Golf for the extremely lazy

A non-invasive BCI controlling a Sphero robot

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Much BCI research focuses on practical applications for disabled users. However, this does not mean BCI cannot be used in a fun way for both disabled and non-disabled users. In this project we developed a game in which users are able to control a Sphero, a robotic toy ball, in a golf-like environment. Instead of using a golf club to strike the ball, users use left and right hand imagined movements to set the direction and velocity of the ball. Although BCI is often unreliable and relatively slow, golf is a slow paced sport making it suitable for a BCI system. Using this setup even non-disabled users are able to experience BCI in an exciting fashion.

Introduction

Much research in the field of brain-computer interfacing (BCI) focuses on building systems which are designed for paralysed or other disabled users (e.g., Birbaumer, 2006; Hochberg et al., 2006). Galán et al. (2008), for example, describe a prototype of a brain-controlled wheelchair that regains paralysed users some autonomy by allowing them to navigate in a building safely. This research direction is not surprising, since BCI's are about a direct communication channel between the human brain and machines which does not require any motor activity (Wolpaw et al., 2002). It thus seems that disabled users can benefit the most from such systems, because it offers them the possibility to control or communicate.

However, the fact that BCI's often focus on disabled people, does not mean that BCI systems by definition cannot be useful or fun for non-disabled people. With BCI's becoming easier to use and more robust, there are numerous examples of systems designed especially for non-disabled users. Most of these systems are framed in the context of BCI games (van Gerven et al., 2009). Krepki et al. (2007), for instance, developed the Berlin Brain-Computer Interface. With this system users are capable of playing games like Pacman and Tetris using motor imagery instead of 'normal' HCI devices like a keyboard or mouse. As described by Nijholt, Reuderink, and Oude Bos (2009) games could benefit greatly from the extra input modalities of BCI, as gamers are always early adopters of new technologies.

In this report we describe a BCI system which enable users to play a golf-like game by controlling a robotic ball using electroencephalography-based (EEG) imagined movements. The game of golf seems perfectly suitable for a BCI game, because there are many parallels between the two. Firstly, both the sport golf and choosing an option with a BCI are slow paced. Adjusting a golf club to make the perfect swing is a precise task which takes some time. The same holds for BCI's where epochs usually takes a few seconds. Secondly, while golfing there is a high latency between strokes. After swinging the ball, one needs to walk the its new position. Unfortunately, BCI's also have to deal with a high latency between epochs. Finally, in both golf and BCI one needs to cope with external factors. In the case of golf the blowing of the wind will influence a stroke. In BCI's one needs to cope with noise coming from artifacts like eye blinks.

In our artificial golf game the user has to navigate the robotic ball between various obstacles and finally hit all holes with the least amount of strokes. The control of the robotic ball is based on the paradigm that each stroke in golf has both a direction and a velocity. The user therefore has to set both parameters in order to let the ball roll in his preferred direction using imagined-movements. Changing the direction can be explained to the user as changing the direction on a compass. Changing the speed can be explained to the user as changing the speed on a speedometer.

The goal of this project is to demonstrate that the game of golf is perfectly suitable for a BCI game. In addition to this proof of concept, we also conducted a pilot experiment showing how usable our system is for first time users. Firstly, the methods of the system are discussed, including an overview of the materials, the signals, and the processing of the signals. In the subsequent part of this report the pilot experiment is described including the results. In the final part the results of the experiment, several improvements of the system, and the applicability of the system are discussed.

Methods

This section focuses on the design of our system and what is expected from the user. Especially, the processing of brain signals is described in detail.

Task

The task of the user is to navigate the Sphero using imagined movements on a miniature golf course. The course has a size of approximately 2 by 2 meters and contains four holes and several obstacles (see Figure 1). It is the user's task to navigate the Sphero from the center of the course via hole 1 to 2 to 3 and finally to hole 4 within the least amount of strokes. The direction and velocity of a stroke are set using imagined movements following the paradigm of a compass and speedometer. Right-handed movements represent clockwise rotation, whereas left-handed movements represent counter-clockwise rotation. The user has 15 seconds to adjust the direction and velocity of each stroke.

Materials

Buffer BCI Toolbox The toolbox written in MATLAB is a wrapper around the FieldTrip buffer primarily maintained by Jason Farquhar. The buffer is an essential part of any brain-computer interface system and is similar to a blackboard architecture in order to exchange messages between different nodes. The toolbox contains all necessary functionalities in order to set-up a brain-computer interface system.

