel nog duurt.

**Game**
In het spel komt steeds een symbool in beeld. Voer deze actie uit.
Bovenin het scherm zie je een zogenaamde voortgangsbalk waaraan je kunt zien hoe lang het spel nog duurt. In deze modus zie je hier ook wat voor acties de computer ziet in jouw hersensignalen. Hoe groter de hoogte van een kleur, hoe meer de bijbehorende actie wordt gezien. De kleuren komen overeen met de kleuren gebruikt in de symbolen.
Als de computer je actie niet goed herkent, kun je de volgende dingen proberen: a) check of je wel ontspannen bent (kaak, nek, schouders), b) stop even met de mentale beweging en begin opnieuw. In het slechtste geval zal het symbool na *1 minuut* verdwijnen waarna je bezig kunt met de volgende actie.
Voor elke actie die het systeem herkent krijg je een punt. Je score staat links naast de voortgangsbalk.
Net als tijdens de training geldt dat je het best ontspannen kunt blijven en niet met je ogen knipperen terwijl je een actie probeert uit te voeren.

**Free Play**
In deze modus zal het systeem het symbool op het scherm tonen van de actie die het heeft herkend. Je kunt dus zelf proberen bepaalde symbolen op het scherm te krijgen. Ook kun je kijken hoe je dit het best voor elkaar kunt krijgen. Andere mogelijkheden zijn het uitvoeren van andere acties om te zien wat dat voor effect heeft op de herkenning.
Er is ook weer een voortgangsbalk in het scherm waarin je de herkenning van de acties kunt zien plus de voortgang van de sessie.

# Appendix E

# User Experience Forms (Dutch)

Three different versions of the game are played during the experiment. After each version (which consists of two training sessions, one game session, and one free play session) a user experience form is filled in.

These forms are based on the Game Experience Questionnaire developed by the Game Experience Lab of Eindhoven University [14], with some inapplicable questions removed.

The user experience forms, as all other materials used during the experiment, is stated in Dutch as this is the mother tongue of most of the test subjects.

# Gebruikerservaring BB toetsenbord

Duid voor elk van de items aan hoe jij je voelde tijdens het spelen. Doe dit met behulp van de volgende schaal.

| *Niet* | *Een klein beetje* | *Enigszins* | *Behoorlijk* | *Heel erg* |
|---|---|---|---|---|
| o | o | o | o | o |

| | | | | |
|---|---|---|---|---|
| 1 | Ik voelde me tevreden | *niet* | o o o o o | *heel erg* |
| 2 | Ik voelde me vaardig | *niet* | o o o o o | *heel erg* |
| 4 | Ik kon er om lachen | *niet* | o o o o o | *heel erg* |
| 5 | Ik was helemaal geabsorbeerd | *niet* | o o o o o | *heel erg* |
| 6 | Ik voelde me vrolijk | *niet* | o o o o o | *heel erg* |
| 7 | Ik kreeg er slechte zin van | *niet* | o o o o o | *heel erg* |
| 8 | Ik was met andere zaken bezig | *niet* | o o o o o | *heel erg* |
| 9 | Ik vond het saai | *niet* | o o o o o | *heel erg* |
| 10 | Ik voelde me zeker | *niet* | o o o o o | *heel erg* |
| 11 | Ik vond het moeilijk | *niet* | o o o o o | *heel erg* |
| 12 | Ik vond het aansprekend van vormgeving | *niet* | o o o o o | *heel erg* |
| 13 | Ik vergat alles om me heen | *niet* | o o o o o | *heel erg* |
| 14 | Ik voelde me lekker | *niet* | o o o o o | *heel erg* |
| 15 | Ik was er goed in | *niet* | o o o o o | *heel erg* |
| 16 | Ik voelde me verveeld | *niet* | o o o o o | *heel erg* |
| 17 | Ik voelde me succesvol | *niet* | o o o o o | *heel erg* |
| 20 | Ik genoot ervan | *niet* | o o o o o | *heel erg* |
| 21 | Ik was snel in het bereiken van de doelen in de game | *niet* | o o o o o | *heel erg* |
| 22 | Ik was geïrriteerd | *niet* | o o o o o | *heel erg* |
| 23 | Ik voelde me onder druk gezet | *niet* | o o o o o | *heel erg* |
| 24 | Ik was prikkelbaar | *niet* | o o o o o | *heel erg* |
| 25 | Ik was mijn gevoel voor tijd kwijt | *niet* | o o o o o | *heel erg* |
| 26 | Ik voelde me uitgedaagd | *niet* | o o o o o | *heel erg* |
| 27 | Ik vond het indrukwekkend | *niet* | o o o o o | *heel erg* |
| 28 | Ik was ten volle geconcentreerd op de game | *niet* | o o o o o | *heel erg* |
| 29 | Ik was gefrustreerd | *niet* | o o o o o | *heel erg* |

| | | | | | |
|---|---|---|---|---|---|
| 30 | Ik vond het een rijke ervaring | *niet* | o o o o o | *heel erg* |
| 31 | Ik was weg uit de buitenwereld | *niet* | o o o o o | *heel erg* |
| 32 | Ik voelde tijdsdruk | *niet* | o o o o o | *heel erg* |
| 33 | Ik moest er veel moeite in steken | *niet* | o o o o o | *heel erg* |

*Herhaling schaalverdeling*

| *Niet* | *Een klein beetje* | *Enigszins* | *Behoorlijk* | *Heel erg* |
|---|---|---|---|---|
| o | o | o | o | o |

*Open vragen:*

Wat vond je van het spel?

Overige opmerkingen?

# Gebruikerservaring BB origineel

Duid voor elk van de items aan hoe jij je voelde tijdens het spelen. Doe dit met behulp van de volgende schaal.

| *Niet* | *Een klein beetje* | *Enigszins* | *Behoorlijk* | *Heel erg* |
|---|---|---|---|---|
| o | o | o | o | o |

| | | | | |
|---|---|---|---|---|
| 1 | Ik voelde me tevreden | *niet* | o o o o o | *heel erg* |
| 2 | Ik voelde me vaardig | *niet* | o o o o o | *heel erg* |
| 4 | Ik kon er om lachen | *niet* | o o o o o | *heel erg* |
| 5 | Ik was helemaal geabsorbeerd | *niet* | o o o o o | *heel erg* |
| 6 | Ik voelde me vrolijk | *niet* | o o o o o | *heel erg* |
| 7 | Ik kreeg er slechte zin van | *niet* | o o o o o | *heel erg* |
| 8 | Ik was met andere zaken bezig | *niet* | o o o o o | *heel erg* |
| 9 | Ik vond het saai | *niet* | o o o o o | *heel erg* |
| 10 | Ik voelde me zeker | *niet* | o o o o o | *heel erg* |
| 11 | Ik vond het moeilijk | *niet* | o o o o o | *heel erg* |
| 12 | Ik vond het aansprekend van vormgeving | *niet* | o o o o o | *heel erg* |
| 13 | Ik vergat alles om me heen | *niet* | o o o o o | *heel erg* |
| 14 | Ik voelde me lekker | *niet* | o o o o o | *heel erg* |
| 15 | Ik was er goed in | *niet* | o o o o o | *heel erg* |
| 16 | Ik voelde me verveeld | *niet* | o o o o o | *heel erg* |
| 17 | Ik voelde me succesvol | *niet* | o o o o o | *heel erg* |
| 20 | Ik genoot ervan | *niet* | o o o o o | *heel erg* |
| 21 | Ik was snel in het bereiken van de doelen in de game | *niet* | o o o o o | *heel erg* |
| 22 | Ik was geïrriteerd | *niet* | o o o o o | *heel erg* |
| 23 | Ik voelde me onder druk gezet | *niet* | o o o o o | *heel erg* |
| 24 | Ik was prikkelbaar | *niet* | o o o o o | *heel erg* |
| 25 | Ik was mijn gevoel voor tijd kwijt | *niet* | o o o o o | *heel erg* |
| 26 | Ik voelde me uitgedaagd | *niet* | o o o o o | *heel erg* |
| 27 | Ik vond het indrukwekkend | *niet* | o o o o o | *heel erg* |
| 28 | Ik was ten volle geconcentreerd op de game | *niet* | o o o o o | *heel erg* |
| 29 | Ik was gefrustreerd | *niet* | o o o o o | *heel erg* |

