Implementation of a New Independent SSVEP-Based BCI

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Abstract. Brain–computer interfaces (BCI) employing steady-state visually evoked potential (SSVEP) modulations have been investigated increasingly in the last years because of their high signal-to-noise ratio and information transfer rate. However, independent SSVEP BCI based on covert attention show a drop in robustness which makes it difficult to use on patients with impaired or nonexistent ocular motor control. In the present paper, offline analysis is aimed at investigating the influence of feature extraction algorithms on the performance of covert SSVEP BCI. We have shown that the use of Thomson multitaper method or Lock-in Analyzer System with our new Checkerboard pattern and only the first harmonic yielded an average accuracy of approximately 79 % across nine subjects (with three subjects at more than 85 %) with 7 s window length. The short 6 or 7 s concentration time, the concise training, the robustness make this method very well suited for detecting command following and testing communication in non-communicating patients.

Keywords: EEG, SSVEP, covert attention, feature extraction.

1. Introduction

Current brain-computer interfaces (BCI) [Wolpaw et al., 2002] relying on steady-state visually evoked potentials (SSVEP), while demonstrating high information transfer rates and considerable robustness, depend on gaze control [Müller-Putz et al., 2005]. This rules out applicability to those whose severe disabilities extend to impaired or nonexistent ocular motor control. Independent SSVEP BCI based on covert attention have been proposed but have shown a drop in robustness. First covert SSVEP BCI were based on block pattern [Kelly et al., 2005]. While this approach works on healthy controls who can control their gaze, it is not suitable for patients without gaze control. They could unintentionally move their gaze on the wrong stimulation or move their gaze away of both patterns preventing detection of their wish. Other stimulation patterns take the advantage of the ability to covertly attend to one of two overlapping stimuli by presenting either mixed vertical and horizontal lines or moving dots. In [Lesenfants et al., 2011], we proposed a new covert "checkerboard" stimulation pattern which enables a better discrimination between two stimuli and compared its performance with lines pattern [Allison et al., 2008]. We showed that the new checkerboard pattern outperformed the lines pattern. We also demonstrated that the addition of second and third harmonics don't lead to significant accuracy increase in covert attention. In the following, we will study the influence of different feature extraction algorithms with this new pattern, 7 s stimulus duration and a single harmonic.

2. Material and Methods

Twelve healthy subjects (5 men; age range 22–43 years old, 28.3 ± 5.7) participated in the study. Subjects were seated 30 cm from self-constructed stimulation panel. The panel is a 7 by 7 cm "checkerboard" made of red and yellow 1 by 1 cm light emitting diode (LED) squares with a white fixation cross in the middle (Fig. 1). During the experiments, yellow and red squares were programmed to flicker at 10 and 14 Hz respectively. EEG signals were recorded at location P_3 , P_1 , P_2 , P_4 , PO_7 , PO_3 , PO_z , PO_4 , PO_8 , O_1 , O_z and O_2 , referenced to P_z . Ground electrode was placed behind the right mastoid. Amplifier used was a BrainVision V-Amp amplifier with a band pass filter between 0.01 and 100 Hz and a sampling frequency of 250 Hz. Each subject underwent a total of 6 runs, each lasting around 5 min. Each run contained 10 7 s trials separated by 23 s period (10 s of rest and 13 s of auditory instruction delivered via headphones). Checkerboard pattern was continuously flashing during a whole run. During a run, an equal number of both stimuli was presented in random order. The subject was instructed to fix his/her gaze on the white cross in the middle and to concentrate on one of the stimulus. EEG signals were preprocessed with a Butterworth fourth order low-pass filter with a cutoff frequency of 60 Hz and a Butterworth fourth order highpass filter with a



Figure 1: Electronic visual stimulation unit.

cutoff frequency of 5 Hz. An IIR Notch filter ($f_c = 50$ Hz, Q = 35) was also apply to the data. Frequency features were extracted from each trial with four feature extraction algorithms proposed in the literature: discrete-time Fourier transform (DFT), multitapers spectral analysis (PMTM), canonical correlation analysis (CCA) and lock-in analyzer system (LAS). Classification performance were computed with a linear discriminant analysis (LDA), and assessed with a 10×10 folds cross validation.

3. Results

The impact of the feature extraction algorithms was evaluated on nine out of twelve subjects. Subjects SC10 to 12 were rejected due to chance level classification. We concentrate on the four state of the art algorithms previously described. Averaged across these subjects produced maximum accuracy of 79.3 ± 9.7 % for PMTM, while the use of LAS produced a mean accuracy of 76.8 ± 9.1 %. Discrete-time Fourier transform and Canonical Correlation Analysis gave worst results for both case (59.3 ± 11.6 % for CCA, and 71.8 ± 9.9 % for DFT respectively).



Figure 2: Classification accuracy and standard deviation (in percent) for each subject obtained with Multitapers Spectral Analysis (PMTM), Lock-in Analyzer System (LAS), Discrete-time Fourier Transform (DFT) and Canonical Correlation Analysis (CCA).

4. Discussion and conclusion

We have demonstrated the feasibility of achieving significantly relevant accuracy with a novel independent BCI based on the brain mechanism of covert attention, by using SSVEPs elicited by a checkerboard pattern. This may encourage the reconsideration of VEPs as a viable option in BCIs that are truly independent of neuromuscular function [Wolpaw et al., 2002]. Subjects succeeded in reaching an average accuracy of 79.3 % with three subjects out of nine at more than 85%, which exceed accuracies of previous covert SSVEP-based BCI ([Allison et al., 2008; Zhang et al., 2010]) by at least 5 %. The short concentration time (6 s or 7 s), the absence of training, the robustness make this method very well suited for detecting command following and testing communication in non-communicating patients.

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