Immersion and affect in a brain-computer interface game

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Abstract

As the scope of the brain-computer interface (BCI) applications is extending from medical to recreational use, the expectations of BCIs are also changing. Although the performance of BCIs is still important, finding suitable BCI modalities and investigating their influence on user experience demand more and more attention. As BCIs have widely been used in medical applications, to facilitate making selections, it would be imaginable to apply similar BCIs to recreational applications. However, whether they are suitable for recreational applications is unclear as they have rarely been evaluated for user experience. In this study two BCI selection methods and a comparable non-BCI selection method were integrated into a computer game to evaluate user experience in terms of immersion and affect. The BCI selection methods were based on the P300 and steady-state visually evoked potential (SSVEP) paradigms. An experiment with fourteen participants showed that the SSVEP selection method was capable of enriching the user experience in terms of immersion and affect. Participants were significantly more immersed and the SSVEP selection method was found more positively affective. Although it was expected that P300 would enrich user experience, it did not.

Preface

While being an undergraduate I quickly became aware that it was the reciprocity between different research fields that really appealed to me. On the intersection of research fields you need to find creative solutions to unify them. Although I had never realised that an academic career could be something for me, in my second year I realised you need knowledge before you can share it, and preferably a lot as some people, including myself, never stop asking 'why?'. These realisations led me to adjusting my goals and I decided to pursue a master's degree. In my final year I started looking for a suitable master programme where I could broaden my knowledge of the interaction between human and computer which is why I enrolled myself at the University of Twente for the master Human Media Interaction (HMI).

During my second year at HMI, I followed a course on machine learning where I came in contact with Boris Reuderink, a PhD student researching brain-computer interfaces in the context for games. Since he was appointed as my supervisor for the machine learning course, we had conversations about his research but also about the differences between HMI and my undergraduate education. I became aware that although I had technical skills, I lacked theoretical competencies and experience which are important for an academic career. At that time I also had to choose a direction for my master thesis and I decided to take brain-computer interfaces as my research topic. It offered ways to gain theoretical competencies and experience, while I was still able to use my practical skills.

I started my master thesis together with Michel Obbink and during the first couple of months we went through a lot of theoretical material and developed Mind the Sheep!, the game we used for both our researches. After these months we took of in different directions and continued our researches separately. My research has led to this thesis in which I try to describe the thought processes which I have been going through, the experiments that I have conducted and of course the results I have found.

Part of the research described in this thesis will be presented at the 13th IFIP TC13 Conference on Human-Computer Interaction (INTERACT 2011) that will be held in September 2011 in Lisbon. The paper will also appear in the proceedings of INTERACT 2011 and can be found in Appendix I.

Gido Hakvoort

Enschede, June 16, 2011

Acknowledgements

When I started my master thesis and chose brain-computer interfaces as my research topic, I knew it would not be easy. However, without the help and support of some important people it would have been much more difficult which is why I would like to thank them.

First of all, I owe many thanks to my best friend and brother, Michiel Hakvoort. I know it must have been hard sometimes, listening while I was reciting my thought processes and ideas. But you were always available, listened and gave valuable feedback, support and technical suggestions which aided in the development of Mind the Sheep!.

Of course I like to thank the members of my graduation committee, Mannes Poel, Anton Nijholt, Job Zwiers, Hayrettin Gürkök and Danny Plass-Oude Bos who have supported me during my master thesis. I had regular meetings with three of them and I would like to thank them in particular. Hayrettin Gürkök, I lost count of how many times I dropped by your office, but after each meeting I left with a renewed sense of motivation. If it were for advice, input or just to talk, you always made time. I enjoyed our discussions and I'm grateful for the opportunity to assist in your research. Danny Plass-Oude Bos, your critical questions and remarks have definitely increased the quality of my research and thesis. Beside our meetings we also went to Researchers' Night to give demonstrations. I remember you had a deadline that same day. I still don't know how you pulled off giving the demonstration, participate in social events and at the same time finish the paper before the deadline. I do know you were so dedicated that you wouldn't stop until they turned off the wireless network and kicked us out of the building. Mannes Poel, I'm aware that I sometimes wandered off or wanted to do too much, you made sure that I stayed close the core of my master thesis.

I was also given the opportunity to turn my research into a paper for a conference and I would like to thank Anton Nijholt for giving me the opportunity to present the paper myself.

Furthermore I'd like to thank Michel Obbink, for the discussions on both our works, his cooperation and valuable input. I'm glad we became good friends. Boris Reuderink who inspired me to choose brain-computer interfaces as my research topic and who was available for technical questions, Christian Mühl for his input on the human aspect of brain-computer interfaces and Jorian Blom and Dick Meijer for their input on statistical analysis.

Last but not least, I'd like to thank my friends and family for providing distraction and relaxation in many ways such as playing games, making sushi, playing sports, watching movies or series, day trips and barbecues. Even when things did not go as planned, you kept me going and cheerful.

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Part I

Define

Chapter 1

Introduction

1.1 Background

A brain-computer interface (BCI) can be described as a direct communication link between the brain and the machine. In a BCI system, signals from the brain are analyzed to determine the user's state of mind or intentions. In order to do this, BCIs rely on the presence of distinctive brain-signals which in turn can be translated into actions [38]. BCI systems have been applied for medical use to help disabled users by giving back mobility [13] and breaking the isolation of people with physiological disorders [11, 16].

As successful applications of BCIs make their appearance in the news and commercial BCI input devices become publicly available, BCIs find their way into recreational use. However, as the scope of BCI applications is extending from medical to recreational use, the expectations for BCIs are also changing. Currently they are unable to meet the high performance and accuracy of existing input modalities such as mouse and keyboard, and are therefore unfit as replacement. Instead they should be seen as separate modalities which can be used beside, or in combination with, existing input modalities [26].

1.2 Motivation

A common method to assess BCIs is by expressing their performance in bits per minute, which can be calculated by using the mean classification accuracy and the number of available classes [40]. Although this gives meaningful details on the information transfer rate (ITR) of a BCI, other factors may be just as important when applying BCIs for recreational use. Where increasing the performance and ITR of BCIs has always been an important goal for medical studies, how BCIs are applied as modalities and the influence they have on the user experience becomes more and more important when they are applied for recreational use.

However, whether BCIs are suitable for recreational applications is as yet unclear as BCIs have rarely been evaluated for user experience. They may turn out to be valuable additions for recreational applications such as games which are developed to be challenging and enjoyable. As gamers love working with new technologies, are capable of adapting quickly to a new environment and are used to the concept that games have to be mastered [25], they will be more indulgent towards BCI modalities and the inaccuracy of BCIs can even become a challenging factor.

1.3 Objectives

The purpose of this study is to evaluate two BCIs for user experience in the terms of immersion and affect. As making selections is an important aspect in many applications and BCIs can be used to make selections, two distinct BCI selection methods will be used in this study. Together with a comparable non-BCI selection method they will be integrated into a computer game to determine if they can enhance user experience. The BCI selection methods will be used as a primary control and are based on P300 and SSVEP which will be further explained in Chapter 2.

The selection methods will be used in parallel with, instead of replacing an, existing modality to make the interface more interesting and engaging. The results and setup of the study will be presented in this thesis.

1.4 Research Question

The question that arises is whether a BCI can enrich the user experience in terms of immersion and affect, furthermore, is there a difference between different types of BCIs in terms of immersion and affect.

1.5 Hypotheses

As there are no intermediate actions required while using a BCI, it lets users engage with an environment on a different level. However, this does not mean it enriches the user experience. For this the BCIs need not only to be engaging but also enjoyable, have a nice flow and be user friendly. As SSVEP is found to be annoying, especially at low frequencies [22], it is expected that it will not match these requirements and possibly even deprive user experience. A BCI based on P300 is less pronounced and therefore expected to enhance user experience in terms of immersion and affect.

1.6 Outline

This thesis is divided into three main parts, Define, Research and Report.

Define is the first part and it will set the context of this thesis by providing related work. What are brain-computer interfaces, how can they be used and how are they applied within games. Readers who are familiar with BCIs, SSVEP and P300 can skip Chapter 2. Related work on user experience will be described in Chapter 3 which will provide more information on immersion, affect and flow and how they can be influenced by input modalities.

Research is the second part of the thesis and it will describe the approach used to answer to the research question, the game, the selection methods and the experimental setup in more detail.

Report is the final part and it will start with the results obtained from the experiments. In Chapter 7 the results are discussed to see whether they were expected and what they imply. In the conclusion, Chapter 8, the thesis is summarized, conclusions are drawn and lessons learned are described.

Chapter 2

Brain-Computer Interfaces

2.1 What Are They?

A BCI can be described as a communication link between brain and machine. In a BCI system, signals from the brain are being analyzed to determine the user's state of mind or intentions, which in turn can be translated into actions [38]. A diagram of a BCI system can be seen in Figure 2.1. BCI systems have been applied for medical use to help disabled people by giving back mobility [13] and breaking the isolation of people with physiological disorders [11, 16]. For the signal acquisition there are many different measurement methods such as electroencephalography (EEG), magnetoencephalography (MEG), functional magnetic resonance imaging (fMRI) or near-infrared spectroscopy (NIRS). All of them are non-invasive methods requiring no surgical procedures. Especially in the area of healthy user BCIs research, EEG measurements have become very popular as its relatively cheap and has a high temporal resolution [38].

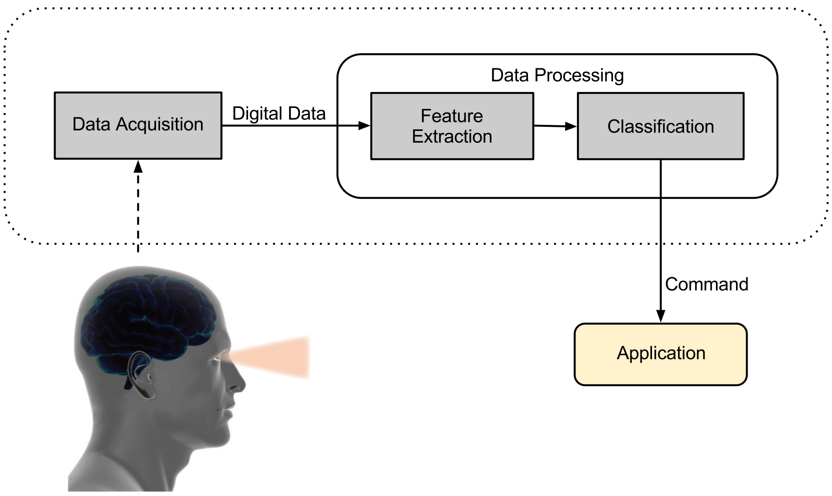


Figure 2.1: Block diagram of a BCI system including acquisition, processing and deployment, based on [36].

To determine a user's state of mind or intentions BCIs rely on the presence of distinctive brain signals. One of the most frequently used brain signals in EEG-based BCI systems are event-related potentials (ERPs) which are responses of the brain that are the direct result of an external or internal event. These ERP usually occur when the brain is exposed to any kind of visual, somatosensory or aural stimulus, mental activity, or when omitting a stimulus that was repeatedly occurring. Two brain signals, which have both been used in medical applications to facilitate making selections, are P300 and SSVEP.

2.2 BCIs for Selections

2.2.1 P300

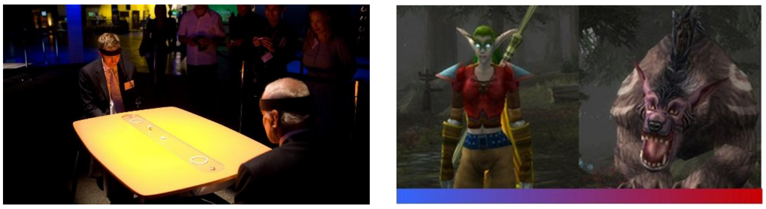
One of the most used ERPs is the P300 which can be triggered by rarely occurring, or significant stimuli. The P300 response appears roughly 300 ms after stimulus presentation as a positive peak in the user's brain signals. Although the P300 can be measured throughout the brain, it is most profound at the parietal region of the scalp [16]. The unpredictability of the stimulus has a strong effect on the P300 and the oddball paradigm is frequently used to increase its amplitude. By mixing low probability targets with high probability non-targets, the unpredictability of a target increases, thereby increasing the P300 amplitude [2]. By determining the difference between target and non-target stimulation responses, P300 can be used to make selections. This functionality is used in the P300 speller applications [11].

2.2.2 Steady-state Visually Evoked Potential

Another member of the ERP family is steady-state visually evoked potential (SSVEP) [2]. In most cases SSVEPs are triggered by presenting a modulated visual stimulus with a periodic signal, usually at frequencies above 5 Hz, to a user. The periodic signal of the stimulus can then be traced back in the measured brain signals which are mostly recorded from the occipital region of the scalp [35]. The power of an SSVEP only covers a narrow bandwidth matching that of the stimulus [21]. This makes them relatively easy to detect, which is why the BCI selection method used in this study was based on SSVEP.

2.3 BCIs in Games

A study by Reuderink [32] summarizes BCI games that were present at that time. Based on the used BCI paradigms, the BCI games were divided into three groups, feedback games, ERP games and imagined movement games. Most feedback games apply the concept of relaxation as modality, where the player's state of relaxation influences the game. Two examples are Brainball [15], where a steel ball moves away from the most relaxed player, Figure 2.2(a), and AlphaWoW [30] where the player's stress level controls the shape of an in-game avatar, see Figure 2.2(b). Although AlphaWoW did not yet exist during Reuderink's summary it is mentioned here as the BCI is applied in a multi modal setting instead of replacing an existing modality like mouse or keyboard.



