Bacteria Hunt: A multimodal, multiparadigm BCI game

C. Mühl (1), H. Gürkök (1), D. Plass-Oude Bos (1), M. E. Thurlings (2,3), L. Scherffig (4), M. Duvinage (5), A. A. Elbakyan (6), S. Kang (7), M. Poel (1), D. Heylen (1)

(1) University of Twente, The Netherlands, (2) TNO Human Factors, The Netherlands, (3) Utrecht University, The Netherlands, (4) Academy of Media Arts Cologne, Germany, (5) Faculté Polytechnique de Mons, Belgium, (6) Kazakh National Technical University, Kazakhstan, (7) Gwangju Institute of Science and Technology, South Korea

Abstract—Brain-Computer Interfaces (BCIs) allow users to control applications by brain activity. Among their possible applications for non-disabled people, games are promising candidates. BCIs can enrich game play by the mental and affective state information they contain. During the eNTERFACE'09 workshop we developed the Bacteria Hunt game which can be played by keyboard and BCI, using SSVEP and relative alpha power. We conducted experiments in order to investigate what difference positive vs. negative neurofeedback would have on subjects' relaxation states and how well the different BCI paradigms can be used together. We observed no significant difference in mean alpha band power, thus relaxation, and in user experience between the games applying positive and negative feedback. We also found that alpha power before SSVEP stimulation was significantly higher than alpha power during SSVEP stimulation indicating that there is some interference between the two BCI paradigms.

Index Terms—brain-computer interfaces, computer games, multimodal interaction.

1 INTRODUCTION

The study of Brain-Computer Interfaces (BCI) is a multidisciplinary field which combines engineering, cognitive neuroscience, psychology, machine learning, human-computer interaction and others. Applications using this direct communication channel from brain to machine are just as diverse, from rehabilitation to affective computing.

With methods like electroencephalography (EEG) it is possible to measure voltage differences over the scalp, which are the result of brain activity in the neocortex. With this method neuroscience has identified several patterns of activity that are associated with distinct cognitive functions. EEG opens therefore a window into the mind, which can be used for a direct communication between brain and computer [17]. It has a number of advantages over other methods, as it is non-invasive, has a high temporal resolution, does not require a laboratory setting, is relatively cheap, and it is even possible to create wireless EEG head-sets. Downsides of EEG are a low spatial resolution and its sensitivity to noise and artifacts [28]. The hardware also requires some time to set up, and afterwards everything needs to be cleaned. Dry caps which do not need conductive gel and are just as easy to set up as head phones are in development, which will solve this problem.

Where originally BCI research has been focused on paralyzed patients, new developments as affordable and wireless dry cap technology make BCI viable for healthy users. Besides the novelty factor, and the magic of being able to use your brain directly for control, BCI also provides private, hands-free interaction. It increases the information users can provide applications, and applications in turn can react more appropriately, for example by also taking the user's mental state into account.

A large potential target group are gamers, as games are an area where novelty is appreciated and learning new skills is often part of the challenge [19]. For research with patients, games can be a very interesting option as well. Virtual worlds can provide a safe environment to learn to produce specific brain activity: Accidentally steering your wheel chair off the stairs is less painful in a virtual environment. Additionally, the game element can keep tedious training fun and motivating.

Unfortunately, there are still issues that cause problems when trying to use a BCI. There are large differences between the brain activity between people, and even within one person the brain activity changes quite quickly over time [5]. This makes it difficult to create a system that will understand what the user is trying to do, especially for a longer duration. Depending on the BCI paradigm used a lot of training may be required (ranging from minutes to months), for the user to be able to generate the correct signal for the system. Alternatively, the system may be trained with user specific data to recognize the user's brain activity associated with a certain (mental) action. However, it is possible that the person trying to use the system falls into the category of the so-called BCI illiterate like 20% of the population [20]. This means that this particular user may not be able to generate the signal in a way that is measurable to the system, and hence will not be able to control it. As a result from using EEG as a measurement method, the recorded brain activity has a low signal-to-noise ratio and is susceptible to artifacts stemming from eye or muscle movements. These problems cause a high level of uncertainty when analyzing and interpreting brain signals. There are also issues with speed and timing, as relevant brain activity needs to be induced, recorded, analyzed, and interpreted, before the corresponding action can be performed in the application.

Although paralyzed patients for which BCI is the only interaction modality left may be willing to accept resulting problems with robustness and speed, healthy subjects will be less forgiving. For them many other input modalities are available. Therefore, now other more traditional usability and user experience challenges have to be solved as well, in order to exploit the full potential of this innovative technology and increase its acceptance among the general population.

Current BCI research applications are often very limited, restricting themselves to the use of one modality (BCI) and one BCI paradigm, to control one type of interaction in a very simplified game [22]. It is a big step from this situation to interaction found in current commercial video games. Besides the large amount of actions that can be taken in game worlds nowadays, gamers will not behave according to the restrictions often applied in current BCI research in order to reduce artifacts in EEG. Gamers will move, multi-task, and use multiple interaction modalities. Because of the problems with BCI at the moment, applying BCI in combination with traditional control modalities enables the use of its advantages, while its downsides can be avoided by other modes of input. The same is true for the use of multiple BCI paradigms.

The goal of this project has been the development of a game that combines traditional game control (e.g. mouse or keyboard) with BCI. This game is a platform for the study of the use of BCI in a game environment, to learn more about the situations mentioned above: using BCI in an efficient and natural way considering usability and user experience, using it in combination with other modalities, using multiple BCI paradigms within one application, allowing for a realistic setting, and possible multiplayer interaction. Besides these specific interests, this platform can also help in yielding new insights into more general issues of applying BCI.

To explore some of these previous issues, an experiment has been conducted using a multimodal, multiparadigm, single-player variety of the game. This functions also an illustration of how this platform can be used for such research. This investigation is focused on one hand on the influence of using a certain BCI paradigm on the user experience, and on the other hand on possible interference effects of using two BCI paradigms simultaneously.

Applying neurophysiological input in games gives rise to specific considerations in the design space. Hence, to start off, this new game design space for BCI is clarified in Section 2.

The third section provides more information on those BCI paradigms that were initially thought suitable for game control, considering the zero amount of training they required and the different types of input they could be applied to. Pilot studies were run to explore the most appropriate paradigm and parameters for the game. The full system consisting of the game and the pipeline for BCI control has been designed according to our specific requirements, as described in Section 4. This is followed by Section 5, which focuses on the conducted experiment and the obtained results. The paper concludes with a discussion and conclusions about the design space, the developed research platform, and the results of the conducted experiment.

2 A BCI Game Design Space

During the last decade, computer games have received increased attention from the scientific community. The academic field of *game studies*, while still in formation, already has given birth to a number of conferences and journals and the design of computer games is taught at universities around the world. These developments created techniques that may support the design of computer games and terminologies that may standardize the description and analysis of games and game design efforts. Within the project, game studies terminology was used to create a coherent description of what forms of BCI are possible in different forms of computer gaming. This "BCI game design space" first of all was needed to enable a precise definition of the couplings of neurophysiological input and game mechanics within the game and its various levels. In addition, it suggests a terminology that may be used to standardize the hitherto incoherent descriptions of these factors in BCI gaming projects.

2.1 Game studies terminology

Computer games, according to [1], consist of a *game world*, *rules* and *gameplay*. The former two comprise the entities that are present within a game as well the rules that connect these entities and define their behavior. Gameplay instead results from interaction. It emerges when a player applies the rules to the world by playing the game.

In order to be able to elicit gameplay, a coupling of the player to the game world must be established. This possibility of interaction yields a subjective experience of causal agency that results from a player's activity and its directly perceivable results in the game world. This experience has been named *effectance* [14]. While effectance is rooted in feedback on the level of in- and output, a player will also experience a game on the level of its rules: She will, for instance, not only move entities in the game world but eventually also win or loose the game. The experience of successfully interacting with a game's rules has been called the perception of *control* [14]. Both, effectance and control, are thought to be crucial factors for the induction of computer game enjoyment [14].

Computer games that not only rely on traditional forms of interaction, but that use physiological sensors pose new challenges for the definition of both: the direct application of inputs to the game world – and therewith the influence of these sensors on the level of effectance – as well as the role of the sensors for the game rules, on the level of control. Notice that neurophysiology is a part of physiology that deals with the nervous system. Therefore, while a BCI component (like an EEG sensor) is better classified as a neurophysiological one, it is also not wrong to refer to it simply as a physiological one.

2.2 Classification of BCI paradigms

A number of BCI paradigms exist and each of those may be suitable to support different forms of effectance. In the following, a two-dimensional classification of this BCI input space is suggested. While being formulated for BCI input, this classification generalizes to all forms of physiological input to computer games.

The dimensions of this classification are defined by (i) the dependence on external stimuli and (ii) the dependence on an intention to create a neural activity pattern as illustrated in Figure 1.

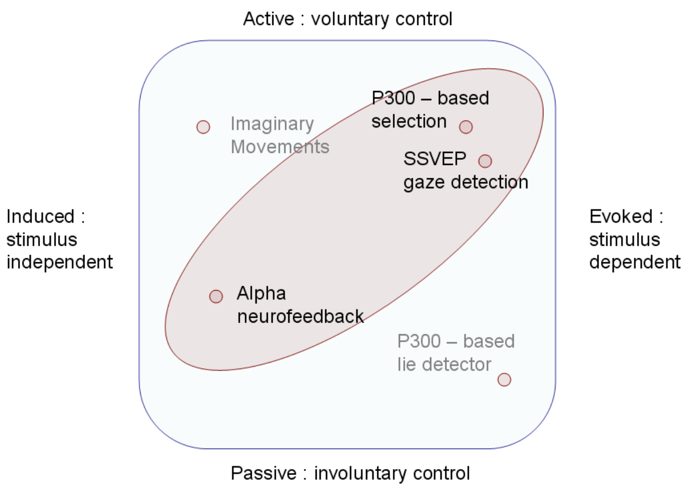


Fig. 1: A classification of BCI paradigms, spanning voluntariness vs. stimulus dependency.

