Chapter 10
Brain-Computer Interfacing and Games

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Abstract Recently research into Brain-Computer Interfacing (BCI) applications for healthy users, such as games, has been initiated. But why would a healthy person use a still-unproven technology such as BCI for game interaction? BCI provides a combination of information and features that no other input modality can offer. But for general acceptance of this technology, usability and user experience will need to be taken into account when designing such systems. Therefore, this chapter gives an overview of the state of the art of BCI in games and discusses the consequences of applying knowledge from Human-Computer Interaction (HCI) to the design of BCI for games. The integration of HCI with BCI is illustrated by research examples and showcases, intended to take this promising technology out of the lab. Future

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research needs to move beyond feasibility tests, to prove that BCI is also applicable in realistic, real-world settings.

10.1 Introduction

Brain-computer interfacing (BCI) research has been motivated for years by the wish to provide paralyzed people with new communication and motor abilities, so that they can once again interact with the outside world. During the last couple of years, BCI research has been moving into applications for healthy people. Reasons for this range from providing applications to increase quality of life to the commercial benefits of such a large target group (Nijholt et al. 2008a). The area of games, especially, receives a lot of interest, as gamers are often among the first to adopt any new technology (Nijholt and Tan 2007). They are willing to put the effort into learning to work with it, if it may eventually provide some advantage. Besides, a large part of the general population plays games, little though it may be. As these abled users have many other interaction modalities at their command, they have a lot more requirements for such an interface than the people for which this is the only option to interact with the external world. Brain-computer interaction is slower and less accurate than most modalities that are currently available. Furthermore, BCIs often require a lot of training. Why would a healthy person want to use BCI in games?

Current BCI games are often just proofs of concept, where a single BCI paradigm is the only possible means of control, such as moving a paddle in the game Pong to the left or right with imaginary movement of the hands (Krepki et al. 2007). These BCIs are weak replacements for traditional input devices such as the mouse and keyboard: they cannot achieve the same speed and precision. The information transfer rate (ITR) of BCIs is still around up to 25 bits per minute (Wolpaw et al. 2002), which is incomparable with keyboard speeds of over 300 characters per minute.[1] Due to these limitations, there is still a big gap between these research games and games developed by the games industry at this time.

Current (commercial) games provide a wide range of interactions: with your avatar in the virtual world, with other gamers and non-player characters, as well as with objects in the game environment. This is also reflected in the game controllers for popular consoles. For example, the PlayStation® DualShock™ 3 controller has fourteen buttons, two analog thumb-controlled mini-joysticks plus motion-sensing functionality. The Nintendo® Wiimote™ has ten buttons, can sense acceleration along three axes and contains an optical sensor for pointing. Apparently this still provides too few interaction possibilities, as this controller is often combined with a nunchuck, which has an analog stick, two additional buttons, and another accelerometer.

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[1]Due to different ITR measures used in BCI, a comparison between keyboard and BCI is hard to make. The entropy of written English text is estimated to be as low as 1.3 bit per symbol (Cover and Thomas, 2006, page 174). A rate of 300 characters per minute would therefore correspond to roughly 400 bits per minute.

Although a large number of inputs is needed for interaction with games nowadays, this also poses a problem. The more input options you have, the more of an effort it is to learn and remember what each input is for. Even the options that are currently provided may not be sufficient for what developers envision for rich interaction in future games. To make it easier for the gamer, companies and research groups are very interested in more natural methods of interaction. If the gamer can interact with the game world in a way similar to the real world, then learnability and memorability may no longer be an issue. The popularity of motion sensors in current game controllers reflects this, as they enable gamers to make gestures that should come naturally with whatever it is that they would like to do in the game. Microsoft®'s Project Natal is a prime example of this movement towards natural interaction, using gestures, speech, and even real-world objects (Microsoft® 2009).

We can take this trend towards natural interaction one step further. Like our thoughts, computer games do not take place in the real world, and are not constrained to what is physically possible. Therefore, it would make sense to express ourselves directly in the game world, without mediation of physically limited bodily actions. The BCI can bypass this bodily mediation—a fact well appreciated by those Amyotrophic Lateral Sclerosis (ALS) patients who now have the ability to communicate with others and their environment despite their full paralysis—enabling the gamers to express themselves more directly, and more naturally given a game context.

As an example, consider the following. Even though we know there is no such thing as magic, in a game world we have no problem with the idea and possibility of casting spells. Although our minds readily accept these new abilities because we are confined to interacting via the real world, we have to press buttons to make things happen in the super-realistic world of the game. If, however, the game were to have access to our brain activity, then perhaps it would be possible to interact with the game world in ways that would be realistic considering the rules of that particular environment. Being able to merge in such a way with the super-realism of the game world should increase presence (Witmer and Singer 1998), but also memorability as the relations between user action and in-game action become more direct. However, using a BCI to bypass physical interaction may seem unnatural, as we are used to converting our thoughts into bodily actions. The implication is that when using brain activity directly, one needs to be more aware of this activity and to develop new levels of control.

Developing control over brain signals is as necessary when signals are used passively to enhance the game experience, for example, by guiding the player towards a state of flow (Csikszentmihalyi 1990). From brain activity the user's mental state can be derived, which makes it possible for applications to respond to this state. When the mental state is known, it can be manipulated via the game to keep the user in equilibrium, where skill and challenge are well matched (see Fig. 10.1). Alternatively, the game could incorporate the user's mood into the story, for example by the appropriate adaptation of interactions with non-player characters (NPCs).

Summarized, to make BCI an acceptable interaction modality for healthy users, it should enhance the user experience by offering something that current interaction modalities do not. Brain activity can provide information that no other input

Fig. 10.1 Flow diagram, based on Csikszentmihalyi (1990)
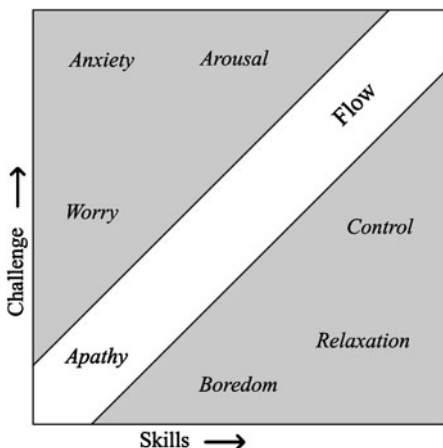
modality can, in a way that comes with its own unique features. Like speech it is hands-free, but as no external expression is required, the interaction is private. And similar to the way in which exertion interfaces that require physical effort will make you more fit, the use of specific BCI paradigms could make you more relaxed and focused. This, in turn, could result in higher intelligence, and better coping with stress (Doppelmayr et al. 2002; Tyson 1987). The following sections will discuss what can be learned from current BCI research prototypes and commercial applications and how BCI can be applied in such a way that it does not violate the usability of the system but actually improves the interaction. Cases and ideas from our own research at the Human Media Interaction (HMI) group at the University of Twente will be provided as concrete examples.