(a) (b)

Figure 2.2: Jay Lauf and Buzz Aldring playing Brainball[2](a). In-game avatar changes based on player's stress level in AlphaWoW (b).

The ERP games apply the concept of brain responses that are the direct result to a stimuli. Two of these responses are P300 and SSVEP which are described in Section 2.2. An example using P300 is a study by Bayliss [1] where participants could interact with a number of objects (e.g. a lamp, a television set) and turn them on or off. The P300 responses were used to determine with which object a participant wished to interact and an action was performed accordingly (e.g. turning on the television set). The SSVEP paradigm is often applied as selection method, for example in the game MindBalance [18], see Figure 2.3(a). Participants had to balance an avatar on a cord by focusing on one of two checkerboards which flickered at different frequencies (to elicit a SSVEP). Another example where SSVEP is applied, is Bacteria Hunt [23], where players had to control an amoeba and hunt down as many bacteria as possible, see Figure 2.3(b). Although Bacteria Hunt does not appear in Reuderink's summary (as it was developed later), it is worth mentioning as it is a multi modal, multi paradigm BCI game. Players steer the amoeba with a keyboard and as they become more stressed, steering the amoeba becomes more difficult. At the same time, eating bacteria is done by focusing on a SSVEP stimulus.

(a) (b)

Figure 2.3: A screenshot of MindBalance (a). Subject playing Bacteria Hunt (b).

The last group defined by Reuderink use the concept of motor activity. In case movement is imagined or performed, distinct brain signals are generated and can in turn be detected. A major advantage of BCI system relying on motor

[2]Picture by Dave Bullock (http://eecue.com)

activity it that they do not depend on stimuli presentation and can therefore be controlled solely from the brain. An example is a virtual meeting room in which users could explore the room by imagining left or right hand movements thereby rotating the view.

Most of the games reported in Reuderink's summary replace an existing input modalitiy (e.g. mouse or keyboard) with a BCI and were evaluated in terms of bits per minute. Although this gives meaningful details on the ITR of a BCI applied in a specific context, other factors such as immersion, flow and affect may be important when applying BCIs in games.

Chapter 3

Experiencing Games

While for gamers the definition of game experience seem to be common knowledge, game studies try to analyze and conceptualize the many aspects described by gamers. Three well known concepts are immersion, affect and flow which are described in this chapter. Although flow is mentioned in other studies as an aspect of user experience, the focus of this study is on immersion and affect. Why flow was left out will be explained in this chapter.

3.1 Immersion

The concept of immersion appears in different contexts. Someone who is reading a book can be immersed, just as someone who is watching a movie or playing a game. Whether the term is used consistently in these contexts is unclear. However, for playing games there seems to be a shared concept of immersion among gamers [5]. Immersion in games is often accompanied by high levels of concentration, losing track of time and empathy.

In a study by Brown *et al.* [5] an attempt was made to define immersion within games. In their study they examined the concept of immersion experienced by gamers. Their results indicate that immersion is not just a static experience, but has different levels of involvement. They defined three levels of involvement: engagement, engrossment and total immersion. They also state that to reach a certain level of immersion a number of barriers must be crossed. An illustration of the levels and their barriers is shown in Figure 3.1.

To reach the first level of involvement (i.e. engagement), there are two barriers that need to be crossed. The first one, access, refers to the players' preferences, the game controls and the game feedback. If a player does not like the style of a game, or when the game controls or feedback are not appropriate it will be hard for a player to become engaged. The second barrier is investment, indicating that a player needs to invest time, effort and attention. With these two barriers crossed, the player can start to feel engaged and wants to keep playing. When a game is well constructed (e.g. it has attractive visuals, interesting challenges, a good plot), it can have a direct effect on players' emotions, who thereby advance to the next level of involvement (i.e. engrossment). At this point players are less aware of their surroundings and their self-awareness has been decreased. If the game construction is also relevant to in-game actions

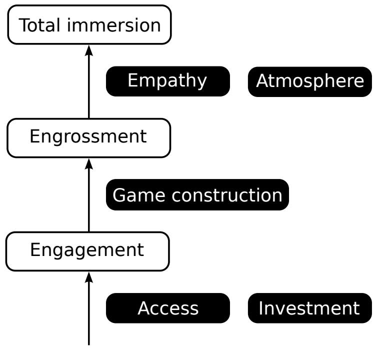


Figure 3.1: Levels of involvement with their barriers as defined by Brown *et al.* [5].

and location, this gives players the opportunity to become fully immersed as they need to invest more attention to the created atmosphere. Besides atmosphere the last barrier which needs to be crossed to reach the final level, total immersion, is empathy. Although it is not necessary for players to empathise with the in-game situation, they can feel attached to in-game characters.

Some of the aforementioned barriers are related to human characteristics, such as personal preferences, empathy and the will to invest time and attention. Others are related to the construction of the game such as the graphics, a plot and atmosphere. However, to reach a state of total immersion an important barrier to take is related to the controls. Through them gamers translate their intentions into in-game actions [28] and controls should become virtually invisible to the gamer. As intentions originate from the brain, users first need to translate their intentions into real world actions to handle the controls. Even if these real world actions become virtually invisible for the user, they still need to be performed. Using a BCI to detect intentions may allow them to be translated directly into in-game actions, making the real world actions redundant.

In a study by Jennett *et al.* [17] immersion in games was further investigated. They identified five factors of immersion: cognitive involvement, real world dissociation, emotional involvement, challenge and control. They also developed a questionnaire to measure the total immersion and its factors. As in the study of Brown *et al.*, some factors were related to human characteristics (cognitive involvement, real world dissociation and emotional involvement) and others were related to the construction of the game (challenge and control).

3.2 Affect

Affect can be referred to as experiencing emotions and has some overlap with immersion [17]. It has a large impact on how well users are able to perform tasks and how they respond to possible usability problems. According to Norman [27], a more positive affect causes users to be more indulgent towards minor usability problems. Although there are many dimensions associated with affect, according to Picard [29] the three most commonly used dimensions of emotion are valence, arousal and dominance. Picard also states that the valence and arousal dimensions are critical in recreational applications.

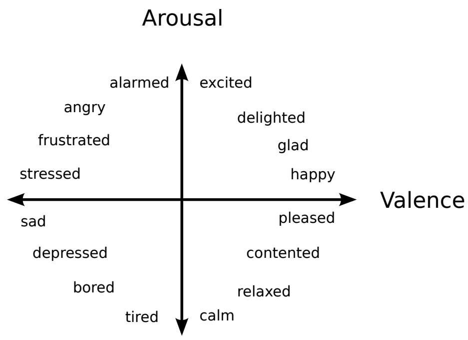


Figure 3.2: Emotions in the valance and arousal space

Bradley *et al.* [4] developed a questionnaire, the self-assessment manikin (SAM), to measure emotional responses in these three dimensions. In Fig. 3.2 some emotions associated with valence and arousal can be seen. Integrating the selection methods into an enjoyable, challenging and task oriented environment, such as a game, should result in a more positive affect in terms of valence and arousal which will aid users to overcome the inaccuracy of the selection methods.

3.3 Flow

Flow is a concept with which many gamers are all too familiar with and it can be described as a state of consciousness in which users achieve a dynamic balance between challenge and skills [6]. The concept of flow is applicable to various fields and Csikszentmihalyi did extensive research on the topic of flow, which according to him could lead towards an optimal experience. In his studies he found that flow was often associated with one or more of the following eight components, high levels of concentration, losing track of time, merging action and awareness, loss of self-consciousness, direct feedback, balance between challenge and skills, sense of control and clear goals [9].

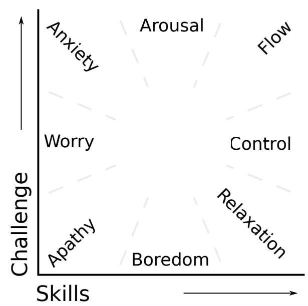


Figure 3.3: Flow as a dynamic balance between challenge and skills [9].

The balance between challenge and skill is important for flow, as a deflection towards challenge results in anxiety and too little of both can result in boredom (Figure 3.3) which will disrupt the optimal experience [6].

Some of the components defined by Csikszentmihalyi seem to have a direct connection with immersion (e.g. high levels of concentration and losing track of time) and indeed, flow can be seen as a successor of immersion [17]. However, there are some differences as flow is a process leading towards an optimal experience, whereas immersion consists of different levels of involvement between which users can switch [5]. Furthermore, immersion does not necessarily leads towards an optimal experience, it does not even need to be enjoyable. As the purpose of this study is to evaluate BCIs for their user experience, which can be negative or positive, flow was not included in this study and the focus was on immersion and affect.

3.4 Game Experience and BCIs

The aforementioned concepts have been the subject of various game studies, aiming for a more thorough understanding of how the concepts are related to user experience and to find a consensus on the terminology. In a study by Nacke *et al.* [24] the user experience of a game was evaluated in terms of flow and immersion using questionnaires and an electromyography (EMG). They found that physiological responses can be used as indicators for the user's state of mind. In a later study by Reuderink [33] *et al.* participants were subjected to short periods of frustration to determine whether the user's state of mind had an effect on EEG signals. Preliminary analysis of their experiment indicate that features used for classification could be affected by the user's state of mind. These studies support the hypothesis that the user's state of mind has an influence on physiological measurements and thereby on BCIs. However, studies on the opposite, whether BCIs have an influence on the user's state of mind, are scarce.

In the few studies that are available, BCIs were used to replace an existing input modality (e.g. mouse or keyboard). In a study by Friedman *et al.* [12] users were able to navigate through a virtual environment by using imaginary movement. The goal of Friedman's study was to demonstrate that a BCI can be used for virtual navigation and to investigate the influence of a BCI on user experience in terms of presence. Although they have shown that a BCI can be used for virtual navigation, they suggested that more research, concentrating on the user experience instead of the performance, is needed. The effects of actual or imagined movements on the user experience has been investigated in a study by van de Laar *et al.* [37]. They found that imagined movements where found to be more challenging, however the signal was less reliable. More research is needed and concepts from game studies, such as immersion and affect, should also be included which is why this study could contribute to a more thorough understanding of how immersion and affect are related to user experience within a BCI system.

Part II

Research

Chapter 4

Method

4.1 Approach

To determine whether BCI selection methods can enrich the user experience, two BCI selection methods were assessed in terms of immersion and affect using standard questionnaires. The results were compared against a non-BCI selection method. All selection methods needed to be alike and comparable. As the selection methods were compared based on their user experience a measurable level of enjoyment was needed in the environment. Since games are developed for being both challenging and enjoyable a simple game would be a perfect ground for the environment. Gamers love working with new technologies, are capable of adapting quickly to a new environment and are used to the concept that games have to be mastered [25]. Therefore a simple game was developed to give the players an enjoyable challenge in which the BCI and non-BCI selection method can be integrated.

4.2 The Game: Mind the Sheep!

Mind the Sheep! consists of a playground representing a meadow on which a few obstacles, such as fences, gates or trees, are placed. There are three dogs in the playground which are controlled by the player. Depending on the objectives of a specific level, the playground can be populated with a number of sheep or collectibles. A screenshot of the game can be seen in Fig. 4.1 with ten white sheep and three black dogs. The goal of the game is to gather all sheep into a pen or gather all collectibles as quickly as possible using the three dogs. Players can use one of the selection methods to select one of the three dogs.

To move a dog, players point at any location on the playground with the mouse and start the current selection method by pressing the left mouse button. As long as they hold down the mouse button the selection method continues to be operative thereby increasing the accuracy of the selection method. Releasing the mouse button stops the selection method and one of the dogs is moved to the location indicated by the player. When players indicate a position unreachable for the dog, the instruction is ignored. As the accuracy of the selection methods increase over time, there is a trade-off between accuracy and speed. It also requires users to multi-task as they need to concentrate on a dog and keep an

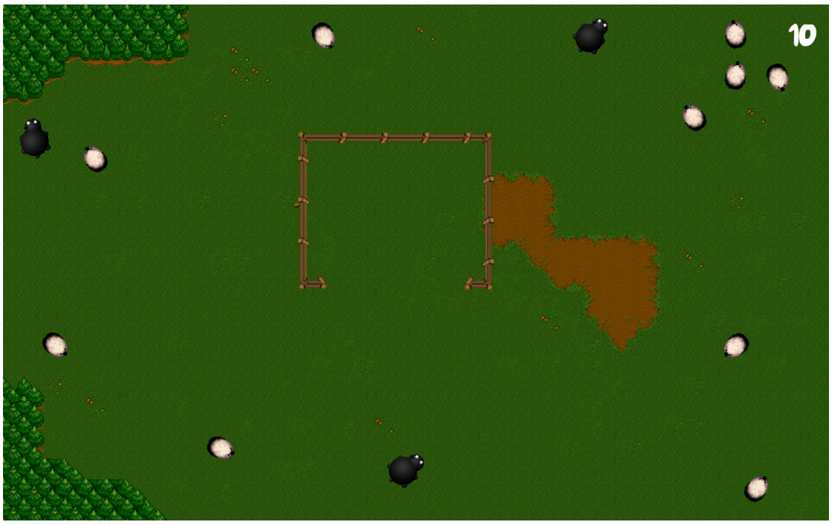


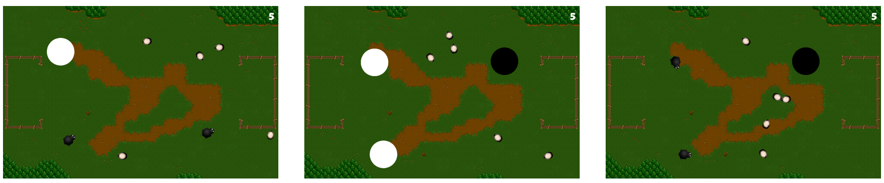
Figure 4.1: Screenshot of Mind the Sheep! with three black dogs and ten white sheep. The pen is located in the center.

eye on the sheep at the same time.