| | | |
|---|---|---|
| 30 | Ik vond het een rijke ervaring | *niet* o o o o o *heel erg* |
| 31 | Ik was weg uit de buitenwereld | *niet* o o o o o *heel erg* |
| 32 | Ik voelde tijdsdruk | *niet* o o o o o *heel erg* |
| 33 | Ik moest er veel moeite in steken | *niet* o o o o o *heel erg* |
| | | |
| 34 | Ik had controle over m'n hersenacties | *niet o o o o o heel erg* |
| 35 | Ik begreep wat ik moest doen | *niet o o o o o heel erg* |
| 36 | Ik begreep het doel van het spel | *niet o o o o o heel erg* |
| 37 | Ik wist wat mijn score was | *niet o o o o o heel erg* |
| 38 | De feedback in de voortgangsbalk was duidelijk | *niet o o o o o heel erg* |

*Herhaling schaalverdeling*

| *Niet* | *Een klein beetje* | *Enigszins* | *Behoorlijk* | *Heel erg* |
|---|---|---|---|---|
| o | o | o | o | o |

*Open vragen:*

Wat vond je van de training?

________________________________________

________________________________________

________________________________________

________________________________________

Wat vond je van het spel?

________________________________________

________________________________________

________________________________________

________________________________________

Wat vond je van free play?

________________________________________

________________________________________

________________________________________

________________________________________

Overige opmerkingen?

________________________________________

________________________________________

________________________________________

________________________________________

# Gebruikerservaring BB kruis

Duid voor elk van de items aan hoe jij je voelde tijdens het spelen. Doe dit met behulp van de volgende schaal.

| *Niet* | *Een klein beetje* | *Enigszins* | *Behoorlijk* | *Heel erg* |
|---|---|---|---|---|
| o | o | o | o | o |

| | | |
|---|---|---|
| 1 | Ik voelde me tevreden | *niet* o o o o o *heel erg* |
| 2 | Ik voelde me vaardig | *niet* o o o o o *heel erg* |
| 4 | Ik kon er om lachen | *niet* o o o o o *heel erg* |
| 5 | Ik was helemaal geabsorbeerd | *niet* o o o o o *heel erg* |
| 6 | Ik voelde me vrolijk | *niet* o o o o o *heel erg* |
| 7 | Ik kreeg er slechte zin van | *niet* o o o o o *heel erg* |
| 8 | Ik was met andere zaken bezig | *niet* o o o o o *heel erg* |
| 9 | Ik vond het saai | *niet* o o o o o *heel erg* |
| 10 | Ik voelde me zeker | *niet* o o o o o *heel erg* |
| 11 | Ik vond het moeilijk | *niet* o o o o o *heel erg* |
| 12 | Ik vond het aansprekend van vormgeving | *niet* o o o o o *heel erg* |
| 13 | Ik vergat alles om me heen | *niet* o o o o o *heel erg* |
| 14 | Ik voelde me lekker | *niet* o o o o o *heel erg* |
| 15 | Ik was er goed in | *niet* o o o o o *heel erg* |
| 16 | Ik voelde me verveeld | *niet* o o o o o *heel erg* |
| 17 | Ik voelde me succesvol | *niet* o o o o o *heel erg* |
| 20 | Ik genoot ervan | *niet* o o o o o *heel erg* |
| 21 | Ik was snel in het bereiken van de doelen in de game | *niet* o o o o o *heel erg* |
| 22 | Ik was geïrriteerd | *niet* o o o o o *heel erg* |
| 23 | Ik voelde me onder druk gezet | *niet* o o o o o *heel erg* |
| 24 | Ik was prikkelbaar | *niet* o o o o o *heel erg* |
| 25 | Ik was mijn gevoel voor tijd kwijt | *niet* o o o o o *heel erg* |
| 26 | Ik voelde me uitgedaagd | *niet* o o o o o *heel erg* |
| 27 | Ik vond het indrukwekkend | *niet* o o o o o *heel erg* |
| 28 | Ik was ten volle geconcentreerd op de game | *niet* o o o o o *heel erg* |

| | | | | |
|---|---|---|---|---|
| 29 | Ik was gefrustreerd | *niet* | o o o o o | *heel erg* |
| 30 | Ik vond het een rijke ervaring | *niet* | o o o o o | *heel erg* |
| 31 | Ik was weg uit de buitenwereld | *niet* | o o o o o | *heel erg* |
| 32 | Ik voelde tijdsdruk | *niet* | o o o o o | *heel erg* |
| 33 | Ik moest er veel moeite in steken | *niet* | o o o o o | *heel erg* |
| | | | | |
| 34 | Ik had controle over m'n hersenacties | *niet* | *o o o o o* | *heel erg* |
| 35 | Ik begreep wat ik moest doen | *niet* | *o o o o o* | *heel erg* |
| 36 | Ik begreep het doel van het spel | *niet* | *o o o o o* | *heel erg* |
| 37 | Ik wist wat mijn score was | *niet* | *o o o o o* | *heel erg* |

*Herhaling schaalverdeling*

| *Niet* | *Een klein beetje* | *Enigszins* | *Behoorlijk* | *Heel erg* |
|---|---|---|---|---|
| o | o | o | o | o |

*Open vragen:*

Wat vond je van de training?

Wat vond je van het spel?

Wat vond je van free play?

Overige opmerkingen?

# Gebruikerservaring achteraf

Duid voor elk van de items aan hoe jij je voelde NA het gamen. Doe dit met behulp van de volgende schaal.

| *Niet* | *Een klein beetje* | *Enigszins* | *Behoorlijk* | *Heel erg* |
|---|---|---|---|---|
| o | o | o | o | o |

| | | | | |
|---|---|---|---|---|
| 1 | Ik voelde me opgepept | *niet* | o o o o o | *heel erg* |
| 2 | Ik voelde me rot | *niet* | o o o o o | *heel erg* |
| 3 | Ik had moeite om terug te keren naar de realiteit | *niet* | o o o o o | *heel erg* |
| 4 | Ik voelde me schuldig | *niet* | o o o o o | *heel erg* |
| 5 | Ik zag het als een overwinning | *niet* | o o o o o | *heel erg* |
| 6 | Ik vond het zonde van de tijd | *niet* | o o o o o | *heel erg* |
| 7 | Ik voelde me opgeladen | *niet* | o o o o o | *heel erg* |
| 8 | Ik voelde me voldaan | *niet* | o o o o o | *heel erg* |
| 9 | Ik voelde me gedesoriënteerd | *niet* | o o o o o | *heel erg* |
| 10 | Ik voelde me uitgeput | *niet* | o o o o o | *heel erg* |
| 11 | Ik vond dat ik meer nuttige dingen had kunnen doen | *niet* | o o o o o | *heel erg* |
| 12 | Ik voelde me machtig | *niet* | o o o o o | *heel erg* |
| 13 | Ik voelde me vermoeid | *niet* | o o o o o | *heel erg* |
| 14 | Ik had spijt | *niet* | o o o o o | *heel erg* |
| 15 | Ik schaamde me | *niet* | o o o o o | *heel erg* |
| 16 | Ik voelde me trots | *niet* | o o o o o | *heel erg* |
| 17 | Ik had het gevoel dat ik van een "reis" terugkeerde | *niet* | o o o o o | *heel erg* |
| 18 | Ik voelde me opgelucht | *niet* | o o o o o | *heel erg* |
| 19 | Ik was teleurgesteld | *niet* | o o o o o | *heel erg* |
| 20 | Ik voelde me leeg | *niet* | o o o o o | *heel erg* |
| 21 | Ik had het gevoel nuttig bezig te zijn geweest | *niet* | o o o o o | *heel erg* |

| | | | | |
|---|---|---|---|---|
| 22 | Op dit moment voel ik me alert | *niet* | o o o o o | *heel erg* |