10.2 The State of the Art

The first BCI game was created by Vidal (1977). In this game, the user can move in four directions in a maze, by fixating on one of four fixation points displayed off-screen. A diamond-shaped checkerboard is periodically flashed between the four points, resulting in 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. Despite being the first game, its performance is remarkable with an information transfer rate (ITR) of above 170 bits/min on average. Using online artifact rejection and adaptive classification, the approach used by Vidal was far ahead of its time. Much lower ITRs of 10–25 bits per minute are often reported as the state of the art in reviews (Wolpaw et al. 2002). One reason to not include Vidal in these overviews could be that the operation of this BCI depends the ability to make eye movements.

A much simpler approach to integrate brain signals in games is based on the interpretation of broadband frequency power of the brain, such as the alpha,

beta, gamma and mu-rhythm. A classic example is Brainball (Hjelm et al. 2000; Hjelm 2003), a game that can be best described as an anti-game. Using a headband, the EEGs of the two players is measured and a relaxation score is derived from the ratio between the alpha and beta activity in the EEG signal. The relaxation score is used to move a steel ball across the table away from the most relaxed player; when the ball is almost at the opponent's side, and players realize they are winning, then get excited and lose. Another example we would like to mention is the experiment of Pope and Palsson (2001), in which children with attention deficit hyperactive disorder (ADHD) were treated using neurofeedback. One group used standard neurofeedback, another group played Sony Playstation™ video games where the controller input was modulated by a neurofeedback system developed by NASA; correct brain-wave patterns were rewarded with a more responsive controller. Other neurofeedback games are listed in the overview in Table 10.1. Characteristic of these neurofeedback games is that the player has to discover how to control aspects of brain activity to play the game. Mastering control over brain signals is often the goal of the game, as opposed to using a BCI as an input device similar to a gamepad or a joystick. While conceptually simple, neurofeedback games do aim at providing a user experience that cannot be provided using other modalities.

In contrast to neurofeedback games, motor-control based BCIs are often used as (traditional) input devices. For example, Pineda et al. (2003) used the mu-rhythm power on the motor cortices to steer a first person shooter game, while forward/backward movement was controlled using physical buttons. No machine learning was involved; the four subjects were trained for 10 hours over the course of five weeks, and learned to control their mu-power. Another movement controlled BCI game is the Pacman game by Krepki et al. (2007). The detection of movement is based on the lateralized readiness potential (LRP), a slow negative shift in the electroencephalogram (EEG) that develops over the activated motor cortex starting some time before the actual movement onset. In this game, Pacman makes one step each 1.5–2 seconds, and moves straight until it reaches a wall or receives a turn command. Users report they sometimes had the feeling that Pacman moves in the correct direction before the user was consciously aware of this decision. This indicates a new level of interaction that can be enabled only by a BCI.

Both the neurofeedback and the motor controlled games use BCIs based on induced activations, meaning that the user can initiate actions without depending on stimuli from the game. Evoked responses, on the other hand, where the application measures the response to a stimulus, require a tight coupling between the game that presents the stimuli and the BCI.

An example of a evoked response is the P300, an event related potential (ERP) that occurs after a rare, task-relevant stimulus is presented. Bayliss used a P300 BCI in both a virtual driving task and a virtual apartment (Bayliss 2003; Bayliss et al. 2004). In the virtual apartment, objects were highlighted using a red translucent sphere, evoking a P300 when the object the user wanted to select was highlighted. A more low-level evoked paradigm is based on steady-state visually evoked potentials (SSVEPs), where attention to a visual stimulus with a certain frequency is measured as a modulation of the same frequency in the visual cortex. In

Table 10.1 Overview of BCI games. Work is sorted by paradigm: F represents feedback games, in which the user has to adapt the power of the different rhythms of his brain, M stands for recognition of motor tasks, including motor planning, imaginary and real movement, P300 is the P300 response to task relevant stimuli and VEPs are visually evoked potentials. In the sensors column, E indicates EEG sensors, O indicates the use of EOG measurements, and M indicates EMG measurements. The number of (EEG) sensors is indicated in column NS, the number of classes for control is listed in the NC column. The last column contains the accuracy of recognition. Due to differences in the number of classes and trial lengths, these accuracies cannot be used to compare individual studies

Work	Type	Paradigm	Sensors	NS	NC	A
Lee et al. (2006)	Game	?	invasive			
Wang et al. (2007)	Game	?	E			
Sobell and Trivich (1989)	Visualization	F	E			
Nelson et al. (1997)	Game	F	E, M			
Allanson and Mariani (1999)	Game	F	E			
Cho et al. (2002)	Virtual reality	F	E	3	2	
Tschuor (2002)	Visualization	F	E	32	2	85%
Hjelm (2003), Hjelm et al. (2000)	Game	F	E			
Palke (2004)	Game	F	E	1		
Mingyu et al. (2005)	Game	F	E	3	1D	
Kaul (2006)	Visualization	F	E, M, O	3		
Lin and John (2006)	Game	F	E	1		
Shim et al. (2007)	Game	F	E	4	2	
Lotte et al. (2008)	Game	F/M	E	1	2	
Vidal (1977)	Game	VEP	E	5	5	80%
Middendorf et al. (2000)	Game	VEP	E	2	3	88%
Bayliss and Ballard (2000)	Virtual reality	P300	E		2	85%
Bayliss (2003)	Virtual reality	P300	E	5	2	
Bayliss et al. (2004)	Virtual reality	P300	E	7	2	85%
Lalor et al. (2004, 2005)	Game	VEP	E	2	2	80%
Martinez et al. (2007)	Game	VEP	E	6	5	96%
Finke et al. (2009)	Game	P300	E	10	2	66%
Jackson et al. (2009)	Game	VEP	E	2	4	50%
Pineda et al. (2003)	Game	M	E	3	1D	
Leeb et al. (2004)	Virtual reality	M	E	4	2	98%
Leeb and Pfurtscheller (2004)	Virtual reality	M	E		2	
Mason et al. (2004)	Game	M	E	12	2	97%
Leeb et al. (2005)	Virtual reality	M	E	6	2	92%
Kayagil et al. (2007)	Game	M	E	1	4	77%
Krepki et al. (2007)	Game	M	E	128	2	100%
Scherer et al. (2007)	Game	M	E, M, O	3	2 + 2	
Bussink (2008)	Game	M	E	32	4	45%
Lehtonen et al. (2008)	Game	M	E	6	2	74%
Oude Bos and Reuderink (2008)	Game	M	E	32	3	
Zhao et al. (2009)	Game	M	E	5	4	75%
Tangermann et al. (2009)	Game	M	E	64	2	

the MindBalance game by Lalor et al. (2004, 2005), a SSVEP is evoked by two different checkerboards, inverting at 17 Hz and 20 Hz. The attention focused on one of the checkerboards is used to balance an avatar on a cord in a complex 3D environment. One advantage of the evoked responses over induced BCI paradigms is that it allows easy selection of one out of multiple options by focussing attention on a stimulus. For example, a 2D racing game with four different directional controls using SSVEP was created by Martinez et al. (2007), and in a similar fashion a shooter was controlled in Jackson et al. (2009).