The dogs use a simple A* search based path finding algorithm to move to a specific location on the map. By default, sheep will walk around and graze randomly. However, when a dog approaches, they will tend to flock and move away from the dog allowing them to be herded in a desired direction. The flocking behavior is introduced by using the boids algorithm [34]. By positioning the dogs at strategic locations on the map a flock of sheep can be directed into the pen.

4.3 Selection Methods

The BCI and non-BCI selection methods were integrated into Mind the Sheep!. However, as players would not want to continuously make selections, they were able to start and stop the selection methods thereby controlling the presence of the stimuli for the BCI selection methods. An illustration of the selection methods when active can be seen in Figure 4.2.



(a) (b) (c)

Figure 4.2: Screenshot of the selection methods when active, with P300, SSVEP and non-BCI selection in (a), (b) and (c) respectively.

4.3.1 P300 selection

To extend Mind the Sheep! with a selection method based on P300, dogs were highlighted for 100 ms with circles in a random order (to elicit a P300 response) while the selection method was operational. As long as a player held the mouse button pressed, EEG data was collected. When the mouse button was released, the collected data was analysed and a selection was made. As players were able to select one out of three dogs, the target stimulus would occur with a probability of $0.\overline{3}$. As higher target probabilities result in lower P300 amplitudes [10], three invisible targets were added to ensure a target probability of $0.1\overline{6}$, equal to the speller application used in work of Hoffmann *et al.* [16].

For the P300 selection method some parameters needed to be determined, such as the inter-stimulus interval (ISI), the size of the stimuli and the classifier. In a study conducted by Farwell *et al.* [11], two different ISIs (125 ms and 500 ms) and four classifiers (covariance, SWDA, peak picking and area measurement) were compared. As multiple target stimulations result in higher classification accuracies and a shorter ISI did not interfere with eliciting a P300 response, an ISI of 100 ms was used. The classifiers based on covariance and stepwise linear discriminant analysis (SWDA) require training and the classifiers based on peak picking is less accurate with a shorter ISI, which is why area measurement was used to detect P300 responses. To be consistent with the other selection methods the size of the P300 stimuli was set to 3 centimeters.

4.3.2 SSVEP selection

For the SSVEP-based BCI selection method, dogs were replaced with circles flickering at different frequencies while the selection method was operational. EEG data was collected as long as the player held the mouse button pressed. Upon releasing the mouse button, the collected data was analysed and a selection was made.

For the SSVEP selection method some parameters needed to be determined, such as the frequencies to use, the size of the stimuli and the classifier. For this a small pre-experiment study with 7 participants was conducted. A complete overview of the setup and results of the pre-experiment study can be found in Appendix B.

Based on the results of the pre-experiment study a canonical correlation analysis (CCA) based classifier was selected as its overall performance was better, had lower inter-subject variability and a better signal-to-noise ratio (SNR). For the frequency set, 7.5 Hz, 8.57 Hz and 12 Hz had the best performance. However, participants noticed differences in stimulus frequencies which could lead to a preference towards one of the three dogs based on its classification accuracy. Therefore, a frequency set with higher frequencies was chosen, namely 10 Hz, 12 Hz and 15 Hz, making it harder to distinguish them. Based on the pre-experiment study the size of the stimuli was set to 3 centimeters.

4.3.3 Non-BCI selection

The BCI selection method introduces a challenge factor when a selection is being made as users need to concentrate on a stimulus to make an accurate selection. The main challenge is to gather enough data to be able to make a good detection, which is directly related to the time the selection method is operative. Although it would be much easier for users to make a selection by pointing and clicking with a mouse, this would offer little challenge and give the non-BCI selection method a great advantage when compared with the BCI selection method. To pose a similar challenge in the non-BCI selection method, it was modelled to be similar to the BCI selection method in terms of the time required for an accurate selection.

Similar to the BCI selection method users were able to start and stop the non-BCI selection method. When operative, the dogs were highlighted one at a time with an increasing highlight period. The diameter of the stimuli was kept the same as in the BCI selection method, 3 centimeters. When users stopped the selection method, the current highlighted dog was selected.

To make an accurate selection, users had to react in time when the dog they wanted to select was highlighted. With a highlight period of 250 ms users should have enough time to react as this is close to the average human reaction time [19]. The highlight period should reach 250 ms only by the time that is equal to the time needed to make a selection using the BCI selection method, which is around 2.5 seconds [20]. Therefore, the highlight period started with 100 ms and was increased with 5% after every highlight, with a maximum highlight period of 500 ms.

4.4 Questionnaires

To measure the affective reaction of players while playing the game, a SAM [4] was used as to measure emotional responses in three dimensions (i.e. valence, arousal and dominance). It was expected that if players became more frustrated by using a selection method, this would result in higher arousal and lower valence scores. The dominance would also be higher if players had the feeling that a selection method was working properly and that they were in control.

The questionnaire by Jennett *et al.* [17] was used to measure players' immersion. It contains 31 questions and is designed to measure the total immersion as well as five different factors of immersion (cognitive involvement, emotional involvement, real world dissociation, challenge and control). Although valence, arousal and dominance scores would probably differ between selection methods for which players have an aversion, this does not necessarily mean players would not become immersed in the game.

Furthermore some game statistics, such as the number of selections, the duration of the selections and the time needed to finish the game were collected while they played the game. Ideally players would use all the dogs as this would make it easier to gather the sheep. The number of times a particular dog was selected and the time needed to finish the game would be good indications of how well a selection method performed for a player.

4.5 Analysis

After the experiments, scores were obtained for the total immersion, the five immersion factors, the SAM questionnaire and the game statistics. The results from the SAM questionnaire were averaged over the three trials to get an average score for the valence, arousal and dominance scales. The number of selections were normalised to the game duration as to get the number of selections per minute and were averaged over the three trials. The game duration was normalised to the time limit per trial and was averaged over the three trials.

The averaged results were examined on evident differences. As each participant used all three selection methods and normally distributed samples could neither be assumed nor proved, the Friedman test was used to determine if there were significant differences ($p < 0.05$) in immersion, affect or game statistics depending on the selection method. In case Friedman's test indicated a significant difference, post-hoc analysis with the Wilcoxon signed-rank tests was conducted on the different combinations of selection methods to examine where the differences occurred. For the post-hoc analysis no alpha correction was applied as it was conducted only to examine where the differences occurred in case Friedman's test indicated a significant difference.

Due to differences in the designs of the statistical tests it is possible that the conclusions of Friedman's test and the post-hoc analysis lead to a contradiction. Should this be the case, all results will be given and a possible explanation of the significant difference will be given in the discussion (Chapter 7).

To determine the relationship between immersion and affect, the Pearson product-moment correlation coefficient (PMCC) was obtained for total immersion and the valence, arousal and dominance scales.

Chapter 5

Experiment

5.1 Participants

Fourteen participants (6 female and 8 male), aged between 17 and 25 ($\mu = 21.14, \sigma = 2.88$) participated in the experiment. All participants except for one had normal or corrected-to-normal vision and described themselves as daily computer users. Although eight participants had at least one-time experience with EEG, eleven participants had no experience with BCIs. Before the experiment, all participants signed an informed consent form and they were paid according to institution's regulations.

5.2 Procedure

Prior to the experiment participants were given a small questionnaire to obtain demographic information and they had to sign an informed consent form. They read the instructions on how to play the game and the setup of the experiment was explained. The experiment held in this study consisted of three different sessions. In each session a participant used one of the selection methods (i.e. P300, SSVEP or non-BCI) while playing Mind the Sheep!. Each participant used all three selection methods. However, a counterbalanced measures design was used to avoid confounding variables such as learning a strategy to play the game.

Each session was divided into three trials, a familiarity trial, an easy trial and a difficult trial. In the familiarity trial participants could get used to the selection method by selecting and moving the dogs. During this trial, participants had to collect 10 objects which were placed across the playground. Next, in the easy trial, participants had to pen a small flock of 5 sheep using the dogs. During this trial two pens were placed on the playground, one on the left and one on the right of the screen to make the task easier for the participants. Finally, in the difficult trial, participants had to gather 10 sheep, which were more scattered across the playground, into one pen that was placed in the center of the playground. After each trial participants were requested to fill in the SAM questionnaire. At the end of a session participants filled in the questionnaire on immersion and were given a break of five minutes. A detailed overview of the experiment's procedure can be found in Appendix C.

The layout of the playgrounds across the trials was kept the same to ensure no playground was more difficult for one of the selection methods. However to ensure that participants did not create an optimal strategy for a specific trial, the positions of the dogs, collectible objects and sheep were altered for the different selection methods. To ensure that the experiment would take too long, a timeout was set for each trial for the participants to finish the level by collecting all objects or gathering all sheep into a pen. Participants had 3 minutes, 5 minutes and 10 minutes for the familiarity, easy and difficult trials respectively. Since immersion in games is often accompanied by losing track of time, the time left was not visible for the participants. Otherwise it could have influenced their perception of the elapsed time.

The game ran on a PC and was connected to a projector[1] which was used to create a more enjoyable environment. The projector was mounted on the ceiling and projected the game on a screen approximately 3 meters away from a participant. The sizes of the stimuli were scaled proportionally with the increased distance to the screen. To make sure the frequencies for the SSVEP based BCI selection method were correctly presented by the projector they were validated with a light sensor. Participants sat on a chair behind a table and by using the mouse, which was placed on the table, they were able to start and stop the selection methods. The data acquisition ran on a separate PC and sent the raw EEG data to the game PC. An impression of the setup can be seen in Figure 5.1.

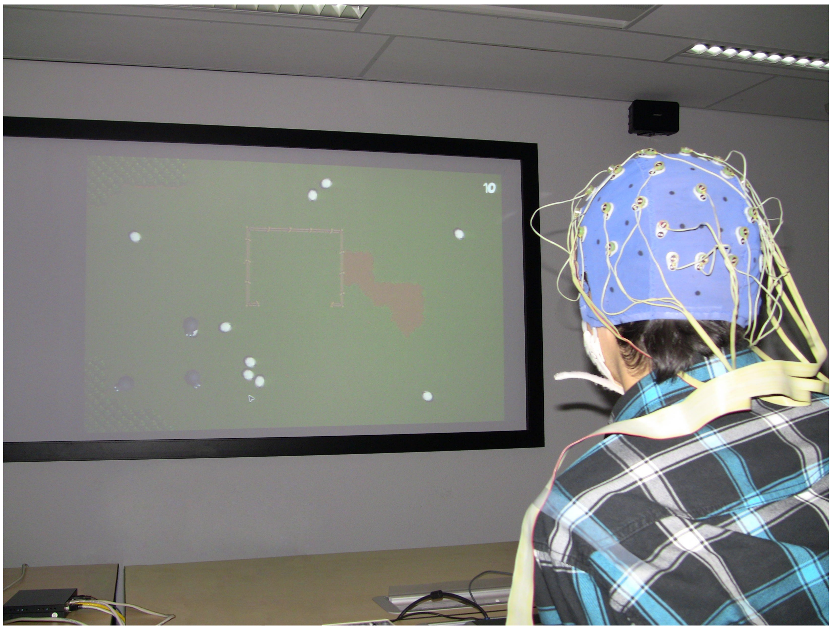


Figure 5.1: Participant playing Mind the Sheep!

[1]Mitsubishi WD510U, 93.3", 60Hz, 1360x768

5.3 Detecting BCI Selections

To make selections using a BCI selection method, EEG data needs to be recorded and analysed. For this 32 electrodes were placed according to the international 10-20 system [31] prior to the experiment. For the EEG data acquisition a BioSemi ActiveTwo system[2] was used. The electrodes and analysis which are used are different for each BCI selection method.

5.3.1 P300

During each P300 selection EEG data was used from the electrode located at *Pz*. Before the data was classified a number of preprocessing operations were applied to the data based on work of Hoffmann *et al* [16].

First the EEG data was re-referenced to the common average reference (CAR) [8] of all 32 electrodes after which the data was filtered with a 2nd order forward-backward Butterworth band-pass with high-pass and low-pass frequencies set to 1.0 Hz and 12.0 Hz, respectively. For each target single trails were extracted, after which the trials were averaged. Trials started at the onset (i.e. at the beginning of the intensification of the stimulus) and ended 1000 ms after the stimulus appeared. To reduce the effect of outliers in the data, caused by eye movement, eye blinks or muscle activity, a 80% Winsorisation was applied to the data where all samples below the 10th percentile were replaced by the 10th percentile and all sample above the 90th percentile were replaced by the 90th percentile. Finally the samples where scaled linearly to an interval of $[-1, 1]$.

For the classification the area measurement based on work of Farwell *et al* [11] was used, which summarizes the area under the P300 curve within a certain window. The window for the P300 ranged from 220 to 500 ms. The target with the largest area was classified as the target a player was focusing on.

5.3.2 Steady-state Visually Evoked Potential

During each SSVEP selection EEG data was used from eight parietal-occipital electrodes (i.e. *Pz, P3, P4, PO3, PO4, Oz, O1, O2*). The EEG data was re-referenced to the CAR of all 32 electrodes, after which the CCA based detection method was used to determine which frequency the participant was focusing on.

Using CCA is a relatively new approach where sets of reference signals are constructed for each one of the stimulation frequencies. Each set contains the *sine* and *cosine* for the first, second and third harmonic of the stimulation frequency. The re-referenced EEG data and each set with reference signals are used as input for the CCA. CCA tries to find pairs of linear transformations for the two sets such that when the transformations are applied the resulting sets have a maximal correlation. The stimulation frequency with the highest maximum correlation is classified as the frequency the participant was focusing on.