Sphero The Sphero is a robotic ball designed by Orbotix and was used as an artificial golf ball. The Sphero can be controlled using various apps and computer applications of which in our case the Sphero Desktop API, maintained by Nicklas Gavelin, was used. The Sphero Desktop API is written in Java and is backwards engineered from the original Android API. Using Bluetooth it is possible to connect to a Sphero and sent commands in order to control all the aspects of a Sphero.

TMSI Mobita The TMSI Mobita EEG cap with 10 electrodes was used during the experiments. During the development of the system our decision to initially use the Emotiv was quickly revoked, since it turned out that the Emotiv was not reliable enough in order to control the system.

Webcam To get a live stream from the webcam, used to get an overview of the golf course, the Webcam Capture API maintained by Bartosz Firyn is used. Webcam Capture allows to connect to a webcam via many different video capture drivers and contains many functionalities of which only a small part is used.

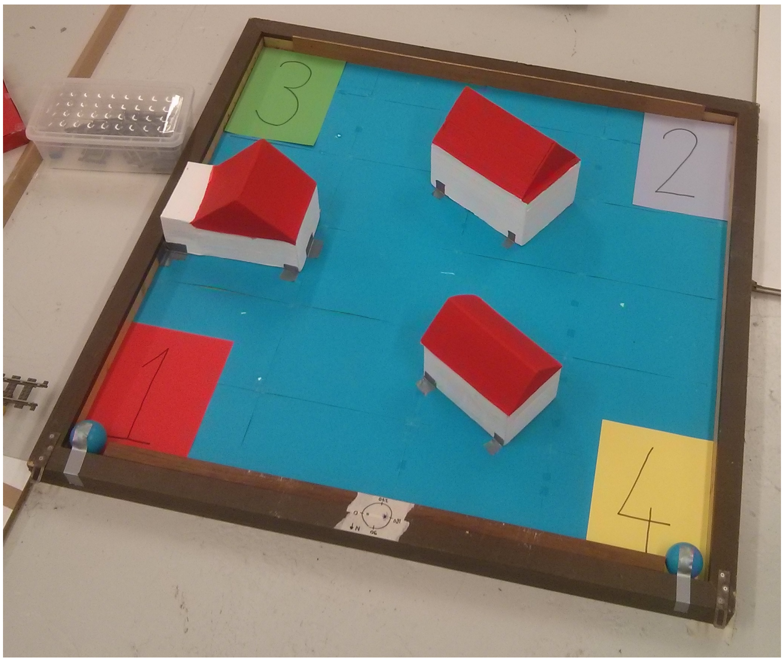

Figure 1: In the present BCI game the user has to Navigate the Sphero from the center of the course via hole 1 to 2 to 3 and finally to hole 4.

Signals

Due to its fine temporal resolution and low-costs EEG is perfectly suitable for an imagined movement system. Therefore, it was decided to use EEG signals in this project as well. The TMSI Mobita cap that was used has 10 electrodes measuring the fluctuation of voltage on scalp of the user. These voltage fluctuations are caused by the neurons under the scalp, but also by muscle movements and other sources. By combining the measurements at a rate of 250 Hz of the signals of multiple electrodes, it is possible to detect relevant differences between brain signals.

In general two different kind of signals can be discriminated (e.g., McFarland & Wolpaw, 2011). On the one hand, there are evoked signals which rely on a response to an external stimulus. Examples of such signals are Event Related Potentials (ERP's), P300 responses and Steady State Evoked Potentials (SSEP). On the other hand, there are induced signals which do not depend on external stimuli. The user can decide when to generate a certain mental state, which in this system is either right- or left-handed imagined movements. We are thus interested in Event-related Spectral Perturbation (ERSP), because they measure the change in the power of a signal in a particular frequency range. Such changes are easily detectable when a user performs a movement (e.g., Jankelowitz & Colebatch, 2002). However, in this system users were ask to make real left- and right-handed movements, because research by J. Farquhar (in press) revealed that these signals are more similar to brain signals of disabled people compared to signals of imagined movements. The process of processing raw EEG signals is discussed in the following paragraphs.

Processing

All brain signals captured by the EEG cap are processed in order to decode the imagined movements produced by the user. The classification pipeline used in this project is shown in Figure 2. In the following paragraphs some relevant aspects of this pipeline are described in more detail.

