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Kessel Run: towards emotion adaptation in a BCI multiplayer game

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"The big moments are gonna come. You can't help that. It's what you do afterwards that counts. That's when you find out who you are."

Joss Whedon

Resumo

O objetivo original de uma Interface Cérebro-Máquina (BCI, do inglês *Brain-Computer Interface*) é o restauro de função a portadores de deficiências motoras, com aplicações que abrangem desde o mover de um cursor de computador ou de uma cadeira de rodas, a dispositivos complexos de soletração que substituem a fala. No entanto, com o recente aparecimento no mercado de aparelhos de BCI portáteis e económicos, as aplicações de BCI têm vindo a migrar lentamente para áreas fora do âmbito da saúde, como é o caso do entretenimento. Em particular, o desenvolvimento de videojogos em que os modos de interação tradicionais (teclado ou botões, por exemplo) são substituídos por controlos BCI é uma aposta frequente em vários grupos de investigação em neurociências. O uso de paradigmas de BCI como controladores de jogos tem a capacidade de não só possibilitar novos meios de interação mais intuitivos (como é o caso de apenas *pensar* em mover a personagem do jogo, em vez de pressionar o botão que a move), mas também de criar novos mecanismos de jogo que não são possíveis com dispositivos tradicionais.

Para a criação destes novos mecanismos a Computação Afetiva é de relativo interesse, já que esta é a área de investigação encarregue de encontrar relações entre o estado emocional de um sujeito, através de BCIs, por exemplo, e utilizá-las para melhorar a interação com um computador (ou um jogo). Apesar de beneficiarem de um ligação direta ao cérebro, poucos são os videojogos BCI que a utilizam para adaptar o conteúdo do jogo ao estado emocional do jogador, em parte porque são poucas as relações conhecidas entre o eletroencefalograma (EEG) e o estado emocional do indivíduo, especialmente em condições pouco controladas e em cenários realistas. De facto, a maioria dos estudos em Computação Afetiva feitos com o objetivo de procurar correlações entre o estado emocional do sujeito e o seu EEG pecam por serem realizados sob condições pouco realistas, e, em particular, nunca durante uma situação de jogo. Por outro lado, apesar da frequente aposta no desenvolvimento de novos videojogos controlados por um paradigma de BCI, poucos têm em consideração as regras de um bom desenho de jogos, resultando muitas vezes num jogo que mesmo sendo funcional, é aborrecido.

Com as perspetivas da aplicação de BCI e Computação Afetiva aos videojogos em mente, esta dissertação tem como objetivo o desenvolvimento de um jogo *multiplayer* controlado por BCI, que ao seguir as regras de bom desenho de jogos, é capaz de desencadear uma sensação de divertimento nos seus jogadores. Para além disso, o jogo também deve ser capaz de evocar um conjunto diversificado de estados emocionais nos seus jogadores, de forma a poder estudar-se as correlações entre o EEG e o estado emocional de cada indivíduo no espectro da frequência. Desta forma, poder-se-á comparar as correlações obtidas num cenário realístico de jogo com o estado-da-arte, frequentemente realizado em situações controladas, e assim contribuir para o avanço da adaptação emocional em videojogos BCI.

Para concretizar estes objetivos, o videojogo *Kessel Run* foi desenvolvido. *Kessel Run*

é um jogo 3D de uma corrida espacial para dois jogadores, em que ambos devem cooperar um com o outro de forma a direcionar uma nave espacial para longe de asteróides e assim conseguir finalizar uma corrida de 2 minutos com o mínimo de danos possível. Neste jogo, as regras básicas de desenho de jogos (Teoria de *Flow* e o Paradoxo de Controlo) foram aplicadas de forma a criar uma sensação de divertimento e de controlo no jogador. A sensação de controlo por parte do jogador é particularmente importante na criação de um jogo BCI, uma vez que a sua falta poderá levar a perda de imersão no jogo e, consequentemente, à diminuição do divertimento. Assim, de forma a garantir o bom controlo do jogo o paradigma SSVEP (do inglês *Steady-State Visually Evoked Potential*) foi escolhido como modo de interação BCI.

De forma a evocarem-se um conjunto diversificado de estados emocionais nos jogadores, várias estratégias de elicitação foram aplicadas no jogo. Em primeiro lugar, este dispõe de dois níveis de dificuldade (um fácil e um difícil). O primeiro nível desafia as capacidades dos jogadores sem contudo ser demasiado difícil, pelo que se espera que evoque emoções mais positivas. Já o segundo nível aumenta bastante a dificuldade do jogo, tornando-se muito difícil batê-lo. Para além da dificuldade acrescida, o nível difícil do jogo foi programado de forma a que o controlo BCI falhe com frequência sem o conhecimento do jogador. Espera-se por isso que o segundo nível evoque níveis de frustação maiores, e estados emocionais mais negativos e excitados.

O jogo *Kessel Run* foi colocado em prática ao desenvolver-se um protocolo experimental onde 12 participantes jogaram os dois níveis de dificuldade do jogo. A cada participante foi pedido a classificação do jogo em termos de experiência do utilizador, e de cada nível relativamente às emoções sentidas no decorrer do jogo, na forma de questionários. Foram também adquiridos os sinais de EEG de cada participante.

De forma geral, o desempenho do paradigma BCI foi menor do o que esperado, conseguindo-se apenas um máximo de 79% classificações correctas. Este resultado deve-se essencialmente a dois factores: o grau deficiente de escuridão da sala laboratorial, responsável pela perda de desempenho na ordem dos 6%, e a deteção individual das frequências escolhidas para estímulo SSVEP (12 e 15 Hz). Neste último, os participantes tiveram maior facilidade em reconhecer o estímulo de 12 Hz, com um desempenho individual médio de 63%, face ao estímulo de 15 Hz com apenas 38%, o que comprometeu a *performance* geral do reconhecimento SSVEP. No entanto, apesar do desempenho fraco do paradigma, os participantes reportaram uma experiência bastante divertida (média de $flow = 2.6$ numa escala $0-5$) e desafiante (média de $challenge = 2.3$ numa escala $0-5$), com apenas um ligeiro aborrecimento (média de $tension/annoyance = 1.1$ numa escala $0-5$), podendo-se concluir o sucesso do emprego das regras de bom desenho de jogos.

As estratégias de elicitação de emoções foram apenas parcialmente bem sucedidas; não foram observadas diferenças significativas entre os níveis de dificuldade do jogo *Kessel Run* em termos de valência e excitação emocionais. No entanto conseguiu-se uma boa distribuição das avaliações emocionais dos participantes pelos quatro quadrantes das dimensões de valência e excitação, possibilitando o estudo de correlações entre o EEG dos participantes e as suas avaliaçes para cada nível de jogo em termos de oscilaçẽs no espectro da frequência e assimetrias na banda alfa.

Encontraram-se correlações significativas na dimensão da valência que parecem contradizer a teoria da assimetria da banda alfa. Em particular, obteve-se uma correlação positiva significativa indicando uma relação de diminuição da activação hemisférica esquerda e consequente aumento da banda alfa. Esta contradição foi também confirmada

pela obtenção de uma assimetria esquerda bastante significativa na banda alfa para o cortéx frontal. Observou-se ainda uma diminuição da potência central da banda beta e um aumento occipital e temporal direito para a mesma banda relacionado com a dimensão da valência.

Para a excitação encontrou-se uma correlação negativa significativa em regiões centrais e frontais na banda alfa, indicando uma activação destas regiões cerebrais aquando de estados mais excitados. Mais ainda, uma correlação significativa indicou uma assimetria direita na banda alfa para um par de eléctrodos fronto-centrais.

Espera-se que este estudo possa contribuir para uma futura geração de videojogos com a capacidade de adaptação ao conteúdo emocional do seu jogador.

Palavras-chave: Interfaces Cérebro-Máquina; Computação Afetiva; Videojogos; *SSVEP*.

Abstract

Lately the field of (digital) game research is rapidly growing, with studies dedicated to capture game experience, adopting new technologies or exploring outside traditional input methods. Alongside, research in Brain-Computer Interfaces (BCI) has significantly increased in its applications for healthy users, such as games. BCIs benefit from access to brain activity which can bypass bodily mediation (e.g. controllers) and enable gamers to express themselves more naturally in a given game context. Moreover, BCI can provide significant insight into the user's emotional state. Recent research points to numerous correlates of emotion in brain signals. A complex challenge is to use BCI for access to the player's affective state in a real gaming context, improving and tailoring the user experience.

The goal of this dissertation project is to introduce affective research to BCI games by creating a novel multiplayer Steady-State Visually Evoked Potential (SSVEP) BCI game, capable of providing a fun experience to its players and eliciting emotions for a study on EEG correlates of emotion.

The multiplayer game Kessel Run was created, resulting in a space exploration game with a flexible system that followed good game design rules with emotion elicitation strategies, controlled by the SSVEP paradigm. Twelve participants played Kessel Run using a 32-electrode EEG cap and rated the emotions felt during gameplay in a questionnaire. The SSVEP game performance achieved a maximum of 79% accuracy and an average of 55%. In addition, players reported that playing the game created a fun and immersive experience.

A significant correlation with increased alpha power on the left hemisphere and positive valence led to the contradiction of the popular alpha asymmetry theory, which states that processing of positive information causes a decrease in alpha power on the left frontal hemisphere. Furthermore, correlates in the beta frequency range have been found for valence on right temporal and central sites. In the arousal dimension a significant central and frontal alpha power decrease was found, along with significant alpha asymmetry on fronto-central pairs for increased arousal.

Keywords: Brain-Computer Interfaces; Affective Computing; Digital games; Steady-State Visually Evoked Potentials.

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List of Abbreviations

aBCI .... active Brain-Computer Interface

BCI .... Brain-Computer Interface

CCA .... Canonical Correlation Analysis

ECG .... Electrocardiography

EEG .... Electroencephalography

EMG .... Electromyography

ERD .... Event-related desynchronization

ERS .... Event-related synchronization

FFT .... Fast Fourier Transform

GSR .... Galvanic Skin Response

HCI .... Human-Computer Interaction

ITR .... Information Transfer-Rate

LCD .... Liquid Crystal Display

LED .... Light Emitting Diode

LRP .... Lateralized Readiness Potential

pBCI .... passive Brain-Computer Interface

PSDA .... Power Spectral Density Analysis

rBCI .... reactive Brain-Computer Interface

SAM .... Self-Assessment Manikin

SSVEP .... Steady-State Visually Evoked Potential

SVM .... Support Vector Machine

VEP .... Visually Evoked Potential

1

Introduction

This chapter aims to introduce the basic concepts of Brain-Computer Interfaces and Affective Computing and their potential be applied in the gaming industry. Particular interest is put on the promising applications of emotional game adaptation, leading to this dissertation's goals and outline presentation.

1.1 Brain-Computer Interfaces overview

A Brain-Computer Interface (BCI) can be functionally described as a communication system between the user's brain activity (e.g. electric or hemodynamic indicators) and a computer. Its objective is monitoring and processing brain signals to obtain features that can be translated into a command to execute an action (see Figure 1.1).

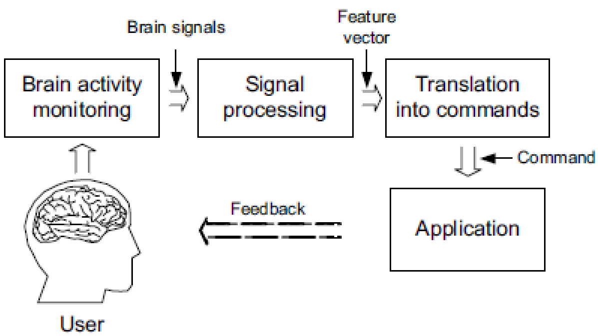
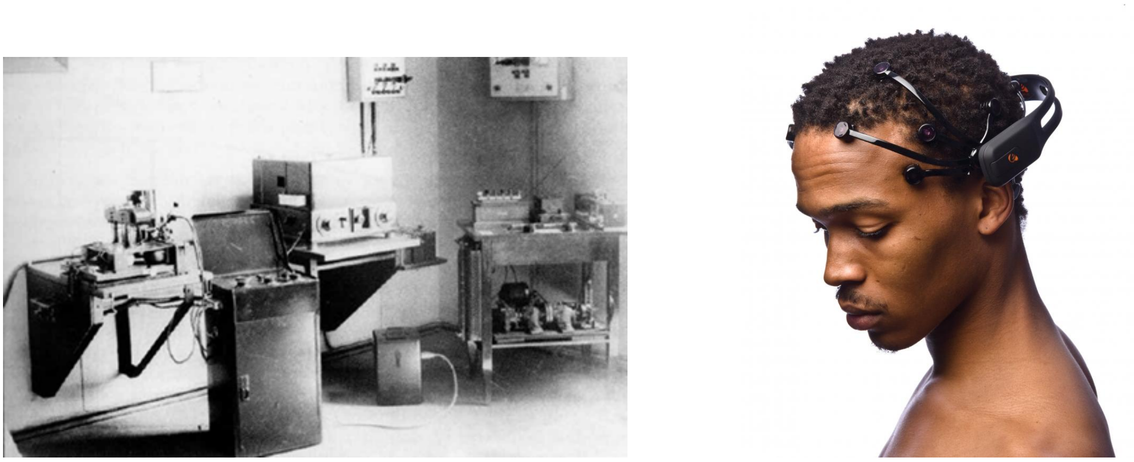


Figure 1.1: Functional model of a BCI (from (Molina et al., 2013)).

For brain activity sensing, measurements such as electrical potentials and hemodynamic responses are of particular relevance. Electrical potentials can be recorded through invasive (e.g. electrocorticography) and non-invasive techniques (e.g. electroencephalography and magnetoencephalography) (Gürkök and Nijholt, 2012). Hemodynamic measurements include functional magnetic resonance imaging, positron emission tomography, and functional near-infrared brain monitoring. Electroencephalography (EEG) is usually the preferred modality due to its high temporal resolution, non-invasiveness, ease of acquisition and cost-effectiveness.

Initially, BCI applications' primary goal was to restore communication for the physically challenged. Applications include moving a wheelchair, using a computer's screen



(a) (b)

Figure 1.2: *(a)* Early EEG machine, circa 1929 (mpiwg-berlin.mpg.de). *(b)* Emotiv EPOC headset, launched in 2008 (Emotiv.com).

cursor, spelling through a device, among others. However BCI devices are progressively becoming smaller and more affordable. Easy-to-use EEG-based BCI headsets such as the Emotiv EPOC or the NeuroSky®'s MindWave have appeared in the market, leading to their usage outside the medical field and towards general audiences, like entertainment industries. In particular, the gaming industry is embracing BCI as an acceptable interaction modality given its potential to enhance user experience by offering something that current interaction modalities do not (Ahn et al., 2014). In addition to the interest in new interaction modalities for video games, the fact that gamers are often among the first to adopt any new technology facilitates BCI introduction in the gaming field.

1.2 Affective Computing overview

There are situations where the human-machine interaction could be improved by having machines naturally adapt to their users. Associating emotional information such as expressions of the user's frustration, confusion, disliking, interest, and more, to its communication adaptation is one way of achieving an improved interaction. Affective computing expands human-computer interaction by including emotional communication together with appropriate means of handling affective information (Picard, 1999).

In affective computing, the goal is to study and develop a system or device that has the ability to recognize, interpret and react appropriately to the user's emotion or affect[1]. A system with this power could potentially gather cues to the user's emotion from a variety of sources like facial expression, speech, or physiological signals, to infer changes in the user's emotional state and have the capacity to respond appropriately, like reducing user

[1]Some confusion could arise from the loose usage of affect and emotion. In psychology, an explicit separation between the behavioral expression (affect) and the experience of a feeling (emotion) is made. *Affect* is a component of emotion, and is the term for emotional reactions that produce changes in awareness, facial expression, body language, physiological function, and behavior. *Emotion* is the conscious experience of affect complete with attribution of its cause and identification of its object. Here, however, we use the terms interchangeably when referring to the physiological aspects of affect, such as user's EEG or heart-rate, due to its unconscious nature and its objective interpretation.

frustration or offering additional information on confusing situations.

When it comes to human interaction, BCIs can benefit from adapting its operation to the emotional state of the user since they have the advantage of direct access brain activity. The BCI can provide significant insight into the user's emotional state and consequently tailor the interaction experience based on states such as engagement, stress, frustration or anticipation. For example, a robot companion for education could help children with an EEG headband learn by understanding their engagement with school tasks and disappointment when having difficulty learning. Detection of user frustration while using a BCI could also lead to better error correction algorithms, enhancing user experience.

In addition to BCI, a broader approach of measuring other physiological peripheral signals offers a wider perspective on affective research. Exploring the interplay between physiology and computer usage can be done by investigating the impact of stimuli to several physiological signals, obtained through electrocardiography (ECG), galvanic skin response (GSR), respiration, electromyography (EMG) and, of course, EEG. In addition to physiology, bodily expressions like facial expression, posture or gaze can also be tracked.

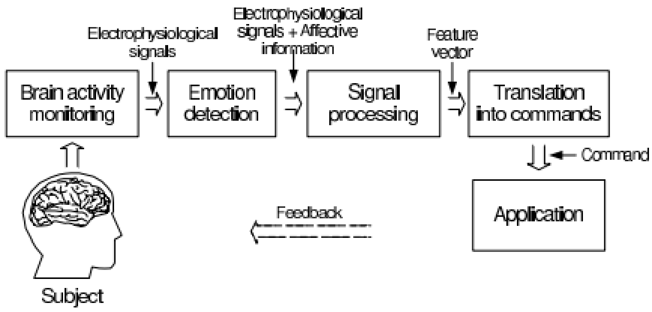


Figure 1.3: Functional model of a BCI accounting for the user's emotional state. (from (Molina et al., 2013)).

1.3 Digital games and Emotion's role in it

A large part of the population plays games, little though it may be (Games, 2013). Commercial games provide a wide range of interaction modalities: between your avatar and the virtual world, other gamers and non-player characters, as well as with objects in the game environment. This variety of interactions is reflected on popular consoles: for example, the PlayStation® DualShock™ 3 controller has fourteen buttons, two analog thumb-controlled mini-joysticks, plus a motion-sensing functionality. The Nintendo® Wiimote™ has ten buttons, can sense acceleration along three axis and contains an optical sensor for pointing. The increasing amount of interaction possibilities in games poses a problem: the more input options there are, the more effort is necessary to learn and remember what each input is for.