# Appendix F

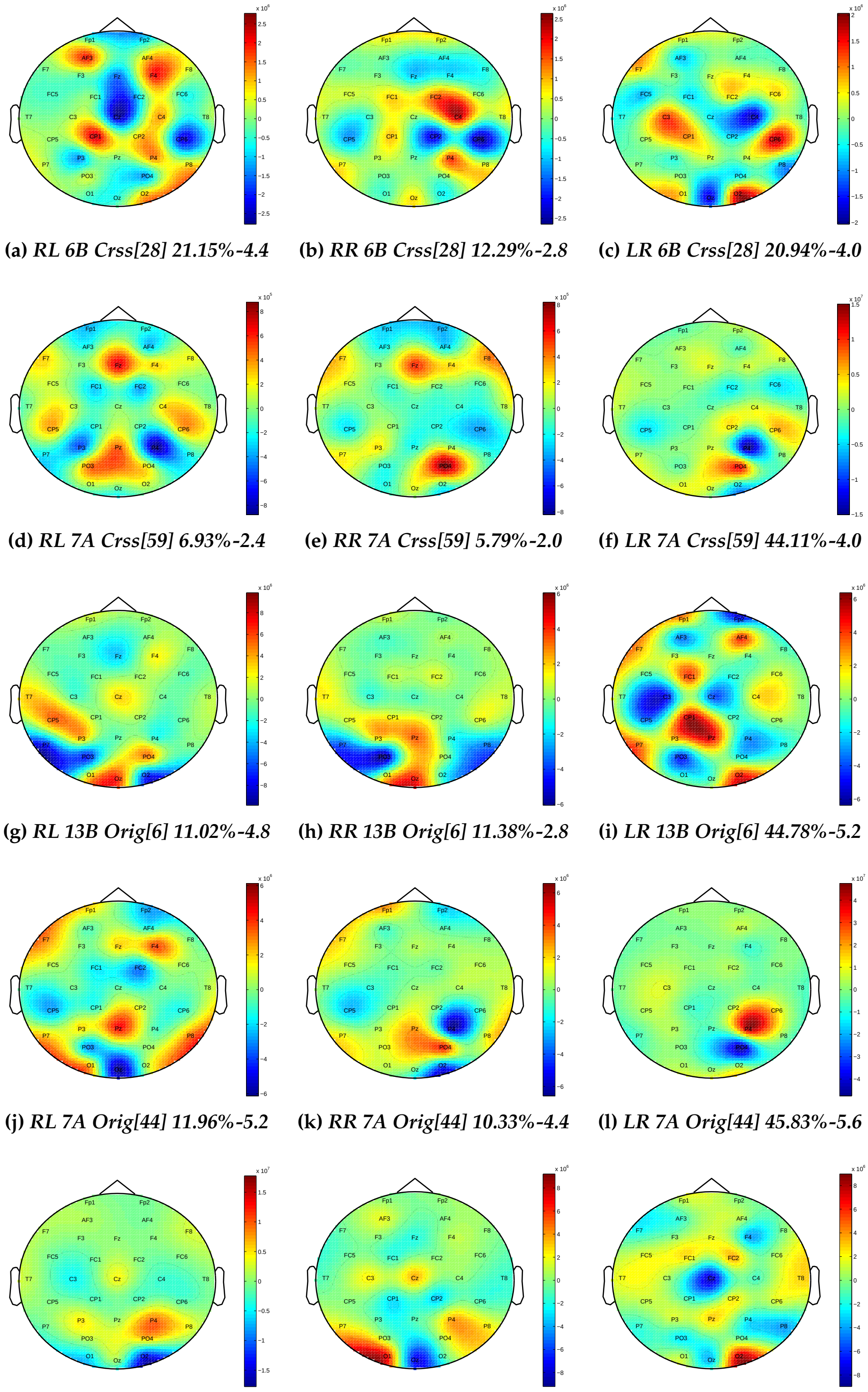
# Classifier Plots

The scalp maps shown in this appendix are derived from the selected CSP filters and the LDA transformation by multiplication. The result of one value per electrode is mapped onto the electrode montage used during the experiments.

In the hopes of providing some insight into which classifiers could be expected to perform well and which not so well, the classifier plots are listed in (increasing) order of the summed cross validation error rate. Within one row, the first plot is the rest vs. left MI classifier, the second rest vs. right MI, and the third left vs. right MI.

For each classifier, the label contains the following information: the classification (RL for rest vs. left MI, RR for rest vs. right MI, or LR for left vs. right MI) the subject, the experiment group (A - got Original first and then Cross, or B - got Cross first and then Original), the version of the game these classifiers were generated for (Orig for Original or Crss for Cross), the game score obtained with this combination of classifiers, the average cross validation rate over five runs for this specific classifier, and the average number of CSP filters used for this classifier. For example: "RL 6B Crss[28] 21.15%-4" indicates that this is the rest vs. left MI classifier for the Cross version for subject 6, who got Cross second and achieved a score of 28. The average error rate derived during training is 21.15% for which 4 CSP filters were used on average.

Based on neurophysiological knowledge, the classifiers for left vs. right MI should show opposing C3 and C4, and/or P3 and P4. For the separation of the resting class, it was expected that the classifiers would zoom in on the electrode positions sensitive to eye and muscle artifacts. When looking at the individual plots, these features do not always show that clearly. The game scores are also not always reflected by the cross validation error rates. One reason for this is the blocking power of the resting class: if the confidence value for rest is very high, the left and right MI classes never get a high enough confidence value to pass the threshold. This would result in a game score of 0. Therefore, apart from the separation between left and right MI, the resting class classification might even be more important.



