35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

A BCI using VEP for continuous control of a mobile robot*

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***Abstract*— A brain-computer interface (BCI) translates brain activity into commands to control devices or software. Common approaches are based on visual evoked potentials (VEP), extracted from the electroencephalogram (EEG) during visual stimulation. High information transfer rates (ITR) can be achieved using (i) steady-state VEP (SSVEP) or (ii) code-modulated VEP (c-VEP). This study investigates how applicable such systems are for continuous control of robotic devices and which method performs best. Eleven healthy subjects steered a robot along a track using four BCI controls on a computer screen in combination with feedback video of the movement. The average time to complete the tasks was (i) 573.43 s and (ii) 222.57 s. In a second non-continuous trial-based validation run the maximum achievable online classification accuracy over all subjects was (i) 91.36 % and (ii) 98.18 %. This results show that the c-VEP fits the needs of a continuous system better than the SSVEP implementation.**

I. Introduction

A BCI is a device that provides the user a communication channel that bypasses the neuromuscular output pathways [1]. People can use a BCI to interact with their environments even if they have limited or no muscle control. Various data acquisition techniques like electroencephalography (EEG) [1], electrocorticography (ECoG) [2], functional magnetic resonance imaging (fMRI) [3] and near infrared spectroscopy (NIRS) [4] can be used to build a BCI system. The EEG is the most common brain imaging method in BCI research because it is inexpensive, portable, non-invasive, and has excellent temporal resolution [5]. However, EEG has only a limited spatial resolution, as each channel is influenced by the activation of millions of neurons, and the signal is blurred and filtered during passage through the scalp.

Most BCIs rely on one of three kinds of brain signals: event related desynchronization (ERD) associated with motor-imagery, event-related potentials and steady-state visual evoked potentials (SSVEP) [1], [6].

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. In SSVEPs, the brain waves derived from the scalp contain enhanced spectral power density in the frequency range of the visual stimuli. This behavior can be used to extract features for target identification, for example with power spectral density analysis [8]. The presence of higher level harmonics may improve the classification accuracy of a BCI system [9], [10], but also decreases the number of frequencies available for visual stimulation [7], [11].

To facilitate a multichannel SSVEP based BCI system with enhanced classification accuracy and information transfer rate, Friman et al. introduced the minimum energy (ME) combination algorithm leading to an improved signal-to-noise ratio (SNR) between the target signals compared to the ongoing EEG [12]. Volosyak et al. used the ME within the Bremen BCI and reached a mean ITR of 61.70 bits/min and a mean accuracy of 96.79 % [13]. An alternative type of stimulation is based on code sequences instead of constant periods and was presented in [14], [15], [16] and [17]. In the paper presented by Bin et al., correlation coefficients between trained templates and the raw EEG were used for target identification [14]. Therefore the canonical vector calculated with a canonical correlation analysis (CCA) was used as a spatial filter to maximize the correlation coefficients. The authors developed a 32 target system with a sequence length of 1.05 s. The resulting mean online accuracy was 85 %, which led to an ITR of 108 bits/min.

In contrast to the c-VEP system in [14], 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 tele-presence application. We want to determine whether users can continuously control a BCI while receiving continuous feedback based on a display overlaid on a remote environment. We present mean and maximum online accuracies of the BCI system itself, as well as the time to direct a robot along a certain path through a video camera.

II. Methods

A. System Overview

The complete experimental setup is shown in Fig. 1. The user sits in a comfortable chair in front of the computer screen and the BCI controls and steers a robot along a given route. A computer screen provides video feedback of the robot's movement via a video camera overlaid the route. This video system was implemented by the Technische Universität München (TUM) and contains a software package to visualize the video stream (Video-Client and Video-Server) coming from a camera for image recording with 60 frames per second. In addition the system provides four BCI controls (a) "turn left", (b) "turn right", (c) "move forward" and (d) "move backward", which were presented within the video feedback on the computer screen. When the user looked at one of the controls, the BCI system (g.BCIsys) identified the target signal and sent the command to the e-puck robot

*Resrach supported by the European Union FP7 Integrated Project VERE (No. 257695).