Axis (i) stretches from exogenous (or evoked) to endogenous (or induced) input. The former covers all forms of BCI which necessarily presuppose an external stimulus. SSVEPs as neural correlates of stimulus frequencies, for instance, may be detected if and only if evoked by a stimulus. They hence are a clear example of exogenous input. Endogenous input instead does not presuppose an external stimulus. One prominent example is the usage of alpha band power in neurofeedback applications. While alpha activity may be influenced by external stimuli, it in principle can be measured when no stimulus is present and hence classifies as endogenous. Another way of separating both poles of the axis is the possibility of building a *self-paced* (or asynchronous) BCI [25]: Only endogenous input can be used to build a system that is self-paced, in the sense that it can decide if a user initiates an action by brain activity, whenever she does so. On the other hand, all forms of exogenous BCI necessarily are synchronous.

Axis (ii) stretches from active to passive input. Active input presupposes an intention to control brain activity while passive input does not. Imagined movements, for instance, can only be detected if subjects intend to perform these, making the paradigm a prototypical application of active BCI. Alpha and other measures of band power instead can also be measured if subjects exhibit no intention to produce it.

A summary of BCI Games by Reuderink [22] distinguishes between the application of band power feedback (F), P300, VEP and the neural correlates of imagined, planned and real movements (M). According to the scheme proposed here, all cases of F listed in [22] classify as passive-endogenous, all applications of P300 and VEP classify as active-exogenous and all cases of M classify as active-endogenous. However, other applications are possible or – outside the context of gaming – even are in use: P300 lie-detectors, for instance, classify as passive-exogenous. Using the changing VEP strength evoked by a stimulus that constantly is present as a correlate of attention would also classify as passive-exogenous.

2.3 Physiological effectance and control

If a BCI input directly affects the game world, the whole BCI feedback cycle is found on the level of effectance. In this case we speak of *direct* interaction. Direct interaction is usually associated with active BCI in which the user makes an effort to create a control signal in order to succeed at an aim. To the contrary, if not the game world but its rules are affected, parts of the interaction take place on the level of control. Here, BCI may be used to change overall parameters of the game, such as its speed or difficulty. Such forms of interaction are less directly perceived and hence can be named *indirect*. Indirect interaction is usually realized through passive BCI in which the user does not put much of his effort on using the BCI but rather on a more important control modality.

Moreover, if physiological activity does affect the game world or the rules, but if influencing these is not necessary in order to win the game, it constitutes a form of interaction that merely is *auxiliary*. An example for auxiliary interaction would be a game in which physiological activity changes the game's appearance or is used to gain bonus points. This sort of interaction is used mostly for non-critical features, and thus is very suitable to employ BCI paradigms which are hard or time consuming to detect.

2.4 Multiplayer BCI

In multi-player games the number of possibilities of affecting the game world or its rules increase: First, the game may be competitive, cooperative or generative. While computer gaming started with competitive games mostly (such as *Spacewar!* and *Pong*) in the age of online multi-player games cooperative gaming has gained much importance. Generative games are comparably rare, one prominent example is *Electroplankton* by Toshio Iwai.

Second, the mapping from physiological measurements to the game may either take place separately for each player or in conjunction. In *BrainBall* for instance, alpha band power of two players is combined to alter the position of one single ball, making it an example for conjunct control of the game [10]. Of course, it also would be possible to control the positions of two balls by one player each, creating a game using separate controls.

3 The BCI Paradigms

Existing BCI paradigms in BCI applications can be divided in several ways. The previous section distinguishes the classification into passive vs. active, and evoked vs. induced paradigms. To control an active BCI, one has to actively perform mental tasks such as motor imagery. For example by imagining left or right hand movement a cursor can be controlled to move up or down. This principle was applied in the game brainpong, where a bat is controlled to move up or down to block an approaching ball, using motor imagery [16]. Typically, active BCIs demand the most intensive user training. Evoked BCIs require probe stimuli, stimuli presented by the system. By attending to one of the stimuli, an interpretable brain signal can be elicited. In an evoked BCI this interpretation is translated into a command of the system. The type of brain signal that is elicited is dependent on the characteristics of the stimuli provided. The Steady State Visually Evoked Potential (SSVEP) and the P300 are both features in the EEG that can be elicited by certain probe stimuli and are explained in more detail later on. These features are interesting for BCI applications, because the signal-to-noise ratio is relatively high and they do not require user training. Passive BCIs detect the changes in cognitive and affective states, and do not require the user's active attention or the performance of cognitive mental tasks. In principle BCIs that belong to this category are not used for direct control (e.g. of cursor movement), but are more suitable for indirect control. Alpha band power can be used in this passive context, as it is related to a relaxed mental state [3]. However, the users can also learn to control their alpha activity, thus complicating the location of this approach along the passive/active dimension.

For the current game, it was decided to forgo paradigms that need extensive user training or machine learning, while at the same time a variety of different types of paradigms was wanted. This resulted in the selection of SSVEP, P300, and neurofeedback based on the power in the alpha band. This section describes these BCI paradigms. Two pilot studies were carried out to check the feasibility of the exogenous BCI paradigms in this game implementation, explore appropriate parameters and test classification algorithms for the BCI paradigms intended for the game control. The first study explored the neurophysiological responses to stimuli flickering with a fixed frequency (SSVEP). The second study investigated the responses to slower changing stimuli (P300). The final subsection provides information about alpha activity, based on literature.

3.1 SSVEP

SSVEPs can be induced if a person is attending to a flickering visual stimulus, such as an LED. The frequency of the attended stimulus [21], as well as its harmonics [18], can then be found in the EEG. SSVEPs are interesting for BCI-applications, because multiple stimuli can be provided simultaneously in contrast to the P300 for which stimuli have to be presented sequentially (see subsection 3.2). If the stimuli are all flickering with a different frequency, then the attended frequency will dominate over the other presented frequencies in the observers EEG. A commonly used method to detect SSVEPs is to apply a Fast Fourier

Transformation on the EEG and compare the amplitudes in the frequency bins corresponding to the frequencies of the stimuli provided. If only one stimulus is used, the amplitude of the corresponding frequency bin is compared to a set threshold. Frequencies of stimuli between 5-20 Hz elicit the highest SSVEPs [9]. SSVEPs are recorded over the visual cortex; O1, Oz and O2 according to the 10-20 system.

So SSVEPs are dependent on provided flickering stimuli, which need to flicker very constantly. The goal of this offline study was to investigate if it is possible to create such stimuli that are able to elicit the SSVEP response with Game Maker™. Furthermore, the parameters for this BCI paradigm were investigated in terms of appropriate frequency and the size, shape and pattern used for the stimulus.

3.1.1 Method

Stimuli: For the creation of visual flickering stimuli, several factors have to be taken in account. Firstly, is the bandwidth of frequencies that in principle can elicit robust SSVEPs, as mentioned above this is between 5 and 20 Hz. Secondly, in the current study it is desired that the stimuli are offered on the screen, so the possible frequencies are dependent on the screen refresh rate and characteristics. Previous experience showed that the SSVEP induction can not done reliably when the stimulus appearance is changed in every frame. At least two frames after each other need to show the same stimulus (color). Accordingly, the maximum stimulus frequency that can be obtained with a screen refresh rate of 60 Hz is 15 Hz (see Table 1). Therefore, a simple flickering stimulus is created by the alternation of two frames presenting a black stimulus and two frames presenting a white stimulus. Similarly, more complex stimuli are created, for example flickering checkerboards, which are often used to elicit SSVEPs. To investigate the robustness of the stimuli created with Game Maker™, such flickering checkerboards were presented with the frequencies 7.5, 8.57, 10, 12 and 15 Hz. To this end, one color of the stimulus was presented for two images, while the other color was presented for 2-6 images (see Table 1), resulting in four to eight images that were connected in one stimulation period.

Frames per period	Frames on (1) and off (0)	Frequency of stimulus (at 60 frames per second)
4	...1100...	15 Hz
5	...11000...	12 Hz
6	...110000...	10 Hz
7	...1100000...	8.57 Hz
8	...11000000...	7.5 Hz

TABLE 1: Possible frequencies of a flickering stimulus on a LCD with a screen refresh rate of 60 Hz are shown.

As imaginable, flickering checkerboards are visually not appealing and are annoying to look at. Therefore besides the standard checkerboard, also other shapes and appearances of stimuli were investigated. The appearance and characteristics are shown in Table 2. To limit the number of experimental sessions, the disk stimuli were only presented in one frequency, namely 12 Hz.

Experimental Setup: For this pilot study only two participants were involved. They were seated in front of a laptop, approximately 60cm in front of the screen. Each stimulus was presented for 60 seconds, and appeared in the middle of the screen. After each stimulus presentation, a pause screen appeared. For details on the recording of EEG, see Subsection 5.1. The sample frequency for this EEG recording was 2048 Hz.

Task: Participants had to sit still in front of the laptop and attend to the stimulus presented. They were instructed to blink as few as possible and to avoid any other movement completely during stimulus presentation. Participants controlled the start of each condition.