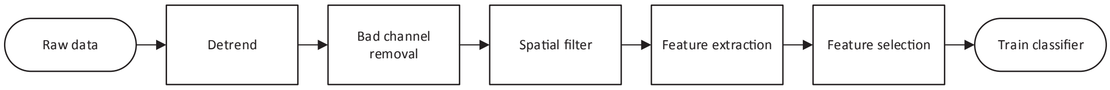

Figure 2: Raw brain signals captured by the EEG cap are processed using this classification pipeline.

Detrending The first step in processing the raw brain data is detrending. In this phase signals are normalised such that the mean of the channels will be zero. The purpose of this phase is to remove the baseline drifting that is often present in electrodes. It also makes sure that there is no difference in the base power of the different electrodes.

Bad channel removal It could be that some channels produce extremely noisy signals (e.g., because they do not connect well). Since these channels contain a lot of noise that can have a negative influence on the classifier, these bad channels are identified and removed. A channel is identified as a bad channel when its total power over all epochs deviates more than 3.5 times from the mean total power of all channels.

Spatial filter In this phase signals from external noise sources are removed. These noise sources usually result in nearby channels having highly correlated signals. Using the surface Laplacian estimate a local average signal is subtracted by removing channel correlation and common signals.

Feature extraction and selection The signals of interest when using imagined movements are changes in power in a particular frequency range. Therefore, the raw signals which are in the time domain have to be transformed. In this project Welch's method was used, which is an estimate of the signals power spectrum. Selection of relevant features is performed by removing all signals outside the frequency range of interest. Previous research indicated that 6-10 Hz and 26-30 Hz are the frequencies of interest, meaning all signals in other frequencies are discarded.

Classification The BCI Buffer Toolbox contains several ways of building a classifier. By default a logistic regression classifier with 10-fold cross validation is selected and trained on 20 samples. When processing one behaviour we get the direction the classifier selected, and how sure it is of this direction.

Experiment

In addition to developing the BCI game, a pilot experiment was also conducted in order to investigate the usability of our system. The following paragraphs describe the design of the experiment and the results.

Participants

3 men and 2 women (mean age = 23.2, SD = 2.2) volunteered to participate in this pilot experiment. Out of the 5 total participants 2 participants had never participated in a BCI experiment before. All participants were students and native speakers of the Dutch language.

Stimuli

During the experiment the participants were exposed to two different stimulus representations (see Figure 3). One representation followed the paradigm of a compass and was used while adjusting the direction of a stroke. This representation consists of circle on which an arrow is drawn. This arrow points to the current direction of the following stroke. The baseline position of the arrow is north (the arrow points to the top). By producing a right-handed movement the arrow moves clockwise. Left-handed movements result in counterclockwise movements of the arrow.

The other representation followed the paradigm of a speedometer and was used while adjusting the velocity of a stroke. Instead of the full circle, this representation contains a semicircle. On top of this circle there is also an arrow. The baseline position of this arrow is the middle of the semicircle (the arrow points to the top), representing a velocity of 50%. Right-handed movement make the arrow move clockwise resulting in a higher velocity, whereas left-handed movements make the arrow move counterclockwise resulting in a lower velocity.

Although both stimulus representations described above were used during the game phase, only the direction representation was used in the training and feedback phase. In these phases the baseline version of the direction representation was presented to the user. In each epoch yet another arrow was drawn on top of the baseline representation. This arrow either points to the right or left and requires the user to produce respectively a right- or left-handed movement.

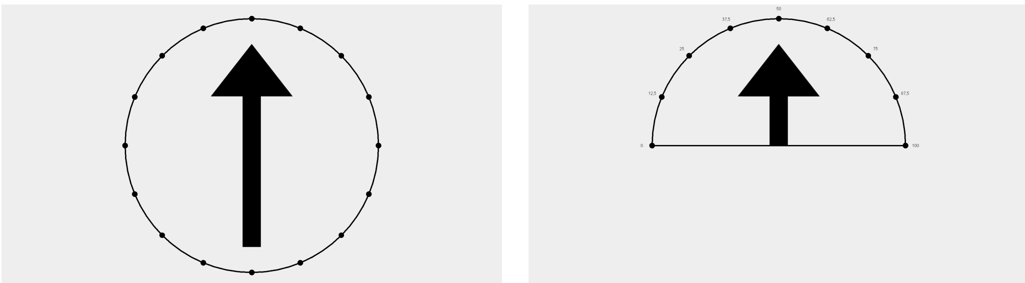

Figure 3: During the experiment participants were exposed to two different stimulus representation. The representation on the left followed the paradigm of a compass and was used to set the direction of a stroke. The representation on the right was used to set the velocity of a stroke and followed the paradigm of a speedometer.