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(GCtronic, Ticino, Switzerland) via Bluetooth connection [18].

Another video camera was recording the movement of the robot which was connected to the EthoVision tracking system (Noldus, Wageningen, Netherlands). This allowed reconstructing the path and gave an additional accuracy measure of the system.

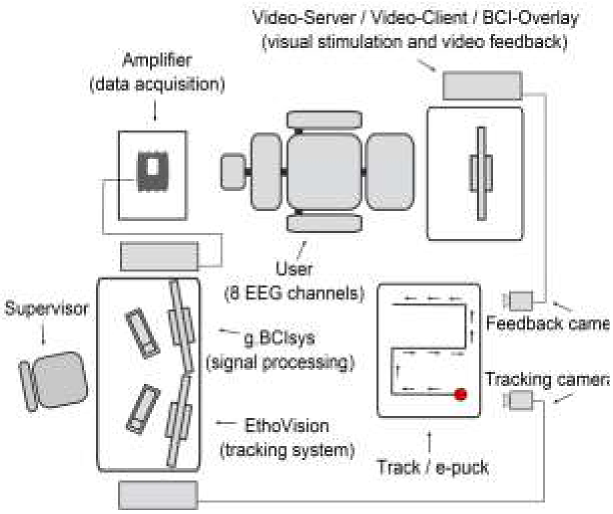

Figure 1. Experimental setup for robot control experiments.

B. Signal Recording

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 according to the international 10/20 electrode system as shown in Fig. 2. An active reference electrode was placed on the right ear lobe and a passive ground electrode was located on the forehead. A built-in 50 Hz Notch filter suppressed power-line interferences.

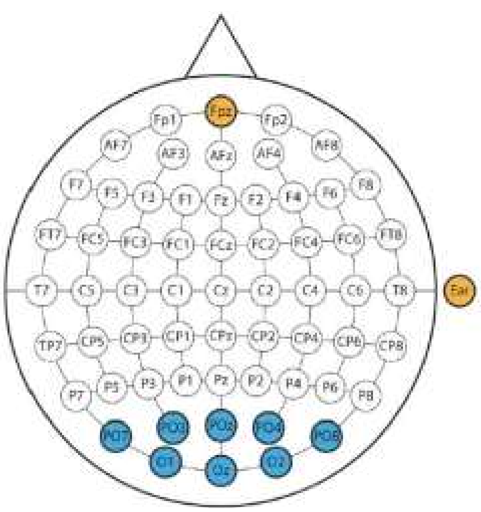

Figure 2. EEG montage to record VEPs.

C. Visual Stimulation

Fig. 4. shows the screen that was presented to the user during the experiment. For the on-screen stimulation in this work an OpenGL based runtime loadable module (BCI-Overlay) was implemented in C++. It allows OpenGL host applications like the used Video-Client to embed targets for visual stimulation into the visualized scene. Here, four white targets filling a rectangular area of 3.0°x2.3° visual angle and flickering with 300 cd/m² luminance were presented to the user.

In the frequency-coded f-VEP system, targets were flickering with a constant frequency of 8.57, 10, 12 and 15 Hz, respectively.

The code-modulated stimulation used 63bit pseudo-random m-sequences. These binary sequences are usually used for non-linear signal analysis and have an autocorrelation function, which is an approximation of the unit impulse function [17]. This is very important, since the used features of the c-VEP configuration are based on correlation coefficients of shifted versions of the same sequence.

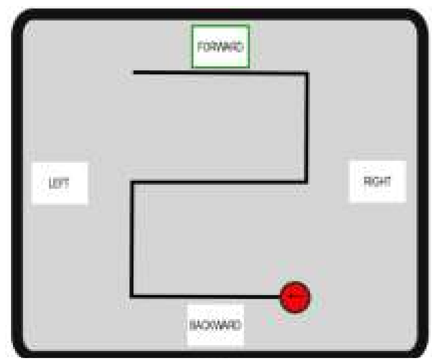

Figure 3. Interface for controlling the robot with the VEP-based BCI and video feedback of the track and the moving robot.