3.1.2 Results

Offline Analysis: The EEG recorded at O1, Oz and O2 was first cut out for each stimulus presentation from 40.000 until 100.000 data points after the start of the stimulus (60.000 data points recorded with a sample frequency of 2048 Hz corresponds to approximately 30 seconds). These extracted signals were first common-average referenced (CAR, see Subsection 4.2.2), and then transformed to the frequency domain with a Fast Fourier Transformation.

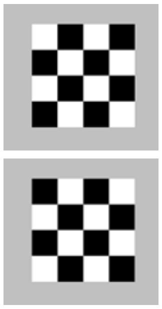
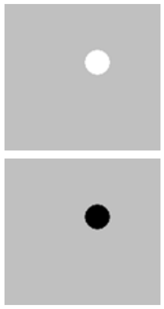
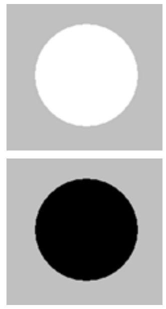
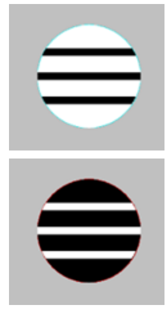
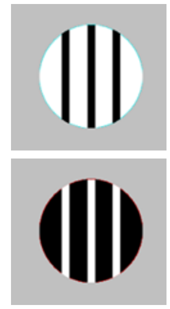
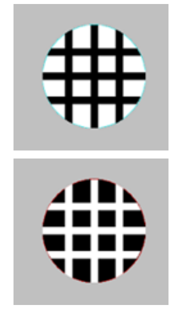
Checkerboard	Small disk	Large disk	Large disk with horizontal stripes	Large disk with vertical stripes	Large disk with horizontal and vertical stripes
					
Stimulus freq. of 0, 7.5, 8.57, 10, 12, 15Hz	12Hz	12Hz	12Hz	12Hz	12Hz
Inner diameter of 4o	1o	4o	4o	4o	4o

TABLE 2: The table shows the presented stimuli and the presentation parameters frequency and size. The images on top were altered with the bottom images to create the flickering stimuli. The third row shows the frequencies each flickering stimulus was presented with. The last row relates the size of the stimuli to the smallest, namely the small disk (o).

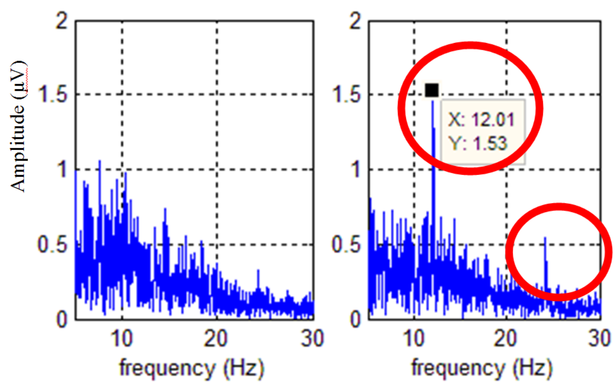


Fig. 2: The frequency spectrum of a participants EEG recorded at Oz during: no stimulus presentation (left) and checkerboard presentation of 12 Hz (right). Here the main response of the SSVEP and its first harmonic are clearly visible.

For the checkerboard stimuli, clear SSVEP responses were found in the EEG of both participants for 7.5, 8.57 and 10 Hz (see also Figure 2). In one participant also the stimuli flickering at a frequency of 12 and 15 Hz evoked SSVEP responses, although from the latter one only the second harmonics was found. From the alternative stimuli, the large disk and the large disk with horizontal and vertical stripes were able to evoke SSVEP responses in both participants. For one participant the large disk with horizontal stripes and for the other participant the large disk with vertical stripes also induced SSVEP responses. No significant differences were found for responses recorded at O1, Oz and O2.

Classification: In order to develop a BCI that uses the SSVEP paradigm, an online classification algorithm is needed. To simulate an online situation, the recording of 60 seconds was sliced into four-second windows, with steps of one second between the start of each window. After CAR and FFT is applied, the SSVEP detection consists of comparing the target frequency power to the maximum peak in the frequency bin around the target, with a size of 3 Hz. If the ratio between these two energy peaks exceeds an experimentally determined threshold of 0.8, the window was said to contain SSVEP. This SSVEP detection method is described in detail in Subsection 4.2.2, and is depicted in Figure 7.

After applying the method described above on the OZ channel the results presented in Table 3 were obtained. The table shows the true

Stimulation frequency	Checkerboard	Small disk	Large disk	Large disk with horizontal stripes	Large disk with vertical stripes	Large disk with horizontal and vertical stripes
Subject 01						
7.5Hz	84%	-	-	-	-	-
8.57Hz	93%	-	-	-	-	-
10Hz	98%	-	-	-	-	-
12Hz	90%	56%	92%	79%	76%	97%
15Hz	90%	-	-	-	-	-
Subject 02						
7.5Hz	87%	-	-	-	-	-
8.57Hz	68%	-	-	-	-	-
10Hz	82%	-	-	-	-	-
12Hz	52%	44%	84%	48%	63%	73%
15Hz	80%	-	-	-	-	-

TABLE 3: The true detection rates of SSVEPs for the different stimuli. The perfect rate is 100 % in the data used here.

detection rates (the recognition of SSVEP during actual SSVEP stimulation) for the different objects and stimulation frequencies. Please note that the optimal performance is 100%, as the true detection rate was calculated only on data with the stimulation present.

Assuming that the ability of the stimulus to elicit SSVEP is the main reason for the obtained true detection rates, those stimuli that yielded the best results qualify for further exploration. The stimuli that resulted in a good classification result for both subjects were:

- Checkerboard pattern flickering at frequencies of 7.5, 10 and 15 Hz
- Large disk and the large disk with both vertical and horizontal stripes, flickering at a frequency of 12 Hz

From these the checkerboard at 7.5 Hz and the large disk at 12 Hz were selected for further evaluation. The large disk was selected because it seemed less obtrusive than a flickering checkerboard, which is relevant for application in the game. The checkerboard flickering at 7.5Hz was selected for further analysis because of the potential interferences of the frequencies from 8 to 12 Hz with the other BCI paradigm used in the game. At all frequencies, except 7.5 and 15 Hz, the SSVEP would be in the alpha frequency range used in the game for the neurofeedback BCI paradigm. Between the true detection rates for 7.5 Hz and 15 Hz stimulation only a minor difference was observed.

For these selected stimuli, the optimal window length was explored. For this, for each window duration, besides the true detection rates, also the false detection rates (detection of the stimulus when no stimulus was presented) and the classification accuracies (total number of correct classifications divided by the total number of classifications) were calculated. The results are presented in Figure 3. As expected, the classification accuracy improves with longer window durations, as it contains more data. The figure shows that windows of at least 3 seconds are required to obtain proper classification results. For shorter windows the true detection rate is still high, but the false detection rates increase dramatically, decreasing the classification accuracies to below 70%.

3.1.3 Conclusion

The offline analysis of EEG recorded while attending to flickering stimuli created with Game Maker^{TM}, shows that SSVEPs can be elicited with these stimuli. The offline analysis and the offline classification both showed well detectable SSVEPs for both subjects for the stimuli: checkerboards flickering at 7.5, 10, and 15 Hz, and the plain large disk and large disk with both horizontal and vertical stripes flickering at 12 Hz. Of these stimuli, the plain large disk is thought to be the least obtrusive, and therefore is implemented in the game. The developed classification algorithm seems to be robust enough for implementation in an online classification structure. Analysis showed that

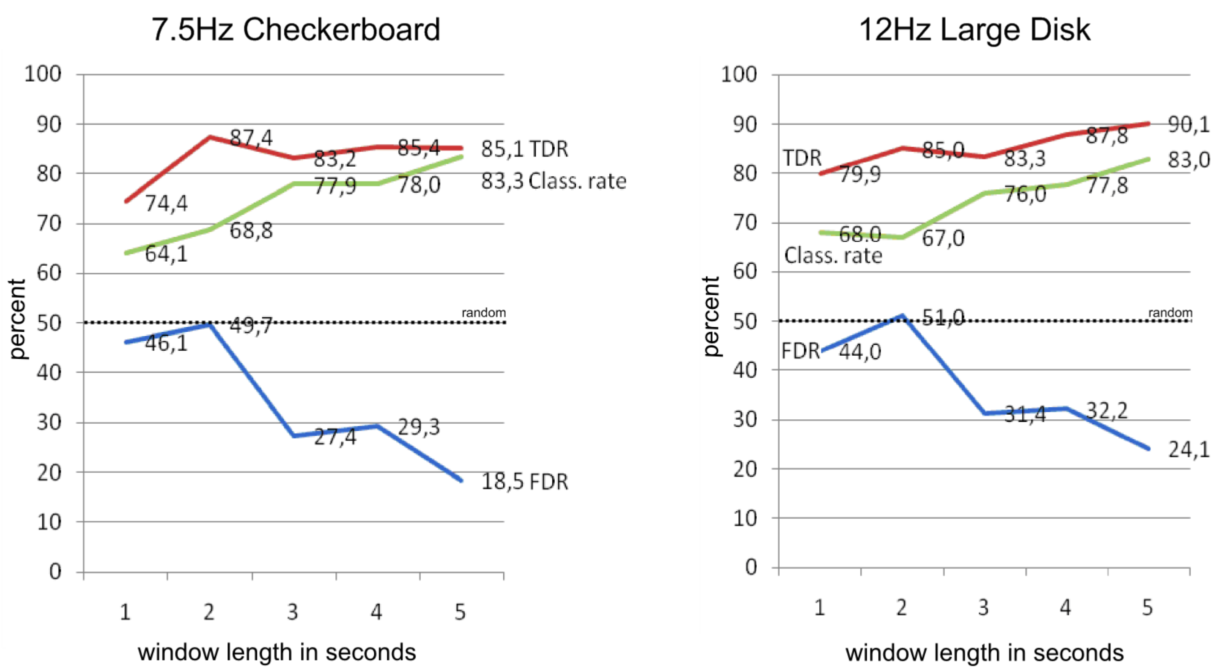


Fig. 3: The classification accuracy, true and false detection rates for the checkerboard and large disk stimuli flickering at 7.5 and 12 Hz, respectively.

windows of at least 3 seconds are required. So the game requires the user to focus for at least 3 seconds at flickering stimuli if presented.

