Implicit Learning of SSVEP-based Brain Computer Interface

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Abstract

Our study shows that subjects can implicitly learn to use a steady-state visually-evoked potential (SSVEP) based brain computer interface (BCI). The SSVEP stimuli were presented in an immersive star field virtual environment. Within the star field the SSVEP stimuli appeared in a pseudo random order. Participants' attention to the stimuli resulted in stars moving within the immersive space. Participants were asked to view four short clips of the scene and try to explain why the stars were moving, without being told that they are controlling a BCI. Two groups were tested: one that interacted implicitly with the interface, and a control group in which the interaction was a sham (i.e., the interface was activated independently of the participants' attention). Following the exposure to the immerisve scene the participants' BCI accuracy was tested, and the experiment group showed higher accuracy results. This finding may indicate that implicit SSVEP BCI interactions are sufficient in inducing a learning effect for the skill of operating a BCI.

1 Introduction

We demonstrate the possibility that BCI can be learned by implicit feedback reinforcement; i.e., without instructions, such as in many other tasks, including motor tasks. Moreover, the subjects in the present study were not even instructed that there was an opportunity to learn, but were led to believe that they are taking part in a passive experiment. The study is based on a generic system we have developed that allows turning any 3D object in a virtual environment into an SSVEP target with reliable flicker rates.

2 Method

2.1 Participants

Twenty one subjects took part in the experiment (10 males, 11 females) with a mean age of 24 (range 19-40). All subjects had normal or corrected-to-normal vision. They showed no signs of neurological or psychiatric disorders and all gave written, informed consent. Each subject was paid the equivalent of 12 Euro for participating in the experiment, and the study was approved by the institutional ethics committee.

2.2 Apparatus

EEG signals were recorded using 8 g.LADYbird sintered Ag/Cl crown active ring electrodes located on the subjects occipital lobe at pO7, PO3, POz, PO4, PO8, O1, Oz and O2 locations according to the international 10-20 system (Figure 1). A reference electrode was positioned on the subjects right ear lobe and a ground electrode was placed at Fpz location according to the international 10-20 system. EEG signals were recorded at 256 Hz sample rate and amplification and analog filtering (5-100 Hz) and notch filtering at 50Hz were performed using a g.USBamp amplifier (Guger Technologies, Schiedlberg, Austria).

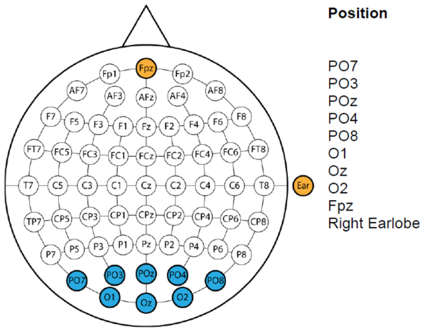

Figure 1: EEG electrode montage

We used a system developed in our lab for turning 3D objects in the Unity 3D game engine (Unity Technologies, USA) into SSVEP targets with reliable flicker rates. The flickering stimuli (at 8.57Hz, 12Hz, 15Hz, and 20Hz flickering rates) were projected on a 182cm (height) by 256cm (width) screen in a dark room that created an immerse virtual environment. Participants were asked to sit on an office arm chair positioned 180cm from the screen. The application was displayed using a 3D ViewSonic 120 screen refresh rate projector at 1280*768 resolution using a high-end graphics card. SSVEP classification was calculated using the algorithm by [1] analyzed using Matlab (MathWorks, US) and implemented by g.tec (Guger Technologies, Schiedlberg, Austria). A linear discriminant analysis (LDA) classification method with a zero class and a 1% confidence interval was applied and one harmonic frequency for each frequency was taken into account for classification.

2.3 Procedure and Data analysis

The experiment included three stages. In the first training stage the system computed a classifier model. The training sessions included 20 stimuli, 5 times of each frequency in pseudo-random order and location on the screen. The first stage might have been repeated until the first successful session, indicated by model fit of 90% accuracy or more to the training data. The second stage was the task stage, including 4 sessions of immerisve experience. The experience included a star field moving towards the subject, with a pseudo random collection of larger stars, which were the SSVEP targets. The instruction to all subjects was to attend to the stimuli and speculate about the reason that the stars were moving. Eleven subjects experienced the experimental group, in which they were only told about their BCI control after 3 of the 4 task trials. After 1 second of continous SSVEP classfication of an on screen star that star began moving towards the subject, possibly ‘exploding’ on screen if attention was kept to it long enough. Ten subjects participated in the sham control group, in which the motion of the stars in the first 3 trials was random. The third stage, a validation trial intended to determine BCI accuracy, was identical to the training trial.

