Sokobrain: An SSVEP-based BCI for playing Sokoban

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June 28, 2012

Abstract

Sokobrain is a Brain Computer Interface (BCI) that uses Steady State Visually Evoked Potentials to play the puzzle game Sokoban. This is achieved by having stimuli on the four edges of the screen that alternate from black to white in different frequencies (30 Hz, 15 Hz, 10 Hz and 6 Hz). The user can indicate in which direction they want their player to move, by attending to the corresponding stimulus. The implementation and usability of the system was tested. Results show large inter-subject and inter-session variability, which is consistent with other BCI studies. Ways to improve the usability of the system are discussed.

Introduction

Brain Computer Interfaces (BCI's) are frequently designed with patients in mind (Leeb et al., 2007; Gerven et al., 2009; Mak et al., 2012). This is not surprising, since these are the people that will benefit the most from such technology. BCI's are generally too slow to compete with other input devices such as mice and keyboards, but for those that cannot use anything else, such as people with Amyotrophic Lateral Sclerosis (ALS), BCI's offer a way to communicate with the outside world (Birbaumer, 2006; Nijboer et al., 2008).

On the other hand BCI's do not have to be designed only for such users. BCI's can also be used/designed for entertainment (Scherer, Proll, Allison, & Muller-Putz, 2012). While games that require quick reactions and much dexterity of the user, will be hard to control with a BCI alone, games with little time-pressure and little movement freedom can be adapted for a BCI. For example Krepki, Blankertz, Curio, and Müller (2007) developed a pacman game (without ghosts), which the user controlled through Lateralized Readiness Potentials (LRP's).

In this paper we will describe the BCI we developed for playing Sokoban: Sokobrain. Sokoban is a puzzle game in which the player controls an avatar in a 2d environment. This avatar can move in four directions (up, down, left and right) in the level. The level contains boxes, goal spaces and walls. The player cannot move through walls, but can push boxes, given that there is an empty space behind the box. The goal is to push the boxes on to the goal spaces.

Steady State Visually Evoked Potentials

The BCI uses Steady State Visually Evoked Potentials (SSVEPs) to infer which direction the user wants to move in. Visually Evoked Potentials can be elicited in a user by (for example) changing the luminosity of the stimulus strongly. If this is repeated over a period of time, the response will keep occuring to each change in luminosity. Therefore, if the change in luminosity of the stimulus happens in a steady frequency, a brain response can also be measured at this frequency. (Vialatte, Maurice, Dauwels, & Cichocki, 2010)

This phenomenon can be used to create BCI's by putting multiple stimuli on the screen, which change luminosity (flicker) at different frequencies. The user then focuses their attention on the stimulus that corresponds to the option that they want to choose. While the stimuli that are not being attended to might also elicit a response in the user, the response is modulated by attention, and will therefore be the larger for a frequency that is attended to (Morgan, Hansen, & Hillyard, 1996). This attention effect is increased when the user is allowed to move their eyes in the selection of a stimulus. The brain response is much stronger when the stimulus is on the fovea (Walter, Quigley, Andersen, & Mueller, 2012).

This concept is not new, for example, SSVEP BCIs have been succesfully used to control a robot hand (Ortner, Allison, Korisek, Gaggl, & Pfurtscheller, 2011), and robotic wheelchair (Muller, Bastos-Filho, & Sarcinelli-Filho, 2011). In a paper by Zhu, Bieger, Molina, and Aarts (2010), numerous SSVEP BCIs were compared and analysed. A distinction was made between different types of stimuli: light, single graphic and pattern reversal stimuli. The first category consists of any systems that use lights (such as LED's) to evoke the SSVEPs. Single graphic and pattern reversal stimuli are generated on a monitor: Single graphic stimuli are created by alternating between drawing an image low and a high in brightness. A checkerboard that flips its white and black patches is an example of a pattern reversal stimulus.

The aim of this project was to design an SSVEP-based BCI for the Sokoban game (SokoBrain) and evaluate its usablity. SSVEPs were evoked by single graphics stimuli switching between black and white squares. We tested our system with the Emotiv Epoc, since it is much quicker to setup than traditional EEG systems, though the system can easily be adapted to work with those. The implementation was done using the Brainstream matlab toolbox, allowing a modular setup and exchangability (Severens, 2009).

Methods

Sokobrain

The system consists of three parts. One is designed for training the classifier, one for training the classifier and finally one for playing the actual game.