We have seen a series of games based on neurofeedback, games based on the imagination of movement, and games based on evoked potentials. Of these BCI paradigms, the neurofeedback games exploit the unique information a BCI can provide best. For example, Brainball uses relaxation both as game goal, and as means of interaction. Using traditional input modalities this game simply could not exist. In contrast, BCI games that are based on evoked potentials replace physical buttons with virtual, attention activated triggers which do not change the game mechanics significantly. These games could be improved by using evoked potentials to measure the state of the user, and use the state as new information source as opposed to as a button. By assigning a meaning to the mental action of concentrating on a game element, for example devouring a bacteria in Bacteria Hunt (Mühl et al. 2010), the user state itself becomes part of the game mechanics. The same holds for games using imagined movement. These games replace movement to interact with buttons with (slow) imagined movement, without adding much other than novelty.

While interesting, most of the BCI games are proofs of concept. The speed of these games is often decreased to allow for BCI control, reducing fast-paced games into turn-based games. In recent publications we see a trend towards more fine-grained control in games using BCI interfaces, Zhao et al. (2009) and Jackson et al. (2009) focus on smooth, application specific interpretation of BCI control signals. The role of precise timing is also gaining attention, as shown in a pinball experiment of Tangermann et al. (2009). We now need to continue this trend to move beyond feasibility tests, and focus on the role that BCI can play in improving the gaming experience.

10.3 Human-Computer Interaction for BCI

While BCI has until recently been an exploratory field of research, it might be profitable to take some insights from Human Computer Interaction (HCI) into account. Of course, fundamental research on hardware, signal processing, machine learning and neurophysiology are a prerequisite for a BCI. However, advances in the usability area are a direction of research that might be just as important for the acceptance and widespread usage of BCIs. In this section we will look at learnability, memorability, efficiency and effectiveness, error handling, and satisfaction, which are the main concepts of usability according to Nielsen (1993). We will look at the most relevant guidelines in these concepts and elaborate on them in the context of BCI games.

10.3.1 Learnability and Memorability

In HCI, one of the most important aspects of a software program or interface is how intuitive it is in its usage. Learnability is defined by ISO 9126 as the effort that is required to learn the application (International Organization for Standardization 1991). Is a user able to use it straight out of the box, or is training needed to use the interface? Memorability is closely related to learnability and deals with remembering an interface (Nielsen 1996). Obviously, when an interface is intuitive and easier to learn, the user will also remember the interface better.

Concerning BCIs, one needs to separate different forms of training that are often needed for use of the BCI, namely training the user to use the right mental task to control the game (interface training), training the user to reliably perform the mental tasks (user training), and training a BCI system to recognize user specific brain signals (system training).

User training is an important factor for getting users to start working with a BCI. As performing a mental task to communicate with a computer is new for most people and as the mental tasks are also new for everybody, it has to be made clear to the users what is expected of them if they want to use a BCI. One illustrative example of this is when using a Motor-Imagery-based BCI. A user is told to imagine movements of his hands for example. But to a lot of naive users it is unclear what is actually meant by imagining. Should they visualize the movement? Should they feel their hand moving? Or should they see someone else's hand moving? Most of the time the sensation of moving ones hand is preferred, as this elicits the event-related desynchronization (ERD) often used as a feature for detecting this mental task (McFarland et al. 2000).

It is certain that for research and comparison of BCIs, all users need to perform the mental task in the same way, id est, they need to be thoroughly and consistently instructed. For more practical applications, this may as well be important. Users might not overcome the first step of performing the mental task in the right way and lose motivation because the BCI is not working properly. It is known from literature that some users are unable to use certain paradigms—this is called BCI illiteracy (Guger et al. 2003), see also Chapter 3 of this Volume. One reason for this problem might be the way in which the relevant part of the cortex is folded in relation to the scalp (Nijholt et al. 2008b). However, user training can be used to overcome some types of BCI illiteracy, namely, those related to incorrect execution of the task by the user. Training to perform the wanted brain activity consistently, for example using feedback, can help to improve performance (Hwang et al. 2009). Of course user training can be a tedious process, especially because performance can sometimes decrease instead of increase (Galán et al. 2007). Moreover, it is important to keep the user motivated through the process. To keep the user motivation high and the task clear, an intuitive mapping from mental task to in-game action is vital. One example of such an intuitive mapping is explained on page 168. The intuitive mapping of the state of relaxation to the shape of the player's avatar is helping the users use this modality to their advantage. This type of BCI is of a more passive

one. Very little or no training at all is needed to use the system. This is often the case with passive BCI's as opposed to active BCI's (see also Chapter 11 of this Volume).

One promising way to combine different techniques is the so-called online "on-the-job" training (Vidaurre et al. 2006). Users get clear instructions how to perform a certain task while at the same time the BCI system gathers data to train its classifier. For games, this online training might consist of some tutorial in which the game itself is explained, or in which the users play some kind of minigame.

10.3.2 Efficiency and Effectiveness

As seen in Sections 10.1 and 10.2, the speed and accuracy of active BCIs (the user intentionally makes an action) does not yet even approach that of traditional game controllers. The advantage of using a BCI for direct control should then be in something other than efficiency (doing things with the least amount of effort). In this case the BCI should not be a replacement for using the keyboard and/or mouse. So if the efficiency cannot be high enough because of technical limitations, the effectiveness (doing the right things) could be higher. In other words: a BCI application should give the user the feeling that the BCI has an added value. In the design of a game, one could think of certain bonuses when using a BCI, or relieving the user of some extra buttons to push by performing this task through the BCI.

However, the low transfer and high error rates are not so much a problem for passive BCIs that try to estimate the user state (Zander et al. 2009). This information is acquired without the active participation of the user and can be used to derive meta-information about the context in which the HCI takes place. Applications can adapt the way they present information or react to user input depending on the users' psychological state in terms of attention, workload, or emotion. A specific example of such a user state sensed by passive BCIs is reaction on machine or user errors, as we will see in the next section.

10.3.3 Error Handling

As with the majority of modalities in HCI that try to extract information from the human body, BCI is one of the modalities that has a fairly high level of error rates. As can be seen in Section 10.2, error rates are typically around 25% and more. When we also consider users that can make errors, error handling becomes an important factor in designing games which use BCI.

Error handling consists of two parts: error prevention and error correction. Error prevention consists of taking measures to prevent an error of ever happening. Within the context of BCI this can be done by applying better classification algorithms, smoothing, hysteresis and artifact filtering (see page 169).