[2]BioSemi, Amsterdam, The Netherlands

Part III

Report

Chapter 6

Results

When the 14 participants were asked which selection method they would choose if they were given the opportunity to play the game again, 2 of them chose the non-BCI selection method, 2 of them chose the P300 selection method and 10 of them chose the SSVEP selection method. This is a first indication that participants preferred the SSVEP selection method over the non-BCI and P300 selection methods. The scores for immersion, the SAM questionnaire and the game statistics are described below and will provide a more detailed insight.

6.1 Immersion

Based on the immersion questionnaire the total immersion scores of each session were calculated for the three selection methods. The five immersion factors were also analyzed and all scores, averaged over participants, are shown in Table 6.1.

	P300	SSVEP	non-BCI
Total*	153.50 (19.35)	160.86 (15.00)	143.29 (23.85)
Cognitive†	55.00 (7.69)	58.43 (5.35)	52.36 (9.75)
Dissociation†	26.93 (5.65)	28.36 (5.12)	25.00 (5.74)
Emotional*	59.64 (9.38)	59.86 (6.26)	54.29 (9.19)
Challenge	20.86 (2.85)	20.71 (2.40)	20.86 (3.03)
Control	34.71 (6.17)	37.86 (5.02)	32.57 (6.16)

Table 6.1: Scores of the five immersion factors and total immersion, averaged over participants. Values are represented as $\mu(\sigma)$ with highest values marked grey. A significant difference ($p < 0.05$) or trend ($p < 0.10$) depending on the used selection method is indicated with * or † respectively.

On average the participants rated the SSVEP session higher in terms of total immersion and there was a significant difference depending on the used selection method ($Z = 6.145, p = 0.046$). Post-hoc analysis indicated no significant differences between the P300 and non-BCI sessions ($Z = -0.910, p = 0.363$) or between the SSVEP and non-BCI sessions ($Z = -1.915, p = 0.056$) despite an overall increase in total immersion in the SSVEP vs. non-BCI sessions.

However, there was a significant increase in total immersion in the P300 vs. SSVEP sessions ($Z = -2.064, p = 0.039$).

The five immersion factors show the same tendency as the total immersion. All immersion factors, except the challenge factor, are rated higher in the SSVEP session. For the emotional involvement factor there was a significant difference depending on the used selection method ($Z = 6.143, p = 0.046$). However, post-hoc analysis could not indicate what caused this significant difference. There was no significant difference in the P300 vs. non-BCI sessions ($Z = -1.635, p = 0.102$), nor in the SSVEP vs. non-BCI sessions ($Z = -1.696, p = 0.090$). There was also no significant difference between the P300 and SSVEP sessions ($Z = -0.409, p = 0.683$).

For the cognitive involvement factor a trend was visible depending on the used selection method ($Z = 5.880, p = 0.053$). Post-hoc analysis revealed a trend between the SSVEP and non-BCI sessions ($Z = -2.122, p = 0.034$) and between the P300 and SSVEP sessions ($Z = -2.081, p = 0.037$). There was no trend between the P300 and non-BCI sessions ($Z = -0.6299, p = 0.5287$).

The used selection method also had an effect on the real world dissociation factor as a trend was visible ($Z = 5.698, p = 0.058$). Post-hoc analysis did not reveal a trend between the P300 and non-BCI sessions ($Z = -0.770, p = 0.441$) or between the P300 and SSVEP sessions ($Z = -1.258, p = 0.209$). However, there was a trend between the SSVEP and non-BCI sessions ($Z = -1.926, p = 0.054$).

Using a different selection method had no significant effect on the challenge ($Z = 0.157, p = 0.925$) and control ($Z = 3.569, p = 0.168$) factors.

6.2 Affect

Based on the SAM questionnaire the total SAM scores were calculated for the selection methods and the average results are shown in Table 6.2.

	P300	SSVEP	non-BCI
Valence	6.14 (1.32)	7.00 (1.38)	6.26 (1.64)
Arousal	4.52 (2.24)	4.40 (2.38)	4.79 (2.40)
Dominance	4.93 (1.60)	6.02 (1.69)	5.64 (2.55)

Table 6.2: Average SAM scores, the values are represented as $\mu(\sigma)$ with highest values marked grey.

Despite an overall increase in valence in the SSVEP session compared to the P300 or non-BCI sessions, there was no significant difference depending on the used selection method for the valence scale ($Z = 2.625, p = 0.269$). Participants were more aroused in the non-BCI session, however, for the arousal scale there was no significant difference depending on the used selection method ($Z = 0.311, p = 0.856$). There was an overall increase in dominance in the P300 vs. SSVEP sessions, however, no significant difference depending on the used selection method was found ($Z = 3.309, p = 0.191$).

6.3 Game Statistics

Most participants were able to finish the familiarity and easy trials, regardless the selection method, within the given time limit. However, of the 14 participants only 5 were able to finish the difficult trial while using the P300 selection method. Whereas for the SSVEP and non-BCI selection methods respectively 13 and 11 participants finished the difficult trial.

The game statistics which were collected during the experiments are shown in Table 6.3, showing the average number of selections per minute, the average selection duration (in seconds) and the normalised game duration.

	P300	SSVEP	non-BCI
Selections*	8.42 (2.84)	11.54 (3.13)	15.48 (14.32)
Selection duration*	3.94 (2.02)	2.15 (1.97)	1.85 (1.12)
Game duration*	0.78 (0.25)	0.50 (0.22)	0.55 (0.27)

Table 6.3: Average number of selections per minute, average selection duration (in seconds) and normalised game duration. All presented as $\mu(\sigma)$ with highest values marked grey. A significant difference ($p < 0.05$) depending on the used selection method is indicated by *.

On average the number of selections per minute was higher in the non-BCI session and there was a significant difference depending on the used selection method ($Z = 14.714, p = 0.0006$). Post-hoc analysis indicated no significant differences between the SSVEP and non-BCI sessions ($Z = -1.726, p = 0.084$). However, there was a significant increase in selections per minute in the P300 vs. non-BCI sessions ($Z = -3.296, p = 0.001$) and the P300 vs. SSVEP sessions ($Z = -2.417, p = 0.016$).

Compared to the SSVEP and non-BCI sessions the average selection duration is much higher for the P300 session. There was a significant difference depending on the used selection method for the average selection duration ($Z = 16.000, p = 0.0003$). Post-hoc analysis revealed a significant difference between the P300 and non-BCI session ($Z = -3.296, p = 0.001$) and between the P300 and SSVEP session ($Z = -2.542, p = 0.01$). However, there was no significant difference in the SSVEP vs. non-BCI sessions ($Z = -0.785, p = 0.433$).

The game duration shows how much of the available time participants needed to finish a trial, where a score of 1.0 indicates that participants needed all available time to finish a trial. On average the game duration was higher in the P300 session and there was a significant difference in game duration depending on the used selection method ($Z = 18.429, p = 0.0001$). Post-hoc analysis revealed a significant difference between the P300 and non-BCI sessions ($Z = -3.296, p = 0.001$) and between the P300 and SSVEP sessions ($Z = -3.233, p = 0.001$). There was no significant difference between the SSVEP and non-BCI sessions ($Z = -1.350, p = 0.177$).

Chapter 7

Discussion

7.1 Immersion

It was expected that only P300 would enrich the user experience since SSVEP is generally considered as annoying. However, for the immersion it seems the contrary is true. Most participants indicated that they preferred playing the game with the SSVEP selection method, which seems to be supported by the results of the immersion questionnaire. There was a significant increase in total immersion between the P300 and SSVEP sessions. This indicates that participants were more immersed using the SSVEP selection method than when using the P300 selection method. Furthermore, there was an overall increase in total immersion between the SSVEP and non-BCI sessions. Although this was not significant it can be seen as a trend, indicating that the SSVEP selection method could enrich the user experience in terms of immersion.

For the P300 and SSVEP selection methods no physical actions were required, whereas for the non-BCI selection method, participants still had to translate their intentions into an physical action (i.e. stopping the selection method at the correct time). However, for the P300 selection method, participants still had to perform a mental action (i.e. count how often a dog was highlighted). This could have interfered with participants becoming fully immersed while using the P300 selection method. For the SSVEP selection method participants only had to stare at the dog they wished to select. As participants were able to translate their intentions directly, without requiring any type of actions, into in-game actions while using the SSVEP selection method, they might have become more easily immersed.

Further inspection showed an overall increase for the SSVEP session compared to the P300 or non-BCI sessions in four of the five immersion factors. The average scores for the challenge factor are virtually identical for the three sessions, indicating that participants did not find the game more challenging using one of the three selection methods. The used selection method had no significant effect on the challenge factor. To determine if participants experienced difficulties while using one of the selection methods, the control factor might be a better indicator than the challenge factor. Despite an overall reduction in the control factor for the P300 and non-BCI sessions compared to the SSVEP session, it was not significant. This would indicate that participants did not experience more (or less) difficulties while using one of the selection methods. However, as there is no ground truth for the accuracy of the selection methods and an overall reduction was observed in the control factor for the P300 and non-BCI sessions compared to the SSVEP session, more data could prove otherwise.

Although post-hoc analysis could not indicate what caused the significant difference for the emotional involvement factor, the average scores for the P300 and SSVEP sessions were almost equal, 59.64 and 59.86 respectively. The average score for the non-BCI session was lower (54.29), which could indicate that SSVEP and P300 together caused the significant difference for the emotional involvement factor. Participants seemed to enjoy making (successful) selections using a BCI, they became more emotionally involved, less aware of their surroundings and needed to focus on the game, which was supported by the real world dissociation and cognitive involvement factors where trends were revealed between the SSVEP and non-BCI sessions and the P300 and non-BCI sessions.

7.2 Affect

The used selection method did not seems to have a significant effect on the results of the SAM questionnaire. However, there was an overall increase in valence between the SSVEP and non-BCI sessions and between the P300 and SSVEP sessions. There was a strong correlation between the total immersion and valence ($\rho = 0.68$), indicating that being more immersed was also found more positively affective. This could have been caused by participants' feeling of control as there was also a strong correlation between total immersion and dominance ($\rho = 0.67$). In other words, in this case the SSVEP selection method let participants translate their intentions directly into in-game actions, giving them an increased feeling of control leading to a more positively affective experience.

7.3 Game Statistics

It was expected that if a selection method performed well, a participant would need less selections and time to finish the game as all three dogs could be placed strategically. The used selection method had indeed a significant effect on the number of selections per minute as there was a significant reduction in selections per minute between the P300 and non-BCI sessions and between the P300 and SSVEP sessions. To deal with the trade-off between accuracy and speed some participants developed a strategy, which could explain the significant reduction in number of selection per minute for the P300 selection method compared to the non-BCI selection method. When they wanted to be accurate in their selections, they waited long enough to make an accurate selection. However, when they wanted to be quick, they moved all three dogs as one by pressing the mouse button rapidly while pointing at a location on the playground. Although this behavior was observed for all three selection methods, for the P300 and SSVEP selection methods participants appeared to switch between precise and quick whenever they wished. For the non-BCI selection method they appeared to prefer only making quick selections.

Although participants needed less selections per minute to finish the game in the P300 session, there was a significant increase in game duration between the P300 and non-BCI sessions and between the P300 and SSVEP sessions, indicating that participants needed more time to finish the game while using the P300 selection method. The P300 selection method apparently gave participants some difficulties as a reduction in both selections and game duration was expected. The used selection method also had a significant effect on the selection duration. There was a significant increase in selection duration between the P300 and non-BCI sessions and between the P300 and SSVEP sessions, indicating that participants used more time to make a selection using the P300 selection method. As participants understood that an accurate BCI selection did require more time, they adjusted the selection duration accordingly. This indicated that the P300 selection method did indeed introduce some difficulties as the game and selections duration increased in the P300 session.

Between the SSVEP and non-BCI sessions there was also an increase in selection duration, although not significant. Participants seemed to accept that for a good P300 or SSVEP selection they had to wait a couple of seconds. However, for the non-BCI selection method they understood that it was related to their own reaction speed and suddenly they appeared to be in a hurry. Although the non-BCI selection method was modeled to be similar to the BCI selection methods, it might have had an effect on the preference of the participants, as they did not want to wait to make a selection. The non-BCI selection method did introduce the same challenge and required participants to multi-task similarly to the P300 and SSVEP selection methods. However, participants seemed to be more indulgent towards the BCI selection methods than towards the non-BCI selection method. This could be caused by the curiosity of participants for the P300 or SSVEP selection methods or the self overestimation by participants while using the non-BCI selection method.

Chapter 8

Conclusion

In this study two BCI system were compared to a non-BCI system to evaluate the user experience in terms of immersion and affect. For the BCI systems, selection methods based on SSVEP and P300 were integrated into a game, introducing a challenge factor. A comparable non-BCI selection method based on time was also implemented into the game, introducing an equal challenge. Fourteen participants played the game with all selection methods in three levels with increasing difficulty. They rated each selection method on immersion and affect.

Based on the results it is evident that in this case SSVEP is capable of enriching the user experience in terms of immersion and affect. Participants were significantly more immersed and the SSVEP selection method was found more positively affective. Although it was expected that P300 would enrich user experience, it did not. For users to become totally immersed, a BCI system facilitating in making selection should effortlessly submit to the intentions of the users and not elicit any disruptions. This is why the SSVEP selection method makes it easier for users to become immersed as they are able to directly translate their intentions into in-game actions. A SSVEP selection method only requires users to focus at the target they wish to select. It does not require any physical action as with the non-BCI selection method, nor any mental action, as with the P300 selection method.