The interface of the system consists of two parts: the stimuli, which are positioned at the four sides of the screen, and the game itself, which is positioned in the center. This layout can be seen in fig. 1.

Stimuli For our system we use four different stimuli. Each of these stimuli alternates between drawing a black and a white square, each at a pre-defined frequency. The stimuli appear at the four sides of the screen, which code for the directions the player can move in: West, North, East, South. These flicker at frequencies of 15hz, 30 Hz, 10 Hz, and 6 Hz respectively. The locations and relative size of the stimuli can be observed in 1

Game The gamestate consists of a matrix of objects. There are five types of objects: empty spots, walls, boxes, players, and goal areas. The rules of the game are as follows: The player can only move to adjacent empty spaces or goal areas, with exception of boxes, which can be pushed by the player, by walking into them. Furthermore boxes can only be pushed onto other empty spaces or goal areas. Once all boxes are moved onto a goal area the game is won.

To investigate the usability of the system, a trivial puzzle was created, shown in Figure 1.

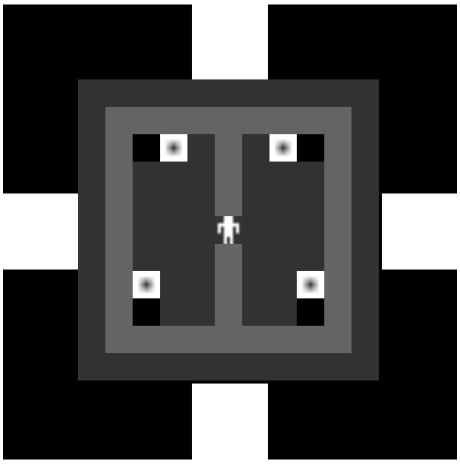

Figure 1: In-game screenshot of the online phase. Boxes are represented as white squares with a black circle in the middle. The goal of the game is to push the boxes to the black patches. The white squares on the edges of the screen are the flickering patches.

Training phase During the training phase only the stimuli are drawn on the screen. At the start of each trail a green target points out the stimulus that is to be attended to by the user. Subsequently each of the stimuli flicker at their frequencies for a fixed period. During this flickering data is obtained in 500 ms segments and labeled with the target class.

Online phase In the online phase, both the stimuli and the gamestate are shown on the screen. The stimuli flicker continuously and the user can simply attend to the stimulus that represents the direction the user intends to move in. Data is obtained from the EEG every 500 ms and and the gamestate is updated every 2 seconds, based on past classification results (see the online feedback generation section for details).

Data Analysis

As mentioned above, data is obtained from EEG every 500 ms. During the training phase this data is saved with the corresponding target label. Once the training phase is over a classifier is trained with this data. Prior to classification the data is pre-processed. For our data analysis we used a pre-existing pipeline. This pipeline is visualized in Figure 2 and is described in .

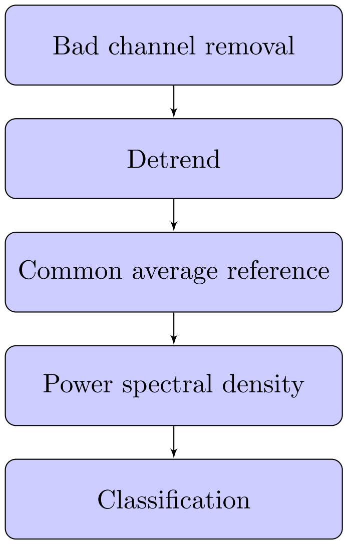

Figure 2: Pre-processing and classification pipeline. In this study, the bad channel detection and removal step was skipped.

Classification Pipeline First, bad channels are removed. A bad channel is a channel for which the total power deviates more than three standard deviations from the mean total power of all channels.

In the next step the data is detrended to remove the baseline drifting in electrodes, as well as the base power difference between electrodes.

After detrending, a spatial filter is applied to the data. This filter calculates the common average for all channels and substracts it from each of the individual channels. The signal that we are interested only shows up locally, while most background noise will show up in all electrodes. The common averaging method will remove this noise, by subtracting it from each of the channels, while the signal of interest remains in the appropriate channels.

The data is then converted to the spectral domain using the Welch's method, which averages the power spectral density over multiple windows (Welch, 1967).