Introducing BCI controllers in digital games can provide a more natural method of interaction, which makes it easier for the gamer to explore a virtual world and expressing his will. In addition, if a gamer can interact with the game in a way similar to that of the real world, then learnability and memorability may no longer be an issue. The popularity of motion sensor use in games reflects this convenience, as they enable gamers to make gestures that should come naturally with their actions in the game (e.g. swinging a tennis racket). Microsoft®'s Kinect is a prime example of such movement towards natural interaction.

Although there is a clear interest in achieving more natural inputs for digital games, why choose BCI for such interaction? Healthy users require more complex interfaces than disabled people for whom BCI is the only option to interact with the external world. BCI is also slower and less accurate than most modalities that are currently available. Furthermore, BCIs often require a lot of training before being usable. The reason behind its attention in game research is that BCIs allow the gamer to express himself directly in the game world, without mediation of physically limited actions. The BCI can bypass bodily mediation and enable the gamers to, for example, choose his character's direction of movement by only thinking of it. Moreover tapping into the gamer's brain activity allows us to create new game mechanisms that are not possible otherwise. As physiological processes measured are mostly involuntary, memorability would no longer be an issue as the relation between user action and in-game action become more direct.

Beyond using BCI as a controller for the player's actions, from brain activity the user's affective state can also be derived. Among other applications, knowing the player's state can lead to game manipulation in order to keep the gamer in equilibrium, where skill and challenge are matched (see Figure 1.4). Maintaining this dynamic balance between abilities and challenge is referred to as *Flow*, and it is key to a fun experience in games. The term was coined in 1990 by Csikszentmihalyi (Csikszentmihalyi, 1990). Alternatively, the game can incorporate the player's mood into the story, for example by the appropriate adaption of interactions with non-playable characters.

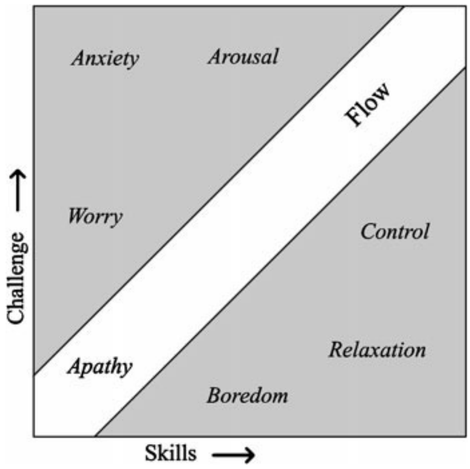


Figure 1.4: Flow diagram in games (from (Plass-Oude Bos et al., 2010)).

Along with Flow, emotions also play a fundamental part in influencing good player experience in digital games. Games have the ability to elicit all sorts of emotion in players, being the main reason people seek them. By using game scenarios where character and world objects are manipulated, we are able to elicit emotions of interest. For instance, inducing fear or anxiety by changing the player's options to cope with a certain challenge or reducing his field of vision. On the other hand, non-player characters can express believable emotions that immerse the player into the storyline, with the character's ability to make the player empathize and believe in their adventures and misfortunes. Parsec Productions' Slender: The Eight Pages, originally known as Slender, is an interesting example of how the game's world environment in a survival horror story can change the gamer's state while playing. Moreover, The Last of Us by Naughty Dog, Inc. shows how the creation of a lovable character with complex emotional development can drive the gamer into deep emotional states, completely immersed in the storyline.

Besides eliciting emotion, a good gaming experience also requires the game to interpret the gamer's emotion. By continuously recognizing the player's state, the game can check whether or not the strategies used to elicit emotion in the player are having the intended effect. Information about the gamer's affective profile and mental states can then be used to adapt game play so as to enhance the gamer experience in some way (e.g. an ally non-player character could try to increase the player's sense of control to mitigate anxiety, or the difficulty level could be adjusted through the user's level of boredom).

Combining BCI and Affective Computing into novel digital games could lead to a new generation of personalized and intuitive entertainment, where gamers are challenged to play with their minds and the game is able to pick up slight changes of mood or emotion in order to grant a fun experience throughout gameplay.

With the prospect of merging BCI and affective research on the gaming field in mind, two dissertation goals are set for this thesis: first is to create a new BCI multiplayer game that offers good and intuitive user experience to its players, following Flow guidelines to keep the gamer engaged; the second goal is to contribute towards emotion recognition in video games by exploring the EEG emotional correlates when implementing different elicitation strategies in the same BCI game.

The structure of this thesis is as follows: **Chapter 2** provides a technical background on BCIs and paradigms often employed, with emphasis on Steady-State Visually Evoked Potentials which are used in this thesis as the BCI paradigm, and on game design theories applied to BCI games. **Chapter 3** delves deeper into the underlying literature, exploring recent approaches in BCI (multiplayer) games, aspects of emotion categorization and neuronal correlates found so far, and current advances of emotion recognition in games. In **Chapter 4** the motivation, objectives and research questions for this thesis are defined. **Chapter 5** discusses the created BCI game in detail regarding its design and implementation. The experimental procedure and methods are outlined in **Chapter 6**, leading to the results presentation in **Chapter 7** and following conclusions in **Chapter 8**.

2

Background

This chapter aims to provide a technical insight on BCI functioning and the different categories of sources of control used, with emphasis on the Steady-State Visually Evoked Potentials' paradigm particularities, which was used on this thesis. Furthermore, we take a deeper look into game design theories and its implication when creating good BCI games.

2.1 Sources of control for BCI

Brain–computer interfaces (BCIs) aim at providing a non-muscular channel for sending commands to the external world using the electroencephalographic (EEG) activity or other electrophysiological measures of the brain function. Its ultimate purpose is to allow an individual with severe motor disabilities to have effective control over devices such as computers, speech synthesizers, assistive appliances and neural prostheses. A BCI system detects the presence of specific patterns in a person's ongoing brain activity that relates to the person's intention to initiate control, and translates these patterns into meaningful control commands (Bashashati et al., 2007).

A functional BCI system therefore requires the user to execute mental activities that appear as distinctive patterns in the EEG. These will be automatically recognized by the BCI and associated with a certain action. The type of mental activities and their corresponding EEG correlates are termed as electrophysiological sources of control. In this section, we introduce three types of BCI in the context of interaction between human and computer, adopting the definition in (Ahn et al., 2014) with respect to categories of sources of control (**active**, **reactive** and **passive**). Bashashati et al. (Bashashati et al., 2007) and Molina et al. (Molina et al., 2013) also provide a comprehensive list of these electrophysiological sources of control in current BCIs.

2.1.1 Active BCI paradigms

In an **active BCI** (aBCI) the user intends to interact with the BCI and purposely generates brain activity; for this reason aBCIs are generally adopted for direct control of an application. One commonly used paradigm in aBCIs is motor imagery, in which a person imagines moving a limb such as right/left hand/foot. Its source of control is related to the resulting changes in the mu (8-12 Hz) and beta (13-30 Hz) rhythms on the sensorimotor cortex while imagining movement, and its discriminative key feature is the contra-lateral *event-related desynchonrization* (ERD) along with the ipsi-lateral *event-related synchronization* (ERS). When imagining right hand movement, the sensorimotor cortex's amplitude of activity in the mu-rhythm decreases in the left hemisphere and increases in the right hemisphere. For motor imagery of the left hand, the converse occurs. Therefore, the motor imagery yields spatially different brain activity according to which hand is employed. Through signal processing and classifiers, the BCI can detect different spacial patterns and decide which is the direction the user intends. This is the same as conventional interfaces like left or right arrows on a keyboard. As its name implies, in aBCI the user initiates brain activity; thus, the information embedded in the signal is captured and employed to control the application, which could be the direction of movement of a wheelchair (Choi and Cichocki, 2008) or a game character (Pineda et al., 2003).

2.1.2 Reactive BCI paradigms

While informative brain signals are consciously generated in aBCIs, this is not always the case. In **reactive BCIs** (rBCI), while the user still intends to interact with the BCI, the information with his intention is embedded in a response signal to external stimulation. In rBCI the user voluntarily attends to a stimulus, causing his brain to react to the stimulus' features in a way that is telling to the BCI. Stimuli type choices vary according to the paradigm selected. When infrequent stimulus are presented (auditory, visual or somatosensory) interspersed with frequent or routine stimuli, a positive peak in the EEG called P300 is typically evoked at about 300 milliseconds onset over the parietal cortex. P300-based BCIs operate by presenting the user with a set of choices and randomly highlighting a different choice, like a speller (Guan et al., 2004). A P300 peak appears in the user's EEG when his intended choice is highlighted, allowing the BCI to know the user's selected choice and executing the corresponding action.

Another prevalent paradigm implemented in rBCI, and the one used on this thesis, are the Steady-State Visual Evoked Potentials (SSVEPs). These are changes in the ongoing brain signal when users are presented with repetitive visual stimuli, in most cases a pattern, at a rate greater than 5 Hz. A continuous oscillatory response at the stimulation frequency (and/or harmonics) is elicited in the visual cortex. SSVEP based BCIs operate by presenting the user with a set of repetitive visual stimuli at different frequencies which are associated with actions. To select a desired action, the user needs to focus her/his attention on the corresponding stimulus. As the power of a SSVEP matches that of the stimulus, its power only covers a narrow bandwidth making it relatively easy to detect.

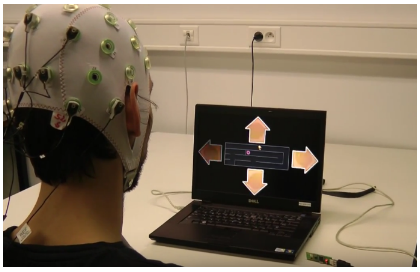


Figure 2.1: (Chumerin et al., 2011) - The Maze, a SSVEP-based BCI game.

Similar with aBCIs, rBCIs can be used to select a direction as one would with arrow keys. In SSVEP each direction is associated with a stimulus repeating at a unique frequency; the user looks at one of the stimuli to go in a certain direction. It is not the act of looking that generates the desired brain activity but the brain's reaction to the repetition frequency of the stimulus.

2.1.2.1 The SSVEP paradigm

Because the reactive SSVEP paradigm was implemented on this thesis, we must take a more in-depth look at this paradigm's characteristics.

The basic idea of using SSVEPs to control a BCI system dates back to 30 years ago when the first ancestor of SSVEP-BCI was depicted in a publication by Regan in 1979 (Regan, 1979). Since then, several advances in the technical aspects of SSVEP-based BCIs have been made regarding the choice of stimuli, the number, location and selection of EEG channels, noise reduction and detection of the SSVEP signal.

Recent studies on the SSVEP paradigm listed by Vialatte et al. (Vialatte et al., 2010) show systems for which 2 to 13 commands have been developed, with an average classification rate in the 64–96.5% range and an average information transfer-rate (ITR - a common BCI performance measure corresponding to the amount of information reliably received by the system (Wolpaw et al., 1998)) between 2.3 and 58 bits/min (maximal ITR 70 bits/min), tending to outperform more traditional BCI systems in terms of information transfer rates.

Before carrying an SSVEP experiment, one must consider the type of stimulus to employ: a complex or simple flicker. The simple stimuli can be merely blinking LEDs or flickering squares on an LCD computer screen, while complex flickers are usually alternatively reversing checkerboards. Checkerboard patterns produce more pronounced SSVEPs than simple stimuli at same frequency (Lalor et al., 2005), however their frequency range is narrower (Silberstein, 2000) and since larger space is required for them, fewer complex stimuli can be displayed simultaneously compared to simple ones.

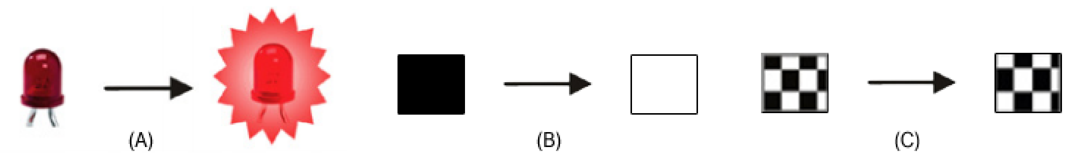


Figure 2.2: Examples of stimuli used to elicit SSVEP responses. (A) light-emitting diode, producing simple flickering light; (B) simple flickering square; (C) reversing checkerboard.

After selecting the stimulus type, one needs to find an appropriate way to generate it. LEDs and liquid crystal displays (LCD) are among the most popular stimulators used to elicit SSVEPs. LEDs are a suitable option for single flickers since they allow us to control brightness, and may also be an attractive alternative to an LCD screen since the later usually has low refresh rates (60-70Hz). On the other hand, LCD screens allow more freedom in terms of stimulus shape and are more convenient for generating complex stimuli (see Figure 2.1).

In addition to the type of stimuli and generator chosen, it is also necessary to determine the optimal stimulus frequency. Since each subject is different, a reasonable approach is to choose the stimulus frequencies depending on the subject's responses (Vialatte et al., 2010). Muscular activity becomes more pronounced at higher frequencies which should also be taken into account and avoided if possible.

Detection of SSVEPs in current BCIs relies on the application of spatial filters along the visual cortex, across occipital electrodes, and temporal filters. One of the most popular methods of SSVEP detection is power spectral density analysis (PSDA) (Hakvoort et al., 2011) which estimates the power spectral density of the user's EEG signal's using the fast fourier transform (FFT). The magnitude of each stimulation frequency can then be used for further classification. On the other hand, the canonical correlation analysis (CCA) method is a relatively new approach to detect the presence of SSVEPs (Kalunga et al., 2013). It uses linear correlation relationships between two multidimensional sets of variables, aiming at finding a new basis such that the two sets have maximum correlation. Kalunga et al. (Kalunga et al., 2013) have shown overall improvements while using a CCA-based detection method, especially in the information transfer rate and accuracy. Tello et al. (Tello et al., 2014) also found CCA to consistently perform better than PSDA, obtaining accuracies up to 80%.

2.1.3 Passive BCI paradigms

Finally, in **passive BCIs** (pBCIs) the user's primary aim is not to interact with the BCI application; it does not give control to the user, nor does it require any effort on his part. The pBCI system watches the user passively in order to adapt the task or the environment for improving and enriching the Human-Computer Interaction (HCI) or the quality of life. This might be by monitoring the attention level, emotional state, or mental load of the user. For example, the ratio of frequency band powers such as beta and theta (4-8 Hz) are used for attention quantification (Kim et al., 2012), and the alpha power for the relation level (van de Laar et al., 2013). In these cases pBCIs rely on brain signals generated during natural interaction of the user with his environment so they do not require any additional effort (such as attention to stimulation). Therefore, they can operate within aBCIs and rBCIs without demanding extra experimental requirements.

Although BCI applications' primary goal is to restore communication for the physically challenged, with the considerable expansion of BCI technology it is being used in a variety of other domains, such as security (e.g. brain activity based biometrics (Marcel and Millan, 2007)) or gaming (Nijholt, 2009). In fact, it should be mentioned that BCI game applications are not that different from BCI medical applications or BCI security applications, being that they all derive from similar sources of control. The next section will provide a brighter light in the technical aspects of the reactive SSVEP, which was chosen as paradigm for this thesis' BCI game and will later be further reviewed within design ad implementation context in Chapter 5.

2.2 Good game design in BCI games

Since we are within the topic of (BCI) games, it is important to understand what makes a good game and what general rules should we follow when attempting to create one. Although several BCI-based games have been described in research (see Chapter 3.1), there is sometimes a discrepancy between the experiments' executed goals and the inclusion of game design in those experiments, being that games created for brain computing research are often adaptations of previously existing games or newly designed ones with very little regard for the gameplay itself.

In cases where game design is not taken into account or is wrongly applied in brain computing experiments, incorrect research conclusions can be drawn. Failing to understand the new requirements of an input mechanism vastly different from a normal game controller (such is the BCI case) might result in bad games and, therefore, limit the potential of BCI devices as game controllers. As Gürkök et al. (Gürkök et al., 2012) emphasize, this results in games that may be functional but often hardly enjoyable. At the same time, BCI games developed by game designers may focus on enjoyment but show little regard for technical aspects related to BCI. Thus, all game research should necessarily consider game design theories. Properly designed BCI games, in particular, will most likely lead to better and more accurate research, and its results could assist in the development of more successful games or even lead to insights into the improvements on signal processing that can be made.

In Chapter 1.3 we briefly touched on the concept of *Flow* and its meaning. Csikszentmihalyi introduced the term used in positive psychology to represent the mental state of someone fully invested in an action, resulting in a sense of high enjoyment and fulfillment (Csikszentmihalyi, 1990). Sweetser and Wyeth (Sweetser and Wyeth, 2005) and Chen (Chen, 2007) showed that the Flow-theory is a perfect fit for gaming since it is comparable to the immersion players experience when playing a game. The Flow Zone (see Figure 1.4) is therefore a balance between challenge and abilities, in which the player is actively engaged and where his skills match the challenge level of the game.

In the scope of BCI games, Salen and Zimmerman's *Paradox of Control*, which is strongly based of Csikszentmihalyi's theory of Flow, seems to also have a relative impact in BCI game design. The Paradox of Control (Salen and Zimmerman, 2004) assumes that a game will be most engaging if a player feels in control of the events that occur in a game, while at the same time feeling the possibility of losing control due to his own failure. Nevertheless, there are limits to his loss of control since it is essential that any failure should only be cause of the player's fault. Losing the game due to imprecise control breaks immersion and leads to a less enjoyable game. If we consider a regular video game's controllers, the Paradox of Control implies that when a players presses the jump key his character should jump immediately but should never jump if the key is not pressed. Hence when a players fall into a pit and dies, he can only blame himself for failing to jump correctly.

For this reason, it has become apparent that finding ways to implement the Paradox of Control is essential for proper BCI games, as is the Flow theory. Since brain signals are hardly similar to pressing buttons on a controller and are arguably more complicated, techniques need to be found to create such a paradox of control, specially concerning the BCI paradigm selection. In order to achieve Flow the player, therefore, has to feel both *in control* and *challenged*.

While the concepts of Flow and the Paradox of Control are easy to understand, putting them into practice might not be immediate. We become, then, in need of a set of rules to follow when creating a well designed BCI game. As noted by Csikszentmihalyi (Csikszentmihalyi, 1990) and summarized by Veen (Veen, 2013), Flow can be split into eight different components, though not all of them are required to achieve Flow:

- *A challenging activity that requires skill* - it requires the creation of a satisfying difficulty level. This can prove challenging, for the difficulty of a game may differ strongly from player to player. Chen (Chen, 2007) suggests the implementation of choice as solution, allowing a broad range of players to adjust the game to their own skill level. For example, a player can opt to simply beat a game or try to gain the high score.

- *Clear goals* - it stems from the definition of a game itself. We expect a game to work in a limiting context with rules in which the player tries to achieve his objectives (goals).