**(a)** ***RL 6B Crss[28] 21.15%-4.4*** **(b)** ***RR 6B Crss[28] 12.29%-2.8*** **(c)** ***LR 6B Crss[28] 20.94%-4.0***

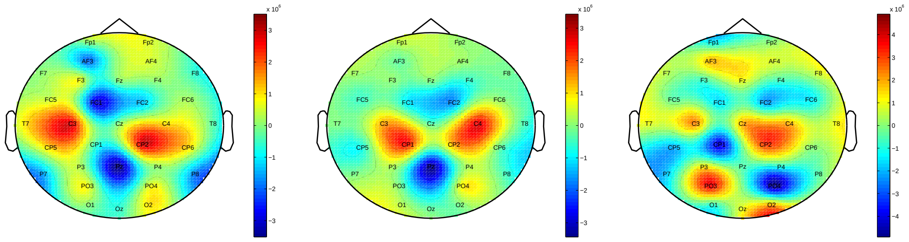
**(d)** ***RL 7A Crss[59] 6.93%-2.4*** **(e)** ***RR 7A Crss[59] 5.79%-2.0*** **(f)** ***LR 7A Crss[59] 44.11%-4.0***

**(g)** ***RL 13B Orig[6] 11.02%-4.8*** **(h)** ***RR 13B Orig[6] 11.38%-2.8*** **(i)** ***LR 13B Orig[6] 44.78%-5.2***

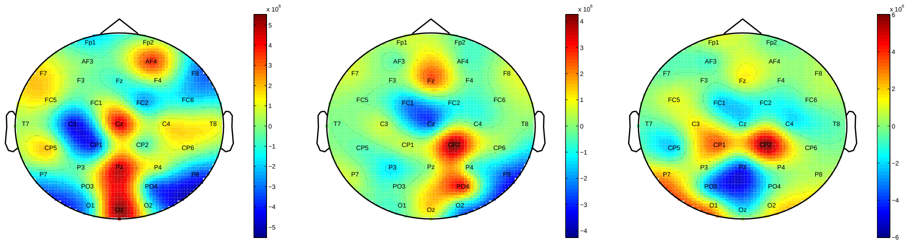
**(j)** ***RL 7A Orig[44] 11.96%-5.2*** **(k)** ***RR 7A Orig[44] 10.33%-4.4*** **(l)** ***LR 7A Orig[44] 45.83%-5.6***

**(m)** ***RL 8A Orig[5] 14.38%-6.0*** **(n)** ***RR 8A Orig[5] 13.29%-6.0*** **(o)** ***LR 8A Orig[5] 43.61%-4.0***

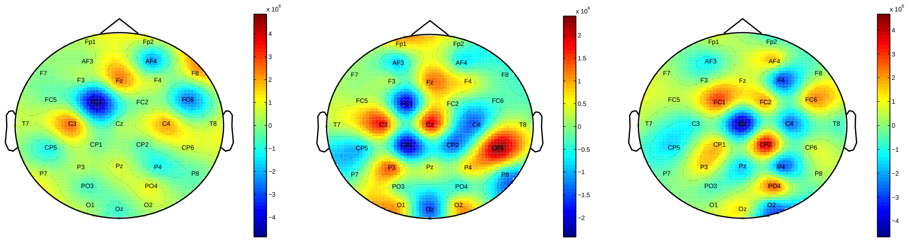
**Figure F.1:** ***All classifier plots - page 1*** *from low to high cross validation error rate, showing from left to right: the rest vs. left MI, rest vs. right MI, and left vs. right MI classifiers.*



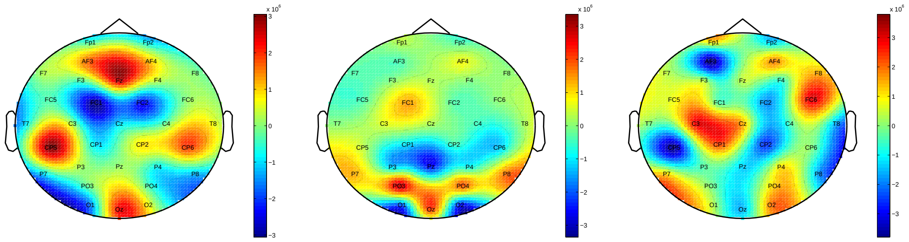
**(a)** ***RL 17A Crss[3] 17.04%-4.0*** **(b)** ***RR 17A Crss[3] 18.15%-2.0*** **(c)** ***LR 17A Crss[3] 37.39%-4.8***



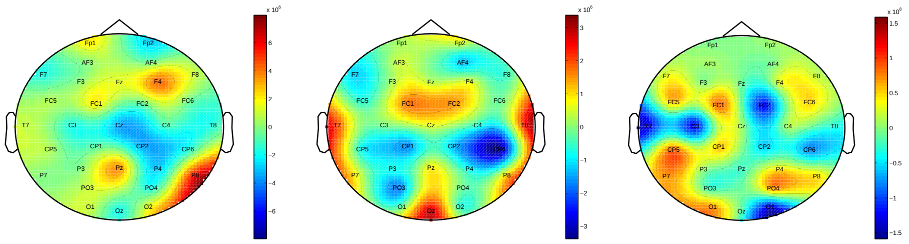
**(d)** ***RL 15B Orig[7] 17.11%-6.0*** **(e)** ***RR 15B Orig[7] 15.31%-4.4*** **(f)** ***LR 15B Orig[7] 40.89%-2.4***



**(g)** ***RL 6B Orig[21] 15.27%-6.0*** **(h)** ***RR 6B Orig[21] 16.62%-5.2*** **(i)** ***LR 6B Orig[21] 42.45%-2.0***

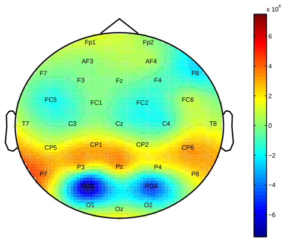


**(j)** ***RL 11B Orig[26] 11.73%-4.8*** **(k)** ***RR 11B Orig[26] 10.73%-5.2*** **(l)** ***LR 11B Orig[26] 53.33%-3.6***

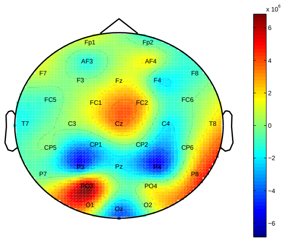


**(m)** ***RL 12A Crss[5] 16.04%-3.6*** **(n)** ***RR 12A Crss[5] 20.41%-4.4*** **(o)** ***LR 12A Crss[5] 40.23%-4.4***

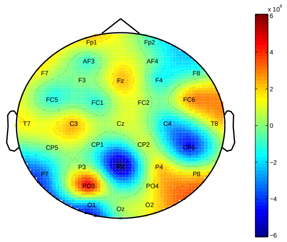
**Figure F.2:** ***All classifier plots - page 2*** *from low to high Crss validation error rate, showing from left to right: the rest vs. left MI, rest vs. right MI, and left vs. right MI classifiers.*



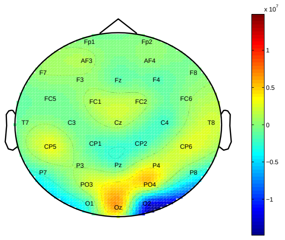
**(a)** ***RL 12A Orig[1] 12.31%-3.2***



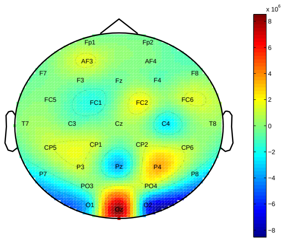
**(b)** ***RR 12A Orig[1] 15.51%-6.0***



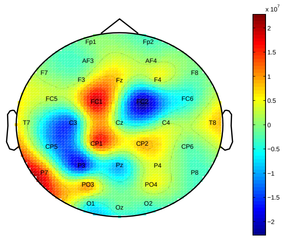
**(c)** ***LR 12A Orig[1] 49.11%-3.6***



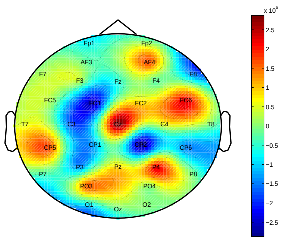
**(d)** ***RL 17A Orig[27] 13.69%-6.0***