Finally the data is classified. The classifier used is linear logistic regression classifier. Quadratic regularisation is used to avoid overfitting by penalising large weights.

Note: We did not use bad channel removal, due to the fact that we used the Emotiv. It has only 14 channels, which makes it much easier to ensure that all channels are working properly.

Online feedback generation The segments of EEG data that are recorded in the online phase are classified once they come in. The results from the classifier are saved in an array. Once four classification results have accumulated, the first result is rejected as it is likely that this contains an artefact caused by decision making processes or eye movements. The confidence values for each of the stimuli are summed over the last three results. The stimulus with the highest confidence is chosen, and if the difference in confidence with the second highest stimulus is larger than the threshold that is set, the gamestate is updated to incorporate a move in the corresponding direction. The threshold is used, because users do not necessarily want to make a move at every oppertunity, but also needs time to plan the coming moves.

Using this mechanism for feedback generation, means that moves can only be generated once every 2 seconds.

Bit rate The effectiveness of a BCI can be measured by measuring the amount of information can be communicated in a given time period.

There are multiple definitions of this bit-rate for BCI's in the literature(Kronegg, Voloshynovskiy, & Pun, 2005). A frequently used definition is that by Wolpaw(Wolpaw, Ramoser, McFarland, & Pfurtscheller, 1998).

$$R = \log_2 N + P \log_2 P + (1 - P) log_2 \frac{1 - P}{N - 1}$$

Where N is the number of classes and P is the probability of a intended class being classified correctly (in this study, the multiclass performance).

For this definition of the bit rate to be accurate several assumptions have to apply:

- The number of symbols recognised equals the number of symbols emitted by the user
- All the symbols have the same a priori probability
- The classifier accuracy is equal for all target symbols
- The classifier error is equally distributed over the non-target symbols

Not all of these assumptions match the system we developed. For example, as described in the previous section, the use of a threshold on the confidence means that there is not always a move generated for every 4 segmens of data. We did use the formula to calculate the bit-rate, but not as a measure of the effectiveness of our implementation of the game, but as an indication of the quality of our stimuli. This way our stimuli set up could be compared to other SSVEP BCI's.

Pilot

A small pilot study was performed for an initial assessment of the system. Two participants used the system, by training first and subsequently completing a trivial level of Sokoban. During the training phase each stimulus was attended 14 times (14 * 4 =56 trials). Each trial lasted 3 seconds, and consisted of 6 epochs of 500 ms.

Experiment

After the pilot, we set up an experiment to test our system. We designed a level specifically for this experiment to make sure it would be solvable in a reasonable amount of time. Furthermore, we made sure boxes could not easily be pushed into corners to decrease the chance of users getting stuck. The level can be seen in Figure 1.

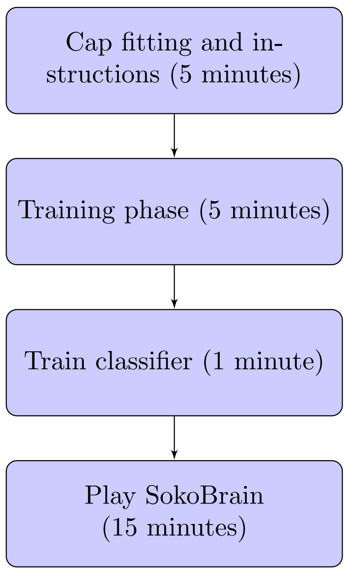

Figure 3: Experiment procedure

Procedure Five students (three had previous experience in EEG/BCI) participated in the experiment, which lasted 30 minutes. The general procedure can be seen in Figure 3.

The experiment started with a five minute preparation in which the cap was fitted on the participant. During this time the general idea behind system was also explained briefly. Finally the subject was positioned straight in front of the screen.