- *Direct, immediate feedback* - we can derive the meaning of a game from the relationship between actions the player performs in the game and the game's outcome. In other words, the player should perceive the result of any action immediately, and this outcome should influence the game system as a whole. For example, in a fighting when the player hits the 'punch' key, he should observe that the enemy was hit and his health was lowered.

- *Sense of control* - as mentioned previously, it is essential that players feel in control of the game as stated by the Paradox of Control. Input should not only be discernible and integrated but also direct and consequent.

- *A merging of action and awareness*

- *Concentration on the task at hand*

- *A loss of self-consciousness*

- *An altered sense of time*

While the first four can be seen as requirements of a well designed game, the final four can be interpreted as the result of being in the Flow Zone, driving the player into an immersed state while he's engaged in the game. In addition to these key components, Sweetser and Wyeth (Sweetser and Wyeth, 2005) also consider social interaction to be a core element of good game design. Although more could be said regarding good game design and its theories, the presented elements should suffice in creating a well designed BCI game. In Chapter 5, we shall came back to these key components when describing this thesis' BCI game.

3

State of the Art

This chapter aims at exploring relevant literature concerning this thesis' work. Studies on BCI applications in the gaming industry, with a special interest in multiplayer BCI games, and the recent advances in emotional EEG correlates research are introduced. Studies concerning affective adaptation in gameplay are also scoped.

3.1 BCI approaches in games

Nowadays, when we look at BCI games we are asking for theory that allows us to distinguish and employ activity in different regions of the brain (using machine learning algorithms) to map commands that are meant to control or adapt a game. The brain activity can be evoked because the gamer gets, among others, frustrated, engaged, irritated, bored or stressed while experiencing the game; because there are external stimuli (visual, auditory, ...) consciously generated by the game to force the making of a decision in the game; or because the player consciously tries to evoke this activity by performing a mental task (e.g. imagining a movement or focusing his attention).

The first BCI game was created by Vidal in 1977 (Vidal, 1977), in which the user can move in four directions in a maze by fixating on one of four points displayed off-screen. A diamond-shaped checkerboard is periodically flashed between the four points, evoking neural activity on different sites of the primary visual cortex. Using an online classification method, this visually evoked potential (VEP) is recognized, and used to move in the maze. Since then, a significant number of approaches to BCI games have been made.

A simple approach is to integrate the broadband frequency power of brain signals, such as the alpha, beta, gamma and mu rhythms. For example, Pineda et al. (Pineda et al., 2003) used motor imagery as an alternative to traditional input devices. The mu rhythm power on motor cortices was used to steer a first person shooter (FPS) while forward/backward movement was controlled using physical buttons. Moreover, in this experiment no machine learning was involved; the four participants were subjected to 10 hours of training and effectively learned to control their mu-power in order to play the game. Another BCI game that controls movement is the Pacman game by Krepki et al. (Krepki et al., 2007), where detection of direction is based on lateralized readiness potential (LRP), a slow negative shift in the EEG that develops over the activated motor cortex starting some time before the actual movement onset. In this game, users report they sometimes had the feeling that Pacman moves in the correct direction *before* the user was consciously aware of this decision, indicating a new level of interaction that can be enabled only by BCI. Other arcade games have been adapted into BCI using the mu rhythm: a pinball machine (see Figure 3.1) was controlled in (Krauledat et al., 2009) by sensorimotor activity. While the player imagines left and right hand movements, algorithms decode in real-time the user's intention. Their primary results show that a fast and well-timed control well beyond chance level is possible, even in an environment which requires precisely timed and complex predictive behavior. Using machine learning methods for mental state decoding, BCI-based pinball control is possible within the first session without the necessity to employ lengthy subject training.

Figure 3.1: BCI game pinball from (Krauledat et al., 2009) demonstrated in the CeBIT exhibit in Hanover, Germany (2010). Here, each flipper of the arcade game was activated by using a sensorimotor activity approach.

While we have motor-control BCI games based on induced activations, evoked response BCI games where the application measures the response to a stimulus require tight coupling between the game that presents the stimuli and the BCI. In evoked responses, the user initiates actions that depend on stimuli from the game. An example of an evoked response is the P300, used by Bayliss (Bayliss, 2003) in a virtual apartment exploration task. Objects were highlighted using a red translucent sphere, evoking a P300 when the object the user wanted to select was highlighted.

Evoked responses show a relative advantage over induced BCI paradigms: they allow easy selection of one out of multiple options by focusing attention on a stimulus. For example, a 2D racing car with four different directional controls using steady-state visually evoked potentials (SSVEP) was created by Martinez et al. (Martinez et al., 2007). Until 2013, the majority of studies conducted on BCI games used active paradigms (motor imagery: 37%) or reactive (P300: 11%; SSVEP: 13%) BCIs (Ahn et al., 2014).

Although interesting, games based on the imagination of movement and on evoked potentials provide only a proof of concept for the applications of BCI in the gaming industry. These games replace physical buttons with virtual, attention triggers that do not change the game mechanics significantly. In contrast, we have seen a series of games based on neurofeedback that exploit the unique information a BCI can provide best.

A classic example of neurofeedback is the Brainball by Hjelm et al. (Hjelm et al., 2000). In this game, a multiplayer competitive perspective is applied to BCI: using a headband, the two player's EEGs are measured and a relaxation score is derived from the ratio between the alpha and beta activity. The relaxation score is used to move a steel ball across a table away from the most relaxed player; this poses almost as an anti game, as when the ball is close to the opponent's side and the player realizes he is winning, he gets excited and loses. Here, relaxation is both a game goal, and a means of interaction.

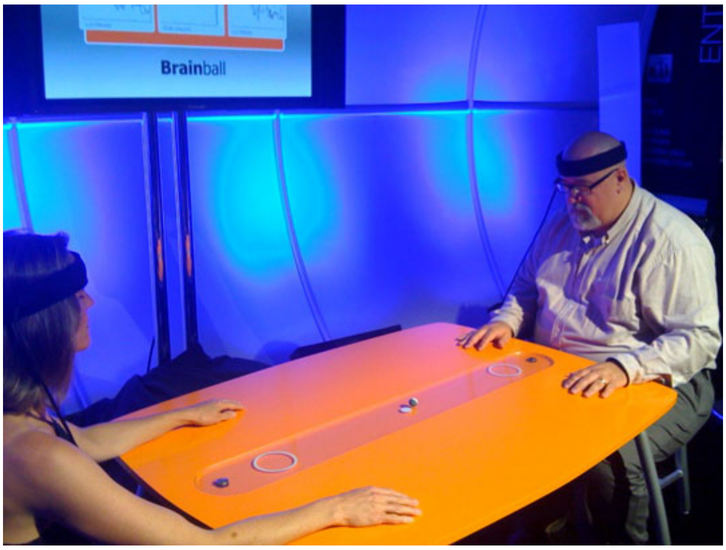


Figure 3.2: Demonstration of the game Brainball from (Hjelm et al., 2000), a multiplayer competitive game in which a steel ball moves away from the player as he relaxes.

In one of the versions in Bacteria Hunt (Mühl et al., 2010), in which the aim is to control an amoeba using arrow keys and to eat as many possible bacteria, the relative alpha power of the player is used. The more relaxed the player is, the easier it is to control the amoeba. This game was adressed in both a multimodal and multiparadigm point of view, as a second version adds a second BCI paradigm into the game: SSVEP, where now eating is performed by concentrating in a flickering circle around the bacteria. By performing both SSVEPs and neurofeedback analysis the study allowed us to look into possible interactions between the BCI paradigms used in the game. The study reports that subjects were able to keep their alpha power up, in compliance with the instructed relaxation task.

3.2 Multiplayer approaches in BCI games

Although the introduction of BCI in the gaming world has been around for a while, few games exist for multiple users. Here, the objective is to connect more than one user to the same video game application in real-time, through their brain activity. Adding to the previously mentioned competitive game Brainball (Hjelm et al., 2000), Blankertz et al. reported using the Berlin-BCI system in a 2-player environment (Blankertz et al., 2007) inspired by the famous video game Pong. This application was successfully exhibited during the CeBIT expo 2006 (Hanover, Germany) on two subjects performing competitive demonstrations all day. Bonnet et al. created BrainArena (Bonnet et al., 2013), a football game controlled by hand motor imagery in which two users move a virtual ball towards a goal located on the left or right side of the screen, respectively. Finally, Hakvoort et al. presented in (Hakvoort et al., 2010) the 2-player game Mind the Sheep!, designed to study the influence on cooperative social interaction using BCI control with SSVEP selection. In the game, players need to herd a flock of sheep across a field by commanding a group of herding dogs, where the aim is to fence in all the sheep as quickly as possible.

As any cooperative or competitive task implies interactions between users, both physical and vocal, it may conflict with the BCI usage itself. EEG systems are prone to muscular artifacts and noise in such situations, which can lead to a trade-off between performance and freedom of use.

Figure 3.3: Two users playing BrainArena in a competitive trial. (Bonnet et al., 2013)

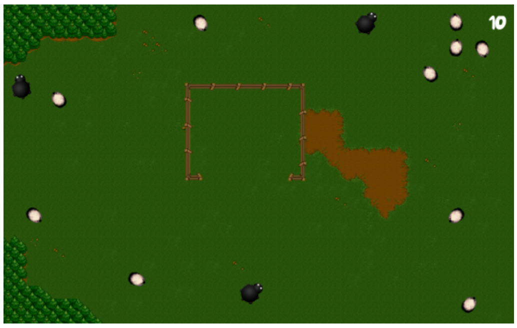


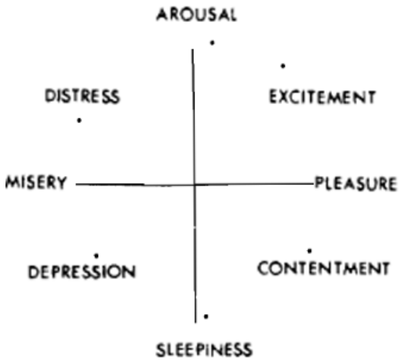
Figure 3.4: Screenshot of the Mind the Sheep! game. (Hakvoort et al., 2010)

3.3 Emotion categorization and its measures

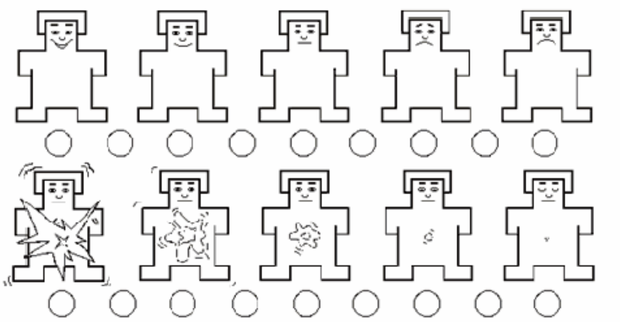
Emotions are psycho-physiological phenomena associated with a wide variety of expressed subjective feelings, observable behaviors and changes in autonomic body state. Due to their complex nature, there is no universally accepted model to categorize emotions. Some theories suggest that emotions can be conceptualized as differing in a degree on one or another dimension. Russell (Russell, 1980) defends these theories with his *circumplex model of affect*, using two orthogonal dimensions to model emotions (see Figure 3.5a). The first dimension is pleasure (or valence) and it explains the pleasantness (hedonic value) related to a given affective state. The second dimension (arousal) explains the physiological activation related to the affective state. From these two dimensions, theoretically all human emotions can be explained in terms of a Valence-Arousal spectrum, similar to a coordinate system. Other theories to model emotion exist, however the Valence-Arousal theory is used to represent the effects of emotions on BCI in most research.

Since emotions differ in their elicitors, appraisals, physiology and behavioral responses, there is no universal method to assess them. The methods trying to measure the affective state can be categorized into two groups: **subjective** and **objective** methods.

Subjective methods consist of questionnaires, adjective checklists and pictorial tools, used to evaluate the (subjective) emotional experience of a person as it is reported by the person himself. There are several standardized methods that are selected according to factors such as the targeted affective theory and emotional aspects of interest. One very compatible method to Russel's Valence-Arousal theory is the Self-Assessment Manikin (SAM) test (Lang, 1980). This method includes a self-evaluation form which provides



(a)



(b)

Figure 3.5: *(a)* Circumplex affect model from Russell (Russell, 1980). Eight emotions are modelled in a combination of pleasure/displeasure in the horizontal dimension, and arousal/sleep in the vertical dimension. *(b)* SAM (Self-Assessment Manikin) (Lang, 1980) questionnaire.

scores for the person's valence and arousal feedback, according to the 9-point scale as shown in Figure 3.5b. The SAM is picture-oriented and devised to directly assess the valence and arousal associated in response to an object or event.

On one side, subjective methods can accommodate any set of emotions, including emotional blends. However, they are cultural and language biased, only measuring affective states which the respondents are consciously aware of.

Objective methods use the physiological cues that arise from responses related to emotional experiences. These measures overcome the limitations of subjective methods, but suffer from individual differentiation in physiological responses to the same emotional state.

3.4 Physiological windows to Emotions in EEG

As discussed earlier in Chapter 1, affective assessment via EEG is of particular interest when enriching HCI by incorporating information about the context of interaction or the user's behavior. Cognitive theories of emotion claim that the primary source of affective reactions is in the brain, as well as is the stimuli, memory or thought's processing that triggered the emotional response (Damasio et al., 2000). Reacting to stimuli, the limbic system is responsible for initial emotional interpretation; the hyphothalamus is the structure in charge of processing incoming signals from the autonomic nervous system and triggering visceral physiological effects (Kandel et al., 2000). From the hypothalamus the stimuli information is passed on to the amygdala, which connects stimuli to emotional reactions like reward/fear and evaluates new stimuli by comparing them to past experience. Although the amygdala is considered as a vital structure for emotion processing (Oude Bos, 2006, Kandel et al., 2000, Damasio et al., 2000), because it is an underlying structure like the rest of the limbic system, it cannot be detected directly in recordings from the scalp. However, it is connected to the temporal and prefrontal cortices, which is thought to be the way visceral sensations are interpreted cognitively, resulting in a consciously experienced feeling of an emotion (Kandel et al., 2000). EEG sensors could offer a faster and direct recognition of emotional states, with the benefit of being a relatively non-intrusive, safe and continuous method.

Correlates of affect have been studied via a multitude of affect induction protocols. Aftanas and Golocheikine (Aftanas and Golocheikine, 2001) found that during a positive 'blissful' experience while meditating, subjects had their subjective scores of emotional experience significantly correlated with theta in anterior frontal and frontal midline leads, whereas scores of internalized attention correlated with both theta and alpha lower synchronization. Huster et al. (Huster et al., 2009) used pictures with emotional content to report significantly lower alpha power density in negative stimuli for the right hemisphere; the difference between right and left hemispheres showed to be larger at parietal positions than at frontal and central electrode sites. This defining hemispherical activation is introduced in the hemispheric valence theory which holds that positive emotions are processed in the left frontal cortex, while negative emotions are processed in the right frontal cortex (Davidson, 1992). Several studies have further shown patterns that corroborate with the processing of negative emotional information being reflected by the decrease of alpha power over the right frontal hemisphere, and the processing of positive information by the decrease of alpha power on the left frontal hemisphere (Davidson, 1992, Huster et al., 2009, Allen et al., 2004, Schmidt and Trainor, 2001).

While frontal asymmetry is the most frequently found correlate of valence, arousal activates neural structures in general and therefore seems to be associated with a global decrease in the alpha band (Barry et al., 2007, Schmidt and Trainor, 2001). More localized effects have been found, however these seem to contradict each other. Schmidt and Trainor (Schmidt and Trainor, 2001) described a correlation between frontal activated regions and the perceived arousal of music excerpts, while Aftanas and Golocheikine (Aftanas and Golocheikine, 2001) reported a frontal deactivation with increasing arousal measured as an increase in low-alpha band power. Other EEG phenomena have been observed by Reuderink et al. (Reuderink et al., 2013). The authors confirmed under a realistic, uncontrolled gameplay environment the following affective correlates: a significant decrease in frontal theta power for increasing positive valence; a significant frontal increase in power in the alpha range associated with increasing arousal; a significant right posterior delta power correlated with increasing arousal; and asymmetry in lower alpha bands correlates with self-reported valence.

In addition to the previously mentioned correlates, Koelstra et al. (Koelstra et al., 2012) described several other interesting findings when presenting their database emotion analysis using EEG, physiological and video signals[1]. Using music videos as emotion elicitors, the authors report a central decrease in alpha power with arousal, agreeing with conclusions found in (Barry et al., 2007). Other negative correlations with arousal were also found in the theta and gamma band power. For valence, Koelstra et al. detailed an increase of power in the theta and alpha band in occipital regions, as well as a central increase and decrease in right temporal and occipital for the beta band. The increased beta power over right temporal sites validates Cole and Ray's (Cole and Ray, 1985) findings for positive emotion self-induction and external stimulation. Additionally, highly significant gamma increase in power was found correlated with valence. However, the meaning behind high frequency correlations remains uncertain due to EMG activity being prominent in this band, especially over anterior and temporal electrodes.

For a more summarized reading of the found neural correlates, Table 3.1 provides an

[1]DEAP dataset for emotion analysis: http://www.eecs.qmul.ac.uk/mmv/datasets/deap/

overview of the previously mentioned literature.

These neural correlates, although not concrete, can be used in the design of an automatic classifier of emotion, and some studies have shown potential to yield estimates of user states with acceptable precision via neurophysiological signals. Nevertheless one important note should be made here: when analyzing and comparing these neural correlates, one must have their emotional elicitors in mind. To ensure the generalization of the findings from the controlled laboratory context to a real-world BCI context, the affective state is best elicited in a way resembling the context of application. To our best knowledge, only Reuderink et al. (Reuderink et al., 2013) performed their experiment under a more realistic as less controlled scenario when looking for neural emotion correlates.

Oude Bos (Oude Bos, 2006) built an emotion recognition system using auditory and visual stimuli, achieving over 90% accuracy for subject-independent with a Fisher's Discriminant Analysis valence and arousal classifiers. In their turn, Lin et al. (Lin et al., 2009) applied Support Vector Machines (SVM) to obtain 94.86% and 94.43% for valence and arousal classification, respectively. In both (Oude Bos, 2006) and (Lin et al., 2009), EEG components defined according to frequency range were used for feature extraction. In (Sourina and Liu, 2011) a SVM was employed using two fractal dimension algorithms for feature extraction, achieving performances between 70% and 100% in valence-arousal classification of music and images.

All previous presented works dedicated to building automatic classifiers of emotion rested their accuracy on training and testing under very controlled experiments, using auditory and visual stimuli with little to no movement. To our best knowledge, no attempt has yet been made in building a classifier for realistic HCI, in particular for gameplay.