3.2 P300

A P300 is an event-related potential (ERP). The P300 (also referred to as the P3) is a positive peak in the EEG that occurs approximately 300ms after the presentation of a *target* stimulus that stands out from other *standard* stimuli or *distractors*. One reason why the stimulus stands out can be due to differences in appearance, e.g. when one black sheep is presented after ten white ones. The experimental paradigm is called an oddball paradigm [12]. The P300 amplitude decreases if the target and stimuli are more similar [6]. Another reason is because a person is attending to a certain stimulus. The P300 is thought to be related to a higher level attentional process or orienting response. In general P300s are detected at Fz, Cz and Pz as defined by the 10-20 system. To elicit a P300, probe stimuli can be presented in the visual, auditory and tactile modality [2].

The first BCI application that used the P300 paradigm is the P300-matrix speller [8]. In this application letter and numbers are placed in a 6 by 6 matrix. The rows and columns flash up sequentially. Every time the symbol of one's choice flashes up and the user is attending to it, a P300 is (potentially) elicited. In this way, users (e.g. patients with neuromuscular diseases) can spell words and communicate with their environment, although very slowly (approximately 1-2 words per minute). As the P300 can be easily modulated with attention, it is an interesting component to use in games.

To test the feasibility of using P300 within a game, an offline experiment has been conducted that tested visual stimuli created in Game Maker^{TM}. The stimuli were shaped like bacteria, testing the potential applicability of such a stimulus in a game. Additionally, the possibilities to let a stimulus stand out (instead of flashing up) were investigated by changing stimulus' color, size and angle.

3.2.1 Methods

Experimental Setup: The general setup was similar to the previous pilot experiment (see Subsection 3.1). Comparable to the spelling matrix, stimuli are grouped, similar to rows and columns. However, visually, the positioning of the stimuli is unstructured, to simulate a game situation. At the start of each trial in this offline experiment, a target stimulus was indicated. Each group was highlighted for 150 ms followed by an inter-stimulus interval of 150ms. The presentation of the groups was done in random order and repeated nine times.

Stimuli: Three different possibilities to let a stimulus stand out were tested. See Table 4 for the visuals.

Task: A target was indicated at the start of each trial, by highlighting it for 2 seconds. The participants were instructed to count the number of times this particular target stimulus was changed, to keep their attention focused on the target. Furthermore they were instructed to sit still, move and blink as few as possible.

Analysis: The P300 potentials were analyzed by averaging the signal of a certain electrode (the most important ones were Cz and Pz) that was recorded from 200 ms before until 800 ms after the stimulus-onset. The signals were baseline-corrected by the subtraction of the average of the 200 ms before stimulus-onset. After that the signals that were related to the target-stimuli were averaged (two signals per trial), and the signals that were related to the non-target-stimuli were averaged (four signals per trial).

3.2.2 Results

The results of the analysis for EEG responses and also the average over the nine trials are shown in the graph below (see Figure 4). The graph shows the P300 elicited by the stimuli that changed color (orange stimuli were neutral and black stimuli were highlighted), as a highlight-effect. The other conditions used, 'change size' and 'rotation', also elicited P300s. However they were lower in amplitude.

3.2.3 Conclusion

Based on this offline analyses, it is expected that the P300 paradigm may be usefull in the game, and good results can be expected if at least two trials are used. This would require 3.6 seconds of data before a classification can be done. The highlight effect that gave the best results was changing the color of the stimulus from orange to black. Unfortunately there was not enough time during the eNTERFACE workshop to also complete the online P300-pipeline. Therefore this is recommended for future work.

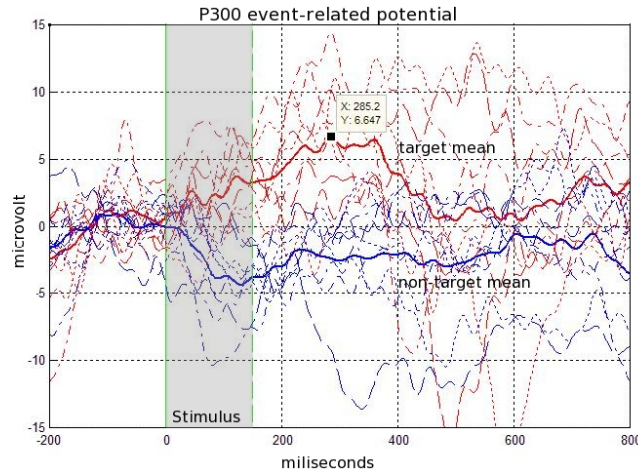


Fig. 4: EEG response of one participant to target stimuli (red) and non-target stimuli (blue) recorded at Cz. The stimulus was present during the grey area. The two thick lines represent the averages over nine trials: the EEG response to targets is clearly different from the response to non-targets. The averaged target line shows a peak at 285 ms after stimulus onset, indicating the presence of a P300.

3.3 Alpha

The term 'alpha rhythm' is restricted to brain activity in the alpha range occurring at the back of the head, which is related to a relaxed wakefulness and best recorded with eyes closed, according to the definition of the International Federation of Societies for Electroencephalography and Clinical Neurophysiology [4]. In our report, alpha band power is used in the more general sense of energy in the frequency band of the alpha rhythm: 8 to 12 Hz, which can be observed over all cortical regions.

Alpha activity used to be considered to be inversely related to neuronal activity. This can be interpreted either as cortical inhibition, or cortical idling. This view is shifting, as alpha is now seen to have functional correlates to movement and memory [26].

As a correlate to relaxed wakefulness, alpha activity could be an interesting measure for passive BCIs. Alpha activity is also considered an important tool in neurofeedback. Besides

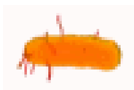
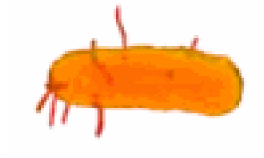
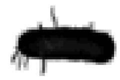
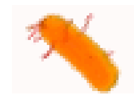
Standard stimulus	Size change	Color change	Rotation
			

TABLE 4: The stimuli for the P300 paradigm. The standard stimulus, and the changes in size, color, and rotation used to elicit the P300.

helping patients, it might also be used to improve our mental capabilities, as research has indicated relations between alpha activity and intelligence [7], and the ability to cope with stress [27]. This is another reason why alpha neurofeedback and neurofeedback in general could be interesting BCI paradigms to use in games.

3.4 Conclusions

For this project, three potential paradigms were looked into, which were selected based on their characteristics and the minimal amount of user training and machine learning they required. These paradigms were looked up in literature, and for the two evoked paradigms small pilot studies have been conducted.

SSVEPs can be elicited with a stimulus looking like a plain large disk, which is considered to be less obtrusive then for example the checkerboard stimulus often used for this paradigm. Although this disk was only tested at 12 Hz, the frequencies of 7.5 and 15 Hz obtained good results for the checkerboard stimuli. To minimize interference with the alpha frequency range used in the neurofeedback paradigm, the flickering of the disk with 7.5 Hz seemed a good stimulus choice for the SSVEP paradigm. To obtain an acceptable accuracy of detection, windows of at least three seconds are recommended.

Alpha could be an interesting correlate for the mental state of relaxed wakefulness, to be used as a passive BCI modality, or in a more active way with potential mental benefits as a result of the training.

For P300, the highlight effect of changing the color of the stimulus from orange to black gave the best results. At least two trials would be recommended for classification, which would require 3.6 seconds of data. An online pipeline for this paradigm has not been implemented during this workshop, but is recommended as future work.

4 The game and BCI design

The application was built in guidance of principles and requirements defined in §4.1.1 and §4.2.1. For the ease of maintainability and optimal performance the system was decomposed into subsystems, namely the game and the data processing. The game subsystem is responsible for running the game and sending the markers depending on the input received from EEG analysis results and other traditional modalities. On the other hand, the data processing subsystem returns to the game the results it computed according to the markers and the EEG signals received. The overview of the system architecture can be seen in Figure 5.

4.1 The Game

This subsection describes how the game world, game levels and game rules are implemented in accordance to the requirements defined.