Furthermore, participants appeared to have more patience when using the BCI selection methods than when using the non-BCI selection method, which could have been caused by the curiosity of participants for the BCI selection methods or the self overestimation by participants while using the non-BCI selection method.

When a BCI is applied in recreational applications to make selections from a small set and an important goal is immersion, according to this study a selection method based on SSVEP is recommended. Although P300 is fit to make selections, it introduces disruptions that hinders immersion and thereby positive affect. Although future improvements on P300 recognition could reintroduce P300 as a viable option, for now it should be applied differently to enrich user experience in terms of immersion and affect. For example, in a more subtle way by detecting whether users noticed that something happened or changed in the environment. This could well be a topic for future studies. It would also be interesting to look at long term effects on immersion and affect. Is the SSVEP selection method still significantly more immersive when participants are used to it and is the indulgence towards the BCI selection methods permanent or only temporary? Given the intended purpose of this research, it would be interesting to use commercial BCI input devices (e.g. Emotiv's EPOC). This requires a proper study comparing the equipment used in this research and commercial BCIs to determine the differences and if they are feasible to use within the setup of this experiment. Adding a selection method based on pointing and clicking, which was left out of this research, could be added in future studies to determine the cognitive load as the selection methods used in this study required participants to multi-task. Finally, other (non-)BCI selection methods, such as speech, gestures or gaze tracking could also prove to increase immersion and affect and should be investigated in future studies.

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Part IV

Appendices

Appendix A

Acronyms used in thesis

BCI brain-computer interface

EEG electroencephalography

MEG magnetoencephalography

NIRS near-infrared spectroscopy

fMRI functional magnetic resonance imaging

ERP event-related potential

SSVEP steady-state visually evoked potential

ISI inter-stimulus interval

EMG electromyography

CAR common average reference

SNR signal-to-noise ratio

ITR information transfer rate

CCA canonical correlation analysis

PMCC Pearson product-moment correlation coefficient

SWDA stepwise linear discriminant analysis

FFT fast Fourier transform

PSD power spectral density

PSDA power spectral density analysis

SAM self-assessment manikin

Appendix B

Determining SSVEP parameters

B.1 Experiment Setup

During this experiment participants sat in a comfortable chair at approximately 70 cm in front of a LCD monitor[1] on which the stimuli were presented. A small white cross was placed at the center of an LCD monitor on a black background (Fig. B.1). During the study participants were exposed to different types of trials, in which the presented stimulus varied in size and frequency. The detailed setup of the pre-experiment study was described in [14].

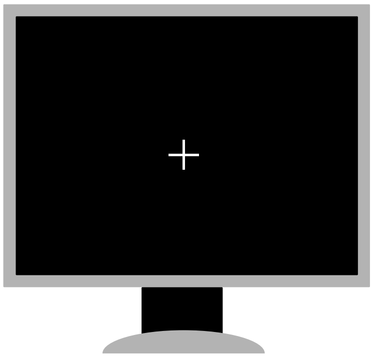


Figure B.1: Screen layout of the monitor during the pre-experiment study

Based on the work of Volosyak *et al.* [39], 7 different frequencies (6.00 Hz, 6.67 Hz, 7.50 Hz, 8.57 Hz, 10.00 Hz, 12.00 Hz and 15.00 Hz) were used. Their study showed that frequencies which are integer factors of the refresh rate of an LCD monitor are more suitable for presenting stimuli. Using the factor of the refresh rate produces a more stable stimulus frequency because only whole frames are visible on the LCD screen. The diameters of the stimuli were set to 2 and 3 centimeters, which is consistent with the work in the literature [7, 20].

In each trial one stimulus, a blinking white circle, appeared at the location of the cross. Participants had to focus for 4 seconds on the stimulus. Between trials, participants had 6 seconds rest to relax their vision. All trials were presented 25 times and were placed in a random order prior to the experiment. Thus, for each participant, 25 segments of 4 seconds of data were recorded for each unique trial. The complete experiment lasted 60 minutes and was divided into 4 sessions of equal length. Between the sessions, participants could relax in order to reduce the effect of visual fatigue.

For offline analysis, continuous EEG activity was recorded using a BioSemi ActiveTwo system[2] with a sampling rate of 512 Hz. Recordings were taken from 32 scalp electrodes, placed according to the international 10-20 system [31].

B.2 SSVEP Classifier

One of the most popular and widely used methods to detect the presence of SSVEPs is power spectral density analysis (PSDA) where a fast Fourier

[1] Samsung SyncMaster 203B, 20”, 60Hz, 1280x1024

[2] BioSemi, Amsterdam, The Netherlands

transform (FFT) is used to estimate the power spectral density (PSD) of a time window of the user's EEG-signal. The magnitude of each stimulation frequency can then be used for classification [7]. A relatively new approach is using CCA where the correlations between the user's EEG-signal and each stimulation frequency can be used for classification. CCA-based detection methods have some improvements and advantages compared to PSDA-based detection methods, such as better SNR, lower inter-subject variability and the possibility to use harmonic frequencies [3, 20]. To determine which classifier to use, all trials in this experiment were classified with a CCA and a PSDA based detection method and the results were compared.

For the PSDA-based detection, EEG data from *Oz* was filtered with a bandpass filter of 4 - 35 Hz. The data was re-referenced with CAR using all 32 electrodes and a FFT was performed every 0.3 seconds with a FFT-size of 512 data points. For each of the stimuli frequencies the sum of the extracted magnitudes of its first and second harmonics were used for classification. The stimuli frequency with the highest value, which also exceeded two times the average magnitude of the FFT, was classified as the presented frequency. The first two classifications of the 4 second stimuli were dropped as they contain non-stimulated data and might influence the performance. The rest of the classifications are used in a majority vote to determine the presented frequency.

For the CCA-based detection, EEG data was acquired from eight different electrodes (*Pz, P3, P4, PO3, PO4, Oz, O1, O2*). The acquired EEG data was re-referenced with CAR [8] using all 32 electrodes. Sets of reference signals were constructed for each one of the stimulation frequencies where each set contained the *sine* and *cosine* for the first, second and third harmonic of a stimulation frequency. The re-referenced EEG data and each set with reference signals were used as input for the CCA. CCA tries to find pairs of linear transformations for the two sets such that when the transformations are applied the resulting sets have a maximal correlation. The stimulation frequency with the highest maximum correlation was classified as the frequency the participant was focusing [14].

The average recall and precision for each of the 7 frequencies are shown in Tables B.1 and B.2. It can be seen that the CCA based detection method has higher recall and precision values than the PSDA based detection method. A Wilcoxon signed-rank test between the average recall values showed that this difference is significant ($Z = -2.20, p < 0.05$). Based on these results a CCA based detection method was used for determining the size and frequencies and for the final experiments.

B.3 Stimulus Size

For the game to be controllable the size of the stimuli should be large enough to elicit well detectable SSVEP responses. However, larger stimuli will take up a larger part of the playground and could get in the way of the rest of the game. This means that the stimuli should also not be to large. In experiments held by Cheng *et al.* [7] and Lin *et al.* [20] the size of the stimuli varied between 2 and 4 centimeters and were well detectable. During this experiment stimuli with 2 different sizes were presented to the participants. The size of the stimuli were set to 2 or 3 centimeters. The recorded EEG activity was classified using

	Recall	Precision
6	72.00	23.91
6.67	29.71	48.15
7.5	45.14	42.47
8.57	48.00	73.68
10	61.71	51.43
12	27.43	96.00
15	17.14	100.00

Table B.1: Average recall and precision for PSDA based classification

	Recall	Precision
6	62.29	46.58
6.67	46.29	61.36
7.5	65.71	55.02
8.57	68.57	63.16
10	80.00	48.28
12	52.00	91.00
15	39.43	98.57

Table B.2: Average recall and precision for CCA based classification

a detection method based on CCA.

The average recall and precision for each of the 7 frequencies are shown in Tables B.3 and B.4. It can be seen that the larger stimuli elicit SSVEP responses which result in higher recall and precision values than the smaller stimuli. A Wilcoxon signed-rank test between the average recall values showed that this difference is significant ($Z = -2.37, p < 0.05$). Based on these results, for the final experiment the size of the stimuli was set to 3 centimeter.

	Recall	Precision
6	53.14	34.70
6.67	36.57	46.04
7.5	50.86	48.63
8.57	54.60	49.48
10	69.14	35.38
12	34.29	86.96
15	17.71	100.00

Table B.3: Average recall and precision for stimuli with size of 2 centimeter

	Recall	Precision
6	62.29	46.58
6.67	46.29	61.36
7.5	65.71	55.02
8.57	68.57	63.16
10	80.00	48.28
12	52.00	91.00
15	39.43	98.57

Table B.4: Average recall and precision for stimuli with size of 3 centimeter

B.4 Stimulus Frequencies

Of the 7 different frequencies only three were used in the game, one for each dog. Which frequencies to use was determind by testing each possible combination. The number of combination can be expressed as $\binom{n}{k}$ and can be calculated with $\binom{n}{k} = \frac{n!}{k!(n-k)!}$. In this case, with $n = 7$ and $k = 3$ the number of combinations is 35. For each combination all relavant epochs were extracted and classified using the CCA-based classifier. The reference signals for the CCA (Y), only contained the reference to the three frequencies available in the combination.

The averaged recall and precision are shown in Table B.5. It can be seen that set 27 with frequencies 7.5 Hz, 8.57 Hz and 12 Hz has the best performance. Since the number of frames used for this combination, i.e., 8, 7 and 5 are all co-prime to eachother, the first harmonic the frequencies have in common is 60 Hz. For sets with only co-prime based frequencies the harmonics used in the CCA based detection do not interfer with eachother. Unlike sets where the number of used frames are not co-primes, such as set 8 where the second harmonic of 6 Hz is similar to the first harmonic of 12 Hz. This increases the possiblity of misclassifications.

	Recall	**Precision**
1: 6, 6.67, 7.5	73.14	74.01
2: 6, 6.67, 8.57	74.10	74.50
3: 6, 6.67, 10	69.52	70.49
4: 6, 6.67, 12	70.29	76.00
5: 6, 6.67, 15	72.38	76.39
6: 6, 7.5, 8.57	81.33	81.63
7: 6, 7.5, 10	73.90	74.47
8: 6, 7.5, 12	75.05	79.40
9: 6, 7.5, 15	72.19	77.73
10: 6, 8.57, 10	76.95	77.47
11: 6, 8.57, 12	76.95	80.46
12: 6, 8.57, 15	78.86	82.56
13: 6, 10, 12	71.62	75.51
14: 6, 10, 15	72.00	77.45
15: 6, 12, 15	73.90	83.67
16: 6.67, 7.5, 8.57	77.33	77.49
17: 6.67, 7.5, 10	74.48	75.26
18: 6.67, 7.5, 12	75.81	76.52
19: 6.67, 7.5, 15	70.86	77.42
20: 6.67, 8.57, 10	76.00	76.50
21: 6.67, 8.57, 12	78.29	78.70
22: 6.67, 8.57, 15	78.29	80.03
23: 6.67, 10, 12	76.76	77.95
24: 6.67, 10, 15	73.33	77.32
25: 6.67, 12, 15	77.90	79.60
26: 7.5, 8.57, 10	82.48	82.91
27: 7.5, 8.57, 12	84.95	85.11
28: 7.5, 8.57, 15	78.29	82.48
29: 7.5, 10, 12	80.76	81.62
30: 7.5, 10, 15	73.14	78.69
31: 7.5, 12, 15	76.19	81.66
32: 8.57, 10, 12	81.90	82.68
33: 8.57, 10, 15	78.10	82.23
34: 8.57, 12, 15	81.71	84.66
35: 10, 12, 15	78.10	83.08

Table B.5: Average recall and precision for each combination

Appendix C

Detailed Experiment Protocol

1. Introduction (30 min)
   (a) Welcome the participant (2 min)
   (b) Give a short introduction (3 min)
   (c) Participant fills in and signs consent form (5 min)
   (d) Participant fills in short questionnairem Measure participant's head circumference and put on EEG cap in the meantime (20 min)
2. Experiment (33 min) x 3
   (a) Short introduction (1 min)
   (b) Part one: familiarity trial (4 min)
      i. Participant plays Mind the Sheep! and must collect 10 objects which are placed across the playground within 3 minutes (3 min)
      ii. Participant fills in SAM questionnaire (1 min)
   (c) Part Two: easy trial (6 min)
      i. Participant plays Mind the Sheep! and must pen a small flock of 5 sheep within 5 minutes (5 min)
      ii. Participant fills in SAM questionnaire (1 min)
   (d) Part Three: Difficult trial (11 min)
      i. Participant plays Mind the Sheep! and must pen a flock of 10 sheep within 10 minutes (10 min)
      ii. Participant fills in SAM questionnaire (1 min)
   (e) Participant fills in questionnaire on immersion (6 min)
   (f) A small brake and some drinks (5 min)
3. Ask for preference of participant
4. End of experiment

Appendix D

Experiment Information for Participants

Welcome Participant,

In a minute you will be playing Mind the Sheep! In this document you'll find a brief explanation on how to play it and some extra information.

The Game

Mind the Sheep! consists of a playground representing a meadow. On this playground there are a few obstacles, e.g. trees, fences, rocks, etc. On this playground you will also find three herding dogs which are under your control.

If you want to move a herding dog, point the Wiimote at any location on the playground and start the current selection methods by pressing the A button. Now you can select one of the herding dogs by using a selection method. When you release the A button the selection methods stops and moves one of the three dogs to the location you indicated. Note: when a herding dog was unable to find a route to the indicated location it will not response.