3.5 Emotion adaption in games

There are multiple ways to optimize user experience in games. Saari et al. (Saari et al., 2009) introduced the term "psychological customization" and suggest the manipulation of a storyline or the presentation of games to create a user-specific affective adaptation. Knowledge about the user profile, tasks and context can be used to regulate the flow of emotions as narrative experiences, or to avoid or limit negative emotions harmful to user experience (or health). This knowledge can also be applied as a response to observed emotional states (e.g. maintain challenge), or to deliberately create new combinations of emotional, psychological states and behavior. However, for an online adaptation, a reliable and robust estimation of the user's affective state is imperative.

Game adaptation through emotion can be done in the BCI context, using only brain signals as affective input. In alpha-World of Warcraft, or alphaWoW, by Nijholt et al. (Nijholt et al., 2009), alpha activity is recorded over the parietal lobe to control shifting between two shapes in the player's character. While conventional controls are used to play the popular game World of Warcraft®, the user plays a druid who can shape shift into animal forms. In bear form the druid is better protected from physical attacks and more damage-effective in fights. In normal elf form, the druid is more fragile but can effectively cast spells for damage to knock out enemies from a distance, as well as heal herself. The alpha activity, related to a relaxed alertness in parietal sites, is used as a premise to map shape-shifting: agitation would have a natural relation to the bear form, as the bear is eager to fight, whereas the relaxed alertness would be a good match for the mentally-adept

Table 3.1: An overview of major findings on EEG correlates to human emotion.

Author, Year	Correlates	Sites
Aftanas and Golocheikine, 2001	Emotional "*blissfulness*" ⇒↑ theta (4-6 Hz)	Anterior frontal and frontal midline
(Context: mindfull meditation)	Internalized Attention ⇒↑ theta; ↑ low-alpha (6-8 Hz)	Frontal midline, anterior/central frotal, and right central regions (theta); Midcentral region (alpha)
Schmidt and Trainor, 2001	Positive stimuli ⇒↓ alpha (8-13 Hz)	Effect more pronounced in right hemisphere
(Context: music excerpts listening)	Negative stimuli ⇒↓ alpha	
	Positive valence elicited less power (i.e. more activity) compared to negative valence	Frontal
	Intense stimuli/Arousal ⇒↓ alpha (i.e. more activity)	Overall frontal
Huster et al., 2009 *(Context: picture visualization)*	Negative stimuli ⇒↓ alpha (8-13 Hz)	Right hemisphere significantly different than left hemisphere
Koelstra et al., 2012	Valence ⇒↑ theta, ↑ alpha, ↑ beta (14-29 Hz), ↓ beta, ↑ gamma	Occipital (alpha, theta); Central (↓ beta); Right temporal and occipital (↑ beta)
(Context: music video watching)	Arousal ⇒↓ alpha (8-13 Hz), ↓ theta (3-7 Hz), ↓ gamma (30-47 Hz)	Central regions (alpha)
Reuderink et al., 2013	Valence ⇒↓ theta (4-7 Hz)	Right fronto-central region (Fc6)
(Context: realistic gameplay)	Arousal ⇒↑ alpha (8-11 Hz), ↑ delta (0-3 Hz)	Right frontal (alpha); Right posterior (delta)
	Valence ⇒↑ low-alpha asymmetry	Frontal alpha (Fp1-Fp2/Fc1-Fc2)

elf (see Figure 3.6).

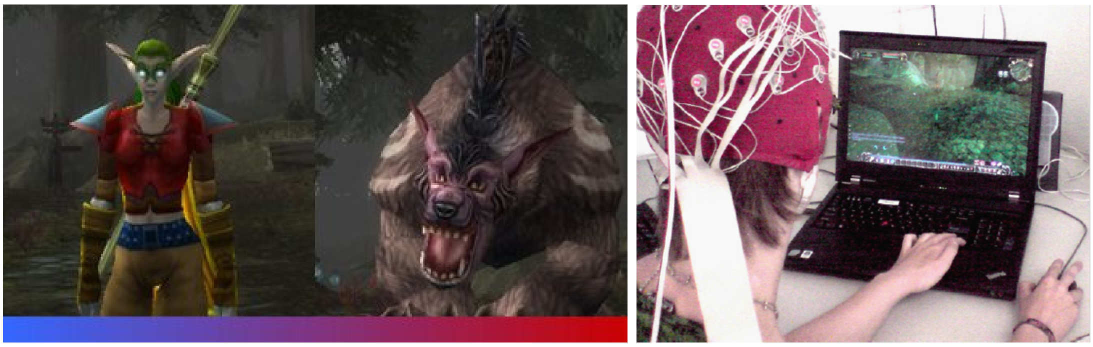


Figure 3.6: A user playing World of Warcraft using brain activity to control her character in the game (Nijholt et al. (Nijholt et al., 2009)).

Another example of a game that uses mental states is Finding Star, by Ko et al. (Ko et al., 2009). In Finding Star, the player has to find a portal to take her home, controlling her cat and animals in the world with emotional signals from a BCI headset, as well as traditional input data from keyboard and mouse to defeat monsters and solve puzzles in the world. While the player plays the game, his brain status (attention and meditation level) is reflected into the game progress. For example, at certain spots during the gameplay the player has to aim in order to shoot enemies. The degree of jittering of the crosshair varies according to the player's attention value. On other occasions, the player's level of meditation value affects how easy it is to find a hidden object. The research was carried out by dividing the participants into 2 groups: one group played a version of the game using the BCI headset, while the other group played a version of the game without emotional adaptation. The participants playing the game with BCI interpretation found the game significantly better than the version without BCI.

Other interesting experience was done by Carofiglio and Abbattista (Carofiglio and Abbattista, 2013). In a virtual exploration task, the player has to explore a 3D reconstruction of a Nazi extermination camp. During the navigation, videos and photos documenting the Jewish and Gypsy's lifestyle are played according to their emotional impact. During each scene, the players instantaneous and long term excitement is detected by the BCI which adapts the next scene to be shown, given the current scene's affective impact on the player. An alghorithm was created in order to maintain the player's sense of immersion, while protecting him from more negative states of emotion.

Despite the obvious efforts put in applying BCI on new and existing games and the improvements in Affective Computing regarding EEG usage on emotion recognition, it seems that a long road is still ahead of emotionally adapted video games. Although a promising start of game adaptation research has been made (Nijholt et al., 2009, Reuderink et al., 2013, 2009), most games still use proprietary algorithms for mental state recognition that due to their confidentiality status, are somewhat unreliable. A better integration of findings for emotion correlates (cf. Section 3.4) and BCI game research (cf. Section 3.1) is still needed.

4

Dissertation Objectives

After reflecting on technical background and state-of-art work on BCI games and Affective Computing, in this chapter the present thesis' motives and goals are defined, along with the subsequent research questions.

4.1 Motivation

The motive behind the present work stems from the combination and personal enthusiasm for three different research fields: Affective Computing, BCI, and digital games.

Affective Computing is already by itself an interdisciplinary field that deals with the complexity of human affects and looks for ways to decode emotional information and translate it into useful technologies. In particular, Affective Computing has a great potential towards increasing user experience. The BCI research field is an expanding area that builds a communication bridge between the brain and an application. New portable and cheap devices for non-invasive BCIs allows for researchers to dip into areas such as entertainment or user experience, complementing or even creating new exciting technologies for the future. Finally, the video game industry is an enticing one for many. Video games are popular across people from different age groups, serve both as entertainment and stress buster, and its community eagerly absorbs new technologies to create new innovative ways to play.

Although extensive work has been made in each field individually, fewer efforts have been put in combining the three together. Particularly, while the scientific community has had great success in finding emotion correlates in EEG and other physiological signals, studies applying affective monitoring to digital games still lack in complexity. On the other hand, BCIs' presence in digital games is expanding by creating new game mechanics and controllers, but it does not yet apply the findings in affective studies to custom adapt the game to player's emotions.

The joining of these three fields could lead to a new generation of video games (and general entertainment) by increasing game input complexity not only in BCI controllers, but with the inclusion of affective data that enables a whole new spectrum of game environment possibilities.

4.2 Objective

The present work is part of a larger research project meant to create a BCI game fit to answers different research questions. As so, its goal is divided in two components:

4.2.1 BCI multiplayer game

As mentioned above this dissertation is part of a joined research project, designed to not only study affect data in a real gaming setting (on the present dissertation), but also to analyze cooperation/defective behaviors in game-related social interaction (on (Moreira, 2016)).

As so, the first goal is to conceptualize and build a functional BCI game based on the SSVEP paradigm, that fits both research intents, allowing cooperative or competitive behaviors between players (resulting in a multiplayer system with 2 players) and gathering conditions suitable for elicitation of different emotions. Additionally, by taking into consideration the simple game design rules presented in Chapter 2.2, we intend to create an enjoyable experience for the players as close as possible to a real gaming one, i.e., providing fast and reliable controls, rich audiovisuals and interesting mechanics that translate well in BCI controls, as well as a decent level of challenge to keep the players engaged.

4.2.2 EEG emotion correlates

The second goal of this dissertation is to explore the EEG correlates of emotion in a real gaming context. Since most studies regarding affective EEG research have been made under controlled laboratory settings (cf. Chapter 3.4), it is important to corroborate these findings within a less controlled context. By implementing emotion elicitation strategies in the created BCI game, we intend to compare the relevant affect EEG data related to Valence and Arousal (see Chapter 3.3) to recent state-of-the-art findings in neuronal correlates in the frequency spectrum. Due to the noisy nature of gaming with signal artifacts originating mainly from muscle movements, we expect that affective indicators in the data may be scarce or difficult to find. However these indicators, if manifested, could potentially lead to the creation of an emotion recognition system applicable in video games and capable of adapting them accordingly.

4.3 Research Questions

Since this thesis' focus is on creating a SSVEP-BCI multiplayer game that is capable of generating relevant affect EEG data by applying different emotion elicitation strategies, the following research questions should be answered:

- *Is the created BCI multiplayer game enjoyable for players?*
- *Are the SSVEP controls implemented reliable?*
- *What correlates regarding valence and arousal can we find in EEG data, during a real gaming context in which noise is prevalent?*
- *Are those correlates comparable to those found for a controlled audiovisual setting in State-of-the-Art work?*

5

BCI Game Design

In this chapter we will explore the methodologies used in the design, development and implementation of the BCI game. The chapter is divided into multiple sections, each focusing on different steps of the progress. Section 5.1 starts by revisiting some of rules for a good game design which we intend to implement throughout our game, before briefly introducing the game - Kessel Run -, its goals and simplified gameplay in section 5.2. Section 5.3 explains the game's mechanics and the different elements introduced in it. In section 5.4 considerations about BCI paradigm selection are made, leading to the SSVEP implementation in section 5.5. Afterwards, section 5.6 deals with the emotion elicitation strategies that are put into action on the game. Finally, section 5.7 approaches the technical side of implementation, touching on the software choices and their integration.

5.1 Game design requirements

Earlier in Chapter 2.2 we introduced a set of rules and concepts for good design in BCI games, mostly based on Csikszentmihalyi's Flow theory and Salen and Zimmerman's Paradox of Control. While the Flow theory describes the immersion in a game as a state in which the player is actively engaged and where his skills match the challenge level of the game, the Paradox of Control assumes that in a state of Flow the player must feel in control of the events, while at the same time feeling the possibility of loosing control due to his own failure. These essentially stated that in order to achieve Flow the player has to feel both in control of his skills and challenged by the game.

To sustain this subtle equilibrium, there are a few requirements one must follow to ensure an enjoyable game. Since we are now designing a BCI game ourselves, and to ensure a proper testing base, we are required to support the game with these requirements. These were introduced in Chapter 2.2 and consist of: a challenging activity that requires skill, clear defined goals, immediate sense of feedback, and sense of control. To keep user experience within the Flow Zone, the game should mix and match these components, offering adaptive choices that are embedded in the core concepts of the game.

Besides good game design, we must also take into account the research questions our experiment must answer. In our case, we are searching for EEG features in the frequency spectrum that correlate with emotion (see Chapter 4.3) and therefore the game should also be capable of eliciting different emotions on its players in the valence and arousal dimension. Besides this thesis' individual requirements, as mentioned previously (see Chapter 4.2) the game is also meant to respond to (Moreira, 2016)'s research questions and should therefore be capable of motivating cooperative/competitive behaviors, resulting in a multiplayer game.

The game to be developed has, therefore, to meet the following requirements:

1. The game must feature a clear goal.
2. The game must have clear rules.
3. The game should be controlled solely by the BCI paradigm.
4. The game must challenge the players' skills.
5. The game must implement emotion elicitation strategies.
6. The game must be multiplayer.

5.2 Kessel Run

Kessel Run is the computer game developed for our experimental purposes. Built on the cross-platform game engine Unity 5®[1], the game world contains a moving spaceship navigating through an asteroid field. Although not crucial to play the game, its story is inspired by Lucasfilm Ltd.'s Star Wars saga, in which the Kessel Run was an hyperscape route used by smugglers to move spice from the Kessel spice mines to their costumers. The route involves several extreme changes in velocity in order to jump to/drop out of light speed, and the time to perform the run proved very difficult to arbitrate.

(a) Main menu (b) Loading panel

(c) Connection warning (d) Gameplay

Figure 5.1: Screengrabs from the Kessel Run computer game.

Being a multiplayer game, the players' goal is to survive a 2 minute space race by cooperating with one another, losing only the smallest possible amount of fuel. Since the steering of the spaceship is shared by both players (each player controls one of the

[1] Unity 5®, from Unity Technologies - *https://unity3d.com*

propellants' movement), cooperation is needed in order to win the game. There are two main actions each player can take while steering the spaceship: move his propellant up or move it down, which allows to either rotate the spaceship or move it in the desired direction (up or down). To win the game, the spaceship should last the entire 2 minute race without loosing all fuel which decreases every time the ship is hit by an asteroid. The game is lost when fuel is zero before the race ends at the 2 minute-mark.

If we look back at the design requirements made in the previous section, we can see that some of them are already met. For a start we have a clear goal (to survive the 2 minute space race with the most possible amount of fuel), which checks requirement n°1. Since the game is meant for 2 players, it also checks requirement n° 6. In the following sections we will explain how the other requirements are satisfied.

5.3 Game mechanics

5.3.1 Elements

To keep Kessel Run interesting for its players, it is necessary to include elements that make it not only enjoyable, but also that aid in deriving meaning from the game's sets of rules and goals. In some cases, these elements can even help navigate the game world by keeping the player informed of his scores, for example.

Bellow are described the elements that we introduced in Kessel Run and that can be seen in Figure 5.2.

The **Asteroids** can be found floating around space and are meant to satisfy requirement n° 4, since these damage the spaceship and reduce fuel. Asteroids are spawned at random locations around the player's perimeter at every frame of the game, and have different sizes and rotations.

The **Fuel Power Ups** are scattered randomly around space, but are more scarce and much smaller than asteroids. By gathering fuel power ups the players are able to keep their fuel level high and therefore win the race. However, because these are small and rare, gathering them is not trivial.

Besides these in-game elements, several on-screen components were added to Kessel Run. The **Fuel Bar** indicates the fuel left on the spaceship, while the **Timer** shows how much time is left until the race ends and the players win. There is also the players' **Control Panel**, which has two arrows that turn red when the player moves in the respective direction. This helps them visually understand one another by following what the other is doing and also keeps them informed of their options in terms of spaceship movement. On a more technical perspective, the **Connectivity Indicator** is always present for each player under his Control Panel and indicates whether or not the BCI software is acquiring data and working with the game. This prevents any experimental mistakes. The indicator is orange when the system is not connected, and turns green when it is.

Two additional elements were added to the game. The first is the possibility for one players to take control of the entire spaceship by himself (**'Take Over'** command). When one player takes over, the other becomes unnecessary since who takes over is now able to control the spaceship alone, although being restricted to only going up or down. Players can only take over when a red button periodically appears on the screen bottom, and the first player to press it takes over the spaceship for a total 5 seconds. This functionality is intended to stimulate players' competitive behavior and was introduced within the

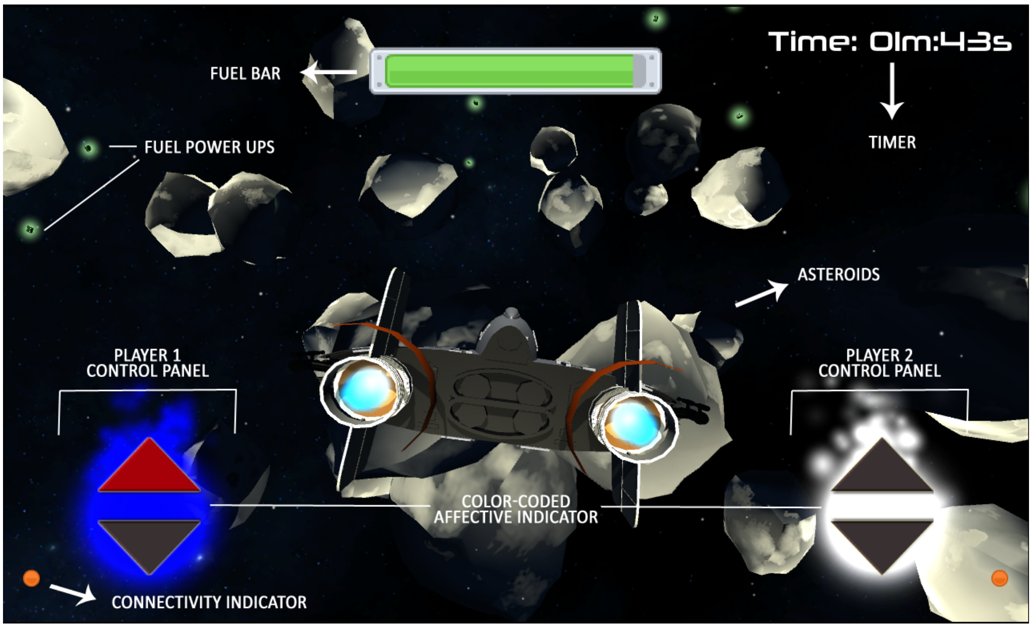


Figure 5.2: Kessel Run - multiplayer BCI game in which players must cooperate with each other to navigate through an asteroid field. Several on-screen elements indicate players' stats such as: time left to win the game, fuel level, affective state and an indicator of software connectivity.