4.1.1 *Requirements*

1. *Scientific*: The game is intended to be a basis for investigation of (1.1) the possibility of combining BCI with conventional controls and (1.2) the possibility of using multiple

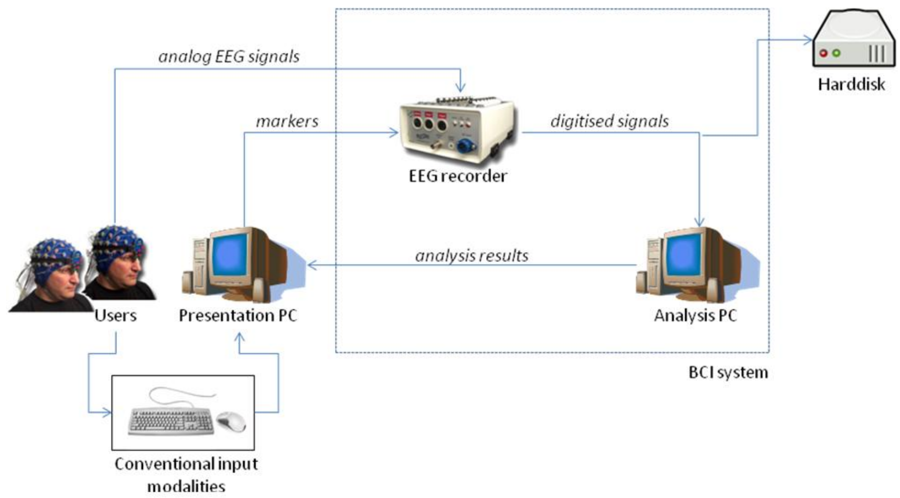


Fig. 5: Overview of the system architecture.

BCI paradigms. In addition, (1.3) it should be possible to easily extend the game with multiplayer functionality.

2. *Usability*: The game should be easy to understand and uncomplicated in use, and thus (2.1) be playable without training. In order to elicit subjective perception of control, (2.2) the game should provide persistent visual information indicating progress in terms of its rules. Finally, if players are meant to perceive causal agency based on neurophysiological recordings, (2.3) the game must provide direct feedback on the neurophysiological inputs used.

The game should equally fulfill both scientific and usability requirements.

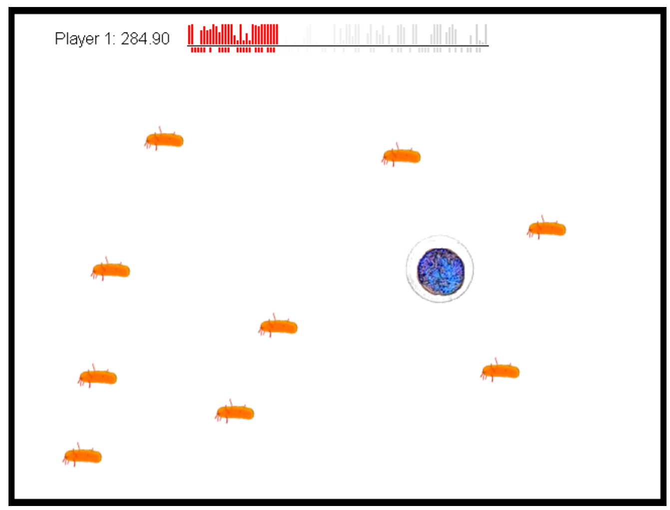


Fig. 6: The game world. Nine targets (orange "bacteria") and one player (blue "amoeba") are present. The player's score is shown at the top left. The histogram above the line depicts her recent alpha band power, below the line the SSVEP classification results are marked.

4.1.2 Game world

The game was built using the Game Maker™ development platform. The game world consists of a small number of entities: player avatar(s) (the amoeba), targets (bacteria), a numeric representation of the points obtained so far, a graph depicting the recent history of alpha band power and SSVEP classification and SSVEP stimulus (which always is associated with one of the target items) when it is triggered. The numeric representation of points functions as a high-level indicator of progress in terms of the game rules (req. 2.2) while the graph depicting alpha band power and SSVEP classification results functions as a low-level indicator of the neurophysiological coupling of the player and the game (req. 2.3).

4.1.3 Game levels

The game comprises various levels, each using the same game world but slightly differing in terms of rules. The levels *Keyboard only* (*K*), *Keyboard+Alpha* (*KA*) and *Keyboard+Alpha+SSVEP*

(*KAS*) have been implemented and tested. Furthermore, a *Keyboard+Alpha+P300* (*KAP*) level has been realized, but not tested. The decision to use alpha band power, SSVEP and P300 was guided by the requirement that it should be possible to play the game without training (req. 2.1). Imagined movements, for instance, presuppose a training phase and thus would violate this requirement. The decision to combine alpha band power with SSVEPs or P300 respectively was taken because it should be possible to analyze the combination (and possible interactions) of multiple BCI paradigms in one game (req. 1.2).

4.1.4 Game rules

Some general rules are the same for all levels, others vary with the specific level which will be explained in this subsection.

General rules: The game world always contains nine target items, which never may overlap. If the distance d between the center of a player avatar and a that of a target is below the radius of d_{min}, the target can be "eaten". Eaten targets disappear and are replaced by a new target, randomly placed on a free spot on screen. Thus, visual disappearance of target items, in addition to the numeric display of score, indicates the progress in terms of game rules (req. 2.2). Target successfully eaten results in points for the player. Eating failures result in negative points. The rules for eating are defined differently in each level. The ultimate goal of the game is to obtain as much points as possible.

Movement is performed using the keys, resulting in direct feedback through changed avatar position. Avatar position also jitters by some random noise and the effect of pressing a key depends on some external values, i.e. game controllability varies. Since the influence of key presses on the position is variable, the change of position per key press also provides direct feedback on how the player currently affects game controllability. If controllability is affected by neurophysiological measures (as in *KA*, *KAS*, and *KAP*), this implies that the feedback provided is direct feedback on neurophysiological activity (req. 2.3). In addition, by affecting controllability with neurophysiological measures, keyboard input (a conventional control) is combined with neurophysiological input (req. 1.1).

Let x and y denote a player avatar's position, s its speed , $c \in [0, 1]$ the external factor determining controllability and $random(x)$ a function that returns a real value from $[1, x]$. Pressing the "right" key results in the following calculation:

$$x_{new} = x_{old} + (s + (random(s) - \frac{s}{2})) \times c$$

$$y_{new} = y_{old} + (random(s) - \frac{s}{2}) \times c$$

In addition, even if no key is pressed, the avatar position changes from frame f to frame $f + 1$ as follows:

$$x_{f+1} = x_f + (random(s) - \frac{s}{2}) \times c$$

$$y_{f+1} = y_f + (random(s) - \frac{s}{2}) \times c$$

Level K rules: This level uses no EEG data at all. Hence the factor c is set to a random value in $[0.4, 0.6]$. In this way controllability will vary but stay within a range from which large deviations of controllability are possible for the other levels. Eating is triggered by pressing a key. It is a success if the nearest target meets the distance condition described above ($d \leq d_{min}$). Points p are calculated by:

$$p = 100 \times (1 - \frac{d}{d_{min}})$$

If the eating attempt is triggered while the distance is above the threshold, p is assigned to -50.

Level KA rules: Eating is performed and evaluated as in level *K*. However, c is linked to the player's relative alpha band power ($\alpha \in [0, 1]$). In a pilot study, relative alpha power was found to be in $[0.15, 0.23]$ for most subjects. Thus, an *ad hoc* scaling $[0.15, 0.23] \rightarrow [0, 1]$ was introduced, creating a scaled α_s. For future versions of the game, subject dependent scaling methods or adaptive scaling are to be considered.

$$\alpha_s = \frac{(\alpha - 0.15)}{0.08}$$
$$c = \alpha_s$$

Therefore, controllability is to be affected by the player's mental state, while the influence on controllability is visualized by the jitter exhibited by the avatar (req. 2.2) and both keyboard and BCI input are combined (req. 1.1).

Level KAS rules: The factor c is linked to alpha band power as in level *KA*. The process of eating is changed as follows: approaching a target closer than the eating distance d_{min} triggers a SSVEP stimulus appearing next to the target. The association of stimulus and target is visualized by a line connecting both. The stimulus consists of a circle with a diameter of 64 pixels and flickers with a frequency of 7.5 Hz, changing from black to white. It is displayed for 6 seconds on the screen. Between the seconds $3-6$, SSVEP classification results are recorded (this specific interval depends on the window size of 4 seconds used in the analysis pipeline). If the mean output of the classifier is above 0.5, the target gets eaten. Points are calculated using the mean alpha power measured between the seconds $3-6$.

$$p = 100 \times mean(\alpha_s)$$

Thus, for players, it is of benefit to control both alpha band power and SSVEP simultaneously (req. 1.3). If SSVEP classification fails, -50 points are given, the target "escapes" and is moved away from its current position.

Level KAP rules: Instead of triggering a SSVEP stimulus, approaching a target now triggers repeated highlighting of groups of targets. To do so, the nine targets on screen are organized in six groups. Each group consists of three targets and each target is part of two groups. Groups are highlighted by replacing the image of its member objects by a bigger version of the same image for $150ms$. Between each flash, an inter-stimulus interval of $150ms$ is used. After each group has flashed once, a P300 response for the selected target is measured and, if classified correctly, the target is eaten successfully. Again, alpha activity during that process is used to scale points received for eating. If no target or a non-target is classified using P300, the target escapes.

4.1.5 Effectance and control

On the level of effectance, players interact with the game world by controlling their avatar's position using the keys. In addition, they control eating and target "escape" behavior by focusing SSVEP or P300 stimuli (in an exogenous-active condition).

On the level of control, players change the game rules based on their alpha band power: a high alpha is to enhance the controllability of the game using keys (in an endogenous-passive condition).