D. Frequency-Coded BCI (f-VEP)

Acquired EEG data was 0.5-60 Hz band-pass filtered and analyzed using a minimum energy (ME) approach to determine a spatial filter, which resulted in improved signal-to-noise ratio (SNR) between the target signal and the recorded EEG. A Levinson AR Model of order 7 estimated the SNR based on 2 s corresponding to 512 samples, every 200 ms. A multiclass linear discriminant analysis (LDA) is used to identify the target signals based on the SNR signals.

To enable real-time classification, an offline trained classifier was necessary. Therefore, a 15 min training run was necessary including 20 trials per class or 80 trials in total. One trial consisted of 3 s rest and 7 s of visual stimulation. The user's gaze was directed by a cue, which was presented as green border around the current target.

E. Code-Modulated BCI (c-VEP)

The c-VEP BCI followed a template matching strategy that required a 3 min training run to generate a reference signal or template. This template consisted of 200 averaged m-sequences visualized in the center of the screen. Data was 0.5-30 Hz band-pass filtered and then used within a 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.

During the online experiment, the user could choose between four targets that showed a phase shifted version of the reference sequence. The system computed correlation coefficients between recorded EEG and the possible phase shifted template versions every 200 ms, based on a 2.1 s (2 sequences) long signal buffer. Then, these correlation coefficients were used within a multiclass LDA, to find the currently selected target.

E. Zero Class

A zero class provided an idle state that occured when no target was selected by the user. Based on the LDA classification scores only, it was not possible to determine whether the user had selected any target. This entails rejecting any classification result for which the residual error probability was larger than a predefined limit. Thereby, a Softmax function transformed the output of the discrimination function into a corresponding probability that the chosen target was selected by the user.

F. Experimental Procedure

Eleven subjects aged 27.36 +/-5.84 years participated in all experiments (ten male and one female). All subjects were in good health, with normal or corrected to normal vision.

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 using a green border around the BCI controls as a visual cue to direct the users‘ gaze (the robot did not move). Next, the subject had to steer the robot along a given track using the four BCI controls and enabled zero class, to suppress arbitrary movement of the robot. A green border around the BCI controls was used as a visual feedback for the currently selected target. The entire track was 170 cm long and contained four 90° turns - two to the left and two to the right. The robot was moving with a speed of 2.5 cm/s. Each subject was told to move as accurately as possible along the track. Additionally, the subjects steered the robot using the keyboard, to see how fast and accurate persons can be with a conventional input device.

III. RESULTS

A. Online Accuracy Test

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, respectively. This results from the individual performance, where each subject shows a trial duration, for which the accuracy gets maximized. For non-specific trial duration, the mean accuracy is 94.51 % for the c-VEP BCI and 84.18 % for the f-VEP BCI, as shown in Fig. 4. If the zero class is enabled, the accuracy reduces about 20-30 %, as the number of false positive classifications decreases, where the false negative selections increase.

B. Robot Control

Table 1 shows the individual task completion time of the subjects to steer the robot through the track. The average duration to finish the track with the keyboard was 94.18 s. The average duration was 240.45 s for the c-VEP BCI and 477.30 s for the f-VEP BCI. However, as the grey highlighted subjects in Table 1 deviated more than 2 standard deviations from the overall mean track, we had to exclude them from the study to provide comparative data sets. Subject 7 was not able to finish the f-VEP run and had to be excluded too. The corrected mean duration through the track was 222.57 s for the c-VEP BCI and 573.43 s for the f-VEP BCI.

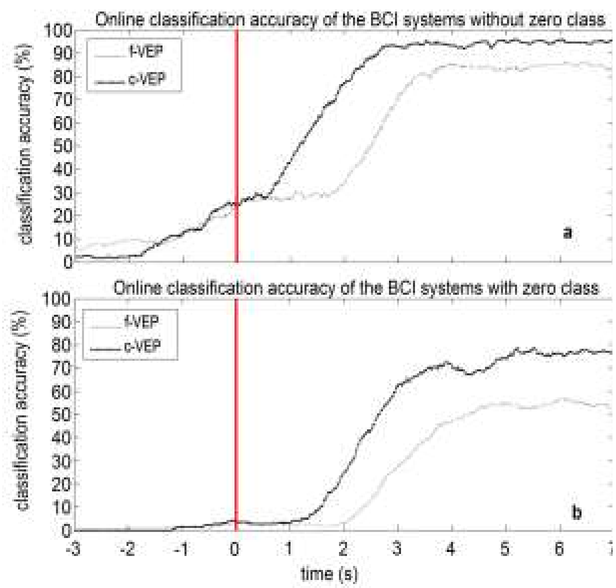

Figure 4. Online accuracy test run. The vertical bar indicates the start of flickering within one trial. The curves show the average online classification accuracy over 20 trials and all subjects.