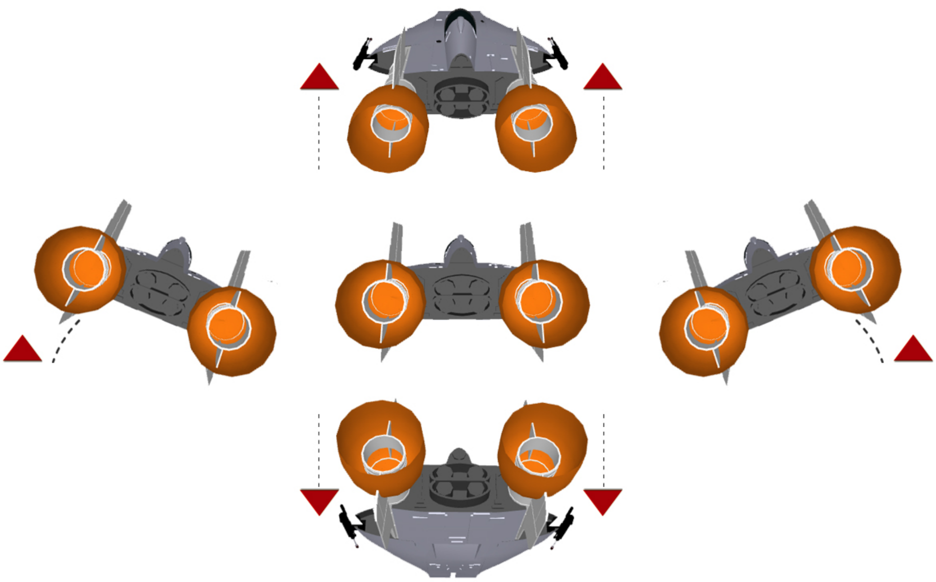


Figure 5.3: Game mechanics in the spaceship movement. Each player controls the direction (up or down) of one propellant. If both player move their respective propellers up/down, the ship moves in that direction. Otherwise, the wing rotates in the selected direction (e.g. left propellant rotates to the right when player goes up).

scope of (Moreira, 2016). The second element is a **visual indicator of the player's affective state**. Behind each players' control panel, an aura-like cloud is color-coded to represent the respective player's affective state regarding the valence-arousal dimension: low arousal/high valence is depicted as blue; low arousal/low valence as yellow; high arousal/low valence as red; and high arousal/high valence as green. While the player's affective state changes the aura shifts from one color to another, letting them know how their partner is feeling and enabling adaptation of their game strategy accordingly. This element was implemented in the game as a future prospect of emotional adaptation, but was not used in the experiments.

5.3.2 Rules

According to requirement n^{o} 2, the game must be governed by a set of rules which the players makes use to achieve their goal and win the game. In Kessel Run, these rules are translated into the restricted movement of the spaceship and on the fuel points system, as well as the timer of the race itself.

As mentioned previously, each player is only able to manipulate one side of the spaceship. As a result both have to work together in order to steer the ship in the desired direction. Since each player controls their respective ship's propellant, they have only two possible movements: up or down. We chose to restrict this motion for two reasons; while being restrained would force the players to work together and create a more fun game, it also reduces the degrees of freedom for the BCI. Because each player only has three choices (steer up, down, or stay in the same place), this simplifies the classification process which we will introduce later on.

Although the players are individually restricted, together they can combine the two movements to steer the spaceship in different directions (see Figure 5.3). Since each player only controls one propellant, if he chooses to move alone the spaceship will be tilted in its respective side. Otherwise, if both chose to go in the same direction they can move the entire ship, or tilt at a higher degree when going on opposite directions. This allows for a higher range of motion and permits space scouting for fuel power ups and the dodging of asteroids.

A points system is a frequent rule implemented in several games. Here, points are disguised as fuel. The race starts with 100% fuel, and every time the ship is hit by an asteroid (by not dodging efficiently) fuel decreases by 5%. The only chance players have of regaining fuel is by passing a Fuel Power Up, which increases fuel by another 5%. If the ship reaches 0% fuel at any given time, then the game is over and the players lose. On the other hand, if players manage to keep fuel above 0% until the timer ends, then the race is won.

In Kessel Run, as in many games, the points system serves two purposes: while they clarify the game's goal (number of points must be above zero to win), they also provide a choice in the game; players can chose whether they simply want to beat the game, or improving their score. Providing these types of choices in the game helps keeping the players in the Flow Zone since the difficulty can be adjusted to the player's needs.

5.4 Paradigm selection

When dealing with BCI games, the paradigm selection must be carefully considered. Some paradigms might prove more useful for BCI gaming than others. Paradigms may be more accurate, have a higher sense of control, or simply offer higher speed or more dimensions of control. Furthermore, all paradigms will have their own potential as well as limitations with respect to the paradox of control. This leaves us with the task of selecting the best paradigm for achieving an occurrence of the paradox of control.

Passive paradigms based on mental states have several limitations. First, achieving a proper sense of control is difficult. When asked to reach a certain state (e.g. relaxed), players can find it awkward, especially when a BCI device is the one determining the mental state. Although training for this paradigms is an option, it is time consuming. Secondly, and most important for Kessel Run, is the pacing. Due to the time required to assign a mental state, passive paradigms should be played at a slow pace. Since it's necessary that players make decisions fast in Kessel Run (e.g. dodging an incoming asteroid, or reaching for power up), these type of paradigms are not adequate to our game.

On the other hand there are active paradigms, of which motor imagery is frequently applied. Much of the same limitations of mental state paradigms can be found in motor imagery. While these paradigms are more similar to normal human interaction and could result in a more natural feel for most players, motor imagery generally requires time for training. It also allows fast performances in games (Gürkök et al., 2012) and in theory many different forms of motion could be detected. However, motor imagery works best when used to detect a single motion, such as the movement of a finger (Quek et al., 2012), and is severely limited by BCI illiteracy, i.e. the inability to use a paradigm. Research by Guger et al. (Guger et al., 2009) showed that after a few minutes of training only 19% of the people trying to use motor imagery got an accuracy of 80% or higher. Although it shows potential, motor imagery might not be an satisfactory paradigm for the Kessel Run game.

We are left with reactive paradigms, in which the interaction is triggered by the player on any desired moment in the game. Stimulus response paradigms allow for many dimensions of interaction, as the player is only asked to attend a certain stimuli when selecting an option. They have relative low illiteracy rate – 89% of the users are able to get an 80% accuracy or higher after only a short training (Guger et al., 2009) – and can be used without requiring long training sessions. For reactive paradigms, the P300 and SSVEPs are the most used. But which of these paradigms are most suitable to be used for a game Kessel Run? Even though the P300 paradigm shows high accuracy with little training required and has a smaller likelihood of tiring the player, this paradigm was not suitable for this thesis. The reason behind not choosing it is the interaction method: P300 research usually employs the oddball paradigm, in which an infrequent stimulus is selected among several other more frequent stimuli. While the recognition itself is fast, one must wait for the appearance of the odd stimulus. In a game in which a continuous interaction is desirable (the player can move continuously in Kessel Run, not by iterations), the P300 paradigm is left out, which leaves us with the SSVEP paradigm that was selected in our game. From the sense of control perspective, we consider the SSVEPs to be the most suitable since they also low illiteracy rates, require little training (Vialatte et al., 2010), and more importantly provide a continuous control since the BCI detects user's intention for as long as he attends the stimuli (flickering lights). Moreover when placing external

LEDs for SSVEP controllers, the space on the computer screen is no longer occupied with BCI and is free to be solely dedicated to the game. However, it is important to note that SSVEP also has downsides. Having the player concentrate on stimuli constantly can become very tiresome and uncomfortable to the player (Gürkök et al., 2012), particularly for the SSVEP paradigm as it features a constant flickering and could potentially break immersion.

5.5 SSVEP Paradigm implementation

After selecting our paradigm, we most now follow requirement nº 3 and implement it as a game controller. The SSVEP paradigm - a periodic brain response evoked by the repetitive presentation of a flickering visual stimulus with a certain fixed frequency - was chosen to allow the players to control the spaceship.

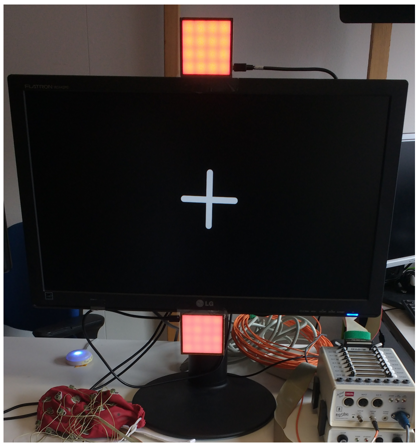


Figure 5.4: SSVEP paradigm implementation: LED light placement at top and bottom of each player's screen.

For our game two red solid LED lights are placed on the top and bottom's midline of each player's screen for the up and down directions, respectively. Using external LEDs as visual stimuli avoids the limited number of frequencies of use due to monitor's refresh rate. The flickering is done at 15 and 12 Hz, detected on the 10-20 system's Pz or/and Oz electrodes, and using Canonical Correlation Analysis (CCA) as a detection method.

CCA is a type of correlation technique that focuses on two sets of variables. Its strength is that it tries to find pairs of linear transformations for the two sets such that when the transformations are applied the new sets of variables have a maximal correlation (Tello et al., 2014). Mathematically, CCA assumes X as a multichannel EEG signal and Y a simulated stimulus signal's "Fourier series", and presumes K targets with stimulus frequencies $f_1, f_2, ..., f_k$. CCA's goal is to find the canonical variables between to two sets, the pair $x = X^T W_x$ and $y = Y^T W_y$, such that the correlation is maximized. Y is the reference signal:

$$Y = \begin{bmatrix} sin(2\pi f_k t) \\ cos(2\pi f_k t) \\ . \\ . \\ . \\ sin(2\pi N_h f_k t) \\ cos(2\pi N_h f_k t) \end{bmatrix}, t = \frac{1}{F_s}, \frac{2}{F_s}, ..., \frac{T}{F_s} \quad (5.1)$$

in which f_k is the frequency stimulus, N_h the number of harmonics, T the number of sampling points, and F_s the sampling rate. Our detection algorithm uses $N_h = 2$, while $f_1 = 15Hz$ and $f_2 = 12Hz$ with $K = 2$.

CCA tries to find the weight vectors W_x and W_y that maximize the correlation between X and Y and satisfy the conditions in Equations 5.2 and 5.3, i.e., measures the linear association between two sets of variables using its autocorrelation and crosscorrelation.

$$E[xx^T] = E[x^T x] = E[W_x^T X X^T W_x] = 1 \tag{5.2}$$

$$E[yy^T] = E[y^T y] = E[W_y^T Y Y^T W_y] = 1 \tag{5.3}$$

The CCA algorithm is implemented in MATLAB® and used in real-time during the game. The algorithm uses only 80 samples ($T = 80$) at time. Since $F_s = 512Hz$ for our system, each player decision is made every 0.15 seconds, which is rather fast considering it is a BCI system. Personal player's settings are defined empirically by selecting which electrode combination (Pz and/or Oz) and CCA threshold has better performance.

5.6 Emotion elicitation strategies

In order to meet our research questions and requirement nº 5, Kessel Run must be able to induce different affective states. To do so, two difficulty levels were implemented in Kessel Run - one easy and one hard.

The easy difficulty level is expected to be challenging yet possible to win: the amount of asteroids in space is lower and fuel power ups are readily available within reach. We expect when on the easy level players should be kept under more positive states (e.g. fun, engaged). In here, the challenge stems only from the BCI sense of control and cooperation between players. On the other hand, the hard difficulty is expected to elevate stress and frustration on players. By increasing the amount of asteroids while decreasing the amount of power ups available to a point of which is very difficult to beat the game, we expect players to feel more disappointed or frustrated when losing. In addition, when hit by an asteroid the spaceship loses 10% fuel compared to the 5% on the easy level. To further increase difficulty and player frustration, the controls are randomly inactivated: every 2 seconds they have a 50% chance of becoming unresponsive for a random amount of time from 0.5 to 2 seconds. This approach, as opposed to simply inactivating controls every certain amount on time, allows us to make the increased difficulty of the level more noticeable without the players suspecting of a systematic and intentional error or unresponsiveness.

Besides the changes in game mechanics, a soundtrack switch was also implemented; while the easy difficulty level has more calm and happy music which is more prone to help the players focus, the hard level plays a more upbeat electronic music that reflects the increase in difficulty.

It is expected that the applied strategies elicit a good combination of emotions within the valence/arousal spectrum, and we anticipate that the easier level will be accompanied by more positive and calmer states, while in the hard one more negative and aroused states should occur.

5.7 Software integration

Now that the main components of our game are completed, we are left with implementing them technically. In the previous sections we have mentioned already two of the core softwares used to build our system: Unity 5® and MATLAB®.

Unity is a cross-platform game engine that focuses on portability, used to develop video games for PC, consoles, mobile devices and websites. The reason why we chose Unity to develop Kessel Run was the easy-to-use editor; it is an engine that focuses on visually simplifying the game development workflow, allowing to build and quickly modify game projects. Unity also allows scripting (JavaScript and C#) more complex object behaviors, giving a greater flexibility of design.

When it comes to processing the players brain signals and applying the SSVEP paradigm, we chose MATLAB as our core software. MATLAB is a programming tool often used for data processing since its notation is simple and powerful, the implementation fast and trusted, and it is very good at generating plots and other interactive tasks.

After developing the game in Unity and implementing the BCI paradigm in MATLAB, we are left with two pieces of software that are not specifically designed to interact with each other. Furthermore, MATLAB is rarely used as a real-time processing tool due to being slower than compiled code, and does not have a library to acquire data from the BCI device used. We are therefore in need of a software that is:

a) able to connect to Unity and MATLAB at the same time, and interact with its different scripting languages.

b) able to acquire data from BCI devices.

c) capable of compiling MATLAB code on the fly.

d) preferably capable of controlling the crucial aspects of the experiment (e.g. start of acquisition, data markers and saving).

While it is difficult to fill all requirements, we were able to find a software that met our specifications. BCI2000®[2] is a free general-purpose software system for BCI research. It can be used for data acquisition, stimulus presentation, and brain monitoring applications. Besides supporting a variety of data acquisition systems, BCI2000 facilitates interactions with other softwares. For example, MATLAB scripts can be executed in real-time from within BCI2000 and its simple network-based interface allows for interactions with external programs written in any programming language, such as Unity. Because of its flexibility and ease of integration with other softwares, BCI2000 was chosen to function as a system manager for the experimental set-up, being in charge of data acquisition and processing, exchange of signals to/from Unity (i.e. player decisions as result of CCA, and markers in the data), and overall handling of all involved software parts.

The BCI2000 software consists of four programs (modules) working together in a certain order to build a BCI/neurofeedback applications. These modules handle acquisition of brain signals (the *Source module*), processing of these brain signals (*Signal Processing module*), user feedback (*User Application module*), and the interface available to the investigator (*Operator module*), respectively. These four modules can be launched individually with a graphical user interface or started automatically using a script (*batch*) file. A full BCI session rests on these four modules.

For our experimental set-up, the following modules were selected:

1. *Source Module* - we chose the `Fieltrip buffer` (from the Fieldtrip toolbox[3] (Oostenveld et al., 2011)) for acquiring data from our BCI device, the Biosemi ActiveTwo system[4]. This module was chosen instead of the standard Biosemi one since Field-

[2]BCI2000®, from Schalk Lab - http://bci2000.org/

[3]Fieldtrip toolbox for EEG/MEG-analysis, developed at the Donders Institute for Brain, Cognition and Behaviour - http://www.ru.nl/neuroimaging/fieldtrip

[4]http://www.biosemi.com

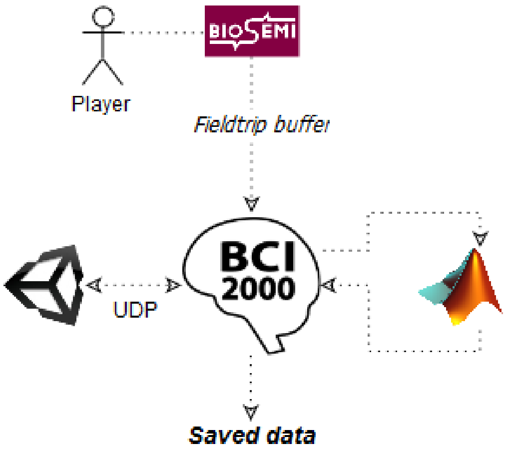


Figure 5.5: Software integration - BCI2000 serves as a manager that handles incoming acquired data and its processing over MATLAB, interacting with Unity which is in charge of running the BCI multiplayer game.

trip allows for the acquisition of other supported peripheral sensors from Biosemi, such as GSR, as opposed to only EEG signals.

2. *Signal Processing Module* - we chose the `MatlabFilter` which implements a mechanism for using the Matlab engine within the BCI200 pipeline. BCI2000 pushes each block of acquired data to a well-specified Matlab function (i.e. `*.m` file) that is executed, and upon processing, returns the output back to the pipeline.

3. *Application Module* - it is set to a `Dummy` module. Since the game is running under the Unity software, there is no need for user feedback or stimulus presentation.

4. *Operator Module* - it's the interface that allows us to start and end recording, adjust acquisition and processing parameters, setting a saving directory, subject code, and initialize data time markers, among others.

Because each module works individually, it becomes an extremely flexible system. If we wish to change the BCI device all we need to do is alter the Source Module for another one, for example the `Emotiv` module. Any changes necessary to be made in the signal processing can be quickly implemented by altering the MATLAB code. However there is one important word of notice: one BCI2000 session only acquires signals from one Biosemi ActiveTwo system at a time; this means that for a multiplayer game such as Kessel Run, we are in need of at least 2 computers. In our set-up, we chose to have 3: the 2 players have dedicated computers that are in charge of acquiring, processing, and sending their signals to the game that is open on a separate pc.

5.7.1 Communication protocol

Although BCI2000 is a versatile software, as you might have noticed in the previous section it does not provide a module for interfacing with Unity. Therefore it is necessary to look for other ways to establish a bi-directional link to exchange information between the two, i.e., the players processed signals and the game information (start and end of game, when and which player takes over, and if the game was lost) that is to be saved on the data for later analysis. One practical way to do so is to set up an UDP (*User Datagram Protocol*) based connection.

There are a few reasons to choose UDP over other network protocols. UDP is used when speed is desirable and error correction isn't necessary since it prioritizes newer incoming data packets over previous data. Most importantly, its introduction to the BCI2000 system has minimal interference with timing, is wireless and supports multicasting to multiple hosts - which is relevant when building a multiplayer game. On the other hand, because newer data packets are prioritized they are susceptible to losses or reordering. To keep the probability for such losses as low as possible, protocol messages have been designed to be short, self-contained, and redundantly encoded in a human readable fashion (Bci2000.org).