4.1.6 Single- and multi-player

The initial prototype of the game is single-player only. But in principle it can easily be scaled to larger number of players (req. 1.3). In a *competitive* mode, players compete for points. In a *cooperative* mode, players try to clear a level from all targets as soon as possible. Both modes employ separate BCI control. Other ways of cooperative game play are planned, such as a mode in which player avatars are merged for conjunct control.

4.2 Data acquisition and processing

This subsection defines the requirements and steps for data acquisition and processing.

4.2.1 Requirements

1. Hardware considerations: The EEG signals should to be acquired by the BioSemi ActiveTwo system. For this purpose, the game should run on a computer with a parallel port to be able to send the signals and markers. The game and analysis pipeline should be able to communicate with each other via TCP. The computer running the game should possess a monitor with a resolution of 1024x768 and a minimum refresh rate of 60 Hz to be able to correctly display the SSVEP frequency. The analysis pipeline should be able to receive the signals from the ActiveTwo system via USB. BioSemi active electrodes should be used in measurements as advised by the BioSemi company.

2. *Performance*: The time lag between the analysis pipeline, game engine, and ActiveTwo system should be kept at minimum for the sake of analysis accuracy and game amusement. Both the gaming and pipeline computers should be fast enough to run continuously, without any halts or delays.

3. *Physical environment*: All the equipment should be operated, preferably, in a room free of electrical noise. Users should be able to access the gaming computer but better be kept away from the analysis computer to avoid distraction.

4.2.2 Design

For signal processing and machine learning purposes, Golem and Psychic libraries by Boris Reuderink were employed in the pipeline [23], [24]. The EEG signals are continuously read as overlapping 4-second-sliding-windows, the interval between window onsets being 1 second. The steps for processing a window is displayed in Figure 7. Brain potentials have to be measured with respect to a reference. This reference can be based on some electrodes (e.g. placed on ear lobes or mastoids) but also be electrode-free by re-referencing, i.e. the reference potential is created from a computation based on a set of electrodes. Common average referencing (CAR) is such a spatial filter used for re-referencing. It consists of computing the mean of the whole set of electrodes per sample and then subtracting it from each EEG channel. It was shown to be superior to the ear-reference and other re-referencing methods [15]. Therefore a data window is first re-referenced by CAR.

Regarding the relative alpha power computation, the data in channel Fz was extracted from the window. Applying fast Fourier transform (FFT) on the data the power within the alpha band [8 Hz, 12 Hz] was calculated and divided by the total power within the frequencies [4 Hz, 40 Hz].

For the detection of SSVEP presence, the data in channel O2 was extracted from the window. Channel O2 was used since no significant difference was found in the response recorded at O1, Oz and O2 (see §3.1) and during experiments recording sites O1 and Oz were problematic. Then the power in the frequency domain was computed by FFT. The power spectrum is expected to contain a peak at the flickering frequency of the circle object on the screen. The flickering frequency ($f_{flicker}$) of 7.5 Hz was used as it was one of the best performing frequencies (see §3.1) and does not interfere with the alpha band. But detection of this peak is a bit tricky task. Sometimes the amplitude of the flickering frequency may not be present in the spectrum but, instead, in the frequencies that are close to it. It can still be approximated by increasing the resolution of FFT, or calculated from known values for neighboring frequencies, but result can be inaccurate. Another point is that the flickering frequency may be unstable on custom computers and LC displays. Therefore, SSVEP in some cases might not be detected correctly. Taking all these challenges into consideration, following procedure was defined for detecting the peaks in the spectrum:

1) Look for the frequency with the maximal amplitude (f_{max}) between the range of [$f_{flicker}$ - 1.5 Hz, $f_{flicker}$ + 1.5 Hz].
2) If $f_{flicker}$ is not represented in the spectrum obtained by FFT, look for the nearest represented frequency ($f_{nearest}$) and set $amp(f_{flicker}) = amp(f_{nearest})$.
3) If f_{max} is next to $f_{flicker}$ in the spectrum, set $amp(f_{flicker}) = amp(f_{max})$.
4) If $amp(f_{flicker})/amp(f_{max}) > threshold$ then conclude that a peak is present. During experiments the optimum $threshold$ was found to be 0.8.

where $amp(F)$ is the amplitude of the frequency F obtained by FFT.

The relative alpha power value and presence of SSVEP were continuously sent to the game PC via TCP.

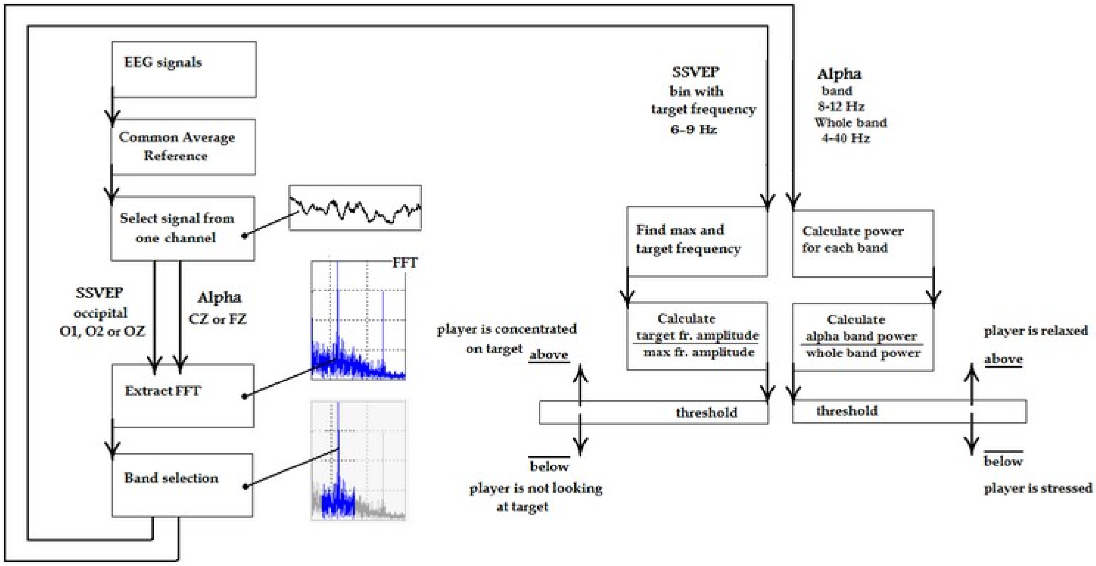


Fig. 7: The signal processing pipeline of Bacteria Hunt.

5 EXPERIMENTS

The overall goal of the project was to develop a game that would be suitable for the use as experimental platform to answer research questions related to BCI. From the underlying research questions on applicability and combinability of BCI control in a game specific hypotheses were posed:

Hypothesis I: The use of a positive neurofeedback paradigm, based on the reward of high alpha values, as a control modality results in an increase in alpha power and in a state of higher relaxation and less tension.

Hypothesis II: The combination of positive alpha neurofeedback and SSVEPs causes no detrimental effects. As alpha feedback should result in a state of relaxed attentiveness, we assumed that the attention on the flickering SSVEP stimuli should not necessitate a change of overall relaxation state.

5.1 Methodology

In order to test the hypotheses stated above, an experimental protocol was devised. Participants were asked to play two versions of a game. Each version was constructed from three levels, namely *K*, *KA*, and *KAS* (see §4.1.3). In keyboard only level *K* the participant had time to get acquainted with the game. Furthermore, it can be used as an alpha baseline condition later on. The difference between both games was in the way the alpha neurofeedback was applied. In the positive feedback version (*pF*) an increase of alpha yielded an increase in controllability of the game. In the negative feedback version (*nF*) we inverted the relationship between alpha level and controllability.

Five participants (2 female, mean age: 26) took part in the experiment. The participants were seated in front of the notebook running the game (1.8 GHz Pentium M). They read and signed an informed consent and filled in a questionnaire assessing prior drug consumption and amount of sleep. After that the electrode cap was placed and the electrodes connected. 32 Ag/AgCl Active electrodes were placed according to the 10-20 system [13]. The EEG signals were recorded with 512 Hz sample rate via a BioSemi ActiveTwo EEG system and processed and saved on a separated data recording and processing notebook (2.53 GHz Quadcore) running BioSemi ActiView software.

The blocks contained the 3 games in the following order: *K*, *KA*, and *KAS*. Each game lasted for 4 minutes. That made a total duration of 12 minutes per feedback session, excluding small breaks between the games. After each feedback session the participants were given a questionnaire to evaluate their experience during the game session.

5.2 Analysis

To test the first hypothesis the alpha power was analyzed as an objective indicator and the user experience as a subjective indicator. Specifically a higher level of alpha power for the positive feedback condition compared to the negative feedback condition was predicted, as alpha power increases were rewarded in the former and punished in the latter.

The Game Experience Questionnaire GEQ [11] was used to measure user experience according to the concepts of competence, immersion, flow, tension, challenge, negative, and positive affect in separate scales. We added a control scale that assessed the felt controllability of the player in each feedback condition. It was predicted that positive neurofeedback would lead to a decrease of tension and subsequently an increase of positive affect.

To test the second hypothesis we analyzed only the objective indicator of relaxation, i.e. alpha power. We compared the power in the alpha band between the *KA* and the *KAS* condition of the positive feedback session. We expected an equal level of alpha power, thus no interference from the SSVEP stimulation in *KAS*. Additionally, to check for temporally limited interactions between the two BCI paradigms, we compared the level of alpha power before and during SSVEP stimulation and expected also there an equal amount of alpha.

5.3 Results

The analyses on the data collected have two sorts of implications. They provide conclusions about applicability and combinability of BCIs while answering the hypotheses posed previously.

