Actual and Imagined Movement in BCI Gaming

Abstract. Most research on Brain-Computer Interfaces (BCI) focuses on developing ways of expression for disabled people who are not able to communicate through other means. Recently it has been shown that BCI can also be used in games to give users a richer experience and new ways to interact with a computer or game console. This paper describes research conducted to find out what the differences are between using actual and imagined movement as modalities in a BCI game. Results show that there are significant differences in user experience and that actual movement is a more robust way of communicating through a BCI.

1 INTRODUCTION

In the field of BCI, brain activity is recorded and automatically interpreted to be applied in various applications. Measuring brain activity is already well known in medicine using the electroencephalogram (EEG). EEG is a proven method, which has a number of advantages over other methods: 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.

BCI systems need to make decisions based on very short segments of EEG data to make it useful for different applications such as wheelchairs, robots, and personal computers. In the case of software applications, BCI can be used as an additional modality of control, for evaluation of the user or the application, or to build adaptive user interfaces (Nijholt et al., 2008a).

Games are usually the first applications to adopt new paradigms, driven by the gamers continuing search for novelty and challenges (Nijholt et al., 2008b). Apart from them being a suitable platform to bring this new interaction modality to the general population, games also provide a safe and motivational environment for patients during training or rehabilitation (Graimann et al., 2007; Leeb et al., 2007). Research has shown that using BCI instead of the conventional mouse and keyboard can add to the user experience by making a game more challenging, richer, and more immersive (Oude Bos and Reuderink, 2008).

Before BCI can be adopted by the general population there are still a number of issues that need to be addressed: artifacts in the recorded brain data (signals that do not stem from the brain), inter and intra-subject variability, inter and intra-session variability, long training periods, low transfer rates (of commands), and BCI illiteracy (Sannelli et al., 2008). Apart from that, more attention from the Human Computer Interaction community is required on how this new input modality influences the user experience, and how the interaction can be improved (Lecuyer et al., 2008).

While most research into using movement for BCI has focused on imagined movement, some clinical research shows that actual movement in fact elicitates a more pronounced and therefore better discernable signal in the motor cortex (McFarland et al., 2000).

Actual movement can also be used with other interfaces than a BCI. Interfaces such as a motion tracking system, for example, which is probably more reliable at this moment. One big potential advantage of a BCI however is that the measured EEG signals at the brains are always preceding actual muscle activity at the limbs. This advantage is amplified by the onset of a potential in preparation of a movement, the so called Bereitschaftspotential, or Readiness Potential (Kornhuber and Deecke, 1965). Krauledat et al. showed that this lateralized readiness potential can be used to classify actual movement even before the movement itself is carried out (Krauledat et al., 2004). This could give a gamer an advantage over other interfaces especially in fast paced, highly reactive games.

2 RELATED WORK

A few BCI games based on imagined or actual movement do already exist. Pineda et al. (2003) designed a first-person shooter game in which the user could move using the keyboard, and turn by imagined movement. Players learned to control the BCI by experimenting; no instructions were given beforehand. Other examples include the virtual environments of Leeb et al. (2005), the board game of Kayagil et al. (2007), and the game BrainBasher (Oude Bos and Reuderink, 2008) that we used in this study.

Both actual and imagined movement can be used for BCIs. Obviously, actual movement is a more natural and intuitive way for users to communicate and express themselves. All these games involve movement tasks, and are based on a neurological process known as Event-Related Desynchronization (ERD) (Pfurtscheller, 2001). ERD is detectable as a decrease in power in the β-frequency band on corresponding motor cortices. Before use the BCI has to be adapted to person-specific examples of the ERD using machine learning techniques.

Actual movement is characterized by a more pronounced and reliable signal in the motor cortex (McFarland et al., 2000). This more pronounced signal is a very welcome advantage in the world of BCI where every extra percent of accuracy is appreciated.

When looking at the success of the Nintendo Wii, it becomes clear that actual movement is well enjoyed by gamers [1]. Moreover, imagined movement in adulthood is not as trivial as actual movement is. Although for example professional sportsmen and musicians use imaginary movement for training an actual motor skill it still is not as trivial to do as actual movement (Jeannerod, 1994). Though one can think of various applications in which imagined movement is used, these are almost always associated with skills which require a lot of training. Actual movement might therefore be a more natural and easier way of interacting with a BCI.