BCI2000 has a built-in feature - the `AppConector` - which supports receiving and sending messages over a UDP IP/port. By setting an UDP connection on Unity's side with the same IP and port, it is now possible to exchange messages between the two. For our experiment, the UDP messages being sent from BCI2000 are related to the player's decision in the game: go up, down, or stay in the same position. Unity sends messages back to BCI2000 regarding the game status: beginning and end of game, and whether it was lost or won, which are then marked on the saved data.

By setting up the UDP connection, we now have a way to communicate between all the computers (the players' and the game's) in a way that the game is being controlled by each player's brain signals, and that all relevant game information is securely saved along with the data. All communication is done wirelessly.

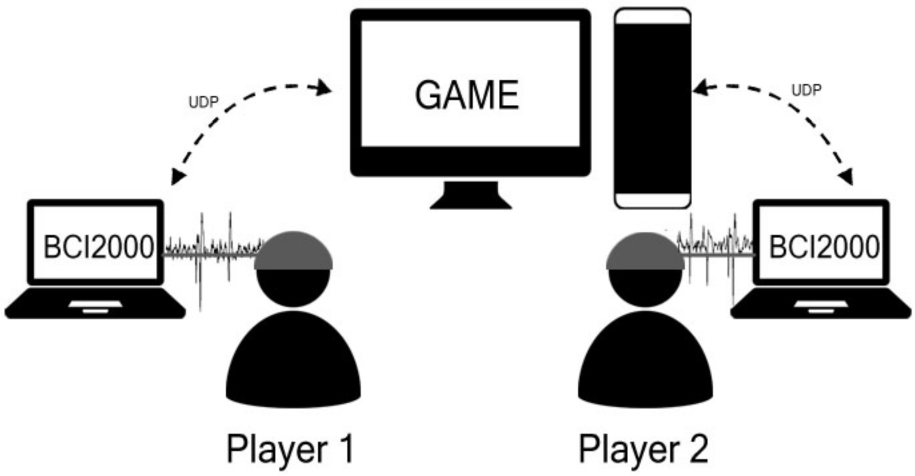


Figure 5.6: UDP connection scheme: each players' computer processes the incoming brain signals, translates them into game actions, and sends them to the dedicated computer game. The computer game returns game information for marking the saved data.

6

Experimental methods

In the present chapter we discuss the experiment carried out for this thesis and its methods. We will first remind the reader of our research goals and requirements, after which we explain our methods for the experimental procedure, data acquisition and analysis.

6.1 Goals

Before elaborating on the experimental design we are required to revisit this thesis' research goals. With clear goals in mind, we are able to translate them into the experimental requirements that we must follow.

In Chapter 4 we reviewed our research's goals and questions. On the whole, with this experiment we intend to see if the BCI multiplayer game Kessel Run is capable of creating an enjoyable user experience for its players (i.e. *Were the implemented game design rules successful?*) and if the SSVEP paradigm is a reliable way to control it (*Did the player feel in control?*). Furthermore, we mean to find out if our emotion elicitation strategies were fruitful (*What emotions are the players feeling while playing the game?*) in order to analyze proper correlates in each player's EEG, while doing it so in a realistic gameplay context.

Our experiment, then, must be prepared to answer these questions by implementing adequate methods of measure. The experiment must be able to evaluate the game's playability and the SSVEP performance as a BCI game controller, and likewise measure the effects of the game in the players' emotion while maintaining a realistic feel of gameplay. In the next sections we will explain in detail how such an experiment was achieved.

6.2 Procedure

6.2.1 Set-up

The experiments were performed in a quiet darkened laboratory environment. Since the game is dependent on the ability of participants to fully concentrate, we try to create a relaxing environment with as little external distractions as possible. By darkening the room, the SSVEP lights also appear brighter. This is, of course, not a completely realistic scenario. Although a somewhat controlled environment is desirable in order to obtain reliable answers, it is important to note that its findings might fail to generalize to real life settings.

The set-up consisted of 3 computers: two for the EEG data acquisition, processing and recording, and one for the participants to play the game. A table with comfortable chairs was placed in the room center, and participants were seated facing each other as seen in Figure 6.1a. By seating this way players could see each other and interact during gameplay while focusing on the game without too strong head movements.

The game was presented using a dedicated desktop (see Figure 5.6) that displayed it on two 1920 x 1080, 60Hz mirrored screens, each facing one of the players, and sent synchronization markers directly to the recording PCs. The LCD screens were placed approximately 50 cm apart from the player. Two pairs of red SSVEP LED lights (10 x 10 cm) were mounted on the top and bottom's midline of each player's monitor as described in Section 5.5.

6.2.2 Participants

Participants volunteered to take part in this experiment after a Call for Participants flyer (see Appendix A) was distributed on University of Twente's campus. We asked all participants to bring a friend, and if no friend was available they were teamed up with another participant.

We instructed participants to talk in their preferred language during the game and informed them that their bodily movements (laughter, talking) could hinder the BCI performance, but did not ask them to refrain from movements or interaction because one of the goals of this study is to obtain emotional data under a realistic gameplay, and preventing players to interact would greatly affect it.

Any participant with neurological disorders, in particular epilepsy due to the use of flickering lights, was excluded from this study.

6.2.3 Questionnaires

As mentioned previously in Section 6.1, to meet our research goals and answer relevant questions, we must apply adequate tools as forms of measure. Here we will detail how we evaluate the game's user experience (to assess the game's playability) and the players' emotion while playing it.

The Game Experience Questionnaire (Ijsselsteijn et al., in preparation) is a self-report tool used to measure the psychological impact of digital games and is meant to be administered immediately after the game session has finished. Its core module assesses game user experience with scores (ranging from *0-not at all* to *4-extremely*) on seven components: Immersion, Flow, Competence, Positive and Negative Affect, Tension, and Challenge. Because some items are difficult to fill in by participants when they only have a short time available to play the game, we adapted the original questionnaire. From the original set of items, we eliminated those regarding the Immersion component as they are predominantly related to the game's storyline (e.g. *'I was interested in the game's story'*) since Kessel Run does not have one. We also excluded redundant spare items from the remaining components in order to keep the questionnaire short. This resulted in the Game Experience questionnaire on Appendix E that was handed to the participants to asses their user experience in regard to the game's playability.

The Self-Assessment Manikin (SAM) (Lang, 1980) is a picture-oriented instrument to directly assess the pleasure and arousal associated in response to an object or event. The manikins illustrate a nonverbal, graphic depiction of various points along each of the two affective dimensions. SAM ranges from a frowning, unhappy figure to a smiling, happy one when representing the pleasure/valence dimension. For the arousal dimension it ranges from a sleepy relaxed figure to an excited, wide-eyed figure. In the version we used of SAM (Appendix D), the subject can place an 'X' over any of the five figures in each scale, or in-between figures, which results in a 9-point rating scale for each dimension. With this questionnaire we can obtain ground truth for the emotion each player felt during the each game level with respect to the Valence-Arousal spectrum. Because we direct the SAM questionnaire to each game level's emotional experience, it is important to note that the typical game duration is different for the two levels, since in the harder mode players are expected to loose well before the 2 minute time mark. However, because of the stability in game events, we expect that emotions remain constant through gameplay.

6.2.4 Experiment

The experiment's protocol was reviewed and accepted by the University of Twente's Ethic Committee. Voluntary participants signed a consent formed (Appendix B) and were asked prior to the experiment to fill in a demographic questionnaire (Appendix C) that also inquired about their gaming habits and previous BCI usage.

After being explained the content of the experiment, the EEG caps and electrodes were placed on each participant. A good connectivity was ensured by applying electrolyte gel until all electrode offsets were lower than $\pm 20mV$. A short SSVEP session of 80 seconds was then recorded for offline performance analysis and participant's CCA parameter definition (threshold and EGG channels used). In this session, participants were asked every 5 seconds to look at the top and bottom LED light, and at the center of the screen, while their EEG data was acquired using BioSemi's software, ActiView.

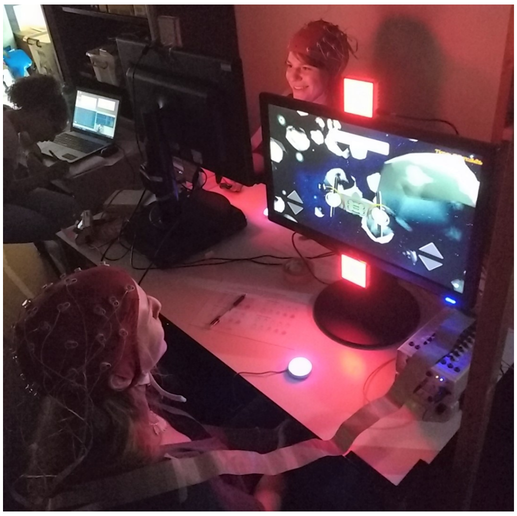
Afterwards each pair of participants were given time to learn the game before playing four rounds in each Kessel Run's difficulty level (easy and hard), giving a total of 8 play sessions per pair of participants. Each play session lasted up to 2 minutes according to Kessel Run's rules. At the end of each round, participants were asked to fill in the SAM questionnaire (Appendix D) according to their emotional experience for that particular round, and the Game Experience questionnaire at the end of the experiment gameplay (Appendix E). The practical protocol can be found in Appendix F, which also includes steps regarding the research in (Moreira, 2016) that was part of this project. In total, the experiment took approximately 1 hour from start to finish.

6.2.5 Signal acquisition

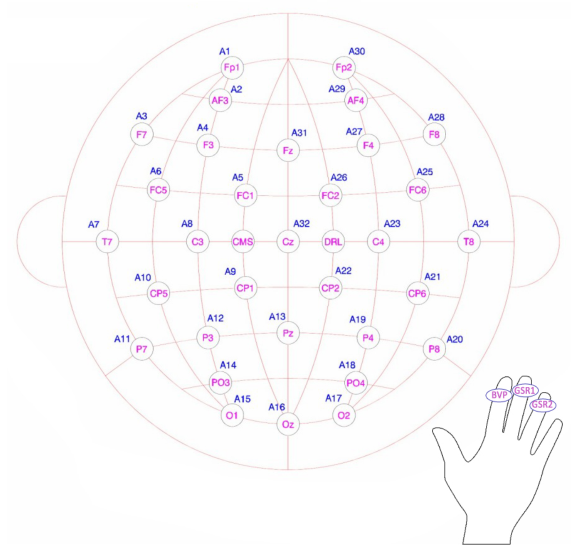
EEG signals were acquired using a Biosemi ActiveTwo system[1] on a dedicated recording PC for each participant. Physiological peripheral data (GSR and BVP (Blood Volume Pulse)) was also acquired using the same system. Due to time constraints and sensor compatibility (only one of the pair of participants had their physiological data acquired) the physiological data was not used in this study.

All signals were acquired at a 512 Hz sampling rate. The 32 active Ag-AgCl electrodes for EEG were placed according to the international 10-20 system, and the peripheral sensors were placed on the non-dominant hand according to Figure 6.1b.

[1]Biosemi ActiveTwo - http://www.biosemi.com



(a)



(b)

Figure 6.1: *(a)* Two participants shortly after beginning playing Kessel Run. *(b)* The 32-electrode placement according to the 10-20 system, and placement of peripheral physiological sensors on non-dominant hand.

6.3 Data analysis

All data was analyzed under MATLAB® and R software environment for statistical computing.

6.3.1 SSVEP Performance and Playability

Subject SSVEP performance was evaluated using the training session recorded during the experiment. Raw EEG signals from the back of the head (Pz, $O_1/_2$ and Oz) were selected and trials of 80 samples were extracted for the three conditions: looking at 12 Hz light source, at 15 Hz light source, and at the center of the computer screen. Each trial was subject to CCA (see Section 5.5) with sine and cosine reference signals at 12 and 15 Hz. Upon visual inspection the best electrode(s) and an empirical correlation threshold were set for each participant, and classification for each condition followed. No preprocessing was performed in order to minimize real-time computing costs.

The resulting trials were classified into game actions according to the maximum of CCA's correlations. If the highest correlation (of the two possible values for each frequency) exceeds the participant's threshold, the decision is set to the corresponding frequency - 12 or 15Hz -, meaning that the player goes either up or down. If the threshold isn't met, the decision to stay in the center is chosen.

For Kessel Run's Playability, each item's scores were grouped according to their respective user experience components: Competence, Flow, Tension/Annoyance, Positive and Negative Affect, and Challenge. After grouping, mean and standard deviation was derived from participant scores.

6.3.2 Emotion correlates

All EEG data was (pre-)processed using the Fieldtrip toolbox[2] (Oostenveld et al., 2011). The 8 game trials (4 easy, and 4 hard game levels) with varying duration were extracted for each of the 12 participants, re-referenced to common average, detrended and bandpassed at 4-45Hz with a Butterworth filter. Because participants were instructed not to refrain from moving during the game, EEG data contained noise from the environment, eye movements or muscle tension. To further deal with these artifacts, each subject's faulty electrodes (visually identified) were repaired by replacing each time point with the average of their neighbors. In addition, trials with higher variance (≥ 0.3, visually identified) were rejected from analysis contributing to the elimination of 11 of the 96 trials. Afterwards, trials were segmented by extracting only the last 20 seconds of each game. By analyzing only the last portion of each game we avoid possible emotion fluctuations that could have happened during gameplay, evaluate the time frame closer to the self-assessment and escape the problem of varying trial's duration.

Finally, only trials with non-neutral self-assessments ($4 \geq valence/arousalrating \geq 6$) were selected before obtaining power spectra using a multitaper method based on an Hanning window, with 1 Hz bins resolution. Preprocessing took approximately 4 minutes.

For narrow-band oscillations on the theta (4-7 Hz), alpha (8-11 Hz), beta (16-29 Hz) and gamma (30-47 Hz) bands, a permutation T-statistic on the Pearson's correlation between self-assessment ratings and each trial's frequency spectrum was performed (1000 permutations) assuming independence (Maris and Oostenveld, 2007). We have chosen to analyze and correlate each spectral bin of 1 Hz, as the emotional response can differ for small differences in frequency bands (Krause et al., 2000). However, because we perform more statistical tests (one for each spectral bin) we chose to not perform any multiple-test corrections, such as the Bonferroni method, since the effects would have to be very strong to pass the significance level. Instead, we chose to substantially lower the significant p-value.

Alpha asymmetries were calculated for lateral sensor pairs, using the following procedure: for each trial and each electrode's averaged alpha band power (8-11 Hz) on the left hemisphere, the alpha band power of the corresponding electrode on the right hemisphere was subtracted. This procedure results in an alpha-asymmetry index for each sensor pair and each trial, which was used to obtain Pearson's correlations between the alpha index and self-assessment ratings. Significance of these correlations was tested under a similar permutation T-test, Bonferroni corrected and assuming independence.

[2]Fieldtrip toolbox for EEG/MEG-analysis, developed at the Donders Institute for Brain, Cognition and Behaviour - http://www.ru.nl/neuroimaging/fieldtrip

7

Results and discussion

In this chapter we present the results obtained from the experiment described in the previous chapter, in which participant pairs were asked to play our BCI game - *Kessel Run* - and rate it according to its playability and their emotional responses. Along with our findings, we derive some comments and discuss the meaning for each result.

7.1 Participants

A total of 12 participants (5 female), divided into 6 pairs, took part in our experiment. The average age is 23.83 ($\sigma = 2.48$), ranging from 21 to 31 years old (all participants were University of Twente's students). All had normal or corrected to normal vision, used computer daily and had at least some experience with digital games.

7.2 BCI Multiplayer game

7.2.1 SSVEP Performance

We start our analysis by looking at SSVEP subject performances (Table 7.1 and Figure 7.1). Of the initial 12 participants, two (one pair) were excluded from performance analysis due to changes in the experiment setup.

Generally speaking, SSVEP performance was lower than it is usually reasonable on a BCI game. Overall classification (i.e. the 3 class decision between choosing the 12 or 15 Hz stimuli, or choosing not to move by looking at the pc's center) was 55% on average, reaching a maximum 79%. Most participants obtained a performance above 50%, although a few remain under the 50% performance line. There are two key factors that influence these values: darkness of the room, and participant detection of the used frequencies.

Table 7.1: SSVEP performances descriptives.

	$\bar{X}(\sigma)$	**Max**	**Min**
Overall	55.3 (14.1)	78.9	34.1
12Hz	62.7 (12.6)	85.6	47.8
15Hz	37.8 (19.5)	80.0	20.0

In order to obtain a good quality SSVEP it is necessary to isolate its visual stimuli from other light sources, usually done by darkening the experimental room to reinforce

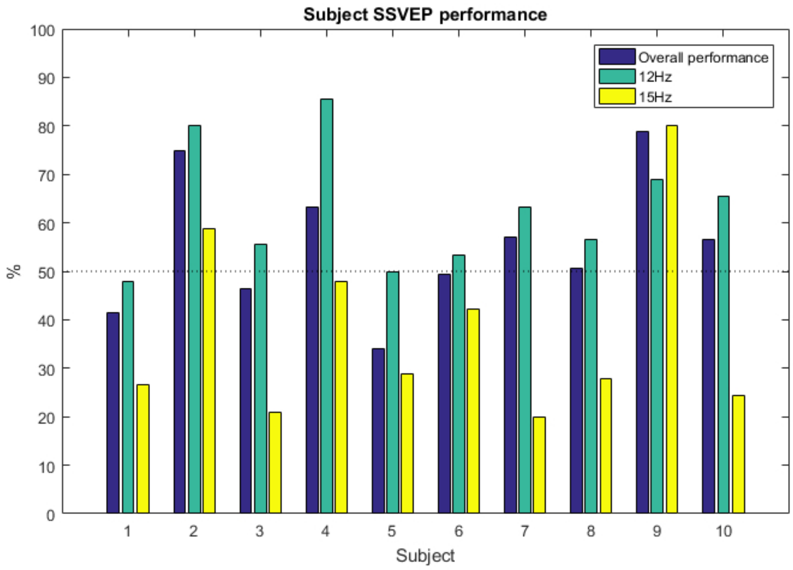


Figure 7.1: SSVEP performance per subject. Light blue and yellow bars correspond to the percentage of trials correctly classified as looking at 12 and 15Hz, respectively. Dark blue bars indicate the CCA's overall performance classifying if the subject is looking at the 12, 15Hz light source, or not looking.

stimuli brightness. Although all of our experiments were performed under a darkened laboratory, ambient light was still present due to window gaps which caused a reduction in LED brightness and consequent loss in performance. In this case, when compared to a completely darkened room, the resulting loss in performance is approximately 6% (see Appendix G for details).