5.3.1 Applicability of BCI

As result of the first hypothesis, concerning the applicability of a BCI paradigm in a game, an effect of the applied neurofeedback on alpha power and user experience was predicted. However, neither objective nor subjective indicators for an effect of the feedback were found (see table 5). No significant difference in mean alpha band power could be shown between the games applying positive and negative feedback. Accordingly, there was no significant difference in the user experience between the positive and negative alpha-feedback conditions.

The failure to find an effect of the feedback on alpha power and user experience might have different causes. In general, it might be due to the small sample size of 5 participants. Furthermore, for both feedback conditions the participants were instructed to relax, which might have lead them to relax in both conditions despite the difference in feedback. Possible differences might be covert then by a floor effect. Complying with this possible caveat, table 5 shows very low scores for the tension scale. This lack of excitement was also reported by the participants in informal interviews after the experiment. To exclude this possibility the stress level during gaming would have to be increased, possible by a higher difficulty and a more dynamic and faster nature of the game.

Interestingly, we found a marked difference of the pre-SSVEP alpha power between *nF* and *pF* conditions, with higher alpha power for the *pF* condition ($p \leq 0.006$). In the absence of an overall difference of alpha power this effect seems contradictory. However, it could indicate the effectiveness of alpha feedback for conditions with higher difficulty, as the *KAS* conditions were potentially more stressful due to the more difficult SSVEP-based scoring. This effect might be too small though to be reflected in overall alpha power and the conscious experience of the players assessed via the GEQ.

5.3.2 Combinability of BCI

As a result of the second hypothesis, concerning the combinability of two BCI paradigms in an application, we expected no interaction of both paradigms, that is no effect of SSVEP on alpha power. Accordingly, we found no significant difference in mean relative alpha power between *KA* and *KAS*.

Unexpectedly, an influence of the SSVEP stimulation on alpha power was found for the alpha feedback condition *pF*. Specifically, alpha power before SSVEP stimulation was signifi-

	negative F mean	std	positive F mean	std	ttest(*nF*,*pF*) H	P
Questionnaire data						
competence	2,03	0,81	2,13	0,81	0	0,850
immersion	1,67	1,10	1,33	0,75	0	0,230
flow	2,17	0,72	1,93	0,85	0	0,535
tension	0,97	0,69	0,87	0,62	0	0,591
challenge	1,47	0,55	1,40	0,25	0	0,688
negative	1,20	0,74	1,37	0,59	0	0,561
positive	1,90	0,74	1,73	0,51	0	0,430
control	2,35	1,05	2,15	0,68	0	0,767
EEG data						
α *KA*	0,18	0,02	0,18	0,01	0	0,723
α *KAS*	0,18	0,02	0,18	0,02	0	0,593
preSSVEP α	0,18	0,01	0,19	0,01	1	0,006
SSVEP α	0,18	0,02	0,18	0,01	0	0,938
preSSVEP α - SSVEP α	0,00	0,01	0,01	0,00	1	0,006
Behavioral data						
Score *K*	4348,34	1118,47	4343,24	1295,33	0	0,991
Score *KA*	4040,04	1038,16	2909,89	1491,15	0	0,176
Score *KAS*	496,70	798,15	205,53	740,25	0	0,621

TABLE 5: The questionnaire results for positive (*pF*) and negative (*nF*) feedback sessions. The items were assessed on a scale from 0 to 4, with 0 indicating the least, and 4 the most agreement to the concepts assessed. The EEG was analyzed in terms of mean relative alpha band power on the Fz electrode during the game 2(α *KA*) and game 3 α *KAS*), the mean alpha power in the 4 seconds before SSVEP stimulation (preSSVEP α) and during SSVEP stimulation (SSVEP α). The minimum observed and the maximum were 0.15 and 0.23, respectively. The behavior was analyzed as points scored in the game.

cantly higher than alpha power during SSVEP stimulation ($p \leq 0.0001$).

The contrast of the pre-SSVEP alpha between the different feedback sessions discussed before, showed that this effect resulted from the higher alpha power during the pre-SSVEP epochs of the *pF* condition. This suggests that positive feedback might work in more difficult conditions, leading to higher alpha. Consequently, the SSVEP stimulation interferes with this state of higher alpha and potentially greater relaxation. This interference could be due to several mechanisms. For example, it could be caused by purely dynamic characteristics of the stimuli. As we compute the relative alpha power, an increase of power in SSVEP-related frequency bands would automatically lead to a decrease of the alpha power. On the other hand, it could be a result of the task that is executed during the stimulus presence.

5.4 Discussion

It was hypothesized that the positive feedback would lead to higher levels of alpha power, lower tension, and more positive affect. No general alpha increase for positive feedback could be shown. Similarly, no effect of the alpha feedback was found in terms of user experience.

Furthermore, we hypothesized that SSVEP stimulation would have no side effect on the alpha power. This was true for the comparison of alpha level between the levels *KA* and *KAS*. However, a difference between the alpha power before SSVEP stimulation to the alpha power during stimulation was observed for the positive feedback condition. This difference was due to a higher alpha power before stimulation. In the negative feedback condition no such difference was found. Hence, we argue that at least for the *KAS* condition the positive alpha feedback led to higher alpha, which was then attenuated by the SSVEP stimulation.

To explore the applicability and value of neurofeedback in computer games the manipulation of the difficulty level of the application might be interesting. Further studies of the influence of SSVEP on alpha power could focus on the origin of the decrease of alpha power.

6 Discussion

We have developed a computer game that uses two BCI paradigms in addition to a conventional control via a keyboard. In pilot studies different BCI paradigms were explored to determine the viability within the game environment and to develop algorithms.

Despite the efforts to develop a BCI pipeline that could be used without prior training of the subject or the classifier, the results of our analyses and interviews with participants suggest that a subject-dependent classifier would overcome the shortcomings of the general classifiers applied. For example, the power in the SSVEP frequency band varied among subjects. Thus a subject-dependent classifier, applying a threshold based on a prior training session, could increase the control of the subjects over the avatar. Similarly every individual has his/her own range for the alpha power measured. In pilot experiments, a generic range determined by observing the lowest and highest alpha power values of the majority of the subjects was used. A more elegant approach could be adapting this range per subject. This can be accomplished via a training session run before the game or by dynamically adjusting the values during the game play.

The SSVEP detection method was developed so as to use signals from only one EEG channel (O2) but as shown in §3.1 SSVEP can be detected in all three occipital channels. Thus, information from these channels can be combined to make detection more robust. Also, instead of relying on peak detection solely in the stimulation frequency, the peaks at the second or later harmonics can be employed. In addition, the parameters like the bin size and the reference amplitude can also be tailored for optimized performance.

The original intention of the project was to build a multiplayer game. For this purpose, during the workshop, multiplayer versions of the game and the analysis pipeline were implemented. However, during the workshop, it was discovered that the proprietary software delivered with the EEG hardware could not send information from multiple systems as necessary for online multiplayer BCI. When this restriction is revoked, the multiplayer version can also be tested.

The results reported in this paper are based on 5 participants and especially the non-findings concerning the first hypothesis might be due to the low number of samples. Despite the missing overall effect of neurofeedback, a difference between alpha power in the positive and negative feedback condition was found in the pre-SSVEP epochs of the *KAS* games. This effect might indicate that the failure to find significant differences in alpha power and user experience might be due to a floor effect caused by the high degree of relaxation in both feedback conditions. To avoid this effect in future studies, it is suggested to increase the difficulty level and thereby decrease the overall state of relaxation during the game.

Furthermore, negative feedback was employed to examine the effect that feedback has on the player. While this method is in principle valid to determine the existence of an effect, it does not enable the differentiation of the effects of positive and negative feedback. To delineate these, an additional no-feedback condition could be employed.

A possible problem of the interpretation of the results could also result from the game instructions given before the experiment. The participants were informed that relaxation would increase controllability. This might have caused confusion or other negative effects when the opposite effect was realized in the negative feedback condition. Differences between feedback conditions could thus be due to this clashing expectations rather than due to the effect of feedback directly.

Finally, the application of small user experience questionnaires after each game would enable the delineation of the effect of the different BCI controls on user experience. However, the difficulty lies with the avoidance of confounds due to entirely different game mechanics, which could also be implemented by other techniques.

7 Conclusion

With the new branch of the BCI research which now considers non-disabled people also as the potential users, BCIs started to be incorporated into everyday applications, like computer games. BCI is an invaluable communication channel that can directly convey information no other modality can: the state and intention of the user. This information can be used to control, modify or adapt a game tailored to the player, and could thereby provide added value. However, the extent that BCIs can tolerate the dynamic environment of games or the existence of other modalities is still under investigation.

In this paper we proposed a design space for physiological game design and described a multimodal, multiparadigm BCI game called Bacteria Hunt which is controlled by keyboard, SSVEP, and relative alpha power. We investigated how well different paradigms can be used together and what effect positive vs. negative neurofeedback creates. The experiments conducted on the initial prototype game developed revealed that in the tested setup no significant difference in mean alpha band power and in user experience between the games applying positive and negative feedback were found. Furthermore alpha power before SSVEP stimulation was significantly higher than alpha power during SSVEP stimulation. Therefore one needs to consider this when combining these two paradigms for control.

Bacteria Hunt is suitable for use as an experimental platform for BCI research. We have the intention to continue experimenting on this platform, especially within multimodality and interaction domains.

Acknowledgments

The authors would like to thank Boris Reuderink for his help with the BCI pipeline.