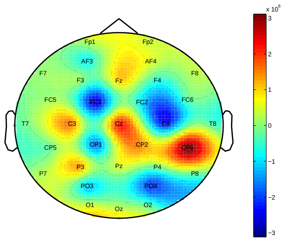
**(e)** ***RR 17A Orig[27] 12.91%-5.6***



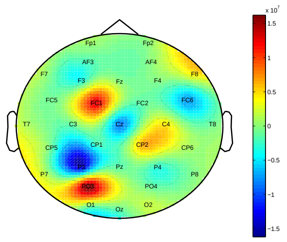
**(f)** ***LR 17A Orig[27] 52.33%-4.4***



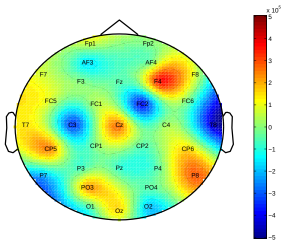
**(g)** ***RL 3A Orig[28] 20.29%-4.0***



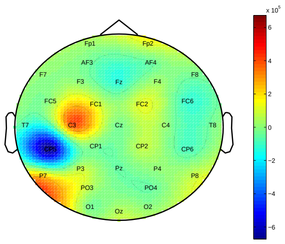
**(h)** ***RR 3A Orig[28] 19.80%-2.8***



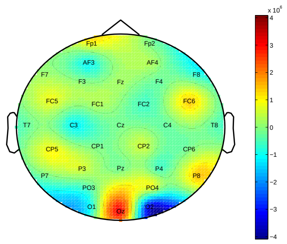
**(i)** ***LR 3A Orig[28] 38.94%-5.2***



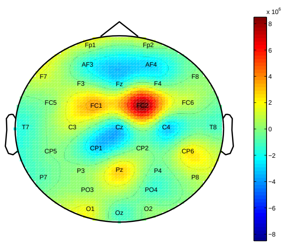
**(j)** ***RL 14A Orig[0] 20.31%-2.0***



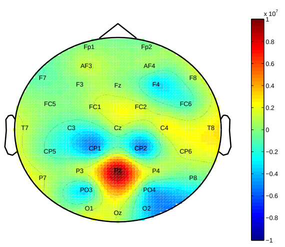
**(k)** ***RR 14A Orig[0] 19.64%-2.8***



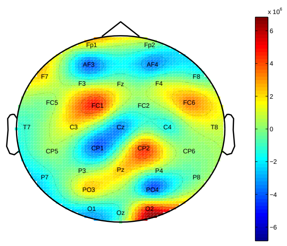
**(l)** ***LR 14A Orig[0] 41.78%-5.6***



**(m)** ***RL 9B Orig[49] 17.11%-6.0***

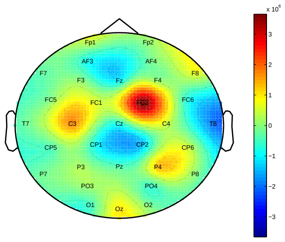


**(n)** ***RR 9B Orig[49] 18.33%-5.2***

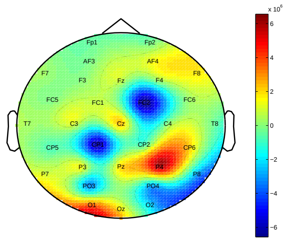


**(o)** ***LR 9B Orig[49] 48.89%-4.8***

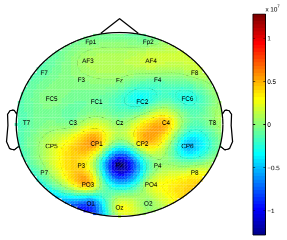
**Figure F.3:** ***All classifier plots - page 3*** *from low to high Crss validation error rate, showing from left to right: the rest vs. left MI, rest vs. right MI, and left vs. right MI classifiers.*