Procedure

Participants were positioned in front of a laptop in a quiet room. Each experiment consisted of five phases as shown in Figure 4. The following paragraphs describes these phases in more detail.

Cap Fitting Phase The experiment starts with instructions about the experiment and what is expected from the participant. Subsequently, the EEG cap is placed on the scalp of the participant. The process of cap fitting usually takes about 3-5 minutes depending on the received quality of the signal.

Training Phase In the following phase data is gathered in order to train the classifier. In this training phase the participant has to produce 10 right- and 10 left-hand movements. The brain data of all 20 training epochs are saved including the stimulus (either right or left) that was presented to the participant.

Classifier Training After gathering all training data, the classifier is trained. This process runs almost automatically and follows the classification pipeline as described earlier in this report.

Feedback Phase Before playing the golf game, the participant gets real-time feedback of what the classifier predicts. By adding this feedback phase the participant learns how the system reacts on his/her actions, which slightly increases the performance of the participant in the gaming phase.

Testing Phase During the testing phase the participant plays the actual game. The user has 15 strokes to navigate the Sphero from hole to hole. Each stroke consists of the following steps. Firstly, the current overview of the golf course is shown using the live webcam stream during which the participant can plan its stroke. Secondly, the participant has 15 seconds to set the direction of the stroke. Subsequently, he/she has 15 seconds to set the velocity. In the final an overview of the golf course is shown again and the Sphero is moved allowing the participant to see the shot happen in real time. After playing the game, participants were asked to answer some questions about their experiences. The whole procedure took about 30-45 minutes.

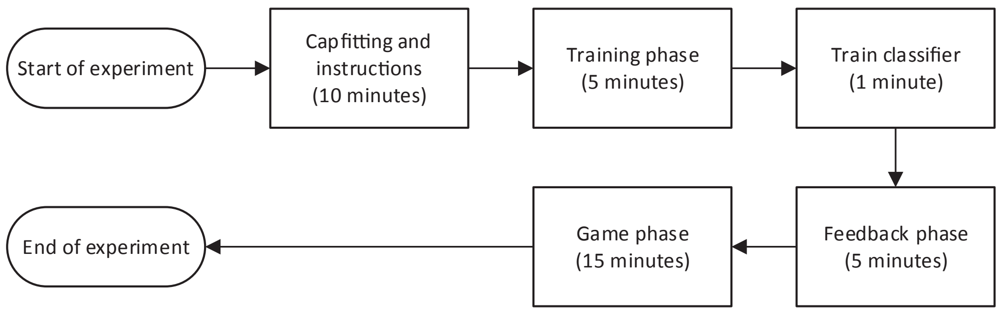

Figure 4: The structure of the pilot experiment.

Results

This section describes the results of the conducted pilot experiment highlighting the classifier performance as well as the game performance. Figure 5 shows the differences in power for the electrodes C3 and C4 for participant 4, and Figure 6 shows a topography plot for the frequency bands of 8 Hz and 12 Hz for both types of imagined movement.

Performance

Performance of the participant is measured in various ways. Not only classifier performance is taken into account, but also how well the participant performed during the game. Game performance is defined as followed:

$$\text{Game Performance} = \frac{\text{Number of Strokes}}{\text{Number of Holes} + 1}$$

Using the above definition the maximum possible score is 15, in case no holes are reached, and a minimum score of 0.8 is possible, in case all holes are reached in a single stroke. However, given the layout of the course a reasonable number of strokes is 7 resulting in a score of 1.4. In Table 1 an overview is given of the individual performances.

Participant	Classifier Performance	Number of Holes	Number of Strokes	Game Performance
1	70	1	15	7.5
2	95	2	15	3
3	80	0	15	15
4	94	4	14	2.8
5	75	0	15	15

Table 1: Overview of the classifier and game performance per participant.

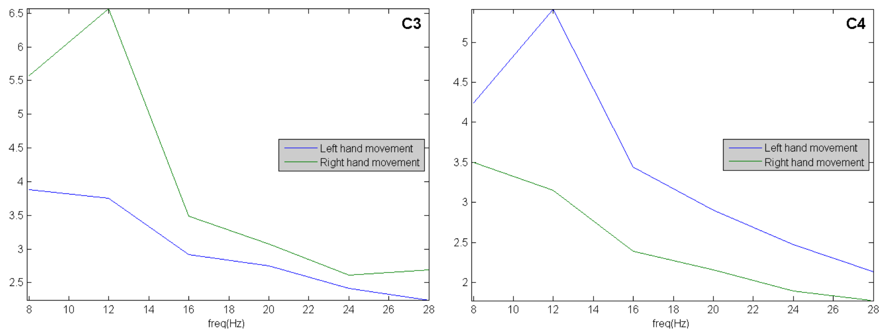

Figure 5: Data obtained from participant 4. The electrodes C3 and C4 are located on the frontal lobe with C3 on the left hemisphere and C4 on the right hemisphere. At 13 Hz a significant difference between the different classes can be observed.