This research has been supported by the GATE project, funded by the Netherlands Organization for Scientific Research (NWO) and the Netherlands ICT Research and Innovation Authority (ICT Regie), by the BrainGain Smart Mix Programme of the Netherlands Ministry of Economic Affairs and the Netherlands Ministry of Education, Culture and Science, and by the European Community's Seventh Framework Programme (FP7/2007-2013) under grant agreement no. 231287 (SSPNet).

References

[1] E. Aarseth. Playing research: Methodological approaches to game analysis. In *Proceedings of DAC*, Melbourne, Australia, 2003.

[2] A. Brouwer and J. Van Erp. A tactile P300 BCI and the optimal number of tactors: Effects of target probability and discriminability. In *Proceedings of the 4th International Brain-Computer Interface Workshop and Training Course 2008*, pages 280–285, Graz, Austria, 2008.

[3] J. Cantero, M. Atienza, C. Gómez, and R. Salas. Spectral structure and brain mapping of human alpha activities in different arousal states. *Neuropsychobiology*, 39(2):110–116, 1999.

[4] G. Chatrian, L. Bergamini, M. Dondey, D. Klass, M. Lennox-Buchthal, and I. Petersen. A glossary of terms most commonly used by clinical electroencephalographers. *Electroencephalography and Clinical Neurophysiology*, 37:538–548, 1974.

[5] B. A. Cohen and A. Sances, Jr. Stationarity of the human electroencephalogram. *Medical and Biological Engineering and Computing*, 15(5):513–518, 1977.

[6] M. Comercho and J. Polich. P3a and p3b from typical auditory and visual stimuli. *Clinical Neurophysiology*, 110(1):24–30, January 1999.

[7] M. Doppelmayr, W. Klimesch, W. Stadler, D. Pöllhuber, and C. Heine. EEG alpha power and intelligence. *Intelligence*, 30(3):289–302, 2002.

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

[9] C. Herrmann. Human EEG responses to 1–100 Hz flicker: resonance phenomena in visual cortex and their potential correlation to cognitive phenomena. *Experimental Brain Research*, 137(3):346–353, 2001.

[10] I. S. Hjelm and C. Browall. Brainball - using brain activity for cool competition. In *Proceedings of the first nordic conference on HCI*, Stockholm, Sweden, October 2000.

[11] W. IJsselsteijn, Y. de Kort, K. Poels, A. Jurgelionis, and F. Bellotti. Characterising and measuring user experiences in digital games. In *International Conference on Advances in Computer Entertainment Technology*, Salzburg, Austria, 2007.

[12] B. Jansen, A. Allam, P. Kota, K. Lachance, A. Osho, and K. Sundaresan. An exploratory study of factors affecting single trial P300 detection. *IEEE Transactions on Biomedical Engineering*, 51:975–978, 2004.

[13] H. H. Jasper. The ten-twenty electrode system of the international federation. *Electroencephalography and clinical neurophysiology*, 10:371–375, 1958.

[14] C. Klimmt, T. Hartmann, and A. Frey. Effectance and control as determinants of video game enjoyment. *CyberPsychology & Behavior*, 10(6):845–848, 2007.

[15] D. J. McFarland, L. M. McCane, S. V. David, and J. R. Wolpaw. Spatial filter selection for EEG-based communication. *Electroencephalography and Clinical Neurophysiology*, 103(3):386–394, 1997.

[16] K. Müller and B. Blankertz. Toward noninvasive brain-computer interfaces. *IEEE Signal Processing Magazine*, 23(5):125–128, 2006.

[17] K. Müller, M. Krauledat, G. Dornhege, G. Curio, and B. Blankertz. Machine learning techniques for brain-computer interfaces. *Biomedical Engineering*, 49(1):11–22, 2004.

[18] G. Müller-Putz, R. Scherer, C. Brauneis, and G. Pfurtscheller. Steady-state visual evoked potential (SSVEP)-based communication: impact of harmonic

frequency components. *Journal of neural engineering*, 2(4):123–130, 2005.

[19] A. Nijholt, B. Reuderink, and D. Plass-Oude Bos. Turning shortcomings into challenges: Brain-computer interfaces for games. In *Intelligent Technologies for Interactive Entertainment*, pages 153–168, May 2009.

[20] A. Nijholt, D. Tan, G. Pfurtscheller, C. Brunner, J. D. R. Millán, B. Allison, B. Graimann, F. Popescu, B. Blankertz, and K.-R. Müller. Brain-computer interfacing for intelligent systems. *IEEE Intelligent Systems*, pages 76–83, 2008.

[21] D. Regan. *Human brain electrophysiology: Evoked potentials and evoked magnetic fields in science and medicine*. Appleton & Lange, 1989.

[22] B. Reuderink. Games and brain-computer interfaces: The state of the art. Technical report, HMI, University of Twente, 2008.

[23] B. Reuderink. golemml: Python machine learning library for EEG processing, October 2009. http://code.google.com/p/golemml.

[24] B. Reuderink. psychicml: Python signal processing library for EEG processing, October 2009. http://code.google.com/p/psychicml.

[25] R. Scherer, A. Schloegl, F. Lee, H. Bischof, J. Janša, and G. Pfurtscheller. The self-paced graz brain-computer interface: Methods and applications. *Computational Intelligence and Neuroscience*, 2007.

[26] M. Schürmann and E. Başar. Functional aspects of alpha oscillations in the EEG. *International Journal of Psychophysiology*, 39(2-3):151–158, 2001.

[27] P. D. Tyson. Task-related stress and EEG alpha biofeedback. *Applied Psychophysiology and Biofeedback*, 12(2):105–119, 1987.

[28] B. L. A. van de Laar, D. Oude Bos, B. Reuderink, and D. K. J. Heylen. Actual and imagined movement in BCI gaming. In *Proceedings of the International Conference on Artificial Intellingence and Simulation of Behaviour (AISB 2009)*, Aberdeen, Scotland, 2009.

Hayrettin Gürkök received his B.S. and M.S. degrees in Computer Engineering from Bilkent University, Turkey. His M.S. thesis was on linguistics and text retrieval. He is currently a member of the Human Media Interaction group at the University of Twente. He is conducting research on multimodality and realistic settings for BCIs. His research interests also include human-computer interaction, social computing and information retrieval.

Danny Plass-Oude Bos got her first experience with online BCI during an internship at the University of Nijmegen in 2007. There she implemented physiological artifact detection in an online EEG-based BCI system. In 2008 she obtained her master degree in Human Computer Interaction, looking into the user experience of using BCI for games. At the moment she is working as a PhD student at the University of Twente, still attempting to merge BCI with HCI by researching how BCI can be made a more intuitive means of interaction.

Marieke E. Thurlings started as a PhD candidate at TNO (The Netherlands Organization for Applied Scientific Research) and at the Utrecht University, in 2008. She currently investigates navigating in Virtual Environments using brain signals as an input, involving the fields of Brain-Computer Interfacing, Games and Virtual Worlds. Marieke is especially interested in using event-related potentials, such as P300s and SSEPs, and exploring covert attention to probe stimuli to evoke these, e.g. by presenting them in unconventional modalities. Marieke obtained her Master of Science degree in Design for Interaction from the Delft University of Technology.

Christian Mühl earned his Master's degree in the Cognitive Sciences in 2007 at the University of Osnabrück, Germany. His education was focused on neuroscientific methods, specifically electroencephalography. Since then he is working as a research assistant in the Human Media Interaction Group at the University of Twente, The Netherlands. In his PhD thesis he searches for neurophysiological and physiological correlates of affective states in the context of brain-computer interaction.

Lasse Scherffig is a PhD student at the Lab3, Laboratory for Experimental Computer Science of the Academy of Media Arts Cologne (Germany). Since July 2006 he also is a member of the artistic/scientific staff of the academy. He graduated in cognitive science at the university of Osnabrck (Germany) and received a M.Sc. in digital media from the University of Bremen (Germany). His dissertation project focuses on the relation of action and perception in Human-Computer Interaction.

Matthieu Duvinage graduated as an electrical engineer in signal processing and telecommunications from the Facult Polytechnique de Mons (Belgium) and SUPELEC (France) in june 2009. He also got a master of fundamental and applied physics from the University of Orsay (France) in june 2009. He has just started a PhD at the Signal Processing and Circuit Theory Lab at the University of Mons (Belgium) on the development of a neuroprothesis to control an artificial leg via BCI.

Alexandra A. Elbakyan graduated from KazNTU with a Bachelor degree in IT in June 2009. She conducted a study regarding person identification by EEG in her final year thesis. She is going to continue her research in brain-computer interfaces and brain implants.

SungWook Kang received the B.S. degree in electronic communication engineering from the Kwangwoon University, Seoul, Korea, in 2009. He is currently working towards the M.S. and Ph.D degree at Biocomputing Lab., Dept. Information and Communication, Gwangju Institute Of Science and Technology. His research interests include bio-signal processing especially EEG and MEG, feature extraction, information theory and brain-computer interface.

Mannes Poel is assistant professor in the Human Media Interaction group at the University of Twente. His main research involves applied machine learning for vision based detection and interpretation of human behavior and the analysis and classification EEG based brain signals.

Dirk Heylen is associate professor in the Human Media Interaction group at the University of Twente where his research involves the automatic interpretation of verbal and nonverbal communication and the of modeling conversational and cognitive functions of embodied conversational agents. His work on the analysis and synthesis of nonverbal communication in (multiparty) conversations has been concerned with gaze, and head movements in particular. His research interests extend to the study of physiological signals that can be used to interpret the mental state of user.