Eureka: Realizing That an Application is Responding to Your Brainwaves

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Abstract. We have conducted an experiment in which subjects controlled a brain-computer interface (BCI) without being aware that their brainwaves were responsible for events in the scenario. Ten subjects went through a stage of model training in steady state visually evoked potential (SSVEP)-based BCI, followed by three trials of an immersive experience where stars moved as a response to SSVEP classification. Only then the subjects were explained that they were using a BCI, and this was followed by an additional trial of immersive free choice BCI and a final validation stage. Three out of the ten subjects realized that they controlled the interface, and these subjects had better accuracy than the rest of the subjects and reported a higher sense of agency in a post study questionnaire.

Keywords: brain computer interface, steady state visually evoked potentials, electroencephalogram, agency.

1 Introduction

Brain-computer interface (BCI) has the potential to become the ultimate interaction paradigm, whereby user's intentions are automatically converted into actions. However, despite much progress in BCI in general and in SSVEP-based BCI specifically, the practice is very different. In order to achieve reasonable accuracy BCI users have to be very concentrated, avoid moving or blinking as much as possible, and often some period of training is required.

We have developed a system that naturally embeds electroencephalogram (EEG) steady state visually evoked potential (SSVEP) targets inside graphical scenes. Using our system any object in a 3D (or 2D) environment can be easily made into a BCI target, with the expectation of this leading to an improved user experience compared to most alternative paradigms. In this study we wanted to push the ease of use to its extreme and ask: would people be able to control an application using BCI without even being told that they are controlling the application? And if so, would people realize that they are affecting the application using their brainwaves?

We have conducted an experiment whereby ten subjects controlled a BCI without being instructed to control it. Our method uses the SSVEP paradigm, which is based on detecting occipital lobe activation that resonates with flickering visual stimuli.

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The subjects experienced an immersive presentation of deep space, including stars flickering with different frequencies, while connected to the BCI system. Whenever the online classification indicated that the subject "selected" one of the stars, the star started to move, thus providing feedback to the subjects. The goal was to find out whether subjects would realize that the application is responding to their brain activity, and how this would affect their BCI performance and their overall experience.

2 Related Work

We suggest a distinction among three types of BCI control: i) implicit – the interface responds to the user's brainwaves but the user is not aware of it, ii) volitional – the user makes an aware mental effort to control the interface, and iii) the control of the BCI has become an automatic process, so the user knows that he is using a BCI but does not necessarily need to dedicate attention to that control. There has been some studies shedding light on the possible transition from volitional to automatic control (e.g., see [1] for a relevant review), but a very small number of studies regarding the differences between implicit and voluntary BCI control.

Shenoy and Tan [2] suggest a paradigm they call human-aided computing that uses an EEG device to measure implicit cognitive processing, processing that users perform automatically and may not even be aware of. They report two experiments whereby subjects were exposed to images for as briefly as 150ms and the category of the image was classified with some degree of success from the EEG patterns. Zander et al. [3,4] suggest a subclass of BCI systems that they call passive BCIs, which provide "easily applicable and yet efficient interaction channels carrying information on covert aspects of user state, while adding little further usage cost"[4]. Our study reported here suggests that SSVEP may similarly be used as a passive BCI.

3 Method

3.1 System

Our generic platform allows easily turning any object in a virtual environment into an SSVEP flickering target. We use the Unity 3D game engine (Unity Technologies, USA). The stimuli were presented in an immersive virtual environment displayed on a back projected large screen ("power wall") 182cm (height) by 256cm (width). Participants were asked to sit on an office arm chair positioned 180cm from the screen. The application was displayed using a 120 screen refresh rate projector at a screen resolution of 1280*768 using a high-end graphics card.

EEG recording, signal processing and algorithm classification were conducted on a laptop that sent the classification results through a user datagram protocol (UDP) over the local network to the computer running Unity. SSVEP classification was calculated using a well-known algorithm [5]. We recorded EEG signals at pO7, PO3, POz, PO4, PO8, O1, Oz and O2 locations according to the international 10-20 system. Reference

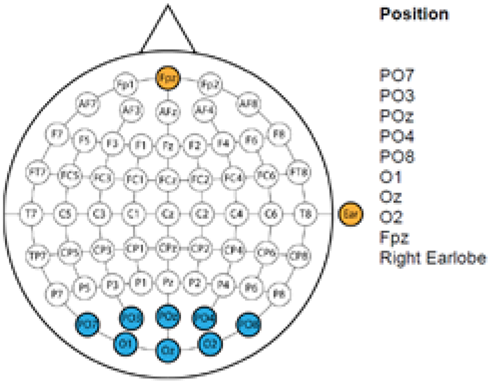


Fig. 1. Electrode locations on the scalp

electrode was positioned on the subject's left ear lobe and ground electrode was placed at Fpz location (Figure 1). EEG signals were recorded at 256Hz and amplification, analog filtering (5-100 Hz), and notch filtering at 50Hz were performed using the g.USBamp amplifier (Guger Technologies, Austria).