[1] “Nintendo wiining the console war”, December 2008. http://www.igizmo.co.uk/articles/news/744-gaming-nintendo-wiining-console-war

3 METHODS

The main question in this study is whether there are differences between imagined and actual movement in a BCI gaming environment. Some of the differences that will be looked into are the gaming experience for the user and the detectability of the signal from the EEG. We also looked at the generalizability of these BCI modalities for different user groups based on demographical characteristics.

3.1 Experiment Setup

To answer these questions an experiment has been carried out in which users communicate with the BCI game BrainBasher (Oude Bos and Reuderink, 2008) using both kinds of movement. First, users fill in a form regarding demographics including handedness as well as characteristics that could influence their ability to focus on the task (like alcohol and caffeine consumption habits). This data is used to check for group differences during analysis. Our experiment consists of two parts: Actual movement and imagined movement. The order of performing actual and imagined movement is randomly assigned for each subject. Each part consists of two sessions.

For the system to be able to recognize the user's actions, a training session is required to create a user-specific classifier. This is followed by a game session, after which the subject fills in a user experience questionnaire. This questionnaire has been designed based on the Game Experience Questionnaire (GEQ) developed at the Game Experience Lab in Eindhoven (IJsselsteijn et al., 2007). With this information the user experience for actual and imagined movement can be compared. Between all sessions are breaks in which the user can relax for a minute or two.

The experiment is set up as a randomized cross-over experiment to eliminate sequence and learning effects induced by the succession of both tasks. After all experiments are done we compare the results of the actual movement sessions versus the results of the imagined movement game sessions. The new questionnaire has also been evaluated so it can be used for assessments of other BCI games and modalities.

The setup is situated in a normal office environment, in contrast to a shielded room. This setting was chosen deliberately as it is a more representative setting for home use. Besides this, the EEG system used has active electrodes which pick up a lot less noise than passive electrodes would. During the experiments themselves, only the researcher and the subject will be in the room. This way distractions will be kept to a minimum, while still being able to provide help when needed.

3.2 BrainBasher

The BCI game used for this research is *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. Game control is achieved by two mental tasks: left hand movement versus right hand movement. For the actual movement task both hands are laid on the desk in front of the user. 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 the same movement, without actually using any of their hand muscles.

Before the user can play however, they will have to undergo a training session in which stimuli (in the form of symbols denoting the user actions, see Figure 1) and breaks are alternated. During the stimulus the subject performs the indicated action: movement of the left or right hand. The user is instructed to stay relaxed and not to move, excluding the break periods, to prevent artifacts in the EEG. This is of course with the exception of the hand movement in the case of the actual movement sessions. In our system, the training consists of two short sessions, taking ten minutes in total. The EEG data from both training sessions are concatenated and used for training the classifier of the BCI system.

During the game session the user is instructed to take care that they carry out precisely the same movement (be it actual or imagined) as in the preceding training session. The difference is that they have to react as fast as they can to each new symbol popping up by performing the action right away. Bashing a symbol is accomplished when the classifier recognizes the action, according to a confidence level of at least 60%. Every *bash* results in one point added to their total score. The goal of the game is to bash as many symbols in the allocated three minutes, to achieve a maximum score. (Figure 2)

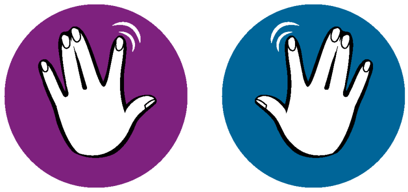

Figure 1. The symbols for left and right hand movement.

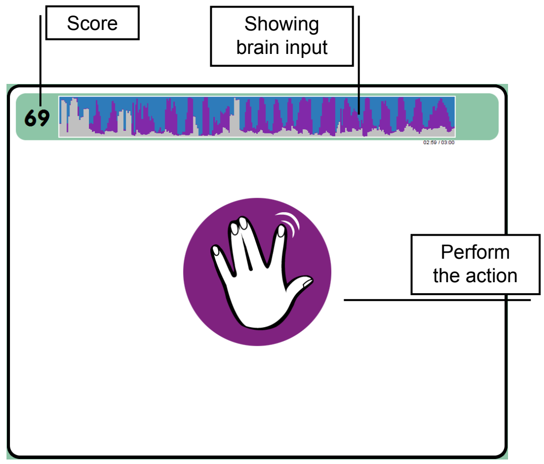

Figure 2. A game session.