On the other hand, a good quality SSVEP relies also on the brain's capacity to react to repetitive flickering at a certain frequency. From Figure 7.1 we can note that subject's performance for the 12 Hz frequency (light blue bars) is consistently higher than at 15 Hz (yellow bars). In fact, its maximum performance is also the highest (86%) of the three classes, meaning that participants could more easily produce SSVEPs when focusing on the 12 Hz light source but had difficulty recognizing the 15 Hz source, dragging the overall performance down. Because the 15Hz source was generally harder to classify, the overall BCI performance is lowered and participants could either control both or only one of the spaceship's directions. Reflecting the fact that each individual has a different capacity of discerning a certain frequency, Hakvoort et al. (Hakvoort et al., 2011) too found that subject's precision in a CCA-based detection method differs according to frequencies used. Similar results were also found in (Allison et al., 2008).

One important remark to be made is that the SSVEP performance presented here, which is extracted from a recording session before gameplay, is not exactly the same as participants experienced in the game; players were able to adapt their strategy, placing their head in different positions for better SSVEP detection or focusing on using only one of the controls (usually the 12 Hz) to play the game. Their adaptation could result in a feeling of higher control than what it is expected by their performance.

While SSVEP might not be a reliable paradigm to control the Kessel Run game, some changes could be made in future game iterations in order to improve its performance. Using a checkerboard pattern instead of a simple flickering LED square could have given stronger SSVEPs responses. We could also resort to machine learning algorithms to improve SSVEP classification, but these might have higher computation costs and could potentially be slower, which is the reason they were not used in this project. In contrast, using Motor Imagery instead of the SSVEP paradigm could lead to a more intuitive and perhaps reliable control, as considered in Chapter 5.4, although at the expense of longer training sessions and possible BCI illiteracy.

7.2.2 Playability

It is important to evaluate Kessel Run not only as a BCI experiment, but also as a digital game. Responses from the Game Experience questionnaire (Appendix E) were grouped into key components and results are summarized in Table 7.2 in order to evaluate Kessel Run's playability.

Perhaps due to low BCI performances, participants only felt slightly competent ($\overline{competence} = 1.083$) to play the game. Interestingly enough, we observed that participants were able to adapt while playing Kessel Run even when not in full control of the BCI, as mentioned in the previous section. Teams often opted to move the spaceship in only one of their controllable directions in order to play together. Otherwise when one player had a better BCI performance, the other would be elected "*captain*" and would order directions for the spaceship to move next. These strategies helped create a greater bond between players and lead to a predominantly positive affect during the game ($\overline{pos.affect} = 2.458/\overline{neg.affect} = 0.750$). Moreover, they also lead to greater feel of immersion ($\overline{Flow} = 2.556$) during the game and a moderate to fair sense of challenge ($\overline{challenge} = 2.333$).

When considering the questionnaires scores we can conclude that *Kessel Run* is an overall enjoyable game, specially when taking into account the participant's Flow scores, suggesting a good employment of the good design requirements appointed in Chapter 5.1.

There is, of course, room for improvement in *Kessel Run*'s enjoyment and the BCI paradigm selection seems to play an important role in the game's playability due to its Competence scores. A good paradigm choice is of extreme importance in terms of a BCI game playability. Not mentioning performance, it is necessary to take into account pacing, controls and game mechanics before choosing an appropriate paradigm. We chose to adopt SSVEP as a game controller due to implementation ease, fast classification and intuitiveness (look at the direction you want to go). The downside is that every time a player wants to make a decision, he must shift his focus onto a LED light mounted in his monitor, taking his attention off the game and considerably interfering with the

Table 7.2: Game experience questionnaire scores, in which 0-Not at all, 1-Slightly, 2-Moderately, 3-Fairly, 4-Extremely.

	Mean	**Std**
Competence	1.1	0.9
Flow	2.6	1.2
Tension/Annoyance	1.2	1.2
Challenge	2.3	2.2
Negative Affect	0.8	1.0
Positive Affect	2.5	1.0

user experience. Additionally, exposure to flicker lights can also strain the eyes after a couple of minutes. It would be advantageous to substitute SSVEP with another equally or more intuitive paradigm such as motor imagery or LRP, which because they are based on induced activations and not in evoked responses could provide a more intuitive and fun experience.

7.3 Emotion EEG correlates

We now have a look at the experienced emotions players felt during gameplay, measured through self-assessment valence and arousal ratings, and its consequent correlates in narrow-band oscillations and alpha asymmetries found in the EEG. The results shown below relate to the last 20 seconds of each game trial's EEG (see Chapter 6.3). We have also performed the same tests for the entire game trial, but chose not to report these results since the same trends were present but in a weaker form.

7.3.1 Valence and arousal dispersion

In order to elicit a good spread of emotions in terms of valence and arousal a few strategies were implemented in our BCI game as described in Chapter 5.6. Participants played the two distinct difficulty levels during the experiment and rated each trial in terms of elicited valence and arousal on a 9-point scale SAM questionnaire (see Chapter 6.2 and Appendix D). Table 7.3 summarizes these ratings according to the two difficulty game levels.

Table 7.3: Mean (standard-deviation) and p-values for Valence and Arousal ratings on the two game conditions - Easy and Hard difficulty levels

	Easy	**Hard**
Valence	6.06 (1.74)	5.69 (1.90)
Wilcoxon test	*p-value* = 0.11	
Arousal	5.17 (1.77)	5.31 (1.82)
Wilcoxon test	*p-value* = 0.28	

Participant ratings in the Valence and Arousal dimensions were very similar for both conditions (Easy and Hard difficulty), and only the Easy condition showed a slight shift towards a more positive valence. Although we expected that Easy game levels would result in higher valence, and Hard levels in more negative valence and higher arousal values, no statistical difference between conditions was found for either Valence or Arousal (bilateral Wilcoxon signed-rank test), indicating that other factors might have influenced participants' ratings. In fact Arousal scores show a slight correlation with participant SSVEP performance (0.428) although the same factor was found to not influence Valence (0.275). The duration of gameplay could be used as a metric of game performance (since the game is won if players are able to finish the 2 minute race) and could possibly influence the two dimensions' ratings, however no correlation with gameplay duration was found for either Valence (0.219) or Arousal (-0.060). These suggest that while Arousal can be influenced by the player's SSVEP performance, the Valence dimension might have been explained by other non-measured factors.

Although one might think that the having two difficulty levels in the game caused no difference, and despite not raising apparent influence in the participant's ratings, the two conditions showed a significant difference between trials' duration (p-value = 0.000, lateral Wilcoxon signed-rank test), where trials in Easy mode were significantly longer than trials in Hard mode. This suggests a true increase of difficulty between conditions which lead to players lasting less time in the Kessel run race when switching to the harder levels.

Despite emotion elicitation strategies applied in *Kessel Run* not being successful in causing the expected Valence/Arousal differences, a good distribution of ratings was still achieved. Figure 7.2 represents trial ratings for both conditions and its respective duration. There seems to be a good representation across all four quadrants, however with greater amount of high valence/arousal (HVHA) trials. As expected there is no difference in rating spread between trials of each condition.

Finally, the participants' ratings resulted in 45 high-valence (score$\geq$6), 21 low-valence (score$\leq$4), 36 high-arousal, and 27 low-arousal trials after noise trial rejection, and these were then analyzed for EEG correlates.

Table 7.4: Number of high/low trials for valence and arousal

	Valence	**Arousal**
High	45	36
Low	21	27
Total # of trials	66	63

7.3.2 Narrowband oscillations

We are now interested in understanding the effects on the brain's frequency with valence and arousal during realistic BCI gameplay. By obtaining information about the emotional context of the player through his EEG, we could potentially enrich user experience in games, enabling them to adapt and respond more adequately to the player. For that, we correlated the higher (≥ 6) and lower (≤ 4) participant's SAM ratings with their

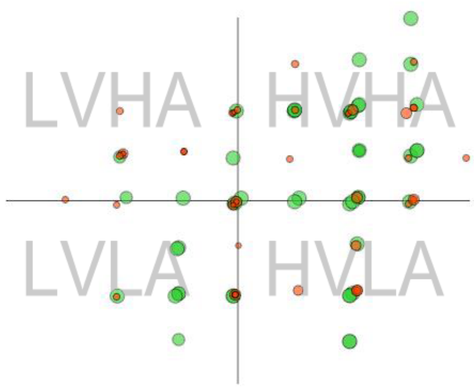


Figure 7.2: Dispersion of Valence-Arousal ratings for easy difficulty trials (in green) and hard difficulty trials (in red), slightly shifted for visualization. Circle diameter indicates trial duration (maximum 2 minutes). Dot opacity is directly related to the number of overlapping scores in different trials.

Table 7.5: Significant narrow-band correlations for the self-assessment ratings.

	Theta		**Alpha**		**Beta**		**Gamma**	
	Elec.	$\overline{R}$	Elec.	$\overline{R}$	Elec.	$\overline{R}$	Elec.	$\overline{R}$
Valence	-	-	F7*	0.33	F7**	0.34	F7**	0.36
	-	-	C3**	0.35			O2*	-0.34
Arousal	F7*	-0.35	F3**	-0.36	Cp5*	-0.40	O1**	-0.40
	T7**	-0.37	C3**	-0.42	Pz**	-0.52	Oz**	-0.39
	Cp5**	-0.38	Cp5**	-0.38	O1**	-0.40	O2**	-0.45
	Cp6**	-0.41			Oz*	-0.43		
	T8**	-0.42			Cp2**	-0.43		
	Cz**	-0.44			C4**	-0.38		

* $p \leq 0.005$
** $p \leq 0.001$

corresponding trial's frequency spectrum, considering only the last 20 second portion of each game (trial). Significant correlations with valence and arousal were tested using a permutation T-statistic.

Table 7.5 presents the significant correlations that were found for the valence and arousal conditions, and Figure 7.3 shows mean subject correlations of oscillations in different frequency bands with valence (top row) and arousal (bottom row). Below we will report and discuss only those effects that corroborate or contradict the literature on narrowband oscillations for emotional EEG.

The valence dimension was the one to show less significant correlations in the EEG signals, and correlates were found for the alpha, beta and gamma bands. In the alpha band we found that frontal and central leads on the left hemisphere correlated positively with valence, indicating an increase of alpha power (and consequent decrease in activation) with increased valence on the left hemisphere. This trend is also visible on Figure 7.3 particularly for 11 and 13 Hz in which a clear asymmetry is noticeable.

The hemispherical activation of valence-related stimuli is a well studied effect, showing patterns that corroborate with the processing of negative emotional information being reflected by the decrease of alpha power over the right frontal hemisphere, and the processing of positive information by the decrease of alpha power on the left frontal hemisphere

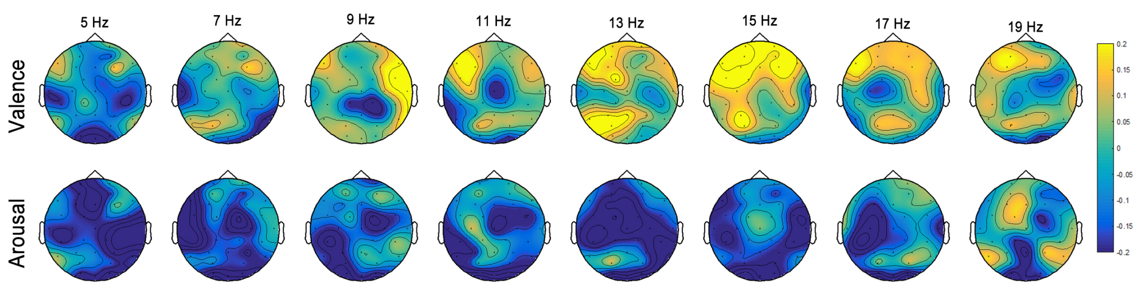


Figure 7.3: Mean subject correlations of oscillations in different frequency bands with the valence (top row) and arousal (bottom row) conditions. Due to space constrains, only every second frequency bin of the lower frequency ranges was plotted.

((Davidson, 1992, Huster et al., 2009, Allen et al., 2004, Schmidt and Trainor, 2001)). However in our results we observe the opposite: increasing valence leads to an increased deactivation of the left hemisphere and an increase in alpha power. Contradictions of this theory were also expressed by Koelstra et al. (Koelstra et al., 2012), who found that for low frequencies, theta and alpha, an increase of valence led to an increase of power for audiovisual stimuli. Our contradictions could either indicate that more complex stimuli such as video and sound (or a game, in our case) could hinder the effects of alpha asymmetry, or these could not apply at all. In fact, in their gameplay study Reuderink et al. (Reuderink et al., 2013) also did not find any asymmetry evidence.

For the valence dimension we also found a significant positive correlation in beta, and a frontal positive and negative occipital correlation in the gamma band. In Figure 7.3 we can also observe a trend of central decrease in power for the 17 Hz, along with occipital and frontal-right temporal increase of power towards larger frequencies. Similar trends were observed in (Koelstra et al., 2012), where a central decrease in beta range was also reported, as well as occipital and right temporal increased beta power. Furthermore Cole and Ray(Cole and Ray, 1985) too showed that an increased beta power over right temporal sites was associated with positive emotional self-induction and external simulation. Reuderink et al. (Reuderink et al., 2013) also found a trend of decreasing gamma activity for increasing valence, however it should be mentioned that EMG activity is prominent in the high frequency spectrum and its left unclear if the found effects are related to emotional processing or artifacts.

For the arousal dimension we found significant negative correlations in all frequency bands. Overall, an increase in Arousal lead to a decrease in power. In particular, there is an inverse relationship between central and frontal alpha power with arousal, indicating a central and frontal brain activation with higher arousal states. This relation has been reported before by (Koelstra et al., 2012, Barry et al., 2007, Schmidt and Trainor, 2001) and there is general consensus that arousal activates neuronal structures in general and therefore seems to be associated with global decrease in the alpha band. In Figure 7.3 this pattern of global alpha decrease is visible at 13 Hz, and seems to be predominant for frequencies in the alpha band.

7.3.3 Alpha asymmetries

Because frontal asymmetry in the alpha band is the most frequently found correlate for valence (see Chapter 3.4), for each user individually we also calculated the alpha asymmetry index as outlined in Chapter 6.3.2.

On Table 7.6 the Pearson correlation coefficients ρ between alpha asymmetry index and SAM ratings averaged over subjects are shown. Significant correlations were found using a permutation T-statistic and are marked as such.

We start by noticing that apart from significant ones, most mean correlations are seldom bigger than $\pm$ 0.1, which is most likely a result of high inter-participant variability. However, both valence and arousal's significant correlations found are stronger and should therefore justify the following report and discussion.

For valence there is a highly significant alpha asymmetry correlation over the frontal cortex. Because we subtract the right alpha power to the left alpha power, a positive correlation indicates that with increasing valence the alpha power is stronger on the left side of the brain. This contradiction of the frontal asymmetry theory was already expected,

Table 7.6: The alpha asymmetry for different sensor pairs, correlated with different labels for each subject individually, and averaged over subjects. *Note: For these correlations, only the **p-values pass the Bonferroni correction The */**p-values themselves are not adapted themselves to reflect the multiple test correction.*

(8-11 Hz)	**Fp1-Fp2**	**Af3-Af4**	**F3-F4**	**Fc1-Fc2**	**C3-C4**	**F7-F8**	**P3-P4**
Valence	0.11	0.09	0.31**	0.13	0.04	0.08	-0.10
Arousal	-0.07	-0.07	-0.14	-0.25*	-0.12	-0.18	-0.22

* $p < 0.05$
** $p < 0.005$

since in the narrowband oscillations we saw a significant relationship between frontal and central left alpha power.

For arousal one significant correlation was found, showing an inverse relationship between arousal and fronto-central sensor pairs. Interestingly enough, Reuderink et al. (Reuderink et al., 2013) also found the same significant trend for the Fc1-Fc2 pair. Although Reuderink et al. did not derive any meaning behind this correlation at the time, perhaps alpha asymmetry has an effect on arousal within the gamming context and could be potentially used for emotion adaptation in games.

8

Conclusion

In this thesis we have set two research goals. First, motivated by the increasing popularity of BCI in the field of gaming, we aimed at creating a multiplayer BCI game that was successful in providing a fun and immersive player experience by implementing good game design rules based on Flow Theory and the Paradox of Control. Second, motivated by the increasing expansion of affective research aiming at improving user experience but with lack of applications in a realistic gaming context, we also aimed at studying the effects of emotion on the player's EEG. For this, the designed BCI game should be capable of eliciting different emotions on its players in order to study EEG correlates of valence and arousal. By studying the effects of emotion on the EEG for realistic gameplay we intend to contribute for a future generation of videogames adaptable to the players' emotional content.

With our research goals in mind, we have created a sophisticated multiplayer BCI SSVEP game, titled *Kessel Run*. In Kessel Run, two players must cooperate with one another to steer a spaceship through an asteroid field, moving away from obstacles and keeping enough fuel to last 2 minutes in space and therefore win the game. The SSVEP paradigm was used with two LEDs as an external stimulus, allowing the players to go up or down by processing their EEG data in real-time using a CCA algorithm with only 0.15 seconds delay.

In Kessel Run, two difficulty levels were implemented in order to elicit a different set of emotions for each one. In the easier level, the game was challenging but winning was possible. It was also accompanied by fun music which was expected to elicit high valence states. The hard difficulty level was very hard to win, since periodic failures of the spaceship's control were applied to the game without the players' knowledge. Along with music at a higher tempo, this level was intended to elicited higher states of arousal and lower valence on the players.

Good game design rules were also followed by having a clear game's goals and rules, challenge to the players' skills, rich audiovisuals and innovative game mechanics and elements. Furthermore, we have also created a supportive software system that is highly flexible. By choosing to integrate several pieces of software together, Kessel Run has the capability to adapt to several other acquisition BCI systems, such as the Emotiv EPOC. It is also possible to run Kessel Run on a computer separate to that of the acquisition systems, decreasing computation costs on a single machine. Kessel Run can also be used as a single-player setup.

With our research goals in mind, we setup an experiment capable of answering the following questions: *Is Kessel Run an enjoyable game? Is the SSVEP paradigm a reliable control? What emotions are elicited during the game? What correlates of emotion can be found in the EEG during gameplay? Are these correlates comparable to State-of-the-Art work?* With these research questions in mind, we had 6 participant pairs (12 players) play Kessel Run's two difficulty levels and answer questionnaires regarding their user experience and feelings throughout gameplay, which lead us to the following results.