Selection Methods

During this experiment you will use three different selection methods. Two of them (SSVEP-based and P300-based) will use data from you brain which will be recorded through electroencephalography (EEG).

SSVEP-based selection

During this selection method, all three herding dogs will start to flicker. You can select a herding dog by focusing on it. Tip: Staring/gazing for a longer period at a herding dog could increase the performance

P300-based selection

During this selection method, the three herding dogs will be highlighted in a random order. Focus on the herding dog you want to select. Tip: Count the number of times the herding dog is highlighted to increase the performance.

Timed-based selection

All herding dogs will be highlighted one at the time. At first the highlighted herding dog will change rapidly. But as you wait longer, this will gradually slow down.

Experiment Setup

There are three different parts for each one of the selection methods. After each part you'll have to answer three simple questions and at the end fill in one slightly larger questionnaire.

Part 1

First you'll get some time to get familiar with the current selection method. During this part there are some bones placed on the playground. Your goal is to collect all of them and at the same time get familiar with the selection method.

Part 2

During this part the playground will be populated with a number of sheep. Sheep will respond to any nearby herding dog by running away from it and try to find other sheep. On the playground you will also find a pen (indicated with a fence). Your goal is to get the sheep into a pen by using the herding dogs.

Part 3

This part is the same as part 2, but with more sheep, making the game more difficult.

Well, thats it. Have fun.

Appendix E

Participant Consent Form

Determining BCI parameters

Participant Consent Form

I have been asked to participate in a research study conducted by Michel Obbink and Gido Hakvoort. My participation in this study is entirely voluntary. It is recommended that I read the information below and ask questions about anything I do not understand before deciding whether or not to participate.

PURPOSE OF THE STUDY

I understand that this study is designed to find a set of parameters for later research that will gain knowledge about physiological interaction with computer games. I understand that the entire process will involve a recording session of up to two hours in which I have several opportunities for a break. We do however advise you to have a toilet break before we start placing the electrodes. Should you at any time during the experiment experience discomfort, then please inform *The Experimenter* immediately.

PROCEDURES

If I volunteer to participate in this study, I will be asked to undergo 32-channel topographic EEG acquisition for approximately 2 hours. During this time I will be asked to sit still and obsere visual stimuli that are presented to me on a computer screen. I understand that *The Experimenter* will remain near me throughout the study and is available for questions at any time.

POTENTIAL RISKS AND DISCOMFORTS

I understand that EEG acquisition requires the placement of electrodes on the scalp for the purpose of recording an EEG. There are few risks associated with this procedure. There is a remote possibility of skin irritation from the electrode gel used to attach electrodes. Techniques used to attach electrodes have been used at numerous research institutions for many years with no significant negative side effects reported.

I understand that I can remove the electrodes or the cap at any time if I desire and there is no risk of electroshock from this procedure. We do not expect any psychological, legal or financial risks for participating in the research, but as always, there may be possible unforeseeable risks that have not been identified. **Important:** If you have illnesses, are undergoing medical treatment or are known to ever had an epileptic seizure, please inform *The Experimenter* as soon as possible. For questions about this please contact *The Experimenter*.

RIGHTS OF RESEARCH SUBJECTS

I understand that the recorded EEG is anonymised and can and will only be processed, published and presented in its anonymised form. Any other information provided by me during the research study will be disclosed to anyone outside the research team without written permission, except if necessary to protect my well-being, e.g., if I am injured and need emergency care or required by law. When the results of the research are published and discussed in conferences, no information will be included that reveals my identity. In any photographs, videos or audiotape records taken during the study my identity will be protected or disguised.

I may withdraw my consent at any time and discontinue my participation without penalty. I am not waiving any legal rights or remedies because of my participation in this research study.

SIGNATURE OF RESEARCH SUBJECT OR LEGAL REPRESENTATIVE

I have read and understand the information provided above. I have been given an opportunity to ask questions and all of my questions have been answered to my satisfaction.

BY SIGNING THIS FORM, I WILLINGLY AGREE TO PARTICIPATE IN THE RESEARCH IT DESCRIBES.

NAME (BLOCK CAPITALS): ....

Signed: .... Date: ....

I, *The Experimenter*, confirm that I have fully explained the purpose and nature of the research study and the risks involved.

NAME (BLOCK CAPITALS): ....

Signed: .... Date: ....

Appendix F

Participant Demographic Information Questionnaire

Participant Questionnaire

Before starting the experiment, we would like to have some demographic information about you. This information will be used only for research purposes and will not be shared with third parties. Your anonymity will be kept in case of scientific publishing. Please answer the questions below correctly with your best knowledge.

Demographic information

1. **Surname; Initial(s) :** ______________________________
2. **Age :** ______________________________
3. **Mother tongue :** ______________________________
4. **Gender :**
   ○ Male
   ○ Female
5. **Vision :**
   ○ Normal
   ○ Corrected
   ○ Not corrected
6. **Handedness :**
   ○ Left
   ○ Right
   ○ Both
7. **Compter usage :**
   ○ Every day
   ○ Every 2-3 days
   ○ Once a week
   ○ More than once a month
   ○ Less than once a month
   ○ Never
8. **BCI experience :**
   ○ Never
   ○ Once
   ○ More than once
9. **EEG experience :**
   ○ Never
   ○ Once
   ○ More than once

Other details

10. Substance consumption 6 hours before the experiment :

	None	1 units	2 units	3 units	More
Alcohol	○	○	○	○	○
Coffee	○	○	○	○	○
High sugar content drink	○	○	○	○	○
Tobacco	○	○	○	○	○
Black Tea	○	○	○	○	○
Energy drink	○	○	○	○	○

11. Hours of sleep before the experiment : ____________________

12. Any drugs / medications used :

____

____

____

13. Attention / neurological / psychiatric deficiencies :

____

____

____

14. Preferred address / number for contact :

____

____

____

Appendix G

Participant SAM Questionnaire

Self-Assessment Manikin (SAM)

On each of the next few pages you will find 3 sets of 5 figures. These sets of figures, called Self-Assessment Manikin (SAM), are used to rate how you felt while using a selection method to play Mind the Sheep!. After each part (as described in the game explanation) you will rate all three figures. For each part you will use one complete page on which three kinds of feelings are shown: unhappy vs. happy, calm vs. excited and controlled vs. controlling.

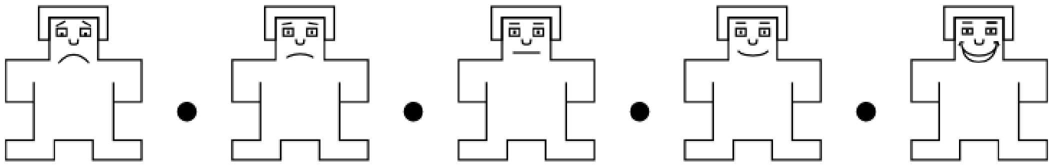
The first SAM scale describes unhappy vs. happy. The figures differ along the scale, ranging from a frown to a smile. At one end of this scale you felt completely unhappy, unsatisfied, bored, melancholic, annoyed, despaired. If you felt completely unhappy while using a selection method to play Mind the Sheep!, you can indicate this by circling the number 1. At the other end of this scale you felt completely happy, satisfied, contented, hopeful, pleased. By circling the number 9, you indicate that you felt completely happy. If you felt somewhere in between while using a selection method to play Mind the Sheep!, you can circle one of the other numbers.

The second SAM scale describes calm vs. excited. Again the figures differ along the scale. At one end of this scale you felt completely relaxed, calm, unaroused, sluggish, sleepy, dull. You can indicate that you felt completely relaxed by circling the number 1. At the other end of this scale you felt completely aroused, excited, jittery, frenzied, stimulated, wide-awake. If you felt completely aroused while using a selection method to play Mind the Sheep!, you can indicate this by circling the number 9. If you circle one of the other numbers you will indicate you felt somewhere in between.

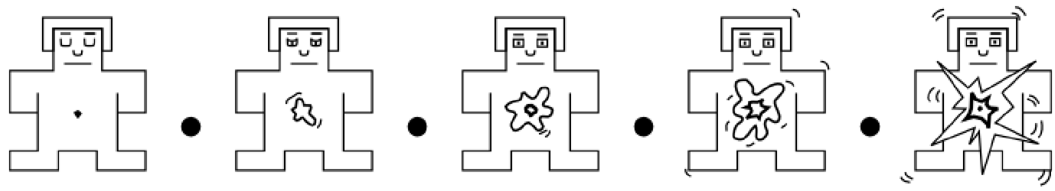
The third and last scale describes controlled vs. controlling. At one end of this scale you felt completely controlled, cared-for, influenced, submissive, awed, guided. If you felt completely controlled, you can indicate this by circling the number 1. At the other end you will again find the opposite feeling, completely in control, controlling, important, influential, dominant, autonomous. If you felt completely in control while using a selection method to play Mind the Sheep!, circle the number 9. Circle one of the other number to indicate you felt somewhere in between.

Important: Please rate each one of the figures as you actually felt while you used a selection methods to play Mind the Sheep!.

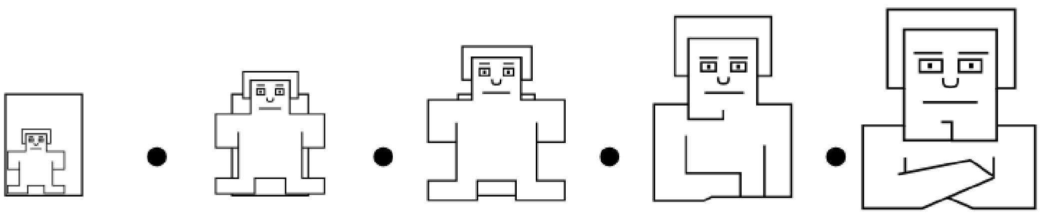
Describe how you felt while using the current selection method



1 2 3 4 5 6 7 8 9



1 2 3 4 5 6 7 8 9



1 2 3 4 5 6 7 8 9

Appendix H

Participant Immersion Questionnaire

Immersion Questionnaire

Please answer the following questions by selecting the relevant number. In particular, remember that these questions are asking you about how you felt at the end of the game using this selection method.

1. **To what extent did the game hold your attention?**
   Not at all 1 2 3 4 5 6 7 A lot
2. **To what extent did you feel you were focussed on the game?**
   Not at all 1 2 3 4 5 6 7 A lot
3. **How much effort did you put into playing the game?**
   Very little 1 2 3 4 5 6 7 A lot
4. **Did you feel that you were trying your best?**
   Not at all 1 2 3 4 5 6 7 Very much so
5. **To what extent did you lose track of time?**
   Not at all 1 2 3 4 5 6 7 A lot
6. **To what extent did you feel consciously aware of being in the real world whilst playing?**
   Not at all 1 2 3 4 5 6 7 Very much so
7. **To what extent did you forget about your everyday concerns?**
   Not at all 1 2 3 4 5 6 7 A lot
8. **To what extent were you aware of yourself in your surroundings?**
   Not at all 1 2 3 4 5 6 7 Very aware
9. **To what extent did you notice events taking place around you?**
   Not at all 1 2 3 4 5 6 7 A lot
10. **Did you feel the urge at any point to stop playing and see what was happening around you?**
    Not at all 1 2 3 4 5 6 7 Very much so
11. **To what extent did you feel that you were interacting with the game environment?**
    Not at all 1 2 3 4 5 6 7 Very much so
12. **To what extent did you feel as though you were separated from your real-world environment?**
    Not at all 1 2 3 4 5 6 7 Very much so
13. **To what extent did you feel that the game was something you were experiencing, rather than something you were just doing?**
    Not at all 1 2 3 4 5 6 7 Very much so
14. **To what extent was your sense of being in the game environment stronger than your sense of being in the real world?**
    Not at all 1 2 3 4 5 6 7 Very much so
15. **At any point did you find yourself becoming so involved that you were unaware you were even using controls?**
    Not at all 1 2 3 4 5 6 7 Very much so

16. **To what extent did you feel as though you were moving through the game according to your own will?**
Not at all 1 2 3 4 5 6 7 Very much so
17. **To what extent did you find the game challenging?**
Not at all 1 2 3 4 5 6 7 Very difficult
18. **Were there any times during the game in which you just wanted to give up?**
Not at all 1 2 3 4 5 6 7 A lot
19. **To what extent did you feel motivated while playing?**
Not at all 1 2 3 4 5 6 7 A lot
20. **To what extent did you find the game easy?**
Not at all 1 2 3 4 5 6 7 Very much so
21. **To what extent did you feel like you were making progress toward the end of the game?**
Not at all 1 2 3 4 5 6 7 A lot
22. **How well do you think you performed in the game?**
Very poor 1 2 3 4 5 6 7 Very well
23. **To what extent did you feel emotionally attached to the game?**
Not at all 1 2 3 4 5 6 7 Very much so
24. **To what extent were you interested in seeing how the game's events would progress?**
Not at all 1 2 3 4 5 6 7 A lot
25. **How much did you want to "win" the game?**
Not at all 1 2 3 4 5 6 7 Very much so
26. **Were you in suspense about whether or not you would win or lose the game?**
Not at all 1 2 3 4 5 6 7 Very much so
27. **At any point did you find yourself become so involved that you wanted to speak to the game directly?**
Not at all 1 2 3 4 5 6 7 Very much so
28. **To what extent did you enjoy the graphics and the imagery of the game?**
Not at all 1 2 3 4 5 6 7 A lot
29. **How much would you say you enjoyed playing the game?**
Not at all 1 2 3 4 5 6 7 A lot
30. **When interrupted, were you disappointed that the game was over?**
Not at all 1 2 3 4 5 6 7 Very much so
31. **Would you like to play the game again?**
Definitely not 1 2 3 4 5 6 7 Definitely yes

Appendix I

INTERACT 2011 Conference Paper

Measuring immersion and affect in a brain-computer interface game

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Abstract. brain-computer interfaces (BCIs) have widely been used in medical applications, to facilitate making selections. However, whether they are suitable for recreational applications is unclear as they have rarely been evaluated for user experience. As the scope of the BCI applications is expanding from medical to recreational use, the expectations of BCIs are also changing. Although the performance of BCIs is still important, finding suitable BCI modalities and investigating their influence on user experience demand more and more attention. In this study a BCI selection method and a comparable non-BCI selection method were integrated into a computer game to evaluate user experience in terms of immersion and affect. An experiment with seventeen participants showed that the BCI selection method was more immersive and positively affective than the non-BCI selection method. Participants also seemed to be more indulgent towards the BCI selection method.