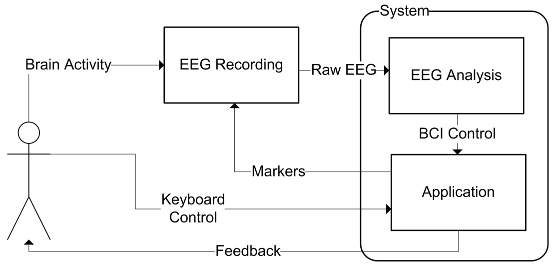

Figure 3. BrainBasher System View

3.3 The BrainBasher BCI

A schematic view of the total system is shown in Figure 3. The user interacts with the system by executing brain actions, and also by keyboard to traverse the menu. Brain activity is acquired with a BioSemi EEG setup using 32 electrodes, sampled at 256Hz. For training the system, examples of the ERD for both the left hand and right hand are used to derive a linear classifier to be used during the online game session. The EEG data is processed as shown in Figure 4. First the raw data is re-referenced to the common average reference (CAR) to remove far away sources of noise. After re-referencing a bandpass-filter isolates the frequency range in which the ERD occurs. Then we train spatial filters with the Common Spatial Patterns (CSP) algorithm (Koles, 1991) to extract activity on the motor cortices. These spatial filters are used to extract the band power in the most discriminative sources. Linear Discriminant Analysis (LDA) is applied to make a final prediction based on the band power features. After training the BCI generates four new predictions every second, based on the real-time EEG data. These predictions are used to play the game.

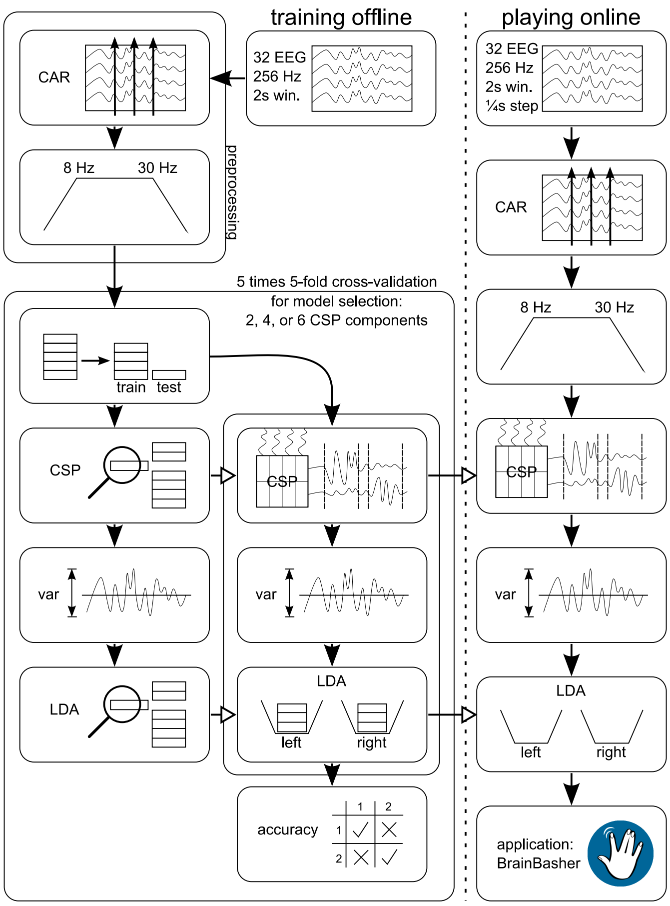

Figure 4. BrainBasher BCI Pipeline

3.4 BCI performance evaluation

After the training session, we evaluate the accuracy of the classifier by a cross-validation procedure. It is to be expected that a classifier has to have a certain minimum performance for pleasurable experience. Another frequently used performance measure for BCIs is the information transfer rates (ITR), representing communicated information measured in bits per minute. The ITR more directly expresses the utility of a BCI for a user that intends to use the BCI to communicate. The advantage of the ITR measure is that the ITR incorporates both the quality of the recognition and the time needed to make a decision – a faster but less accurate BCI could be preferred over a precise, but slow BCI. Current BCI are reported to obtain ITRs of up to 10–25 bits per minute (Wolpaw et al., 2002). Unfortunately, different formulas to calculate the ITR have been used. The most popular formula is:

$$B = \log_2 N + P \log_2 P + (1 - P) \log_2 \frac{1 - P}{N - 1}, \quad (1)$$

where N is the number of classes, P is the probability of correct recognition, defining B, the number of bits communicated with one trial. When given the number of trials per minute one can calculate the ITR. This formula is frequently used due to it simplicity, but this simplicity comes at the expense of a number of assumptions: all classes have the same prior probability, and all classes have the same probability for correct and for incorrect selections (Wolpaw et al., 1998). These assumptions are often violated in practice, sometimes leading to inflated ITRs.