3.2 Experimental Protocol

Ten subjects participated in the experiment, aged 19-40, 8 females and 2 males. The experiment included three parts (Fig. 2): i) training, ii) free choice immersive BCI scenario, and iii) classification validation. Throughout the study we used five classes, four SSVEP frequencies: 8.57Hz, 12Hz, 15Hz, and 20Hz, and a null class.

Fig. 2. The experimental protocol included three stages

In the first part (training), the system computed a classifier of the EEG patterns elicited by the stimuli (stars) (Fig. 3). Each of the training sessions included 20 stimuli, 5 times each frequency in pseudo-random order and location on the screen. A red square appeared before each stimulus that the subject was expected to attend to.

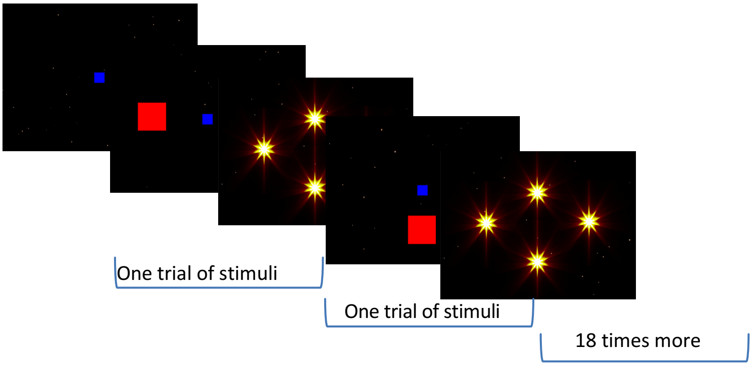


Fig. 3. The training stage claffication trial: before stimuli appearance a red square directs towards the location of the star that the participant needs to attend to in the following trial.

In the second stage (Fig. 4) the scene included an immersive experience of deep space with small stars moving towards the subject. Occasionally, larger stars would appear, all with the same texture, and each flickering at one of the four frequencies (there were up to four large stars simultaneously on the screen and never more than one with the same frequency). When an SSVEP response to a specific star has been detected in the participant's online signal, the star began moving towards the user. Each trial in this stage lasted 155 seconds of free choice BCI, and every participant went through four such trials.

In the first three trials the subjects were not told that the experience is responding to their brainwaves. After the first three trials and before the fourth trial the subjects filled in a questionnaire, and were then divulged about the nature of the interface and asked to do their best at moving the stars. The questionnaire included some demographic information as well as five questions on a 1-7 Likert scale that measured their sense of agency and control of the interface. For example, the participants were asked “Was the movement of the stars random? 1 (no) – 7 (yes) ___”. A reliability test yielded a α-cronbach of .651 that validates the similarity between questions so they could be used as a single control measure.

Fig. 4. The experience: a subject controlling the star field using the BCI

During the online classification of the signals at the second part of the experiment, a 2-second running window was used for data collection. The algorithm computed 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 (1 second) were required of the same class in order to activate a game object (star) command. Since we also used a sliding window of two seconds, the minimum possible response time of the stars (game objects) was 3 seconds.

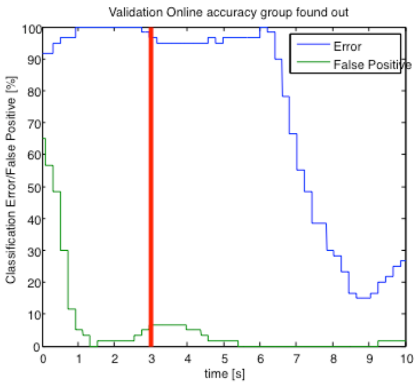
In the free choice task we cannot provide accuracy measurements since we do not know the subject's intentions. However, we can provide an approximated metric as follows. Whenever the classifier indicated a non-zero class we could test whether a star with that frequency was present on screen at that moment or not; if it did this is considered a hit and if it did not we consider it a false positive. For the hits we do not know whether the subject intended to select that specific star or not, but the results are nevertheless of interest. Because the SSVEP has a residue duration reflected in the SSVEP even after the star has disappeared from the screen, we have ignored false positives in the first 3 seconds following the disappearance of a star.

In order to validate model fit the experiment included a third stage of validation for all subjects, which was constructed similarly to the training trial described above.

4 Results

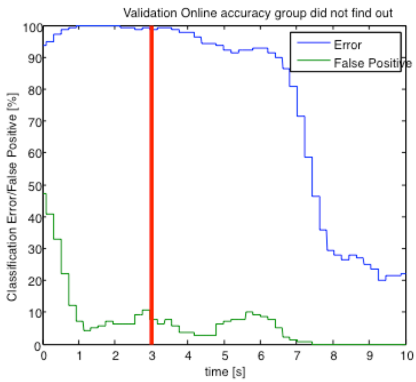
Three subjects out of 10 realized that they were controlling the application, and the rest did not. We will refer to the first group as the Eureka group and to the second group as the non-Eureka group. Due to the small number of subjects in both groups statistical tests did not always reveal significant results, but we can see some clear trends.