At this point the training phase was started. In this training phase each of the four stimuli were presented on the screen. At the start of each trial, a green tar-

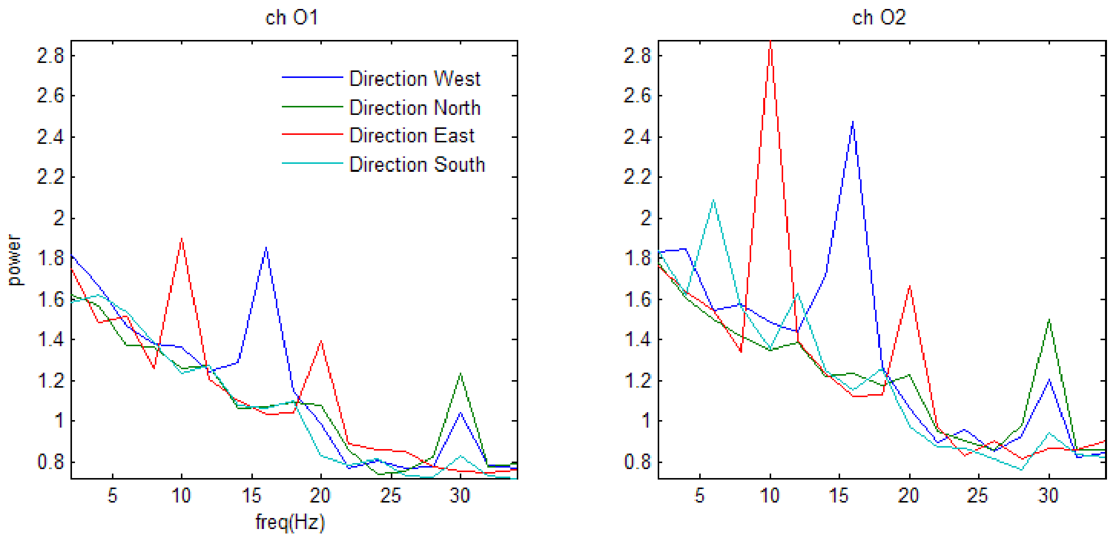

Figure 4: The pilot training data obtained from participant K. The O1 and O2 electrodes are located in the occipital area, with O1 on the left, and O2 on the right hemisphere. In the figure, in channel O2, the peaks at the different frequencies can strongly be observed. Harmonics can also clearly be seen for some of the frequencies (e.g. the 20 Hz harmonic for East (10 Hz)). For data of participants with lower performance, the different frequencies were also less distinguishable.

get pointed out the stimulus that was to be attended to by the participant. As in the pilot, each stimulus was attended 14 times. Each trial lasted 3 seconds, and consisted of 6 epochs of 500 ms.

After the training phase, the classifier was trained on the collected data.

With a trained classifier the online phase could be performed. In this last phase the participants were instructed to simply play the game. To move the player around they could attend to the stimulus that corresponded to the direction they desired to move in.

During the online phase, the time to task completion (TTTC) was measured, and any moves that could not be interpreted as advancement of the game were counted as errors. Recall that the level was created to be simple enough to count every error as a system error, and not as a user mistake.

Results

Results are reported for both the pilot and the experiment by means of their cross-validated confusion matrix on the training examples, which for all classes show how their predicted are distributed. The multiclass performance is then computed by avaraging the percentages of correctly classified examples (the diagonal in the confusion matrix).

Pilot study

Table 1 shows the performance obtained by the two participants during the pilot study. In both cases, enough control was achieved to complete a trivial puzzle. Figure 4 shows the power spectral density for participant K.

	Predicted Class (%)			
	West	North	East	South
West	74.44	6.67	1.11	12.22
North	5.56	74.44	1.11	13.33
East	1.11	6.67	77.78	8.89
South	5.56	15.56	5.56	66.67

Multiclass performance: 77.88%

(a) Participant K

	Predicted Class (%)			
	West	North	East	South
West	54.44	13.33	6.67	18.89
North	17.78	48.89	10.00	17.78
East	16.67	10.00	57.78	10.00
South	17.78	14.44	8.89	53.33

Multiclass performance: 56.93%

(b) Participant T

Table 1: Cross-validated confusion matrices and multiclass performances for both participants on the pilot experiment.

Experiment

Table 3 shows the usability results (errors and total time to task completion) for all participants. 3 out of 5 participants did not have enough control to complete the task, mostly due to one direction never getting correctly classified. The performance of all participants with the

	Predicted Class (%)			
	West	North	East	South
West	76.67	16.67	6.67	1.11
North	11.11	71.11	10.00	7.78
East	1.11	15.56	78.89	4.44
South	5.56	13.33	3.33	77.78

Multiclass performance: 75.90%

(a) Participant D

	Predicted Class (%)			
	West	North	East	South
West	75.56	6.67	2.22	15.56
North	14.44	66.67	4.44	14.44
East	4.44	4.44	74.44	16.67
South	14.44	7.78	5.56	73.33