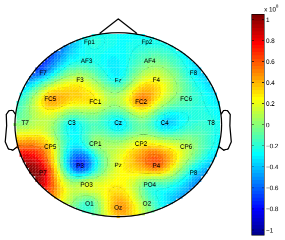
**(a)** ***RL 9B Crss[9] 24.67%-5.2***



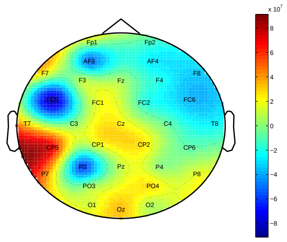
**(b)** ***RR 9B Crss[9] 29.76%-5.6***



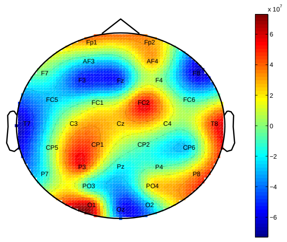
**(c)** ***LR 9B Crss[9] 30.03%-5.6***



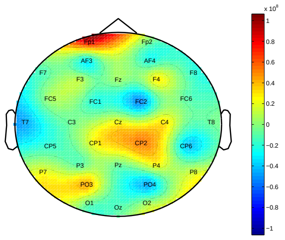
**(d)** ***RL 2B Orig[28] 23.29%-4.0***



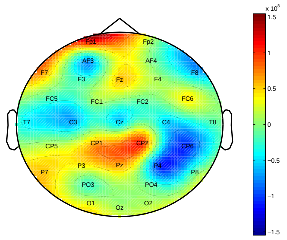
**(e)** ***RR 2B Orig[28] 24.22%-2.8***



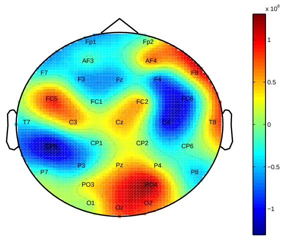
**(f)** ***LR 2B Orig[28] 43.61%-2.4***



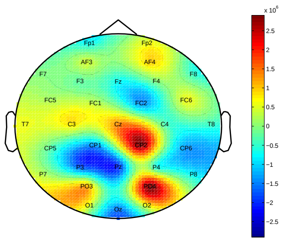
**(g)** ***RL 2B Crss[10] 21.76%-3.6***



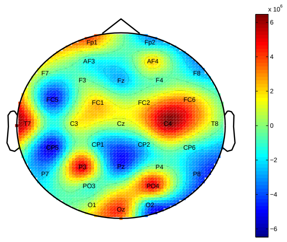
**(h)** ***RR 2B Crss[10] 23.58%-5.2***



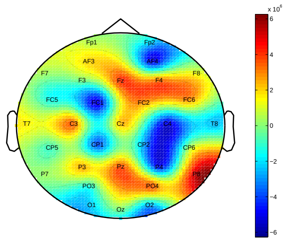
**(i)** ***LR 2B Crss[10] 48.28%-3.6***



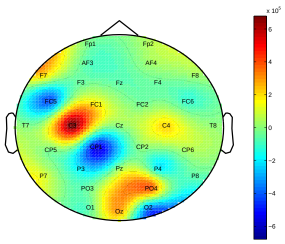
**(j)** ***RL 16A Orig[8] 21.69%-3.6***



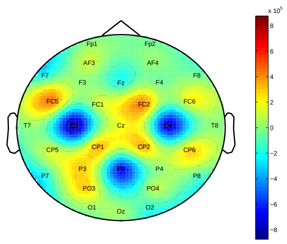
**(k)** ***RR 16A Orig[8] 23.78%-4.8***



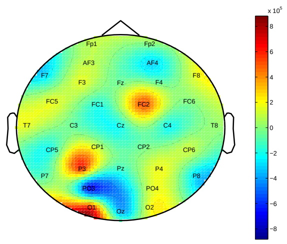
**(l)** ***LR 16A Orig[8] 50.44%-4.4***



**(m)** ***RL 5B Orig[1] 20.76%-4.4***

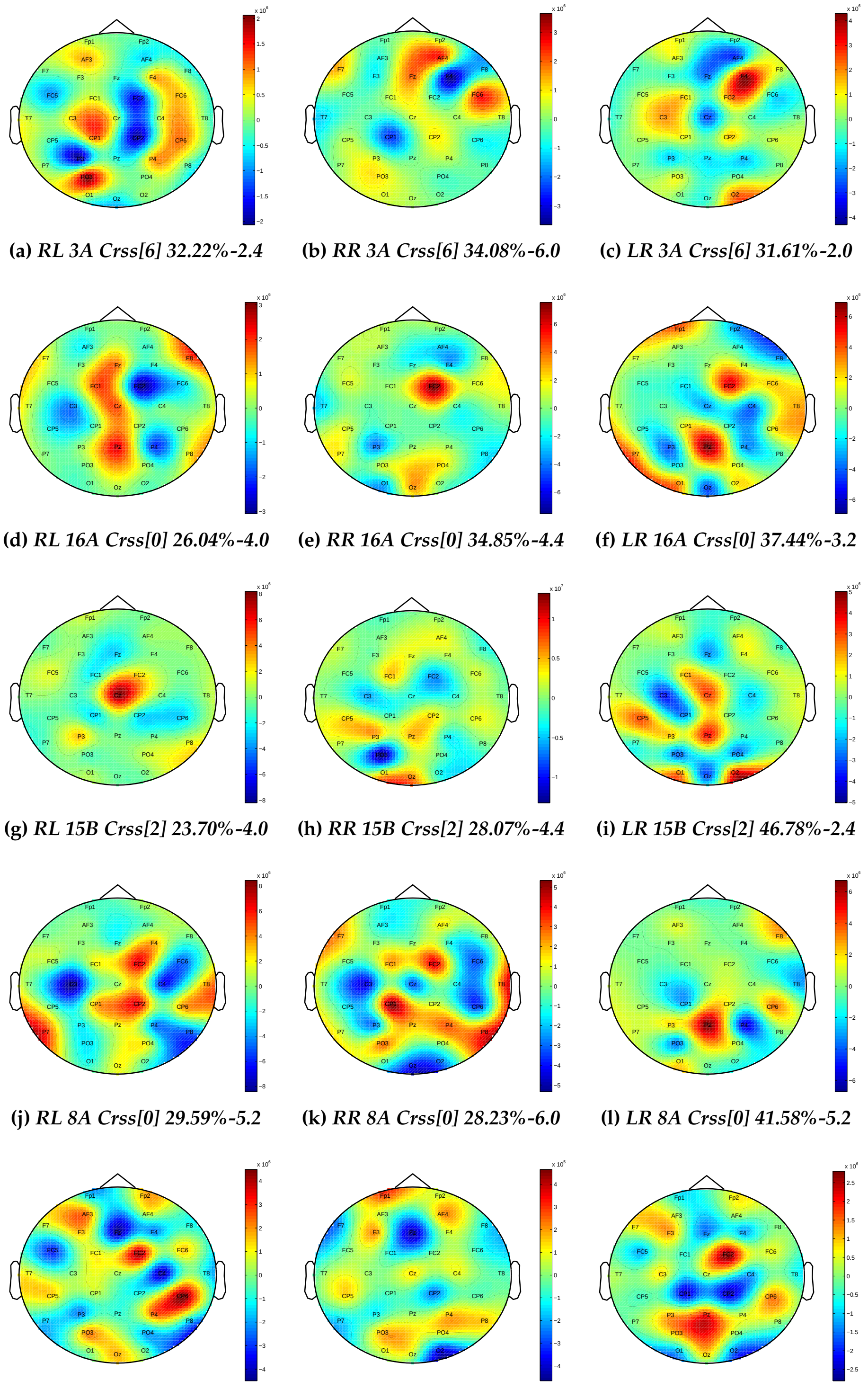


**(n)** ***RR 5B Orig[1] 19.40%-2.4***



**(o)** ***LR 5B Orig[1] 55.83%-4.0***

**Figure F.4:** ***All classifier plots - page 4*** *from low to high Crss validation error rate, showing from left to right: the rest vs. left MI, rest vs. right MI, and left vs. right MI classifiers.*



**(a)** ***RL 3A Crss[6] 32.22%-2.4*** **(b)** ***RR 3A Crss[6] 34.08%-6.0*** **(c)** ***LR 3A Crss[6] 31.61%-2.0***

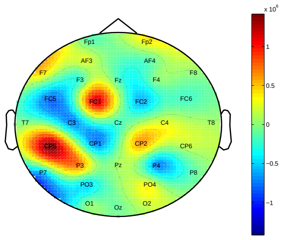
**(d)** ***RL 16A Crss[0] 26.04%-4.0*** **(e)** ***RR 16A Crss[0] 34.85%-4.4*** **(f)** ***LR 16A Crss[0] 37.44%-3.2***

**(g)** ***RL 15B Crss[2] 23.70%-4.0*** **(h)** ***RR 15B Crss[2] 28.07%-4.4*** **(i)** ***LR 15B Crss[2] 46.78%-2.4***

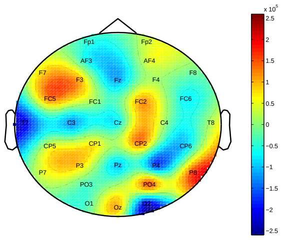
**(j)** ***RL 8A Crss[0] 29.59%-5.2*** **(k)** ***RR 8A Crss[0] 28.23%-6.0*** **(l)** ***LR 8A Crss[0] 41.58%-5.2***

**(m)** ***RL 4A Orig[47] 21.04%-3.2*** **(n)** ***RR 4A Orig[47] 19.02%-3.2*** **(o)** ***LR 4A Orig[47] 60.17%-2.8***

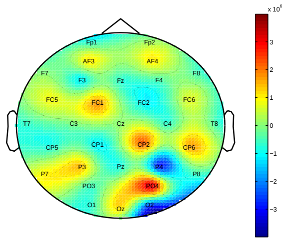
**Figure F.5:** ***All classifier plots - page 5*** *from low to high Crss validation error rate, showing from left to right: the rest vs. left MI, rest vs. right MI, and left vs. right MI classifiers.*