A more precise way to measure the amount of information per trial is based on mutual information:

$$I(X;Y) = \sum_{y \in Y} \sum_{x \in X} p(x,y) \log_2 \frac{p(x,y)}{p_1(x)\, p_2(y)} \quad (2)$$

where X and Y are the predictions and the ground truth respectively, $p(x,y)$ is the joint probability distribution function of X and Y, and $p1(x)$ and $p2(y)$ are the marginal probability distribution functions of X and Y respectively. Mutual information measures the decrease in uncertainty in a signal Y (the desired action) given signal X (a derivation of the EEG).

As with Equation 1, the duration of a trial is needed to calculate the ITR, but it does not depend on its assumptions. In our analysis, we will calculate the ITR using Equation 2. For another view on the differences between ITR formulas see (Kronegg et al., 2005).

3.5 Questionnaire design

To evaluate the user experience a questionnaire based on the GEQ (IJsselsteijn et al., 2007) is developed. Although the GEQ consists of a lot of useful questions for evaluating various games, its main purpose is evaluating complex and immersive 3D virtual games. Therefore the questionnaire has been adapted to evaluate the user experience especially in BCI games. Questions that are not applicable, (e.g. the questions about the storyline, the complexity and the flow of the game) were left out. On the other hand we added questions, specifically on the amount of control the user experiences. The amount of control is a trivial aspect when using mouse and keyboard. These are reliable ways of communicating with the computer compared to a BCI system which is not so reliable. Also items about user concentration and alertness were added. This is an important aspect because users will have to concentrate to use a BCI game and possibly get tired more quickly than normal.

The questionnaire consists of statements to which users can respond on a 5 point Likert-scale ranging from ‘completely disagree’ to ‘completely agree’. Some examples of items in the questionnaire might be: “I liked playing the game.”, “I felt the computer recognized my actions.” or “I’m exhausted.”

To analyse the results of the questionnaire, we will use Cronbach's Alpha (Cronbach, 1951). Alpha is a measure of internal consistency. It is (to a certain extent) a measure of how reliably a scale constructed out of the selected items will measure one concept. This does not necessarily mean that you are measuring the concept you intended to measure, therefore further (qualitative) validation is needed. Alpha is only an estimator of reliability: it measures to what extent the different items are correlating and are consistent, taking subject and environment variance into account. In this research the Standardized Alpha will be used because we want to sum standard scores to construct scales from Likert scale items. A commonly accepted threshold for Alpha of 0.7 is the goal for every scale (Cortina, 1993).

4 RESULTS

First we describe the demographics of the test subject pool, then we analyse the questionnaire used for evaluation. Using the results from the questionnaire we can look at the differences in user experience between actual and imagined movement.

Participants Twenty healthy persons participated as test subjects in this study. The average age across the group was 26.8 (standard deviation: 12.3, minimum: 13 and maximum: 58). Of the twenty participants 10 (50%) were male and 10 (50%) were female. Test subjects were randomly assigned to either group A or group B. Group A would do imagined movement as their first task and actual movement second, group B would do exactly the opposite. Each group had ten (50%) participants. 19 (95%) participants were Dutch, 1 (5%) participant German. Apart from standard demographics we also asked participants their handedness, because this characteristic might be of influence: 5 (25%) participants were dominantly left-handed 15 (75%) were right-handed. 14 (70%) received an education higher than average. Computer usage and game experience varied a lot among participants: 8 (40%) participants used a PC for more than six hours a day, 5 (25%) used a computer on a less than daily basis. The same variance goes for game experience: 2 (10%) played games two hours a day, 8 (40%) on a weekly basis, 6 (30%) on a monthly basis and 4 (20%) never played a video game.

Questionnaire construction All participants filled in the questionnaire after both tasks without missing any questions. The responses on the same items for both movement tasks were stored in the same respective variables for scale analyses and in separate variables to analyse the differences in user experience between both tasks. Scale reliability analysis was carried out in order to evaluate if the newly developed questionnaire would be useful as a reliable tool to assess user experience in BCI games. The total user experience questionnaire consisted of 42 items over 8 scales. Each item consists of responses to a statement on the user's experience on a 5 point Likert-scale.