For this section error, correction is of particular interest. With the use of error related negativity (ERN) it is possible to detect that a user is conscious of his error and undo the previous movement (Ferrez and Millán 2008). One way to implement this in the design of a game is to use it as a "rewind" function which breaks the strict timeline often incorporated into games. This calls for creative game design but can also lead to more immersive games. The user can interact with the game in a completely different way. This kind of interaction might even be applied without the user being aware of it: at some point the user will be conscious of his fault and the BCI will have recognized it already. In other applications it can be used as a more classical method of error correction and/or improve the system's perceived accuracy.

10.3.4 Satisfaction

Satisfaction is often said to be heavily influenced by acceptance and success of the system (Rushinek and Rushinek 1986; Goodwin 1987) which can be attributed to the system's effectiveness and efficiency. Of course, there are also social aspects and the personal preferences of the user involved (Lucas 1975; Ives et al. 1983; Hiltz and Johnson 1990).

In the context of BCI games we can consider satisfaction to be the end result of all of the design choices that were made, the functionality of the game, the ease with which the user could learn and memorize the control of the BCI and with what accuracy they could control the game. In other words, satisfaction can be seen as everything the user experienced during the game.

The user satisfaction after playing a game can be measured, for example, by using a post-game questionnaire (IJsselsteijn et al. 2008) for quantitative, or by interviewing the user for a more qualitative, analysis. Both can lead to interesting findings on the BCI game. For an example of a quantitative analysis, in van de Laar et al. (2009) it was found that users liked the challenge of imagining movements, but were also quickly mentally tired by performing this task.

Besides using the quite reliable method of administering questionnaires to measure the user experience, an interesting possibility to measure certain parts of the user experience is to let the BCI itself measure whether the user is satisfied or not. In Garcia Molina et al. (2009) it is shown that certain moods can be recognized. Especially if the system then adapts itself, depending on what the user feels, such a kind of feedback loops can be helpful in creating a satisfying user experience. This system might be able to make certain choices in HCI design or in the machine learning and classifying techniques it uses, specific for every user. This might open up completely new ways of playing and interacting with games. In turn, this would lead to user-specific games with fine-tuned parameters for different aspects of the game. With such a great feature implemented, BCI games will have an advantage over traditional games which will boost acceptance and popularity.

10.4 BCI for Controlling and Adapting Games

So far in this chapter we have discussed BCI games generally in the context of HCI research. In this section we would like to narrow the focus down to the research conducted and applications developed within our research team at the Human Media Interaction research group of the University of Twente. We will touch on the critical issues of user experience, affective BCI games, BCI for controlling games, intuitiveness and multi-modality in BCI games.

10.4.1 User Experience

Today, BCI research is still investigating the extent of the performance this technique can achieve. A lot of research effort is spent on improving speed and accuracy, but in spite of the many BCI applications created for healthy people, the HCI aspect of them is still often overlooked. As already stated in the previous section, how the user feels about using a particular BCI paradigm, and about using it for a particular task, can have a great influence on the acceptance of this new technology.

BCIs for healthy users have to deal with a different environment, and therefore different challenges, different from BCIs for patients. Differences in the environment can be split into the effect the environment has on external user behaviour during gameplay (moving, shouting, sweating), and more internal effects (changes in the user state due to the game, such as, frustration, boredom or anger).

In our research group, a simple platform has been developed to test and demonstrate BCI in a game environment. BrainBasher, as this setup is called, was initially used to compare the user experience for keyboard interaction with imaginary-movement control (Oude Bos and Reuderink 2008). More recently, it was used to compare imaginary and actual movement as paradigms to control the game (van de Laar et al. 2009). See the case description below:

10.4.1.1 Application: BrainBasher

In 2008, we conducted research to find out what the differences were in user experience and in performance, between real and imagined movement in a BCI game. This was one of the first BCI studies in which not only the speed and accuracy of the paradigms used was considered, but also the user's affect through the use of a post-game questionnaire. The BCI game used for this research was BrainBasher (Oude Bos and Reuderink 2008). The goal of this game is to perform specific brain actions as quickly as possible. For each correct and detected action you score a point.

The goal is to score as many points as possible within the limited amount of time. For the actual-movement task users must lay both hands on the desk in front of them. When the appropriate stimulus appears they have to perform a simple tapping movement with their whole hand. When performing the imagined movement task, users are instructed to imagine (feeling) the same movement, without actually using any of their muscles.
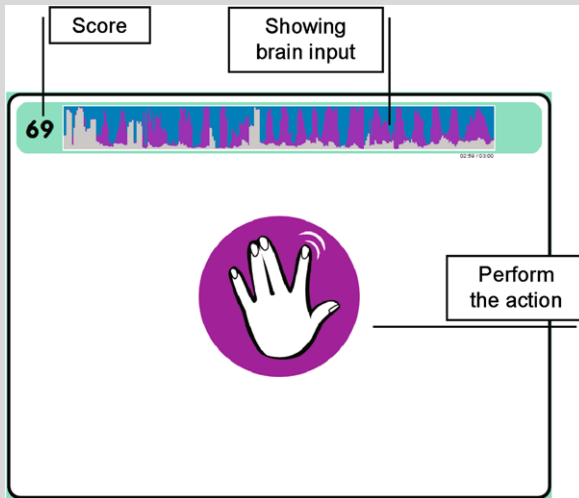
A screen capture of a BrainBasher game session, showing the score, the current target task, and feedback on previous and current brain activity.

Twenty healthy persons participated as test subjects in this study. The average age across the group was 26.8 years, 50% was male and 50% was female.

Our experiment consisted of two conditions: actual movement and imagined movement. The order of performing actual and imagined movement was randomly assigned for each subject respecting equal groups for each order. Each part consisted of one training session, in order to create a user-specific classifier, followed by one game session, after which the subject filled in a user experience questionnaire. This questionnaire was designed based on the Game Experience Questionnaire (GEQ) developed at the Game Experience Lab in Eindhoven (IJsselsteijn et al. 2008).

Results show that differences in user experience and in performance between actual and imagined movement in BCI gaming do exist. Actual movement produces a more reliable signal while the user stays more alert. On the other hand, imagined movement is more challenging.

10.4.2 Passive BCI and Affect-Based Game Adaptation

Despite the increasing numbers of controller buttons and various ways to provide input to the computer, HCI in its common form is a highly asymmetrical exchange of information between user and machine (Hettinger et al. 2003). While the computer is able to convey a multitude of information, users are rather limited in their possibilities to provide input. Specifically, the flexible incorporation of information on contextual factors, such as the users' affective or cognitive states, into the interaction remains difficult. Such flexibility might be seen as one of the hallmarks of a natural

interaction between humans, and would add great value when available in HCI, in particular to improve the user experience. For example, when humans are playing together, one can realize that the other is bored or frustrated and subsequently adapt their behaviour accordingly to motivate the other player again.