Classification data was collected during each training session. For each frequency 5 trials each 7 seconds long were entered into the algorithm for classifier training, while comparing these 7 seconds with the 6 second trial interval rest periods for zero class classification. During the online classification of the signals at the second stage of the experiment, a 2-second running window buffer was used for classification. The algorithm produced a classification result 5 times per second (i.e., every 200ms). In order to decrease false positive classification errors a filter was applied to the stream of classification results; a total of 6 consecutive results were required of the same class in order to activate a game object (stars) command. This corresponds to one second of consistent classification. Since a running buffer of 2 seconds was also used, this entails that the minimum response time of the stars (game objects) was 3 seconds.

3 Results

The hypothesis that implicit reinforcement induces a learning effect was tested using the two groups accuracy results obtained at the validation stage using T-test analysis. First, optimal time point in terms of classification accuracy was obtained; this time point for all subjects was exactly 6 seconds post stimuli onset, and thus the accuracy per session in the following analysis was based on the accuracy between seconds 5 and 6. The experiment group achieved an average of 82.5% accuracy while the sham group achieved an average of 55.55%. The difference between the groups was found to be significant (t (19) = 2.23, $p < 0.05$; Figure 2).

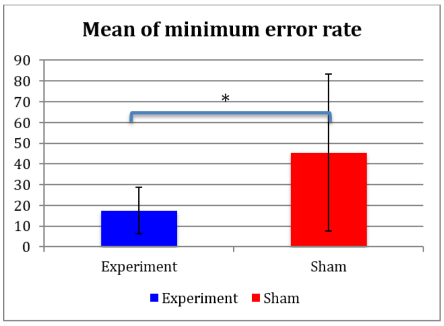

Figure 2: Minimum error rates between groups at optimal accuracy time stamp (5-6 seconds post stimuli onset).

In order to further confirm this finding an ANOVA with repeated measures analysis was used (Figure 3). The within variable considered was time, sampled once per second, the between variable was group, and the dependent variable was accuracy rate. A significant main effect was found for time (F (9,171) = 36.43, p <.001, partial eta = 0.66). A significant effect for group was not found (F (1, 19) = 1.05, n.s), but taking into account time a significant interaction was found (F (9,171) =.4.05, p < .05, partial eta =.17): after five seconds of stimulus presentation, the accuracy between the groups changed, and the sham group displayed lower accuracy rate past that time point, while the experiment group accuracy rates continued to rise. Note that in the first five seconds post stimuli the classification is approximately random. We do not know why the classification in the sham group was slightly higher in this early duration.The optimum performance in this study was around 6 seconds after the trigger, in contrary to 3-4 seconds as reported in most SSVEP studies; we suspect that the result is the combination of a 2 second buffer and a 1 second filter that we have applied. This, together with the minimal training, can also explain the realtively low accuracy rates. When comparing false positive results, a significant effect for time was also found (F (9,171) = 12.21, p < .05), but no significant effect was found between groups (F(1,19) = 0.91, p > .05 , n.s.), and no interaction was found

(F(2,171) = 1.88, p > .05, n.s). These results indicate significantly higher accuracy rate for the experiment group, but only in the duration when classification was not random.

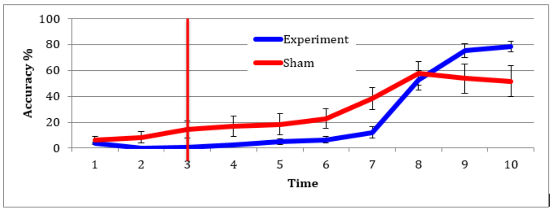

Figure 3: Linear comparison between the groups error rates; a significant interaction was found between time and group BCI accuracy (F (9,171) = 4.05, p < .05, partial eta =.17).

4 Discussion

The present findings support the hypothesis that the developed interface is easy to use and that its activation can be accomplished without prior knowledge. Moreover, it was found that implicit SSVEP BCI interactions are sufficient in inducing a learning effect for the skill of operating a BCI. Middendorf et al. [3] have shown that subjects can voluntarily learn to regulate their SSVEP amplitude by explicit training. Guger et al. [2] demonstrate that very short SSVEP training is often enough to reach high performance. In this study we show that an implicit reinforcement method can result in improved accuracy rates. This suggests the possibility that BCI control may be an acquired ability similar to motor abilities; this has both theoretic implications for understanding how BCI skills are acquired, as well as practical implications, e.g., for locked in patients who cannot learn to control a BCI that is based on explicit control startegies.

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