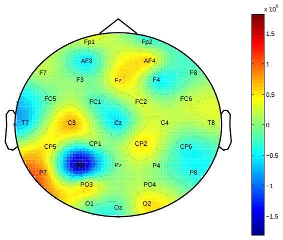
**(a)** ***RL 5B Crss[1] 29.78%-6.0***



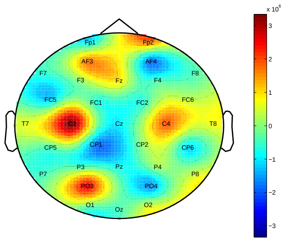
**(b)** ***RR 5B Crss[1] 34.54%-2.0***



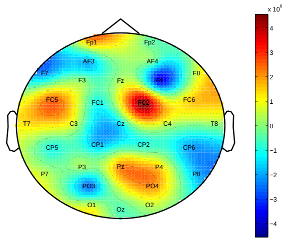
**(c)** ***LR 5B Crss[1] 37.07%-5.4***



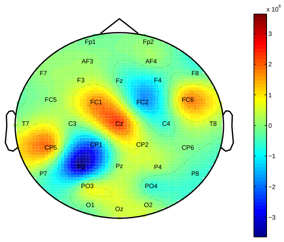
**(d)** ***RL 14A Crss[2] 33.37%-3.6***



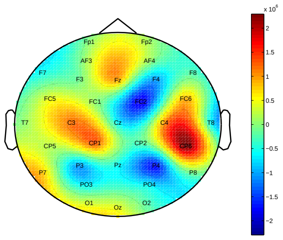
**(e)** ***RR 14A Crss[2] 32.33%-5.2***



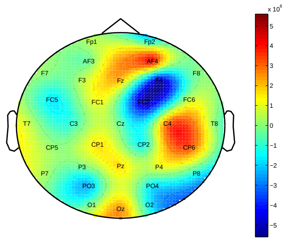
**(f)** ***LR 14A Crss[2] 38.67%-5.2***



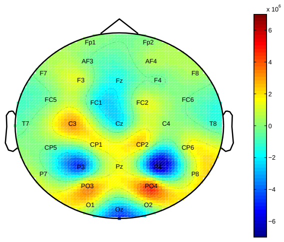
**(g)** ***RL 13B Crss[4] 32.41%-3.6***



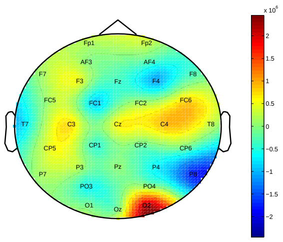
**(h)** ***RR 13B Crss[4] 29.00%-3.6***



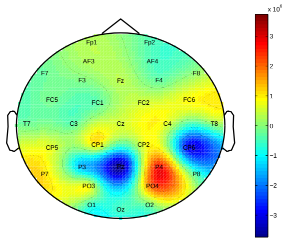
**(i)** ***LR 13B Crss[4] 45.11%-3.6***



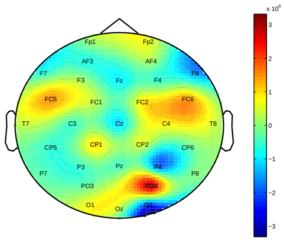
**(j)** ***RL 4A Crss[3] 28.96%-4.4***



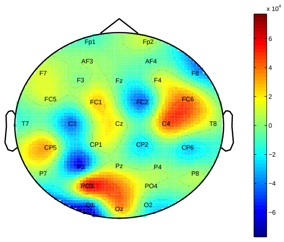
**(k)** ***RR 4A Crss[3] 31.67%-6.0***



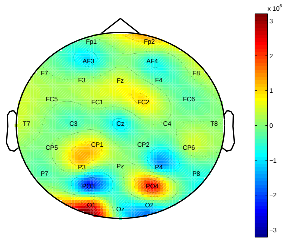
**(l)** ***LR 4A Crss[3] 47.00%-4.0***



**(m)** ***RL 11B Crss[3] 32.18%-5.2***



**(n)** ***RR 11B Crss[3] 32.19%-4.8***



**(o)** ***LR 11B Crss[3] 50.09%-4.8***

**Figure F.6:** ***All classifier plots - page 6*** *from low to high cross validation error rate, showing from left to right: the rest vs. left MI, rest vs. right MI, and left vs. right MI classifiers.*

# Appendix G

# Prototype To-Fix List

## G.1 Fixes

### High Priority

1. **Timing issues.** For valid research, the timing should be more accurate. Steps that can be undertaken are: reduction of the amount of threads, and using OpenGL directly. The timing of the symbols can also be all set at the beginning of the session, instead of one by one.
2. **The symbol disappears prematurely** in Original if it is not 'hit' for a too long period of time.
3. **Let the EEG markers be 20ms bursts** instead of the continuous signal it is now. That way it matches the standard that can also be detected with EEGlab and other Matlab tools.

### Medium Priority

4. **When the profile names no longer fit within the menu screen, make it scrollable.** Currently, at some point the ¡Quit¿ menu item will just 'fall off' the screen when many profiles exist. At the moment, the solution is to remove profiles that are no longer used when this is about to happen.
5. **Include the goals of each mode explicitly** in the session mode explanations.

### Low Priority

6. **Force the player to do at least one training session** after creating a new profile to ensure that the pipeline is able to detect certain brain actions.
7. **Continue automatically after the training of the classifiers.** At the moment it just waits for a set time, but it can also wait for BCI classification results to come in.

8. **Give the user some time before the start of a session** to switch from keyboard (menu control) to hands on table or knees for brain input?
9. **Use getResource** to extract images and files from the jar file.
10. **Whether the game itself already provides sufficient information** to the user so no external help is required should be evaluated.

## G.2 Features

1. **Random generation of training and game stimuli order** (the fixed order should also remain possible for research purposes).
2. **Random duration for breaks and symbols during training** based on a minimum and maximum value is an option that could be used to avoid the Bereitschaftspotential.
3. **Separate action detection thresholds per class.** One class may give relatively lower values consistently compared to the other classes but this may not be because the subject is not performing the action. Of course it could also be said that this is a normalization responsibility of the classifier and not of the application.
4. **Automatic adjustment of the difficulty of the game**, for example by leaving out symbols that the user or classifier cannot return, lowering the confidence thresholds for hard symbols and perhaps raise the thresholds for easy ones.
5. **The higher the confidence, the higher the score for a correct brain action.** The confidence level would then also be used as an indication of how well the brain action was performed. This indication could then be used to rate the action for example with 'good', 'great', 'marvellous' (like in DDR), and the score could be increased accordingly.
6. **The option to pause a session** could come in handy, especially when sessions will get longer. For the current three-minute sessions, this feature is not really necessary.
7. **Timing and duration can add extra dimensions to brain actions.** Timing is the requirement to perform an action at some specific point in time or during a specific period. Duration is the requirement to perform the action for a specific length of time.

For more details and research ideas, also check out Section6.4 Future Work.

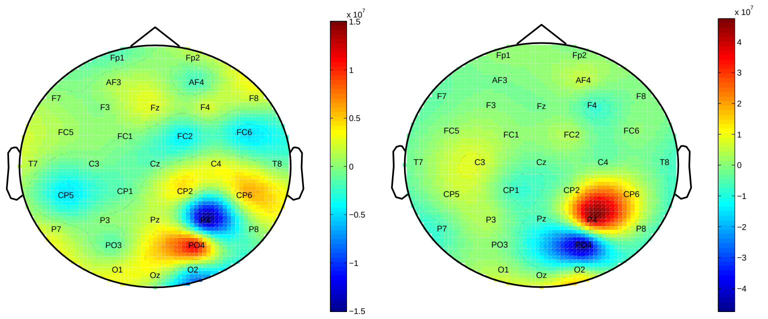
# Appendix H

# Encore

There are some minor issues that have been looked into that did not easily fall into one of the sections of the main part of the thesis. In order not to leave these out completely, they have been added to this appendix.

## H.1 High-scoring Subject 7A

One of the subjects scored especially high both with the Original and Cross versions, with scores of 44 and 59 respectively. When looking at the cross validation error rates, the classifiers are particularly well at discerning the resting class from the movement imagery classes.




**(a)** *LR 7A Crss[59] 44.11%-4.0* **(b)** *LR 7A Orig[44] 45.83%-5.6*

**Figure H.1:** ***Classifier plots subject 7A*** *for the classification of left vs. right MI for the Cross and Original versions of the game.*

The identification of left vs. right MI seems not that easy, with error rates of 44.11% and 45.83% for Cross and Original. Contrary to most of the other plots, the scalp maps to discern left from right MI for this subject are very specific and indicate positions P4 and PO4 clearly as opposing factors. Electrode P4 has been identified as a location that might activate with MI as it helps in the evaluation of both actual and imagined movement.