There are multiple ways to optimize user experience in games. Saari et al. (2009) introduce the term "psychological customization" and suggest the manipulation of the story line or the presentation of games to realize a user-specific affective adaptation. Knowledge about the user profile, task and context can be used to regulate the flow of emotions as narrative experiences, to avoid or limit negative emotions harmful to user experience (or health), to respond to observed emotional states (e.g., to maintain challenge), or to deliberately create new combinations of emotional, psychological states and behaviour. For the online adaptation to the user during the game, however, a reliable and robust estimation of the affective user state is imperative. Unfortunately, despite their increasing computational capacities and sensory equipment (camera and microphone), modern computers are limited in their capability to identify and to respond appropriately to the user state.

Some applications try to take user states into account using indirect measures, mostly behavioural indicators of efficiency. Examples are speed boosts for players that are fallen behind in racing games ("rubber banding"), to keep them engaged, or the adaptation of number and strength of opponents in first person shooter games according to the performance of the player. These techniques make assumptions about the relation between in-game performance and user states. And while these assumptions might hold most of the time and for most of the users, they are only rough estimations and can lead to misinterpretations of user states. Such behavioural estimates could be complemented by more direct methods of user state estimation.

10.4.2.1 User State Estimation

The automatic recognition of affective user states is one of the main goals of the field of affective computing (Picard 1997), and great efforts have led to promising results for user state estimation via behavioural and physiological signals. The principal possibility of deriving information about affective user states was shown for visible and audible behaviour (Zeng et al. 2007). Alternatively, and especially in the absence of overt behaviour, one can observe physiological responses of the user, for example heart rate, respiration, or perspiration to derive the user's affective state (Picard et al. 2001; Benovoy et al. 2008; Kim and André 2008). Interestingly, it was shown that game-related user states, such as boredom, flow, and frustration, can be differentiated via physiological sensors (van Reekum et al. 2004; Mandryk et al. 2006; Chanel et al. 2008; Nacke and Lindley 2008; Tijs et al. 2009). However, all of those measurements are indirect and thus potentially modulated by a number of factors. Behaviour, for example, can be scarce in HCI or biased due to the (social) context. Physiological signals are influenced by exercise, caffeine and other factors. Neuro-physiological sensor modalities on the other hand, while not being free of those influences, enable a more direct recording of affective experience.

Affective neuro-science has shown the capability of EEG to discriminate between affective states (Davidson 1992; Müller et al. 1999; Keil et al. 2001; Marosi et al. 2002; Aftanas et al. 2004). These neural correlates of affective processes are explained and predicted by cognitive appraisal theories (e.g. Sander et al. 2005). These associations between EEG and affective processes suggest the viability of neurophysiology-based affect classification. Accordingly, several studies showed that such a classification is in principle possible (Chanel et al. 2006, 2009; Lin et al. 2009). Chanel et al. (2006) even showed that EEG contributes additional information about the affective state to physiological sensor modalities, and that a fusion of both sensor modalities delivers the best classification performance.

It has to be noted that many of those (neuro-)physiological studies are still done in a very simple and controlled context. This has implications for the applicability of the techniques in a real-life context. As in other BCI fields, affective BCI also has to deal with artifacts and other noise sources in order to deliver robust and reliable measurements. Additionally, the complexity of affective and cognitive processes requires special care in design and analysis of such experiments inducing specific user states to ensure the validity of the induced states (van den Broek et al. 2009; Fairclough 2009). So, if measurements are to be collected in more realistic scenarios, the risk of possible confounds increases and endangers the reliability of the psychophysiological inferences intended.

Two fundamental issues associated with the reliability of affect classification are those of specificity and generality. That is, it is important to identify physiological markers or patterns that are specific to the target emotions (e.g., independent of the method of elicitation), but that general over different contexts (e.g., laboratory versus real world). Especially for neuro-physiological measures, the independence of measurements from a specific elicitation or the tasks participants are performing cannot be assumed. To test it, experiments could use carefully constructed multimodal stimuli (Mühl and Heylen 2009) to manipulate affective states via different stimulus modalities. On the other hand, a measurement of physiological correlates in the context of different tasks and environments might provide evidence for their context-independence. In this respect, computer games offer an interesting research tool to induce affective states, as they have the potential to immerse players into their world, leading to affective reactions.

10.4.2.2 Application: AlphaWoW

In Alpha-World of Warcraft (alphaWoW) affective signals couple the mood of the player to her avatar in an immersive game environment. Alpha activity recorded over the parietal lobe is used to control one aspect of the game character, while conventional controls are still used for the rest.

World of Warcraft® is a very popular massively-multiplayer online roleplaying game (Blizzard Entertainment®, Inc 2008). For our application, the user plays a druid who can shape-shift into animal forms. In bear form, with its thick skin, the druid is better protected from physical attacks, and is also quite the fighter with sharp claws and teeth.

In her normal elf form, she is much more fragile, but can cast effective spells for damage to knock out enemies from a distance as well as to heal herself. In alphaWoW, the shifting between these shapes is controlled by the user's alpha activity.

A user playing World of Warcraft using both conventional controls and brain activity to control her character in the game.

How changes in alpha activity are experienced by the user, depends on the location where the activity is measured. According to Cantero et al. (1999), high alpha activity measured over the parietal lobe is related to a relaxed alertness. This seems a beneficial state of mind for gaming, especially compared to drowsiness, which is said to be measured frontally. The premises for mapping alpha to shape-shifting in the game was that the opposite of this relaxed state would be some kind of sense of stress or agitation. 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 night elf.

An example of a game that is used to induce mental states is the Affective Pac-man game (Reuderink et al. 2009). This games induces frustration in users by manipulating the keyboard input and the visual output. During the experiment, users regularly rate their emotions on the valence, arousal and dominance dimensions (Morris 1995). In addition to these ratings, important events in the game—such as dying, scoring points and advancing a level—are all stored, and can be analyzed for correlations with the EEG and physiological sensors.

10.4.2.3 The Application of User State Estimates

Once the measurability and classifiability of specific psychological concepts, for example boredom, engagement and frustration, are shown in a context related to a specific application, the recognition technique can be integrated in a cybernetic control loop. The determination of the reaction of the application now allows the

incorporation of the current user state. With models guiding the dynamic behaviour of the application according to the effect aimed for (potentially a specific user state or positive experiences in general), affective-BCI-enriched interaction could be a more natural, efficient, and enjoyable activity.

Combining behaviour dependent and independent indicators of user state might lead to more robust and more reliable state recognition and thus to more effective game adaptations. Affective BCI could qualify for such a system as a fast and sensitive method to directly measure affective states. Evidence for the value of the adaptation of game difficulty based on physiologically determined anxiety level was found by Liu et al. (2009) in the form of a reduced anxiety level, higher user satisfaction, increased feeling of challenge, and higher performance. A similar result was found in a study monitoring facial expressions to discriminate between positive and negative affective states (Obaid et al. 2008).