TABLE I. ROBOT CONTROL. GREY HIGHLIGHTED RESULTS SHOWED MORE THAN 2 STANDARD DEVIATIONS DIFFERENCE COMPARED TO THE MEAN PATH.

Subject	Time of Movement		
	Keyboard	***f-VEP BCI***	***c-VEP BCI***
	Time (s)	***Time (s)***	***Time (s)***
1	93.00	170.00	149.00
2	92.00	187.00	163.00
3	97.00	426.00	194.00
4	91.00	252.00	272.00
5	100.00	312.00	233.00
6	96.00	183.00	209.00
7	99.00	-	507.00
8	91.00	1158.00	298.00
9	89.00	679.00	145.00
10	97.00	1256.00	298.00
11	91.00	150.00	177.00
mean	**94.18**	**477.30**	**240.45**
std-dev	3.56	395.42	99.71
corrected mean	**93.29**	**573.43**	**222.57**
corrected std-dev	3.57	431.36	64.26

IV. Conclusion

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 workable control accuracies. The c-VEP BCI outperformed the other BCI configuration across multiple dependent measures: average accuracy, maximum accuracy, and completion time.

The c-VEP BCI also seemed to reflect a shorter latency, as the system takes less time until classification performance settles (Fig. 4.). This is an important point, as the user has to anticipate the perfect timing to change direction. However, this is only possible, when the route is already known and nothing unexpected happens. Since the user will have to react in everyday life situations, the reaction time of the system has to be as short as possible.

The introduced zero class allowed the user to stop the robot and to suppress randomized movement, which is absolutely necessary to stay on track. The expected side effect was an increased latency.

The EEG buffer sizes affect the classification accuracy as well as the latency of the system. The update rate of 200 ms does not guarantee a short reaction time, as the features are based on at least 2 s signal buffers. Therefore the real update rate or latency highly depends on the used buffer. However, a shorter buffer decreases the accuracy of the BCI. In a previous study we presented a comparable classification accuracy of 95.5 % using the f-VEP system with 3 s buffer size, instead of 2 s and 91.36 % in this study [19]. Therefore, a tradeoff has to be found between accuracy and latency, which is quite more critical in a continuous system compared to speller devices.

Aim of further research is to improve the reaction time of the system, but keeping high classification accuracy.

Acknowledgment

The authors want to thank Thomas Schauß from the Institute of Automatic Control Engineering at the Technische Universität München for his assistance in implementing the video overlay.

References

[1] J.R. Wolpaw, N. Birbaumer, D.J. McFarland, G. Pfurtscheller, and T.M. Vaughan, "Brain-computer interfaces for communication and control," *Clinical neurophysiology : official journal of the International Federation of Clinical Neurophysiology*, vol. 113, (no. 6), pp. 767-91, Jun 2002.

[2] E.C. Leuthardt, G. Schalk, J.R. Wolpaw, J.G. Ojemann, and D.W. Moran, "A brain-computer interface using electrocorticographic signals in humans," *Journal of neural engineering*, vol. 1, (no. 2), pp. 63-71, Jun 2004.

[3] N. Weiskopf, K. Mathiak, S.W. Bock, F. Scharnowski, R. Veit, W. Grodd, R. Goebel, and N. Birbaumer, "Principles of a brain-computer interface (BCI) based on real-time functional magnetic resonance imaging (fMRI)," *Biomedical Engineering, IEEE Transactions on*, vol. 51, (no. 6), pp. 966-970, 2004.

