SSVEP Based Brain-Computer Interface Combined With Video for Robotic Control

C. Kapeller[1], C. Hintermüller[1], M. Abu-Alqumsan[2], R. Prückl[1], A. Peer[2], C. Guger[1]
[1]*Guger Technologies OG, Schiedlberg, Austria;* [2]*Technische Universität München, Munich, Germany*

Correspondence: C. Kapeller, Guger Technologies OG, Sierningstrasse 14, Schiedlberg, Austria. E-mail: kapeller@gtec.at

Abstract. Many BCIs rely on visual stimuli with constant stimulation cycles that elicit steady-state visual evoked potential (SSVEP) activity in the electroencephalogram (EEG). This study compared frequency-coded and code-modulated VEP methods in a new type of BCI that used streaming video to help control a robotic device.

Keywords: EEG, BCI, SSVEP, c-VEP, robot

1. Introduction

Most BCIs rely on one of three kinds of brain signals based on the EEG: event related desynchronization (ERD) associated with motor-imagery, event-related potentials and SSVEP [Wolpaw et al., 2002]. This work is focused on BCIs based on visual evoked potentials (VEP), which can be derived over the visual cortex during appropriate visual stimulation. Frequency coded systems use targets with different stimulation frequencies, where visual stimuli over 6 Hz lead to a phenomenon called steady-state VEP or SSVEP. This behavior can be used to extract features for target identification, for example with power spectral density analysis [Cheng and Gao, 1999]. An alternative type of stimulation is based on code sequences instead of constant periods and was presented in [Bin et al., 2011; Bin et al., 2009; Sutter, 1992]. In contrast to the c-VEP system in [Bin et al., 2011], we want to investigate, if the (i) frequency-coded (SSVEP or f-VEP) or the (ii) code-modulated approach (c-VEP) is more applicable for continuous control with on-screen stimulation to steer a robot in a telepresence application.

2. Material and Methods

The EEG was recorded with 256 Hz sampling frequency using a g.USBamp biosignal amplifier (g.tec medical engineering GmbH, Schiedlberg, Austria) from 8 active EEG electrodes placed on PO7, PO3, POz, PO4, PO8, O1, Oz and O2 position. The user sat in front of the computer screen including video feedback and overlaid BCI controls. The aim was to steer the robot through a given path, by using the video system and the BCI controls only. This video system was implemented by the Technische Universität München (TUM) and contains a software package to visualize the video stream coming from a camera.

The f-VEP BCI acquired data 0.5-60 Hz band-pass filtered and used a minimum energy (ME) method to determine a spatial filter that improves the signal-to-noise ratio (SNR). A Levinson AR model (order 7) estimated the SNR based on 2 s EEG data. The c-VEP BCI followed a template matching strategy that required a 3 minute training run to generate a reference signal or template. This template consisted of 200 averaged pseudo-random sequences visualized in the center of the screen. Data was 0.5-30 Hz band-pass filtered and then used within a canonical correlation analysis (CCA) to find a base that maximizes the correlation between the template and the target EEG. The resultant spatial filter was then used together with the templates for online classification. Both approaches used a linear discriminant analysis (LDA) for target identification, where the classification result was updated every 200 ms. A zero class provided an idle state that occurred when no target was selected by the user. This entails rejecting any classification result for which the residual error probability of the classification result was larger than 3 %, which was an empirical value.

Eleven subjects aged 27.36 ± 5.84 years participated, where each subject first performed a BCI training run to set up a subject specific weight vector. In the next run, the on-line accuracy of the BCI system was tested across 20 trials without moving the robot. One trial consisted of 3 s rest and 7 s of visual stimulation. Next, the subject had to steer the robot along a given track using the four BCI controls, presented as squares on the screen and enabled zero class. The entire track was 170 cm long and contained four 90° turns - two left and two right. Additionally a tracking system recorded the taken path of the robot during movement. Subjects having more than 2 standard deviations error from the average path were excluded, to provide valid results for movement duration comparison.

3. Results

The online accuracy test run showed that the maximum achievable accuracy without the zero class is 98.18% for the c-VEP BCI and 91.36% for the f-VEP BCI. For trial duration above 4 seconds, the mean accuracy is 94.51% for the c-VEP BCI and 84.18% for the f-VEP BCI, as shown in Fig. 1. If the zero class is enabled, the accuracy reduces about 20-30%, as the false positive selections decrease and the false negatives increase. Without zero class, the random accurcy of 25% was reached around 0 s. From -3 to 0 s the buffer from the previos trial got emptied.

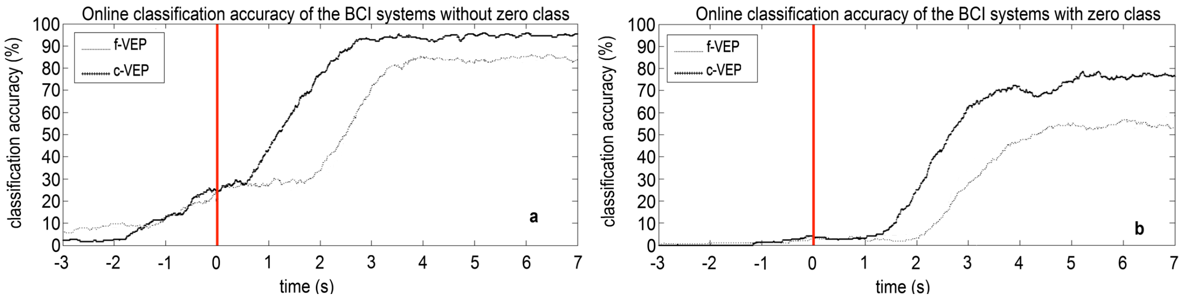

Figure 1. *Online accuracy test run. The vertical bar indicates the start of flickering within one trial. The f-VEP accuracy rises later, as it requires larger moving window filters.*

Table 1 shows the individual task completion time of the subjects to steer the robot through the track. The average duration was 240.45 s for the c-VEP BCI and 477.30 s for the f-VEP BCI.

Table 1. *Time to finish the route for every input method and each indiviual subject.Grey highlighted subjects had to be excluded, as they showed high deviations from the given track (corrected mean and std. are shown in paranthesis).*

Subject	*S1*	*S2*	*S3*	*S4*	*S5*	*S6*	*S7*	*S8*	*S9*	*S10*	*S11*	***Mean***	***Std.***
f-VEP (s)	170	187	426	252	312	183	-	1158	679	1256	150	**477.3 (573.4)**	**416.8 (466.0)**
c-VEP (s)	149	163	194	272	233	209	507	298	145	298	177	**240.4 (222.5)**	**104.6 (69.4)**

4. Discussion

We successfully validated two ways of a BCI based on VEP and showed that they could be used to continuously control a remote robot with high control accuracies. The c-VEP BCI showed higher performance and seemed to reflect a shorter latency, as the system takes less time to settle classification performance. The zero class allowed stopping the robot and suppressing randomized movement, including the side effect of increased latency. Also, the 2 s EEG buffer sizes affect latency and accuracy of the system. Therefore, the update rate of 200 ms does not guarantee a short reaction time. Aim of further research is to reduce latency of the system, while keeping high accuracy.

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