The neuro-physiological inference of the user's affective and cognitive state might also help to increase safety and efficiency in work environments. This particular perspective will be discussed in Chapter 12 of this Volume.

10.4.3 BCI as Game Controller

While using a BCI to measure mental state is the most valuable way to integrate BCIs in games—a new information source is tapped—a BCI can be useful as a traditional game controller. To act as a game controller, the predictions of the BCI need to be translated into meaningful commands in a way that enables fluent game play. This implies that commands have to operate at the correct time scale, are issued with minimal delays, and are invariant to changes in user state. We will now explore these implications in more detail.

10.4.3.1 The Time Scale of a BCI

The time scale on which commands are issued needs to be congruent with the game. For example, in slow-paced games, fewer commands are issued during a unit of time, and the BCI output can be interpreted in a similar slow fashion by filtering out the fast changes in the BCI output. A faster-paced game might require quick responses, and hence short spikes in output are required for control. The slow changes in the output would work counter-productively, as they would make the game biased to a specific action. Some BCI paradigms are inherently more suitable for slow games (sensorimotor-cortex rhythms), others are more suitable for fast-paced action (the lateralized readiness potential, LRP). See Table 10.2.

An example of a game that requires operation on a small timescale is Affective Pacman (see Application: Affective Pacman). Control in our Affective Pacman game is analyzed using the lateralized readiness potential (LRP). For this game, multiple commands are usually issued within one second. This requires a BCI that can respond quickly but is insensitive to changes that take place on the minute scale.

Table 10.2 Overview of BCI paradigms information transfer rates (ITR), and the timescale they operate on, sorted on latency. This table is based on the median values for the ITR and the latency from Tonet et al. (2008, Table 2). As LRP was not presented in the overview of Tonet et al., we used numbers from Krepki et al. (2007) to illustrate negative latencies. EMG was added as reference modality

Paradigm	ITR (bits/min)	Latency (sec)
LRP	20.	−0.120
P300	28.2	1.58
ERD/ERS	28.8	1.5
SSVEP	26.4	2.10
Sensorimotor cortex rhythms	16.8	2.20
SCP	3.6	65.75
(EMG)	(99.6)	(0.96)

Alternatively, AlphaWoW (see Application: AlphaWoW) is an example of a game that operates on a large time scale. Alpha power requires at least a few seconds to be measured accurately. Therefore the game is most sensitive to changes in this time range; faster and slower changes are attenuated. Due to its time scale, alpha activity is less fit for fast-paced commands.

In order to adapt the system to changes in brain activity that occur over a longer period of use, and also to individual differences in brain activity, z-score normalization is applied to the measured alpha band power values. As a result, even if a user has a tendency for, for example, high alpha values, they will still be able to change into a bear. This is because the system looks at changes relative to the observed situation. The game is sensitive to medium-term changes, and adjusts itself for long-term changes and differences between subjects.

In addition, short term changes—due to noise and artifacts—could result in frequent, involuntary shape shifting. In alphaWoW, three methods are applied to deal with this issue and make the interaction more deliberate: smoothing, hysteresis, and dwelling. With smoothing, the current value of alpha power is not only dependant on the latest measurement, but also on the two previous ones. However, the most recent band power value is still the most influential. This attenuates peaks caused by outliers. Hysteresis is applied to the mapping from alpha value to changing into elf or bear form. Alpha below a certain threshold results in a change to bear, and alpha above a certain level transforms the user into elf form. In between these levels no change occurs, giving the user some leeway, and only letting the more extreme values have an effect. Finally, the user also has to stay in the range of effect for a little while for the shape-shift to occur. This dwelling also reduces the effect of unintentional peaks in the values. Dwelling has not been applied to BCI before, but is not an unknown method for other interaction modalities, such as for pointing in gesture recognition (Müller-Tomfelde 2007). The combination of these measures make alphaWoW sensitive to intended changes, and robust against unintended short-term changes in the BCI output.

With alphaWoW, we have seen a few ways to adapt the time scale of the BCI to a game. Due to the nature of shape-shifting, small delays are not much of a problem in

alphaWoW. But for other games, the latency will have a huge impact on gameplay. Some latency is inherent in BCI control, as the brain signals need to be observed over a period before they can be analyzed. But in some paradigms, such as the LRP for actual movement, preparation can be observed before the actual action takes place. These characteristics could be exploited for fluent gameplay, resulting in potentially *negative latencies* (Krepki et al. 2007). For slower paradigms, the only solution may be to backfit the command in the game history, resulting in only a visual delay, and not a semantic one. The translation of a working BCI to meaningful game commands will be the most challenging, and most import, aspect of building BCIs for games.

10.4.3.2 Influence of Mental State on BCI

A more complex challenge for BCI control is posed by the influence the content of the game can have on the mind of the player. It is very likely that the mental state of the player changes, as players often play games to relax, or are frustrated when they cannot win. This variability in user state cannot be eliminated, as it is the core of experiencing video games. The influence of mental state on BCIs is well known in the BCI community; changes in the ongoing EEG signal are often attributed to boredom (Blankertz et al. 2007). Boredom during training can be eliminated to a degree by making training part of the game environment. Frustration is another mental state that will occur frequently during game-play, for example, caused by a challenge that is too difficult, or due to a BCI controller that malfunctions. This makes the influence frustration has on the EEG signal a very relevant and interesting topic. It has also been proposed to use the influence emotions might have on measured brain activity to enhance BCI operation, for example, by using emotion-eliciting pictures as SSVEP stimuli (Garcia Molina et al. 2009).

10.4.3.3 Application: Affective Pacman

normal   frustration
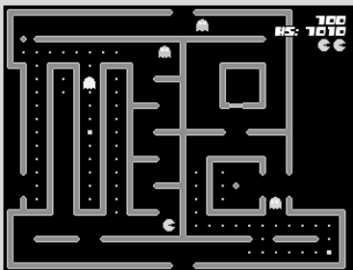
Affective Pacman is a Pacman clone, controlled using only two buttons; one to turn clockwise, and one to turn counter clockwise. For short periods, the buttons act unreliable to induce frustration.

In our Affective Pacman game (Reuderink et al. 2009), we induced frustration in a
Pacman game to measure the potential influence of frustration on BCI performance.
Frustration was induced by simulating a malfunctioning keyboard for a few minutes,
interspersed with periods of normal game control. Self assessments indicate more neg-
ative mental states during the frustration condition.

Results indicate increased BCI accuracy during the frustration condition for
ERD/ERS based classification.[2] For the (better performing) LRP classification, no in-
fluence of frustration was found. User frustration does not seem to pose a problem for
BCI operation, but more research is needed to investigate if this generalizes to other
context and other BCI paradigms.