In the validation stage the number of false positive classifications of the Eureka group was significantly smaller than that of the non-Eureka group ($t = 3.6$, $p = 0.03$) and the overall accuracy was nearly significantly higher in the Eureka groups than in the non-Eureka group ($t = 1.83$, $p = 0.066$) (Figure 5).



a)

Fig. 5. Accuracy (number of errors and false positive classifications) over time, averaged over all subjects in group (a) Eureka and (b) non-Eureka



b)

Fig. 5. *(continued)*

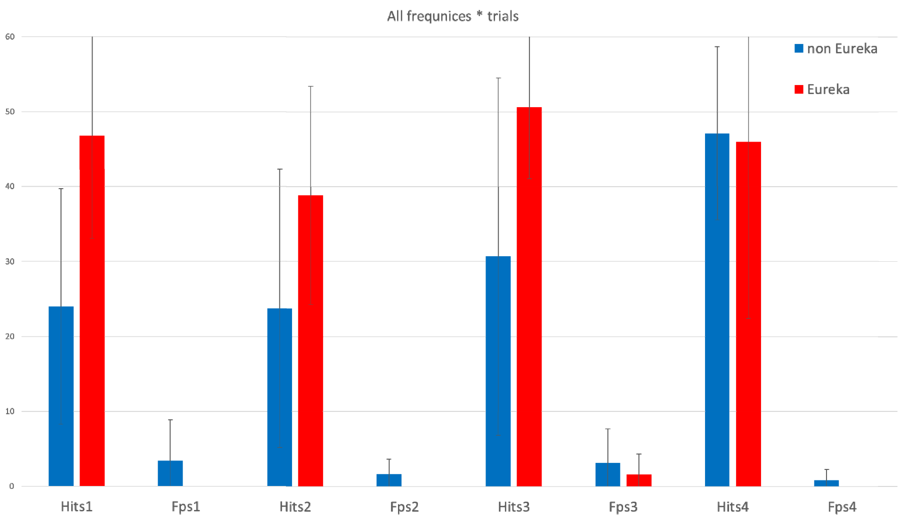


Fig. 6. A comparison between subjects who realized the task and those that did not, in terms of the number of hits and false positives of star classification in the free choice stage, over the four sessions

Figure 6 provides a comparison between the Eureka and non-Eureka groups in the four free choice sessions. We see that the number of false positives was always larger in the non-Eureka group than in the Eureka group; in the latter case there was only a small number of false positives in the third session. In addition, in the non-Eureka group the number of hits was smaller in the first three runs, when the subjects were not aware of their control, than the number of hits in the fourth run, after they have been notified about their control of the stars. In the Eureka group there was no such trend.

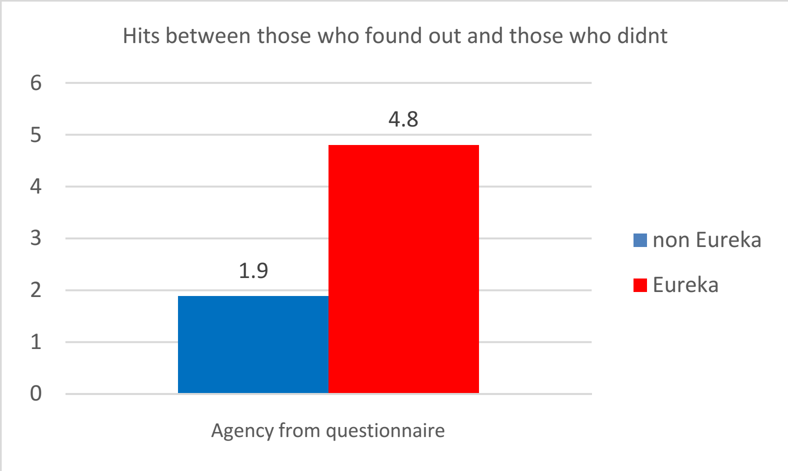


Fig. 7. Hits ratio between participants who found out they are controlling the interface (Eureka) and those who didn't (non eureka)

The subjects in the Eureka group reported a higher sense of agency (mean = 4.8) than in the non-Eureka group (mean = 1.9). Again the small number of the subjects prevents a statistical analysis but the difference seems substantial (Fig. 7).

5 Discussion

Our study shows that subjects can control an SSVEP BCI without being instructed at all. Only a small part (30%) of the subjects realized that the content of the display was responding to their brainwaves. Those subjects that did realize this were more successful in controlling the BCI and reported a significantly higher sense of agency.

Our study indicates that SSVEP, especially when embedded naturally inside 3D environments, can be used as a natural mode of interaction. Even those subjects that did not know that the content was responding to their brainwaves were able to perform the task much beyond chance levels.

Our hypothesis is that the relatively small number of subjects that realized that they were using a BCI is due to the high latency, of approximately 6 seconds between the appearance of the stimulus and the optimal point of classification. The neuroscience community assumes that a delay of 500 ms between stimulus and feedback already diminishes the sense of agency significantly (e.g.,[6]).

Finally, we see this early result as a trigger for two types of studies. First, we intend to further explore this paradigm and test whether implicit learning of such a BCI is possible. Second, we see this as an indication that SSVEP embedded naturally in the media is promising as a natural user interface, and hope to explore it in additional scenarios and experimental paradigms.

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