Some items were recoded to avoid an expected negative correlation. Correcting the scales for items that did not constitute to the scales consistency, e.g. deleting items with a low or negative Inter-Item Correlation, Standardised Alpha's ranged from 0.620 tot 0.865 and all scales consisted of at least three items.

To evaluate the usefulness and dimensionality of the resulting scales, a factor analysis was done on all scales separately. The first dimensions in the factor analyses of every scale explained more than 56% of the variance in the data, except for the Negative Experiences scale. Scree plots (Catell and Vogelmann, 1977) also indicated strong unidimensionality across all scales except for the Negative Experiences scale, which turned out to be a two dimensional scale. The corrected questionnaire consisted of 32 items divided over 8 scales. An overview of all corrected scales with their respective Alpha's and variance explained by the first dimension in factor analysis can be found in Table 1. The variance explained by the first factor measures to what extent a scale is measuring only one underlying attribute or construct.

Construction of Scales			
	No. of items	Alpha	Var. explained
Alertness	3	0.783	70.4%
Challenge	5	0.777	56.4%
Control	3	0.783	69.9%
Goals	3	0.754	67.7%
Fatigue	3	0.759	67.6%
Immersion	3	0.620	57.0%
Negative Experiences	5	0.638	41.9%
Positive Experiences	7	0.865	55.8%

Table 1. Constructed Scales including alpha and variance explained by 1th principal component

Differences in user experience The final corrected scales were used to compare the user experience for users performing both kinds of movements. A direct comparison by means of paired *t*-tests was done. The results of these test can be seen in Table 2. The first column is the difference of the means of both scales, the second column is the total standard deviation, the third the *t*-score and the last column is the two-tailed significance of the difference. The data show that the differences in the user experience for the Alertness as well as the Challenge scales are significant. Actual movement scored significantly higher on the Alertness scale ($t(19)$=-2.42, p=0.03) which could be attributed to mental tiring process of performing imagined movement. The same trend is also shown in the Fatigue scale, while there is no significant difference between actual and imagined movement (p=0.12). One possible explanation for this can be found in the correlation between the Fatigue and Alertness scale. These show a strong negative correlation in actual movement (r=-0.707, $p<0.001$). Challenge also significantly differs between both kinds of movement ($t(19)$=2.17, p=0.04). User experience data therefore indicates that performing imagined movement is more of a challenge than actual movement is.

Differences of Imagined vs. Actual Movement				
	Diff of avg	StDev	t	Sig (2-tail)
Alertness	-.65	1.20	-2.42	.03
Challenge	.40	.83	2.17	.04
Control	-.30	1.34	-1.00	.33
Goals	-.18	.50	-1.63	.12
Fatigue	.40	1.11	1.62	.12
Immersion	-.15	.60	-1.12	.28
Negative Experiences	.00	.59	.00	1.00
Positive Experiences	-.24	.89	-1.22	.24

Table 2. Paired *t*-Tests Scales, comparing imagined and actual movement

Performance Using the error rate calculated by the classifier from the EEG data we can compare the performance achieved on different subjects. For each subject two error rates are available, one for actual and one for imagined movement. The average rate for actual movement is 38.67%, while the average error rate for imagined movement is 42.28%. A Wilcoxon signed-rank test showed that actual movement error rates are significantly lower ($W_{+}(20)$ = 48, p = 0.0328). Looking at performance across different groups there are no significant differences between men and women in actual ($t(19)$=0.584, p=0.570) or imagined ($t(19)$=0.205, p=0.840) movement. Comparing left handed with right handed test subjects also didn't show any significant differences in actual or imagined movement ($t(19)$=-0.876, p=0.403 and $t(19)$=0.99, p=0.923 respectively).

The Information Transfer Rate or ITR (see Section 3.4) is another performance measure we calculated for every subject. This makes our results more comparable with other BCI's as well it is more informative than purely an accuracy rate. Note that the ITRś are calculated just for the training data and that therefor the maximum achievable ITR is 15 bits per minute. In the actual game session the bitrate can be higher, for the best subjects probably over 30 bits per minute. It is however difficult to give accurate numbers for this prediction because our BCI is self paced without a definite window time.

The calculated ITR's can be seen in table 4. (Due to an unfortunate loss of data we were not able to calculate the ITR for all subjects.)