To counter the effect of boredom on the (necessary) training of BCI systems, the
training can be made part of the game (Nijholt et al. 2009). During the start-up phase
of the game, players can start playing using more traditional modalities such as key-
board and mouse. During this phase, the BCI collects training data, with ground-
truth based on events in the game. A simple approach would be to use the key presses
as ground truth for an actual-movement paradigm. The computer collects training
data until a BCI can be trained with sufficient performance. BCI control is then en-
abled, while still allowing the user to continue playing with the keyboard. Slowly
the influence of the keyboard can be decreased, until the player is playing using
only the BCI. This approach keeps the online situation very similar to the training
period, reducing the surface for generalization errors. More interesting game events
can be used as well, for example, when the user casts spells by imagining (an EEG
recognizable) spell, and subsequently presses the relevant button. This creates train-
ing data in a similar fashion, with EEG examples tied to ground truth (the button).
When the BCI recognizes the spell successfully, the spell is cast before the button is
pressed, again allowing a gentle transition from training to online performance.

10.4.4 Intuitive BCI

There are many BCI prototype examples where the mapping between mental task
and the in-game action are not intuitive. Lotte et al. (2008) map the task of imaginary
foot movement to floating an object in the air. The Berlin BCI selects the best pair
of mental tasks to map to two controls in the applications—without any respect to
what actions it might actually get mapped to (Blankertz et al. 2008). This lack of
logic in the mapping may reduce the measured performance, as the subjects will
have to mentally translate what they want to do into the mental action they have to
perform. The less natural this translation, the more time and effort it will take to
actually perform the task. It does not help with the memorability of the mapping
either.

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[2]To be published.

The BCI paradigms that are currently most common have only a limited applicability when one is trying to find intuitive mappings between the task and the in-game action. P300 and SSVEP are intuitive for visual, auditory, or haptic selection. Imaginary movement of the left hand is easily mapped onto moving your avatar to the left, and movement of the right hand to the right. But at the moment, there are not many alternatives. This means that it is important to keep our eyes open to possible new paradigms that might match all kinds of game interactions.

Beyond waiting for neuro-scientists to come up with the next best thing based on knowledge from cognition and neurophysiology, another option is to look at it from the user point of view. What would the user like to map to certain in-game actions, and is that perhaps something that can be recognized from EEG measurements? As users will not have knowledge about the neurophysiology that would help in choosing mental tasks that might be detectable, many of the ideas that they come up with may not work. On the other hand, when something does work, it will probably be more natural to use, considering the source.

Although people do take suitability of the task for the in-game action into account, the effort it takes to perform the task adds more weight to their preference. When the participant is given feedback as to how well the system can detect the mental task, that information outweighs all other considerations. One can imagine however that there is a break-even point from where the task takes more effort than users are willing to spend, even if the detection was certain to be correct. And even though the detection is this important to the user, one has to realize that although the detection can be improved with better hardware and better software, the mental task will remain the same.

10.4.4.1 Application: IntuiWoW

Based on some informal, open discussions we have had with a small selection of World of Warcraft® players, we decided to try the following three paradigms, to be applied to the same shape-shifting action as used in alphaWoW:

1. Inner speech: the user casts a spell in their mind, e.g. "I call upon the great bear spirit" to change into bear form, and "Let the balance be restored" to change back into the basic elf form.
2. Association: to change into a bear, the user tries to feel like a bear. To change into an elf, the user tries to feel like an elf.
3. Mental state: the user goes into bear form, they stress themselves out, and to return to elf form they relax. This task is similar to the tasks used in AlphaWoW, but this time it is not explicitly related to alpha power.

A series of experiments with these three paradigms was run for five weeks, with fourteen participants returning each week. The first week all participants were asked to just perform the tasks, without getting any feedback as to how well the system was recognizing any of it. In the last week everybody was given feedback, and in between half the group was given feedback and half was not.

Results indicate interesting differences between the feedback and non-feedback groups. The mental state paradigm was well-liked by the feedback group, because of the accurate recognition by the system, but disliked by the non-feedback group because of the effort it took to perform this task. Also, people did not like to put themselves into a stressed state voluntarily. On the other hand, inner speech was liked by the non-feedback group as it was most like a magic spell, and took very little effort and concentration to do. Participants also considered this task to be the most easy to interpret. However, the feedback group quickly discovered that the current system was not well-equipped to detect this task, quickly moving this paradigm to the bottom of their list of preference. The association task set seemed generally well-liked, as people felt it fitted well with the game. It encourages the player to become one with the character they are playing, and to immerse in the game world.

## 10.4.5 Multimodal Signals, or Artifacts?

In order to measure clean brain signals, BCI experiments are usually conducted in isolated rooms, where the subjects are shielded from electrical noise and distractions. Healthy subjects are instructed to behave like ALS patients; they are not allowed to talk, to move or blink their eyes, as these activities would interfere with the brain signals and the cognitive processes being studied. But such laboratory-based controlled setups are far from a natural environment for gamers (Nijholt et al. 2009). To realize the ultimate automatic intuitive "think & play" game console (Lécuyer et al. 2008), experiments should be conducted in a realistic HCI setting, which implies first a natural game environment, such as a private home or even outdoor public place, and second natural behaviour of the user.

In an ordinary computer game, the players would be situated in a home environment and express themselves—willingly or not—through mimics, gestures, speech and in other ways. The increase in body movement imposed or allowed by the game results in an increase in the player's engagement level (Bianchi-Berthouze et al. 2007), so the reactions and movements would become more intense as the game gets immersive. Players would regularly receive auditory or visual feedback from the game. Additionally, in multi-player games, players interact with each other by means of talking, listening, and the like.

10.4.5.1 Application: Bacteria Hunt

During the eNTERFACE'09 Summer Workshop on Multimodal Interfaces, we started a project to build a multi-modal, multi-paradigm, multi-player BCI game. The project resulted in the Bacteria Hunt game in which the aim is to control an amoeba using arrow

keys and to eat as many bacteria as possible. Three versions of the game were imple-
mented. In the basic non-BCI version, eating is accomplished by moving the amoeba on
a bacterium and pressing the space key. In the second version, the relative alpha power
of the player is also used. The high alpha measured at the parietal lobe is related to a
relaxed alertness (Cantero et al. 1999). In the game, the more relaxed the player is, the
easier it is to control the amoeba. The third version adds a second BCI paradigm into
the game: SSVEP. Eating is now performed by concentrating on a flickering circle that
appears when the amoeba is on a bacterium.
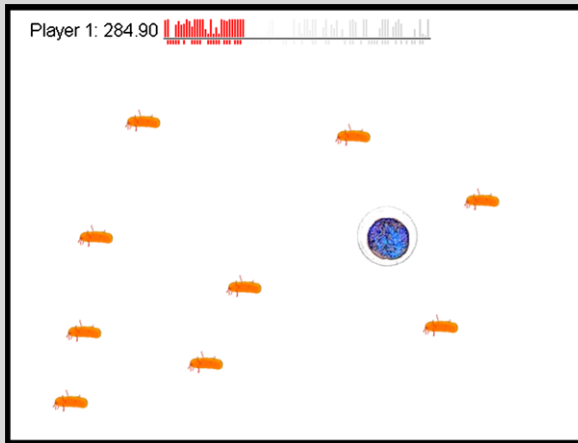
A screen shot of the Bacteria Hunt game