Multiclass performance: 72.30%

(b) Participant K

	Predicted Class (%)			
	West	North	East	South
West	52.22	20.00	12.22	15.56
North	16.67	41.11	11.11	32.22
East	11.11	16.67	58.89	13.33
South	15.56	28.89	13.33	42.22

Multiclass performance: 48.48%

(c) Participant J

	Predicted Class (%)			
	West	North	East	South
West	38.89	23.33	15.56	22.22
North	14.44	51.11	14.44	20.00
East	22.22	20.00	50.00	7.78
South	24.44	20.00	8.89	47.78

Multiclass performance: 46.81%

(d) Participant T

	Predicted Class (%)			
	West	North	East	South
West	47.78	31.11	14.44	6.67
North	26.67	33.33	21.11	18.89
East	18.89	18.89	40.00	22.22
South	7.78	24.44	28.89	40.00

Multiclass performance: 40.17%

(e) Participant I

Table 2: Cross-validated Confusion matrices and multiclass performances for all participants on the experiment, note that K and T participated in the pilot as well. Every class consisted of 90 examples, yielding 360 examples per participant.

Participant	Completed goals	Errors	TTTC
K	4/4	16	3.36
D	4/4	20	4.54
J	1/4	-	-
T	0/4	-	-
I	0/4	-	-

Table 3: Usability results of the online phase for all five participants. The results are sorted by performance. A dash means that system performance was too low for this participant to complete the task. TTTC stands for total time to task completion, i.e. the time (in minutes) it took the user to push all the blocks on their adjacent goal areas. Errors were scored by the experimenter by counting the number of 'wrong moves'

corresponding confusion matrices are shown in Table 2.

The average multiclass performance over all participants is 56.73%.

The bitrate per minute was calculated for each of the participants. The mean bitrate was 46.91 with a standard deviation of 41.56. For comparison, other studies using the same on-off type of flicker stimuli reported bitrates in the range of 21 to 58 bits/min (Zhu et al., 2010).

Discussion

This project was undertaken to design a BCI for the Sokoban game and evaluate its usablity. The results of this study indicate a high inter-subject and inter-session variability in SSVEP-based BCI systems. Participants whose classification performance was high enough (larger than 50%) reported a sense of control, which was reflected in their task completion times and number of errors.

The high inter-subject variability is not uncommon to BCI's and SSVEPs and in several studies, so called "BCI illiterates" are excluded from analysis (Volosyak, Valbuena, Luth, Malechka, & Gräser, 2011). The high inter-subject variability is also the cause of the large standard deviation of the bit rate.

Our experiment results indicate that Sokobrain is currently only usable for users with a high training performance (50%+). The feedback generation currently takes multiple data segments (4) into account. It was designed this way to make sure that users with lower performance would not make too many errors. This seems to not have worked as intended, since it appears that only users with a high performance can generate enough 'momentum' to move, and users with lower classifier performance, simply have a harder time moving at all. This could also be an effect of the threshold, though it did not appear as if moving sooner would have improved this situation. As said, this set up does work for users that obtained a high training performance, but in that case it is perhaps not nessary to combine data from so many segments, which makes the BCI relatively slow.

The BCI could be made more usable for lower performance users, by creating better compensation mechanisms in the generation of feedback. For example, there are generally a lot of instances in Sokoban levels where a player can only move in a reduced number of directions. The directions that are not eligible for a move could be ignored, and thus reducing the number of classes that needs to be distinguished for that particular decision. Apart from ignoring these directions, stimulus locations could be dynamically switched, based on which frequencies can be easily distinguished between and allocating those to the directions the user can still move in.

Different stimulators could also be tried, as this study was restricted to the 60Hz monitor refresh rate to select the frequencies, where for example Light-emitting diodes allow for a wide range while evoking the same or stronger signals (Wu, Lai, Xia, Wu, & Yao, 2008). Research suggests that using higher frequencies (30+ Hz) is more comfortable for the user(Zhu et al., 2010). Higher frequencies also have the benefit that the length of an epoch can be shortened. A 30 Hz frequency will show complete its period 15 times in 500 ms, while a 6 Hz frequency only completes three times.

Another option is to use phase information: Jia, Gao, Hong, and Gao (2011) use phase coding in combination with frequency coding to be able to distinguish more classes. However, whether such methods work for the Emotiv and LCD screens has not been reported.

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