But what is the purpose of PO4? This electrode is located above the parieto-occipital lobe which is part of the visual cortex. A study with macaque monkeys indicated that the V6 complex, which activity would also be measured around this area, has a function in integrating visual and somatosensory information which is used for controlling trunk and limbs [42]. Based on this information, perhaps this area of the brain gets activated when using a visual movement imagery method.

However, this still does not explain why these activations are opposite. More neurophysiological information about the processes involved in movement imagery could be valuable in understanding our observations, and possibly also in improving the feature selection and extraction steps.

## H.2 Unexperienced and Experienced Gamers

A side question that arose from the experiments is the following: do hardcore gamers have an advantage with the BrainBasher game, or does the novel input method level the playing field? The subjects were divided into two groups: unexperienced gamers who play video games one hour a day or less, and experienced gamers who play three hours daily or even more. This resulted in a nice split of seven subjects versus eight subjects respectively.

In case of the keyboard version, the more experienced subjects showed a trend towards feeling more competent ($t(14) = 1.82$, $p < 0.10$), but also more pressured ($t(14) = 1.80$, $p < 0.10$) than the others. The subjects with less game-experience thought the game was more fun ($t(14) = 2.42$, $p < 0.05$), more impressive ($t(14) = 3.48$, $p < 0.005$), and experienced a higher level of immersion ($t(14) = 2.20$, $p < 0.05$). For Cross, the experienced gamers showed more contentment ($t(14) = 2.56$, $p < 0.05$), less moody ($t(14) = -2.47$, $p < 0.05$), more confident ($t(14) = 1.83$, $p < 0.10$), less tiresome ($t(14) = -2.04$, $p < 0.10$), and a lower negative affect ($t(14) = -4.53$, $p < 0.001$) than the casual gamers. With the original version, the experienced gamers were less aware of their current score than the inexperienced subjects were (t(13)=-4.53, p¡0.001). At the end of the experiment, the casual gamers showed a trend towards feeling more recharged ($t(13) = 1.78$, $p < 0.10$) and proud ($t(13) = 2.01$, $p < 0.10$).

Interestingly, there was no significant difference between the obtained scores in the game modes, even when using the conventional keyboard for input.

## H.3 Male versus Female

As there were about as many male as female participants in the user experience evaluation experiments, we did a quick comparison to see whether there would be any significant differences between these two user groups.

Women felt less competent ($t(14) = 1.82$, $p < 0.1$) and less successful ($t(14) = 1.81$, $p < 0.1$) with the keyboard-controlled version than men, and felt less time pressure ($t(14) = 1.94$, $p < 0.1$). The experience was also more immersive ($t(14) = 1.92$, $p < 0.01$) for the female group.

With the original version controlled by BCI, the female participants indicated to have less understanding of the goal ($t(13) = 2.33$, $p < 0.05$) and what they had to do ($t(13) = 2.55$, $p < 0.05$). On the other hand they experienced a higher sense of immersion ($t(13) = 2.17$, $p < 0.05$), thought it less difficult ($t(13) = 2.36$, $p < 0.05$), and found the whole thing a richer experience ($t(13) = 1.91$, $p < 0.1$) than their male counterparts. Maybe as a result, the women marked less negative affect ($t(13) = 1.83$, $p < 0.1$).

Despite all this, and also the more impressive experience ($t(14) = 1.93$, $p < 0.01$) felt by the female subjects with the Cross version, the men did feel more victorious ($t(13) = 2.03$, $p < 0.1$) and powerful ($t(13) = 1.83$, $p < 0.1$) than the women at the end of the experiments.

The women indicated to feel less competent, less successful, and to have less of an understanding of the goals and what to do. Nonetheless, there were no significant differences between the achieved game scores for the three different versions when comparing male versus female. Apparently this is more a psychological phenomenon. The same could be said for the results showing that the men felt more victorious and powerful afterwards. The female subjects also noted a more immersive and richer experience, which is not so easily explained.

# Summary

The research described in this thesis is a continuation of the research into imaginary movement for game control done by Bussink[3]. Whereas he mainly focused on getting a working system, this research takes it one step further. Two questions derived from a literature survey were addressed: (1) How does controlling a computer game with the brain influence the user experience, compared to conventional input methods like a keyboard? and (2) How does using game elements (e.g. a clear goal, feedback) within a BCI experiment influence the user experience and performance, compared to a clinical design? Chapter 1 provides more information on the motivation for this project, and Chapter 2 describes some existing BCI games both for research and commerce.

In order to find the answer, a simple brain-computer interfacing (BCI) game called BrainBasher has been developed, in tight collaboration with Boris Reuderink, so a user study could be conducted. The application consists of three modes. The training mode provides a very controlled environment in which stimuli symbols for each brain action are shown for a set amount of time, interleaved with rest periods during which the user is allowed to move and blink. This mode is used to obtain relatively clean data to train the classifiers with which will then be able to detect the different brain actions. In this case, the chosen brain actions to control the game were imagined movement of the left hand, and of the right hand. In the game mode, a stimulus symbol is shown to indicate a certain brain action. The user tries to perform this brain action as quickly and correctly as possible. When the system detects the correct brain action the user scores a point, and the next symbol appears. The goal is to get a high score within a set amount of time. Then there is the free play mode, which essentially just shows the symbol of the brain action that is being detected by the system. This allows the user to see and learn how the system reacts to certain actions. The part of the system that analyses the brain activity to detect brain actions is a simple pipeline consisting of a bandpass filter to zoom in on the alpha and beta frequencies, followed by Common Spatial Patterns for feature extraction, and Linear Discriminant Analysis (LDA) to arrive at a classification. More details can be found in the design Chapter 3: BrainBasher.

For the first research question, the user got to play two versions of the game where one was played using a plain old keyboard, and the other using brain actions. After each version, the test subject filled in a game experience questionnaire so the user experience could be evaluated and compared afterwards. For the second question, the subject also had to play a version of the BCI game

with a more clinical look and none of the extra feedback. Again a questionnaire was handed over to record the experience. The keyboard version of the game was so easy that it even got tiresome. The brain-controlled game was more challenging, resulting in a more immersive, richer experience. The clinical BCI version resulted in significantly lower game scores (which unfortunately could also be caused by the slightly shower window sizes). The original game had a more enjoyable design, and was more immersive. It can be concluded that BCI can improve the game experience, and vice versa: game elements may improve the results in a BCI experiment. For more information, refer to Chapter 4 on the User Experience Evaluation.

A short heuristic evaluation has been performed as well, in order to identify potential issues which may need to be addressed before proceeding with any future work. Many of the guidelines provided ideas on how to improve the concentration, immersion, and information provided to the user. It also pointed out some potential issues which will require follow-up research, like optimal visualizations for the stimuli symbols and evaluating the workload. Finally, it indicated some things to consider if certain extensions would be made in the future, like introducing new brain actions gradually, and encouraging social interaction. A list of heuristics and the detailed evaluation can be found in Chapter 5.

Although BCI shows a lot of promise, some issues remain unanswered. What is the influence of using different movement imagery methods (like kinesthetic or visual movement imagery)? Are the differences big enough to limit the user to specific tactics? What is the influence of using BCI on the workload and on user fatigue? For more inspiration, check out the Conclusions and Recommendations in Chapter 6.