Concerning the SSVEP performance as a game control, we obtained a maximum of 79% and average of 55% in overall accuracy (Table 7.1). Although only slightly reasonable, the low performance was mainly due to two reasons: inter-subject variability in frequency detection for SSVEP, and not enough darkness in the room. By not darkening the room enough, approximately 6% was lost in performance (estimate based on a single test with a single subject - see Appendix G). For inter-subject variability, participants showed a tendency to better classify one of the two frequencies used for SSVEP (12 and 15 Hz); in fact, the 12Hz stimulus obtained an average of 63% accuracy and maximum of 85%, well above the reciprocate at 15 Hz.

Although performance of multiplayer game was lower than expected, it serves as proof of concept for usability. Better performances can be achieved with individual analysis and darkening the environment, but a more intuitive paradigm suitable to gaming is desirable such as imaginary movement.

Regarding Kessel Run's playability and overall successfulness in the application of design rules, we looked into the reported user experience to find that despite SSVEP's control problems, Flow was still achieved (Table 7.2). We believe that applying good game design rules in Kessel Run helped in creating an enjoyable experience to its players.

In terms of elicitation strategies for emotion implemented on Kessel Run, these were only partly successful. Players' ratings in the valence and arousal dimension showed no significant difference between easy and hard level trials (Table 7.3). However, a good spread of emotions was still achieved between the four quadrants of high-low valence-arousal (Figure 7.2), enabling the study of EEG correlates to emotion as anticipated.

First we have looked at narrowband oscillations that correlate with the valence and arousal dimensions from participants' ratings. We have found significant correlations that contradict the alpha asymmetry theory by showing that in a gaming context the left hemisphere suffers a decrease in activity translated by an increase in alpha power (Table 7.5, Figure 7.3). Contradictions of this theory have been found before, leading to the belief that the alpha asymmetry theory might be stimuli-dependent.

A central decrease in the beta range along with occipital and right temporal increase beta was also observed as a trend for valence, which agrees with studies done previously.

In the arousal dimension a significant negative correlation in central and frontal alpha power was found, indicating central and frontal brain activations for high arousal states. This finding agrees with the general consensus that arousal leads to an activation of brain structures and therefore seems to be associated with the global decrease of the alpha band.

Secondly, an alpha asymmetry index was calculated, correlated to the players' emotional ratings and tested for significance (Table 7.6). In the valence dimension the expected contradiction of the hemispherical alpha asymmetry theory was observed with high significance over the frontal cortex. For arousal we found one significant negative correlation on fronto-central sensor pairs. Because this inverse relationship between aroused states and right brain side deactivation was previously observed on a gameplay-related study, we believe that the alpha asymmetry might be a good link to arousal in games and propose further studies on the matter.

One important note is to be left here. Although we mean to come closer to emotional game adaptation, we can only draw a few conclusions from these results alone. Because there's a great uncertainty behind emotional brain processes and stimuli effects, we are left with comparisons between studies to find meaning behind these correlates.

There is, of course, room for improvement in this thesis. The implementation of a new paradigm in Kessel Run's control could improve playability by being more reliable, intuitive and less straining. New methods of emotion elicitation are also appreciated when corroborating the EEG correlates found, which need further investigation before their usage in emotionally adapted games.

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Appendix A

Call for participants

Want to play a game with your brain signals?

What?

We're looking for participants to take part in a Brain-Computer Interface experiment in which you play a **multiplayer game using only your brain signals as a controller**. The game is multiplayer, which means **you can bring a friend with you and play together**!

When? Where?

The experiment takes place in Zilverling building at University of Twente, and takes approximately 1 hour. You can choose to participate when it is more convenient to you (and your friend).

How?

You can participate by filling the form at *goo.gl/forms/TWBQgmblwJBB3yQu2*

Attention: the experiment is for a multiplayer game, which means you should bring a friend to play with you. In case you cannot bring someone, let us know so we can pair individual participants together ☺

Questions? *Any burning questions can be sent to* i.palmadelimaecruz@student.utwente.nl

Appendix B

Participant Informed Consent Form

UNIVERSITY OF TWENTE.

Human Media Interaction

Informed Consent Form

Title of Study: *User affective state and cooperative decision making in a multiplayer BCI game*

Investigators:

Inês Cruz	**Dept:**	HMI	**Email:**	ines.cruz@campus.ul.pt
Carlos Moreira	**Dept:**	HMI	**Email:**	cfmoreira@campus.ul.pt

Introduction

Before agreeing to participate in this research study, it is important that you **read the following explanation of this study**. This statement describes the purpose, procedures, risk, discomforts, and precautions of the experiment. Feel free the ask for clarification if you encounter any term or expression that you do not understand.

Your participation is voluntary; you are free to withdraw consent in this project at any time without penalty and without giving a reason.

Purpose of Study

This is a multi-purpose study that investigates the different affective states a player experiences during a realistic gameplay using a multiplayer brain-computer interface system. Moreover, it investigates the brain activity patterns related to the players' cooperative/defective actions.

Description of the Study Procedures

If you agree to be in this study, you will be asked to do the following things:

Before the experiment, you will complete a questionnaire to provide some demographic information;

Afterwards, the BioSemi cap and electrodes will be mounted on your head. To ensure good connectivity between your brain activity and the electrodes, a **gel will be applied to your scalp**. This leaves a residue on your hair. **We provide towels and shampoo after the experiment**, but feel free to bring your own toiletries.

Meanwhile, the game will be explained and you will have some time to practice and become familiar with the gameplay. Note that the game makes use of **flickering lights**. **Participants with any neurological disorder (epilepsy in particular) cannot participate in the study.**

During the experiment you will play the game with another person and fill in questionnaires. After the game, two quick additional tests will be performed.

The whole experiment, including preparation of the setup, game playing, and questionnaires will last less than 2 hours. **You can ask for breaks** before and in between game levels.

Risks/Discomforts of Being in this Study

There are no reasonable foreseeable (or expected) risks for people with no neurological health conditions.

Confidentiality

You will have your brain activity recorded via the BioSemi system that you will wear on your head. Your keyboard activity will be recorded as well, and some behavioral observations (such as talk between players) will be documented. All the recorded data and the results of measurements may be used for research and publications. The data will be anonymized and may be made public for research purposes.

Right to Ask Questions and Report Concerns

You have the right to ask questions about this research study and to have those questions answered before, during or after the research.

If you have any further questions about the study, at any time feel free to contact one of the investigators aforementioned.

Consent

I have read the foregoing information, or it has been read to me. I have had the opportunity to ask questions about it and any questions I have been asked have been answered to my satisfaction. I consent voluntarily to be a participant in this study and state I have no known neurological disorder.

Subject's Name: ______________________________

Subject's Signature: ______________________________ Date: ____________________

Investigator's Signature: ______________________________ Date: ____________________

A copy of this ICF will be provided to the participant at his request.

Appendix C

Demographic form

Demographic Questions

*Required

1. **Please insert subject ID** *
First and last name initials and date (dd-mm-yyyy), separated by -. (e.g. JS-25-07-2016)

2. **Select player** *
Mark only one oval.
   - Player 1
   - Player 2

3. **Age** *

4. **Gender** *
Mark only one oval.
   - Male
   - Female

5. **Eyesight** *
Mark only one oval.
   - Normal
   - Corrected to normal
   - Impaired

6. **Handedness** *
Mark only one oval.
   - Left-handed
   - Right-handed
   - Ambidextrous

7. **Computer usage** *
Mark only one oval.
   - Daily
   - Weekly
   - Monthly
   - Less than once a month
   - Never

8. **Gaming experience** *
How often do you play digital (computer, console, mobile) games?
Mark only one oval.
   - Daily
   - Weekly
   - Monthly
   - Less than once a month
   - Never

9. **BCI experience** *
How many times have you used a brain-computer interface technology before?
Mark only one oval.
   - Three or more
   - Two
   - One
   - None

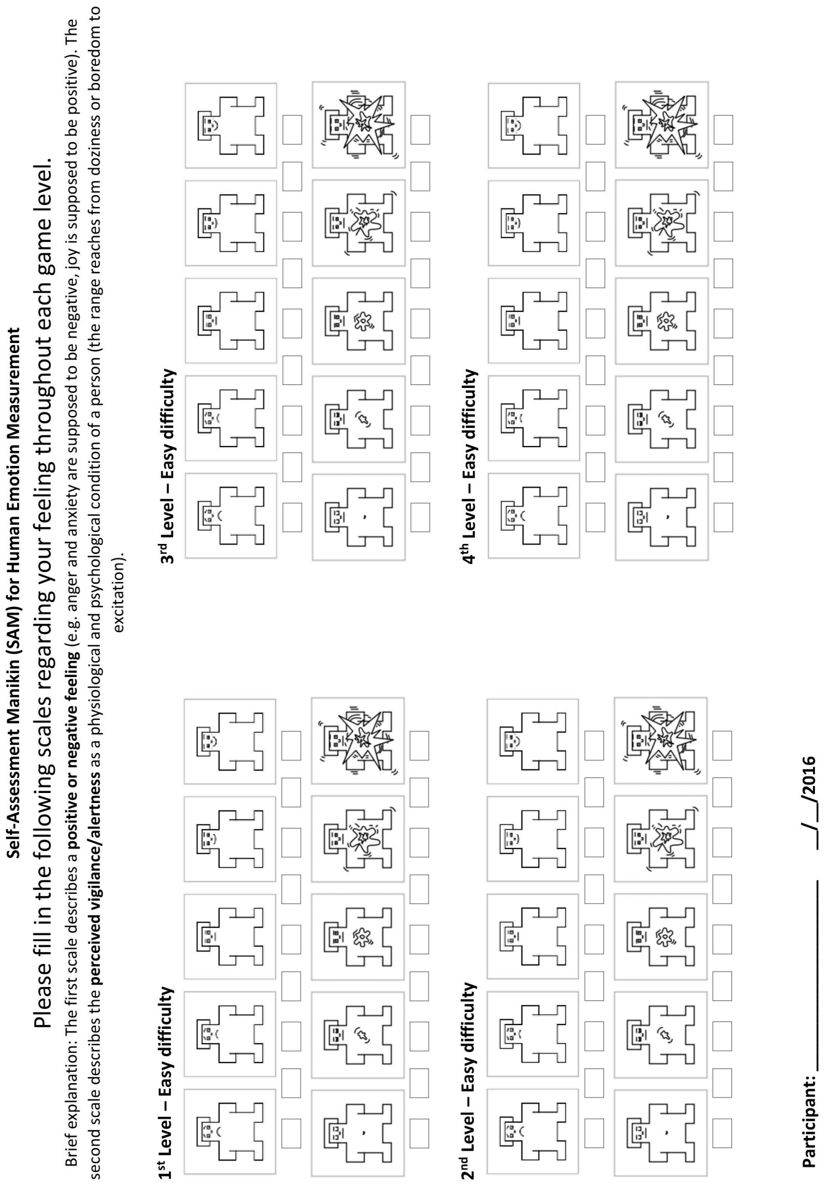
10. **Do you have any neurological (or other relevant) diseases?** *
Mark only one oval.
   - Yes *Skip to question 11.*
   - No *Skip to question 12.*

Relevant diseases

11. **Which neurological (or other relevant) diseases do you have?**

Appendix D

Subject SAM form



Self-Assessment Manikin (SAM) for Human Emotion Measurement

Please fill in the following scales regarding your feeling throughout each game level.

Brief explanation: The first scale describes a **positive or negative feeling** (e.g. anger and anxiety are supposed to be negative, joy is supposed to be positive). The second scale describes the **perceived vigilance/alertness** as a physiological and psychological condition of a person (the range reaches from doziness or boredom to excitation).

1st Level – Easy difficulty

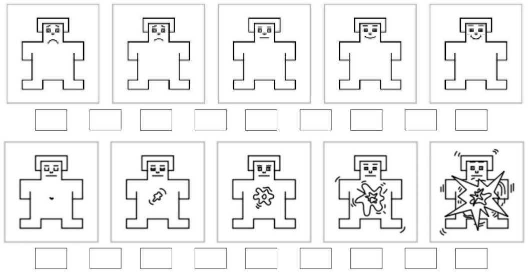
2nd Level – Easy difficulty

3rd Level – Easy difficulty

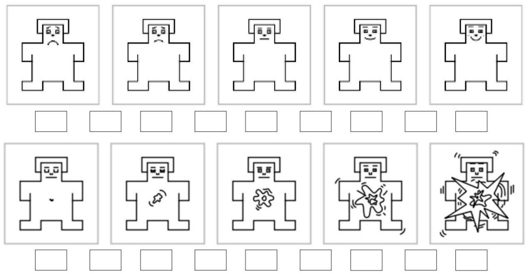
4th Level – Easy difficulty

Participant: ______________ __/__/2016

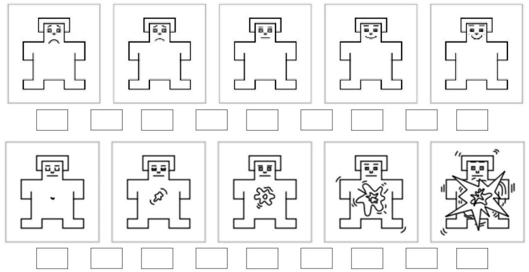
5th Level – Hard difficulty



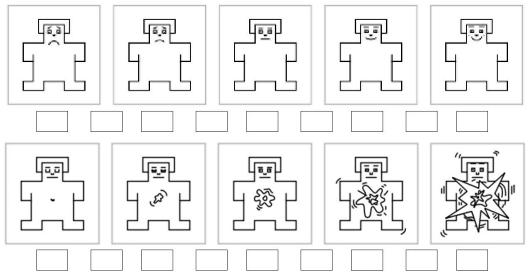
6th Level – Hard difficulty



7th Level – Hard difficulty



8th Level – Hard difficulty



Participant: ______________________ __/__/2016

Appendix E

Game experience form

Game Experience Questionnaire

Please fill in this questionnaire only after you are finished with playing the game.

12. **Game Experience Module** *

Please indicate how you felt while playing the game for each of the items:
Mark only one oval per row.

	Not at all	Slightly	Moderately	Fairly	Extremely
I felt annoyed					
I felt happy					
I was good at it					
I felt irritable					
I felt good					
I had to put a lot of effort into it					
I thought it was fun					
I found it tiresome					
I lost track of time					
I was fully occupied with the game					
I felt competent					
I enjoyed it					
I felt bored					
I felt challenged					
I was deeply concentrated in the game					
I felt pressured					
It gave me a bad mood					
I felt successful					
I felt frustrated					
I thought it was hard					

Appendix F

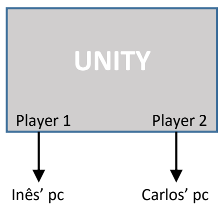
Experiment protocol

Protocol for Kessel Run Experiment

0. *Send consent form via e-mail to the subjects prior to experiment*
1. Have the subjects read and sign the consent form, and fill the demographic google form
    a. **Make sure a subject ID/player is correct for both participants!**
2. Briefly explain what the experiment is about, what will happen and how long it should take
3. Couple both participants with BioSemi
    a. Player 1 should have GSR and Plethysmograph sensors as well (Inês' computer).
    b. Check ActiView electrode offset is under +-20mV and signal is good
    c. Instruct player 1 to move sensor hand as little as possible
4. In ActiView (in each computer) run the performance test
    a. Ensure trigger serial cable is connected
    b. Key *F1* for looking up, *F2* for looking center, *F3* for looking down
    c. **START WITH LOOKING UP AFTER 5 SECONDS OF RECORDING**
    d. Record for 80 seconds
5. Start fieldtrip buffer with the right config.txt file

```
> cd C:\Program Files (x86)\MATLAB\R2015b\toolbox\fieldtrip-20160414\realtime\bin\win32
> biosemi2ft config.txt out -
```

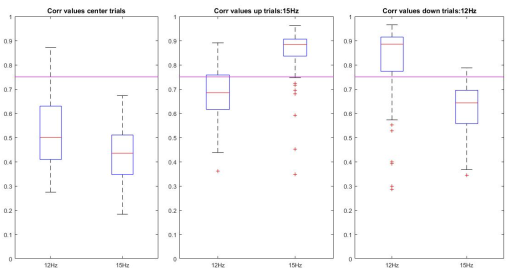
6. Start BCI200 from appropriate batch
7. Insert player ID in folder
    a. Play 4 runs of Easy level, and 4 runs of Hard level
    b. After each run, ask to fill in affective questionnaire
    c. **Always start BCI2000 before game level begins**
    d. **Always suspend BCI2000 after game ends**
8. Close Unity before closing BCI2000
9. Ask to fill in Game Experience part of the questionnaire
10. Open BCI2000 with prisoners' dilemma batch
11. Open Unity prisoners' dilemma game
    a. **Always start BCI2000 before game begins**
    b. **Always suspend BCI2000 after game ends**
12. Close Unity before closing BCI2000
13. Ask to refill in Game Experience part of the questionnaire



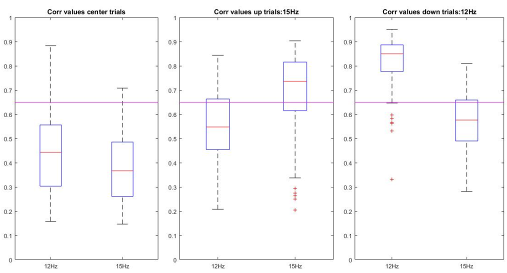
Appendix G

Light influence in SSVEP performance

In order to further explore the influence of light leaks in SSVEP classification, a same-subject performance test was done under two conditions: first in a completely darkened room and later in the laboratory used to carry out experiments. As stated before (c.f. Section 7.2.1) the laboratory, although darkened, contained light leaks from the windows gaps. The subject concerned did not participate in the study and his data was used only to test light influence in SSVEP. The performance test's protocol is identical to that used in Section 6.2.



(a)



(b)

Figure G.1: CCA's correlation values dispersion for same-subject performance test in condition *(a)* completely darkened room, and condition *(b)* experimental darkened laboratory with light leaks. Boxplots indicate (*from left to right*) correlation values with 12 and 15Hz in trials in which the subject is looking at the monitor's center, at the 15Hz source on top of the monitor, and a the 12Hz source on the bottom. Pink line indicates classification threshold.

Figure G.1 shows CCA's trial correlation to 12 and 15Hz values in a darkened room and in the laboratory a light leaks. Class separation seems to be more evident in G.1a given the established threshold, in particular for trials in which subject is focusing on 15Hz, when compared to G.1b. In fact the presence of light appears to decrease correlation values for all trials, and class separation becomes less discernible since dispersion is greater. As a result, the subject's performance decreased 6% (from 87.500% to 81.481%) when exposed to light leaks, a considerable difference in terms of BCI performance. Despite the possible existence of other environment variables (tests were performed in different days and rooms), there seems to be a clear influence of light in terms of SSVEP performance.