Keywords: Brain-computer interfaces, affective computing, immersion, games

1 Introduction

A brain-computer interface (BCI) can be described as a communication link between the brain and the machine. In a BCI system, signals from the brain are analyzed to determine the user's state of mind or intentions, which in turn can be translated into actions [9]. BCI systems have been applied for medical use to help disabled users by giving back mobility [8] and breaking the isolation of people with physiological disorders [7,11].

As successful applications of BCIs become news and commercial BCI input devices become publicly available, BCIs are finding their way into recreational use. However, as the scope of BCI applications is expanding from medical to recreational use, the expectations for BCIs are also changing. Currently they are unable to meet the high performance and accuracy of existing input modalities such as mouse and keyboard, and are therefore unfit as replacement. Instead they should be seen as separate modalities which can be used beside, or in combination with, existing input modalities [17]. However, using BCI as input modality still comes with many challenges. Where increasing the performance of BCIs has always been an important goal for medical studies, the way they are applied as modalities and the influence they have on the user experience is becoming more and more important for recreational BCI applications.

Whether BCIs are suitable for recreational applications is as yet unclear as they have rarely been evaluated for user experience. They may turn out to be valuable additions for recreational applications such as games which are developed to be challenging and enjoyable. Moreover the inaccuracy of BCIs can become a challenging factor in games. As gamers love working with new technologies, are capable of adapting quickly to a new environment and are used to the concept that games have to be mastered [16], they may be more indulgent towards BCI modalities.

The purpose of this study was to evaluate a BCI system for user experience in the terms of affect and immersion. As making selections is an important aspect in many games and BCIs are frequently used to make selections, a BCI selection method was used in this study. One of the most frequently used brain signals in BCI systems to make selections is the steady-state visually evoked potential (SSVEP) [1]. In most cases SSVEPs are triggered by presenting a modulated visual stimulus with a periodic signal, usually at frequencies above 5 Hz, to a user. The periodic signal of the stimulus can then be traced back in the measured brain signals which are mostly recorded from the occipital region of the scalp [23]. The power of an SSVEP only covers a narrow bandwidth matching that of the stimulus [15]. This makes them relatively easy to detect, which is why the BCI selection method used in this study was based on SSVEP. The BCI selection method and a comparable non-BCI selection method were integrated into a computer game where both introduced a challenge factor. As the BCI selection method would be able to directly translate the user intentions into in-game actions, it was expected that it would enrich the user experience in terms of immersion and affect.

How immersion and affect can be influenced by input modalities will be explained in the background in section 2. The BCI and non-BCI selection methods and how they were integrated in a game will be described in section 3. In section 4 the experimental setup and how both selection methods were evaluated will be explained. After this, the results of the experiment will be reported, followed by the discussion and the conclusion.

2 Background

2.1 Immersion

Immersion has meaning in various contexts, such as while reading a book, watching a movie or playing games. Whether the term is used consistently in these contexts is unclear. However, for playing games there seems to be a shared concept of immersion among gamers [4]. Immersion in games is often accompanied by high levels of concentration, losing track of time and empathy.

In a study by Brown *et al.* [4] an attempt was made to define immersion within games. In their study they examined the concept of immersion experienced by gamers. Their results indicate that immersion is not just a static experience, but has different levels of involvement. They defined three levels of involvement: engagement, engrossment and total immersion. They also state that to reach a certain level of immersion, a number of barriers must be crossed. Some of these barriers are related to human characteristics, such as personal preferences, empathy and the will to invest time and attention. Others are related to the construction of the game such as the graphics, a plot and atmosphere. However, to reach a state of total immersion an important barrier to take is related to the controls. Through them gamers translate their intentions into in-game actions [19] and virtually controls should become invisible to the gamer. As intentions originate from the brain, users first need to translate their intentions into real world actions to handle the controls. Even if these real world actions become virtually invisible for the user, they still need to be performed. Using a BCI to detect intentions may allow them to be translated directly into in-game actions, making the real world actions redundant.

In a study by Jennett *et al.* [12] immersion in games was further investigated. They identified five factors of immersion: cognitive involvement, real world dissociation, emotional involvement, challenge and control. As in the study of Brown *et al.*, some factors were related to human characteristics (cognitive involvement, real world dissociation and emotional involvement) and others were related to the construction of the game (challenge and control). To measure these factors, as well as the total immersion, they developed a questionnaire which was also used in this study to measure the immersion while using the BCI and non-BCI selection methods.

2.2 Affect

Affect can be referred to as experiencing emotions and has some overlap with immersion [12]. It has a large impact on how well users are able to perform tasks and how they respond to possible usability problems. According to Norman [18], a more positive affect causes users to be more indulgent towards minor usability problems. Although there are many dimensions associated with affect, according to Picard [20] the three most commonly used dimensions of emotion are valence, arousal and dominance. Picard also notes that the valence and arousal dimensions are critical in recreational applications.

Bradley *et al.* [3] developed a questionnaire, the self-assessment manikin (SAM), to measure emotional responses in these three dimensions. In Fig. 1 some emotions associated with valence and arousal can be seen. Integrating the selection methods into an enjoyable, challenging and task oriented environment, such as a game, should result in a more positive affect in terms of valence and arousal which will aid users to overcome the inaccuracy of the selection methods.

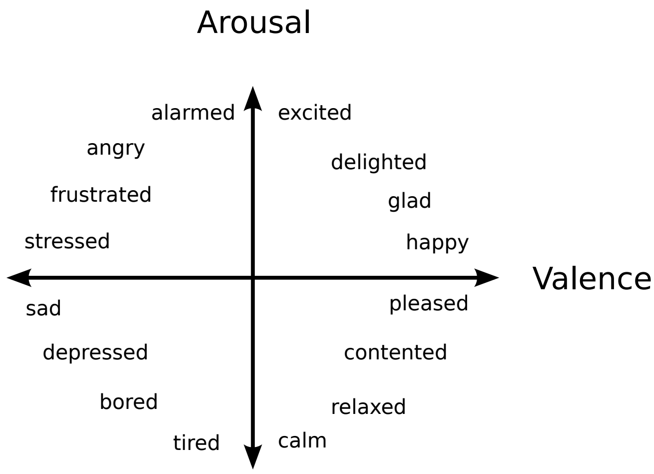

Fig. 1. Emotions in the valance and arousal space

3 Selection Methods

To measure the effects of the BCI and non-BCI selection methods on the user experience in terms of immersion and affect, the selection methods were integrated into a simple game. The game, called Mind the Sheep!, offered the players an enjoyable, challenging and task oriented environment.

3.1 Mind the Sheep!

Mind the Sheep! consists of a playground representing a meadow on which a few obstacles, such as fences, gates or trees are placed. There are three dogs in the playground which are controlled by the player. Depending on the objectives of a specific level, the playground can be populated with a number of sheep or collectibles. A screenshot of the game can be seen in Fig. 2 with ten white sheep and three black dogs. The goal of the game is to gather all sheep into a pen or gather all collectibles as quickly as possible using the three dogs. Players can use one of the selection methods to select one of the three dog.

To move a dog, players point at any location on the playground with the mouse and start the current selection method by pressing the left mouse button. As long as they hold down the mouse button the selection method continues to be operative thereby increasing the accuracy of the selection method. Releasing the mouse button stops the selection method and one of the dogs is moved to the location indicated by the player. When players indicate a position unreachable for the dogs, the instruction is ignored. As the accuracy of the selection methods increase over time, there is a trade-off between accuracy and speed. It also requires users to multi-task as they need to concentrate on a dog and keep an eye on the sheep at the same time.

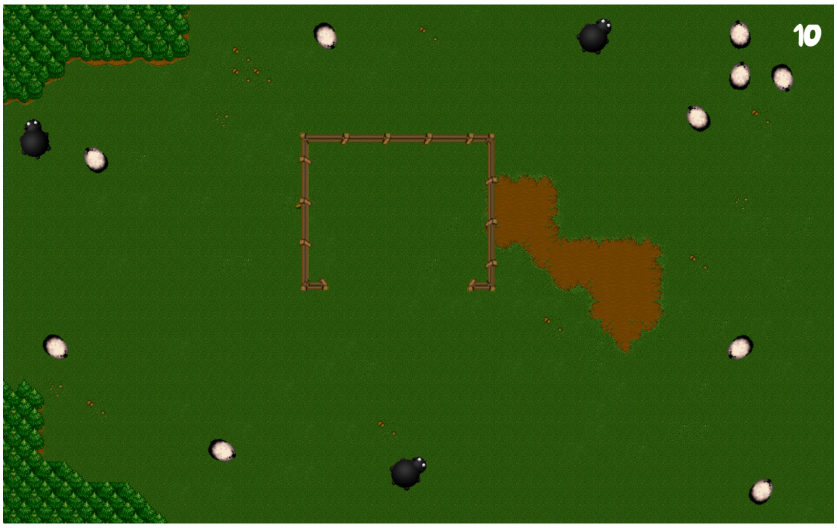

Fig. 2. Screenshot of Mind the Sheep! with three black dogs and ten white sheep. The pen is located in the center.

The dogs use a simple A* search based path finding algorithm to move to a specific location on the map. By default, sheep will walk around and graze randomly. However, when a dog approaches, they will tend to flock and move away from the dog allowing them to be herded in a desired direction. The flocking behavior is introduced by using the boids algorithm [22]. By positioning the dogs at strategic locations on the map a flock of sheep can be directed into the pen.

3.2 BCI Selection

To use SSVEPs for making selections, stimuli emitting unique periodic signals should be presented to a user simultaneously. When a user focuses on one of the stimuli, the periodic signal of that stimulus can be traced back in the user's brain signals. As each stimulus represents a single target, the corresponding target can then be determined as the selected one. As users would not want to continuously make selections, they were able to start and stop this selection method thereby controlling the presence of the stimuli. The size of the stimuli and the frequency of their periodic signals have an influence on the how well they are reflected in user's brain signals. Therefore, these properties were determined in a pre-experiment study.

In the pre-experiment study a small white cross was placed at the center of an LCD monitor on a black background (Fig. 3). During the study participants were exposed to different types of trials, in which the presented stimulus varied in size and frequency. The detailed setup of the pre-experiment study was described in [10].

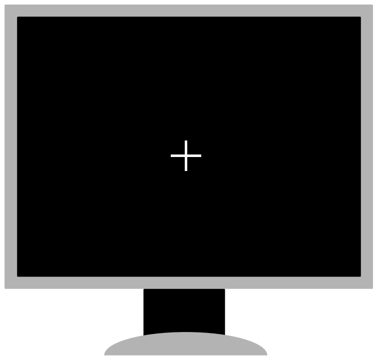

Fig. 3. Screen layout of the monitor during the pre-experiment study

Based on the work of Volosyak *et al.* [24], 7 different frequencies (6.00 Hz, 6.67 Hz, 7.50 Hz, 8.57 Hz, 10.00 Hz, 12.00 Hz and 15.00 Hz) were used. Their study showed that frequencies which are integer factors of the refresh rate of an LCD monitor are more suitable for presenting stimuli. Using the factor of the refresh rate produces a more stable stimulus frequency because only whole frames are visible on the LCD screen. The diameters of the stimuli were set to 2 and 3 centimeters, which is consistent with the work in the literature [5,14].

In each trial a simple stimulus, a blinking white circle, appeared at the location of the cross. The participant focussed for 4 seconds on the stimulus. Between trials, participants had 6 seconds rest to relax their vision. All trials were presented 25 times and were placed in a random order prior to the study, thus for each participant, 25 segments of 4 seconds of data were recorded for each different trial.

The results of the pre-experiment study with 7 participants indicated that a good set of frequencies is 10 Hz, 12 Hz and 15 Hz with a diameter of 3 centimeters. Without any training, the frequencies in this set were classified correctly with an average recall of 78.1 % ($\sigma = 18.5$) using a CCA-based detection method which will be further explained in section 4.2.

3.3 Non-BCI Selection

The BCI selection method introduces a challenge factor when a selection is being made as users need to concentrate on a stimulus to make an accurate selection. The main challenge is to gather enough data to be able to make a good detection, which is directly related to the time the selection method is operative. Although it would be much easier for users to make a selection by pointing and clicking with a mouse, this would offer little challenge and give the non-BCI selection method a great advantage when compared with the BCI selection method. To pose a similar challenge in the non-BCI selection method, it was modelled to be similar to the BCI selection method in terms of the time required for an accurate selection.

Similar to the BCI selection method users were able to start and stop the non-BCI selection method. When operative, the dogs were highlighted one at a time with an increasing highlight period. The diameter of the stimuli were kept the same as in the BCI selection method, 3 centimeters. When users stopped the selection method, the current highlighted dog was selected.