[4] S. Coyle, T. Ward, C. Markham, and G. McDarby, "On the suitability of near-infrared (NIR) systems for next-generation brain-computer interfaces," *Physiological measurement*, vol. 25, (no. 4), pp. 815-822, Aug 2004.

[5] S.G. Mason, A. Bashashati, M. Fatourechi, K.F. Navarro, and G.E. Birch, "A comprehensive survey of brain interface technology designs," *Annals of biomedical engineering*, vol. 35, (no. 2), pp. 137-69, Feb 2007.

[6] J.R. Wolpaw and E.W. Wolpaw, "Something new under the sun," in Brain-Computer Interfaces: Principles and Practice: Oxford University Press,Inc., 2012, pp. 3-14.

[7] I. Volosyak, C. Guger, and A. Graser, "Toward BCI Wizard - best BCI approach for each user," *Conference proceedings : ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Conference*, vol. 2010, pp. 4201-4, 2010.

[8] M. Cheng and S. Gao, "An EEG-based cursor control system," in Proc. [Engineering in Medicine and Biology, 1999. 21st Annual Conf. and the 1999 Annual Fall Meeting of the Biomedical Engineering Soc.] BMES/EMBS Conference, 1999. Proceedings of the First Joint, 1999, pp. Pages.

[9] G.R. Müller-Putz, R. Scherer, C. Brauneis, and G. Pfurtscheller, "Steady-state visual evoked potential (SSVEP)-based communication: impact of harmonic frequency components," *Journal of neural engineering*, vol. 2, (no. 4), pp. 123-30, Dec 2005.

[10] C. Brunner, B.Z. Allison, D.J. Krusienski, V. Kaiser, G.R. Muller-Putz, G. Pfurtscheller, and C. Neuper, "Improved signal processing approaches in an offline simulation of a hybrid brain-computer interface," *Journal of neuroscience methods*, vol. 188, (no. 1), pp. 165-73, Apr 30 2010.

[11] I. Volosyak, H. Cecotti, and A. Graser, "Optimal visual stimuli on LCD screens for SSVEP based Brain-Computer Interfaces," *I Ieee Embs C Neur E*, pp. 440-443, 2009.

[12] O. Friman, I. Volosyak, and A. Graser, "Multiple channel detection of steady-state visual evoked potentials for brain-computer interfaces," *IEEE transactions on bio-medical engineering*, vol. 54, (no. 4), pp. 742-50, Apr 2007.

[13] I. Volosyak, "SSVEP-based Bremen-BCI interface--boosting information transfer rates," *Journal of neural engineering*, vol. 8, (no. 3), pp. 036020, Jun 2011.

[14] G. Bin, X. Gao, Y. Wang, Y. Li, B. Hong, and S. Gao, "A high-speed BCI based on code modulation VEP," *Journal of neural engineering*, vol. 8, (no. 2), pp. 025015, Apr 2011.

[15] G.Y. Bin, X.R. Gao, Y.J. Wang, B. Hong, and S.K. Gao, "VEP-Based Brain-Computer Interfaces: Time, Frequency, and Code Modulations," *Ieee Comput Intell M*, vol. 4, (no. 4), pp. 22-26, Nov 2009.

[16] E.E. Sutter, "The Brain Response Interface - Communication through Visually-Induced Electrical Brain Responses," *J Microcomput Appl*, vol. 15, (no. 1), pp. 31-45, Jan 1992.

[17] E.E. Sutter, "Imaging visual function with the multifocal m-sequence technique," *Vision research*, vol. 41, (no. 10-11), pp. 1241-1255, 2001.

[18] F. Mondada, M. Bonani, X. Raemy, J. Pugh, C. Cianci, A. Klaptocz, S. Magnenat, J.-C. Zufferey, D. Floreano, and A. Martinoli, "The e-puck, a Robot Designed for Education in Engineering.," in Proc. 9th Conference on Autonomous Robot Systems and Competition, 2009, pp. Pages.

[19] C. Guger, B.Z. Allison, B. Großwindhager, R. Prückl, C. Hintermüller, C. Kapeller, M. Bruckner, G. Krausz, G. Edlinger "How Many People Could Use an SSVEP BCI?" *Frontiers in neuroscience*. 2012; 6:169.