The non-BCI version of the game allows the comparison of BCI and other modali-
ties with respect to features such as enjoyment, ease, and exertion. The second version
enables exploration of how well BCI can be used together with another modality—
keyboard in this case—and what implications this might have on concentration and
performance matters. And by the third version of the game the critical issues that may
arise due to using different BCI paradigms together—namely, the alpha power and the
SSVEP—such as overlapping measurement sites and frequencies, ability to extract and
decode information produced by complex brain activity can be investigated.

The feasibility of using BCI technology has already been proven with many ap-
plications (Section 10.2). The time has come to explore how BCIs can function in
combination with other modalities, and whether it is realizable to use BCIs in real
HCI environments. Recently, there was a study defining a set of guidelines to em-
ploy fNIRS in realistic HCI settings (Solovey et al. 2009). Another attempt was
Bacteria Hunt, a multi-modal, multi-paradigm BCI game utilizing EEG, built and
demonstrated during the eNTERFACE'09 workshop (Mühl et al. 2010). We argue
that this kind of research needs to be extended to cover multiple users, different
modalities, different contexts, and different BCI paradigms and signal types.

Using EEG-based BCIs in combination with other modalities poses a few extra
challenges due to the nature of EEG. One of these problems is that EEG sensors

tend to pick up other electrical signals as well, such as electrical activity caused by eye movements (electrooculogram, EOG), and electrical activity from muscle contraction (electromyogram, EMG). Especially BCI based on potentials, as opposed to BCIs based on band power (such as ERD/ERS based BCIs) can suffer from the big amplitude change caused by eye movements and eye blinks. As we cannot ask that a player stops eye movement and blinking altogether, the negative impact of eye movements has to be removed from the signals. In contrast to medical BCIs, we do not have to remove all eye movement in our recordings, decreasing the negative influence should be enough.

There are two main approaches when dealing with occular artifacts. The first is to simply remove EEG episodes contaminated with eye movements. For some games, where the BCI is applied to detect long-term changes, such as mental state, this method can be applied. As a result, the game then needs to be able to deal with missing episodes. The other approach, filtering, is applicable to a wider range of applications. Removing the EOG signal has an additional benefit; consciously blinking, or even suppressing movement is known to cause a Readiness Potential (RP).[3] Allowing the user to move their eyes freely could potentially reduce the number of non-task related RPs, making the EOG movements simpler to interpret and remove. One huge drawback associated with filtering the EOG artifacts is the need for additional sensors to record the activity of the eyes. EEG headsets designed for gamers often do not contain sensors specifically placed at traditional EOG locations. This poses the technical challenge of removing EOG influence without the use of these sensors.

Another challenge that BCIs will face when applied to games is the influence of speech, facial expressions and movement. The EMG signal, characterized by a high-power signal in a broad frequency range, has a profound impact on the EEG recordings. While speech and facial expressions are easier to suppress during game play than eye movements, a BCI that can work robustly while the player laughs and talks is preferable.

So far we have approached the EOG and EMG signals as noise, that has to be removed from the EEG signal. But if we can identify the influence of EOG and EMG signals, as is required to perform filtering, these signals can be isolated, and used as a separate eye gaze or muscle modality. In this context, the artifact becomes another signal, and can be used as an additional source of information.

In IntuiWoW, one of the reasons mental state is so easy to recognize, is because many users tense up facial and neck muscles to enter a more stressed state, and relax these for the relaxed state. The EEG system is sensitive to this muscle activity, and as a result the BCI pipeline can easily classify these clear muscle tensions into the two states. For these users, the actual brain activity related to these states will mostly be ignored. In medical BCI, often aimed at paralyzed people, a system that uses muscle activity in order to distinguish different user states is considered useless. The patients who might end up using the system will not be able to produce

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[3]Whether automatic eye movements and blinks also display a RP remains to be seen (Shibasaki and Hallett 2006).

this muscle activity, so the system will not work for them. The healthy subjects in our experiment did not experience this as a problem, however. The system recognized their mental state, even though it may have been an external expression of it. They were just amazed that they could control their avatar by changing their mental state, and did not care about whether it was a "pure BCI" or not. We propose that the usability and user experience are more important when looking at the general population as a user group, than the consideration of only using brain activity for the interaction.

10.5 Conclusions

Applications for healthy people are becoming more and more important in BCI research. Gamers are a large potential target group, but why would a healthy person want to use BCI when it has still so many issues (delays, bad recognition, long training time, cumbersome hardware)? BCI needs to prove it can be used in distinctive new ways that will make it a valuable addition to current input modalities with a combination of features that no other modality can offer. Unconstrained by what is physically possible, it might also be a very natural interaction modality, allowing gamers to express themselves in their own unique way.

Some of such valuable features have already been uncovered. In human computer interaction the amount of information the user can provide is limited. In addition to control commands, BCI can provide new kinds of information, specifically on the user's mental state. There have been reports by users that the system seems to recognize a decision before they were consciously aware of it themselves. As with LRP, it may also be possible to detect actions before they are actually executed.

The medical research that lies at the foundation of current BCI research has been and still is very important. However, to move BCI forward as a viable interaction modality for everybody, the human element has to be given a more prominent place in the research. Whether the system is a 'pure BCI' is of secondary importance to healthy users. Usability and user experience, which lie at the core of human-computer interaction, should be considered when designing systems and applications, in order to increase the user satisfaction and acceptance of this new technology.

We believe that BCI could be seamlessly integrated with traditional modalities, taking over those actions which it can detect with sufficiently reliable accuracy. For game adaptation, affective BCI could be a fast and sensitive method on its own, or combined with other user state indicators it could help to create more robust and reliable systems. Timing and fine-grained control are important topics to look into, as these features are important for many applications. Artifacts and noise that are inherent to using BCI in a real-world environment should be dealt with or even better, used as additional information about the user.

We need to move beyond feasibility tests, to prove that BCI is also applicable in realistic, real-world settings. Only the study of BCI under ecologically valid

conditions—that is within realistic HCI settings and with behaving users naturally—will reveal the actual potential, and also the real challenges, of this promising new technology. Another way of thinking is required to make BCI part of HCI. 'The subject' should become 'the user'. The first steps have already been taken.

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