ITR for all subjects					
Subject	AM	IM	Subject	AM	IM
A1	3.8	4.2	B1	2.0	4.1
A2	8.7	2.3	B2	2.6	2.1
A3	2.4	2.0	B3	3.8	2.1
A4	4.5	3.8	B4	4.8	10.5
A5	6.5	3.8	B5	6.0	2.3
A6	4.1	1.8	B6	2.6	4.2
A7	2.3	2.3	B7	2.7	5.3
A8	3.3	3.9	B8	2.3	2.3
A9	x	2.4	B9	5.1	1.7
A10	x	x	B10	5.7	2.6

Table 3. ITR for actual and imagined movement for all subjects (in bits/minute), missing data is marked with x

These findings support the accuracy measure in that actual movement provides a more usable signal on average.

5 CONCLUSIONS AND DISCUSSION

Results from this study showed 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.

To be able to assess the differences in user experience between actual and imagined movement, we developed a questionnaire for evaluating BCI games. While this questionnaire was found to be a numerically grounded tool to be used in this setting, further research for validation is needed.

User experience data from this questionnaire showed two significant differences. Users found more challenge in performing imagined movement. This might be due to a higher error rate, which makes sense; looking at the average error rate, it is harder to perform imagined movement. If we assume imagined movement is a skill that can be learned this might be an advantage for using imagined movement. Gamers are always looking for challenges and limitations that they can overcome by practice (Nijholt et al., 2008b).

On the other hand, for a few test subjects, the BCI system could not correctly recognize any movement. This corresponds to an error rate of 50%, in which case simple random 'guessing' would be as good as classification. Participants who achieved a high error rate also were not able to score any game points (other than maybe by chance). This is an issue that frustrates the user and is something that has to be resolved for wider acceptance of BCI gaming. This problem of not being able to be *understood* by a BCI is referred to as BCI illiteracy (Sannelli et al., 2008).

Alertness is the other scale in which a difference was found. This alertness has to do with the state of mind of the user after they played the game. The fact that they felt less alert after performing imagined movement is explainable. Imaginary movement requires more concentration and is a less natural action to perform. Doing something you do everyday does not tire you as much as doing something completely new. This was also reflected in the Fatigue scale, which scored slightly higher for imagined movement.

The generalizability over various demographic groups was good and there were no significant differences in performance. While there have been some anecdotal findings that women would be better in communicating through a BCI, results show no significant differences between men and women. Data also did not show any differences between left and right handed people. While the gathered data does not provide a clear view on how age is related to performance in the game, one might hypothesize that imagined movement is a skill of young children who mimic movements of others. A child sees someone performing a certain movement that can be of advantage to the child, for example grabbing something, they then try to perform it themselves. This probably is a skill that fades over time when a person gets older. While at a higher age humans are still able to mimic movements, it takes more time to learn them. This is possibly a ground for older people not performing to well at imagined movement. This was also reported by test subjects to the experimenter. They don't know how or what they should imagine.

Future work could include research into the different ways of imagining movement. As McFarland et al. (McFarland et al., 2000) already explain: when given the instruction to imagine a movement, most people will try to sense the movement. Other kinds of imagination (e.g. visualizing the movement) might activate different cortical areas. Some users might even prefer to visualize a movement if they find it more natural or less tiring. Evaluating the performance and user experience of these different tasks are a valuable addition.

The developed questionnaire seems to be a instrument that can aid us in evaluating differences in user experience between different modalities for BCI, but it might also be of interest for evaluation of BCI games other than BrainBasher. Then further research on the validity and generalizability of the questionnaire is needed.

Although the game works in an online manner and the classification algorithm is fast enough to be computed realtime, there always is an inherent delay in feedback. This is due to the fact that the classification algorithm needs a measurement of EEG data of a few seconds. Currently this measurement is two seconds. The consequence is that users get feedback of what they did with a two second delay. This delay sometimes leads to confusion and a lower positive affect towards the system. Future research might include shortening the response time of the underlying system of the game and finding out what this does for acceptance of and positive affection towards the BCI.

Because of the similarities in brain activity between actual and imagined movement and the somewhat lacking of intuitivity for imagined movement one might suggest using actual movement as a training for using imagined movement. The user of the BCI can get accustomed to using movements for communications and at the same time trying to imagine the movement. With the acquired data from the actual movement, the imagined movement could be classified.

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