Discussion

In this report a BCI system in the form of an artificial golf game has been described. The system has been successfully implemented and tested in a small pilot experiment. This experiment revealed interesting results and improvement possibilities.

Classifier performance varied from 70% up to 95% among participants. A correlation can be seen between the performance of the classifier and the game performance. Participants with a higher classifier performance perform slightly better in the game. A similar effect can be seen in the questionnaires filled in by the participants after playing the game. Participants having a low classifier performance experienced almost no adequate control, whereas other participants experience more control. Surprisingly, although the game performance and experienced control is low, participants having a lower classifier performance do not evaluate the game as being more frustrating or less fun.

Although these effects are not novel, they once again highlight that BCI games should become more reliable. Otherwise, traditional input modalities like a keyboard and mouse are probably preferred over BCI's. One way of making our system more reliable is by adding a third class. Now, the classifier only discriminates two classes, namely right- versus left-handed movements. If the participant does not make a movement, for example because the current direction is already ideal, this 'movement' has to be classified as a right- or left-handed movement. Adding a non-movement class might improve the game performance. Furthermore, a threshold could be introduced which discards uncertain classifications.

In the present system the participant only sees the course at the beginning and end of a stroke. By implementing the stimulus representation as an overlay on top of the video feed can make the game more intuitive. However, implementing such an overlay in a proper way was too time consuming and difficult for the course.

The results indicate that two of the five participants were not able to reach even one hole. For both

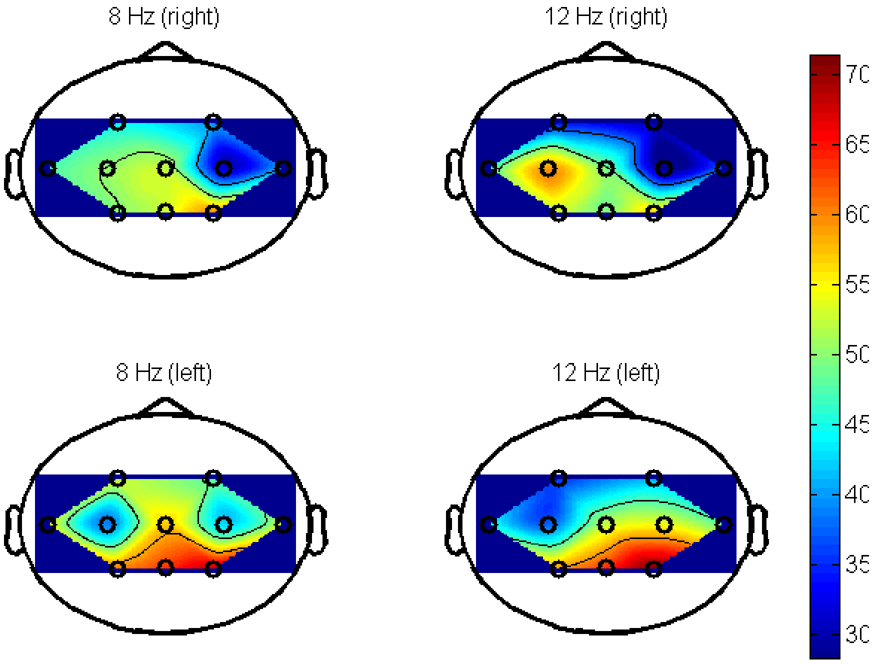

Figure 6: Topography plot of participant 4 with for the frequency bands of 8 Hz and 12 Hz for the left-handed and right-handed imagined movement.

participants the classifier performance was over 75%. Future work should thus focus on enabling even people with lower classifier performances to play BCI golf.

Finally it is good to think about the applicability of our research. Although it is possible to play the game we do not expect people to actually play it, since other modalities, such as a mouse and keyboard, allow for a more fine-grained control. The same system could be implemented with the same representation for direction and speed on an electric wheelchair. Whether this would work can be left for future research.

We conclude that our system is a good step in the direction of BCI's that are also designed for non-disabled users, however, it seems that more research is needed in order to make the system more robust.

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