To make an accurate selection, users had to react in time when the dog they wanted to select was highlighted. With a highlight period of 250 ms users should have enough time to react as this is close to the average human reaction time [13]. The highlight period should reach 250 ms only by the time that is equal to the time needed to make a selection using the BCI selection method, which is around 2.5 seconds [14]. Therefore, the highlight period started with 100 ms and was increased 5% after every highlight, with a maximum highlight period of 500 ms.

4 Methods

4.1 Experimental Setup

The experiment held in this study consisted of two different sessions. In each session a participant used one of the selection methods (BCI or non-BCI) while playing Mind the Sheep!. Each participant used both selection methods. However, a counterbalanced measures design was used to avoid confounding variables such as learning a strategy to play the game.

Each session was divided into three trials, a familiarity trial, an easy trial and a difficult trial. In the familiarity trial participants could get used to the selection method by selecting and moving the dogs. During this trial, participants had to collect 10 objects which were placed across the playground. Next, in the easy trial, participants had to pen a small flock of 5 sheep using the dogs. During this trial two pens were placed on the playground, one on the left and one on the right of the screen to make the task easier for the participants. Finally, in the difficult trial, participants had to gather 10 sheep, which were more scattered across the playground, into one pen that was placed in the center of the playground. Between the two sessions, participants were given a break of ten minutes.

The layout of the playgrounds across the trials were kept the same to ensure no playground was more difficult for one of the selection methods. However to ensure that participants did not create an optimal strategy for a specific trial, the positions of the dogs, collectible objects and sheep were altered for the different selection methods.

A timeout was set for each trial for the participants to finish the level by collecting all objects or gathering all sheep into a pen. Participants had 3 minutes, 5 minutes and 10 minutes for the familiarity, easy and difficult trials respectively. Since immersion in games is often accompanied by losing track of time, the time left was not visible for the participants. Otherwise it could have influenced their perception of the elapsed time.

The game ran on a PC which was connected to a projector[1]. The projector was mounted on the ceiling and projected the game on a screen approximately 3 meters away from a participant. The sizes of the stimuli were scaled proportionally with the increased distance to the screen. To make sure the frequencies for the SSVEP based BCI selection method were correctly presented by the projector they were checked with a light sensor.

Participants sat on a chair behind a table and by using the mouse on the table they were able to start and stop the selection methods. The data acquisition ran on a separate PC and sent the raw electroencephalography (EEG) data to the game PC.

4.2 SSVEP Detection

Prior to the experiment, 32 electrodes were placed according to the international 10-20 system [21]. For the EEG data acquisition a BioSemi ActiveTwo system[2] was used. During each SSVEP selection EEG data was used from eight parietal-occipital electrodes (i.e. *Pz, P3, P4, PO3, PO4, Oz, O1, O2*). The EEG data was re-referenced to the common average reference (CAR) [6] of all 32 electrodes, after which a detection method was used to determine which frequency the participant was focusing on.

There are various methods to detect the presence of SSVEP. One of the most popular and widely used detection methods is power spectral density analysis (PSDA) where a fast Fourier transform (FFT) is used to estimate the power spectral density (PSD) of a time window of the EEG signal. The magnitude of each stimulation frequency can then be used for classification. A relatively new approach is using canonical correlation analysis (CCA) where sets of reference signals are constructed for each one of the stimulation frequencies. Each set contains the *sine* and *cosine* for the first, second and third harmonic of the stimulation frequency. The re-referenced EEG data and each set with reference signals are used as input for the CCA. CCA tries to find pairs of linear transformations for the two sets such that when the transformations are applied the resulting sets have a maximal correlation. The stimulation frequency with the highest maximum correlation is classified as the frequency the participant was focusing on.

As CCA-based detection methods have some improvements and advantages compared to PSDA-based detection methods, such as better signal-to-noise ratio (SNR), lower inter-subject variability and the possibility of using harmonic frequencies [2], a CCA-based detection method was used in this study.

4.3 Questionnaires and Data Acquisition

To measure the affective reaction of the participants while playing the game, they were requested to fill in a SAM [3] after each trial. It was expected that

[1] Mitsubishi WD510U, 93.3", 60Hz, 1360x768

[2] BioSemi, Amsterdam, The Netherlands

if participants became more frustrated by using a selection method, this would result in higher arousal and lower valence scores. The dominance would also be higher if participants had the feeling that a selection method was working properly and that they were in control.

After each session participants filled in a questionnaire on immersion. The questionnaire by Jennett *et al.* [12] was used for this. It contains 31 questions and is designed to measure the total immersion as well as five different factors of immersion (cognitive involvement, emotional involvement, real world dissociation, challenge and control). Although valence, arousal and dominance would probably differ between selection methods for which participants have an aversion, this does not necessarily mean participants would not become immersed in the game.

Furthermore some game statistics, such as the number of times a dog was selected, the total number of selections, the average selection duration and the time participants needed to finish a trial were collected while participants played the game. Ideally participants would use all the dogs as this would make it easier to gather the sheep. The number of times a particular dog was selected would be a good indication of how well the selection methods performed for the participants.

At the end of the experiment participants were asked which selection method they would like to use if they were given the opportunity to play the game again. This should have given a good indication of which selection method the participant preferred.

After the experiments, scores were obtained for the total immersion, the five immersion factors, the SAM questionnaire and the game statistics. The results from the SAM questionnaire were averaged over the three trials to get an average score for the valence, arousal and dominance scales. As each participant used both selection methods, the scores were compared using a Wilcoxon signed-rank test to determine if there was a significant difference between the two selection methods.

4.4 Participants

Seventeen participants (7 female and 10 male), aged between 17 and 37 ($\mu = 22.00, \sigma = 4.74$) participated in the experiment. All participants except for one had normal or corrected-to-normal vision and described themselves as daily computer users. Although eight participants had at least one-time experience with EEG, fourteen participants had no experience with BCIs. Before the experiment, all participants signed an informed consent form and they were paid according to institution's regulations.

5 Results

When the 17 participants were asked which selection method they would choose if they were given the opportunity to play the game again, 5 of them chose the non-BCI selection method and 12 of them chose the BCI selection method. This is a first indication that participants prefer the BCI selection method over the non-BCI selection method. A detailed insight might be provided by the scores for immersion, the SAM questionnaire and the game statistics, which are described below.

5.1 Immersion

Based on the immersion questionnaire the total immersion score was calculated for both selection methods. On average the participants rated the BCI selection method ($\mu = 160, \sigma = 14.55$) higher than the non-BCI selection method ($\mu = 144, \sigma = 21.89$). This difference was significant ($Z = -2.155, p = 0.031$).

The five immersion factors were also analyzed and the scores, averaged over participants, are shown in Table 1. The scores for all factors, except for the challenge factor, are higher for the BCI selection method. The five immersion factors were examined for significant differences between the BCI and non-BCI selection methods. There are significant differences for the cognitive involvement factor ($Z = -2.219, p = 0.026$), the real world dissociation factor ($Z = -1.992, p = 0.046$), the emotional involvement factor ($Z = -2.013, p = 0.044$) and the control factor ($Z = -2.310, p = 0.021$). For the challenge factor no significant difference ($Z = -0.476, p = 0.634$) was found.

Table 1. Scores of the five immersion factors, averaged over participants. Values are represented as $\mu(\sigma)$ with * indicating a significant difference with $p < 0.05$.

	non-BCI	BCI
Cognitive*	53.12 (9.01)	58.47 (5.36)
Dissociation*	25.18 (5.64)	28.06 (4.79)
Emotional*	54.35 (8.54)	59.88 (5.95)
Challenge	20.88 (2.89)	20.71 (2.34)
Control*	32.06 (5.77)	37.06 (5.08)

5.2 Affect

Based on the SAM questionnaire the total SAM scores were calculated for both selection methods and the average results are shown in Table 2.

For the valence scale the difference was significant ($Z = -2.012, p = 0.044$), however, no significant difference was found for the arousal ($Z = -0.315, p = 0.752$) or dominance ($Z = -0.403, p = 0.687$) scores.

Table 2. Average SAM scores, the values are represented as $\mu(\sigma)$ with * indicating a significant difference of $p < 0.05$

	non-BCI	BCI
Valence*	6.37 (1.55)	7.08 (1.31)
Arousal	4.82 (2.31)	4.53 (2.37)
Dominance	5.65 (2.46)	6.08 (1.64)

5.3 Game Statistics

The game statistics which were collected during the experiments are shown in Tables 3 and 4. They show the number of selections and the average selection time. For the number of selections (Table 3) there are significant differences for the easy task trial ($Z = -2.202, p = 0.028$) and the difficult task trial ($Z = -2.107, p = 0.035$). However, no significant difference was found for the familiarity trial ($Z = -1.866, p = 0.062$).

Table 3. Average number of selections for each trial, presented as $\mu(\sigma)$ with * indicating a significant difference of $p < 0.05$.

	non-BCI	BCI
Familiarity	12.53 (4.87)	10.47 (2.67)
Easy*	43.00 (26.27)	27.88 (7.86)
Difficult*	98.88 (65.90)	74.12 (30.28)

Table 4. Average selection time (in seconds) for each trial, presented as $\mu(\sigma)$.

	non-BCI	BCI
Familiarity	1.92 (0.86)	2.49 (1.71)
Easy	1.96 (1.04)	2.64 (2.63)
Difficult	1.95 (1.31)	1.71 (0.85)

Although no significant differences were found for the average selection time (Table 4) between the BCI and non-BCI selection methods for any of the three trials, it can be seen that for the familiarity and easy task trials the average selection times for the BCI selection were around 0.5 seconds higher. However, for the difficult task trial the average selection time was lower.

6 Discussion

Most participants indicated that they preferred playing the game with the BCI selection method. This seems to be supported by the results of the immersion questionnaire. The total immersion score was significantly higher for the BCI selection method, indicating that participants were more immersed than when using the non-BCI selection method. For the BCI selection method participants only had to make their intentions clear to the BCI system by concentrating on the dog they wished to selected. Besides starting and stopping the selection method, there were no other actions required. However, for the non-BCI selection method, participants still had to translate their intentions into an action, stopping the selection method at the correct time. As participants were able to translate their intentions directly into in-game actions while using the BCI selection method, they might have become more easily immersed.

Further inspection of the five immersion factors showed that all factors, except for the challenge factor, were significantly higher for the BCI selection method. The questions related to the challenge factor were about the game itself. As the averages of the challenge factor were almost equal for the two selection methods, they indicate that participants did not find the game more challenging using one of the two selection methods. For using the selection methods, the control factor might be a better indicator. As the control factor was significantly lower for the non-BCI selection method, it indicates that participants had more trouble using the non-BCI selection.

The results of the SAM questionnaire indicate that participants were more content using the BCI selection method. The results of the cognitive involvement and real world dissociation factors were also significantly higher for the BCI selection method. This could have been caused by the fact that participants had to concentrate on a dog while using the BCI selection method and did not have to translate their intentions into real world actions.

Some participants developed a strategy to deal with the trade-off between accuracy and speed. When they wanted to be accurate in their selections, they waited long enough to make an accurate selection. However, when they wanted to be quick, they moved all three dogs as one by pressing rapidly at a location on the playground. Although this behavior was observed for both selection methods, for the BCI selection method participants appeared to switch between precise and quick whenever they wished. However, for the non-BCI selection method they appeared to prefer only making quick selections, explaining the significantly higher number of selection for the non-BCI selection method.

For the BCI selection method the number of selections was lower and, although not significant, the average selection time was higher. Participants were also more immersed and content. Apparently, participants accepted that for a good SSVEP detection they had to wait a couple of seconds. However, for the non-BCI selection method they understood that it was related to their own reaction speed and suddenly they appeared to be in a hurry. Although the non-BCI selection method was modeled to be similar to the BCI selection method, it might have had an effect on the preference of the participants, as they did not want to wait to make a selection. The non-BCI selection method did introduce the same challenge and required participants to multi-task similarly to the BCI selection method. However, participants seemed to be more indulgent towards the BCI selection method than towards the non-BCI selection method. This could be caused by the curiosity of participants for the BCI selection method or the self overestimation by participants while using the non-BCI selection method.

7 Conclusion

In this study a BCI system was compared to a non-BCI system to evaluate the user experience in terms of immersion and affect. For the BCI system a selection method based on SSVEP was integrated into a game, introducing a challenge factor. A comparable non-BCI selection method based on time was also implemented into the game, introducing an equal challenge. Seventeen participants played the game with both selection methods in three trials. They rated each selection method on immersion and affect.

The results show that the BCI selection method was found to be more immersive and positively affective than the non-BCI selection method. While using the BCI selection method participants were able to directly translate their intentions into in-game actions, which made it easier for them to become more immersed. In this case, the user experience in terms of immersion and affect seemed to be improved while using the BCI selection method. Furthermore, participants appeared to have more patience when using the BCI selection method than when using the non-BCI selection method, which could have been caused by the curiosity of participants for the BCI selection method or the self overestimation by participants while using the non-BCI selection method.

For future studies it would be interesting to look at long term effects on immersion and affect. Is the BCI selection method still significantly more immersive and affective when participants are used to it? Another question is whether the indulgence towards the BCI selection method is permanent or only temporary. It would also be interesting to add a selection method based on pointing and clicking which was left out of this research. Thereby testing for the cognitive load as the selection methods used in this study required participants to multi-task. Given the intended purpose of this research, it would also be interesting to use commercial BCI input devices (e.g. Emotiv's EPOC). This would also require a proper study comparing the equipment used in this research and commercial BCIs to determine the differences and if they are feasible to use within the setup of this experiment. Other (non-)BCI selection methods, such as speech and gestures could also prove to increase immersion and affect.

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