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Exploiting the temporal patterning of transient VEP signals: A statistical single-trial methodology with implications to brain–computer interfaces (BCIs)

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HIGHLIGHTS

- Single-trial TVEPs encode information about stimulus that can be robustly detected within a well-defined latency-range.
- The response is readily enhanced by means of an operator that forms a spatial difference.
- Attention modulates the TVEPs in a way that is decodable from the enhanced response by means of a Mahalanobis-Taguchi system.

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ABSTRACT

Background: When visual evoked potentials (VEPs) are deployed in brain–computer interfaces (BCIs), the emphasis is put on stimulus design. In the case of transient VEPs (TVEPs) brain responses are never treated individually, i.e. on a single-trial (ST) basis, due to their poor signal quality. Therefore their main characteristic, which is the emergence during early latencies, remains unexplored.
New method: Following a pattern-analytic methodology, we investigated the possibility of using single-trial TVEP responses to differentiate between the different spatial locations where a particular visual stimulus appeared and decide whether it was attended or unattended by the subject.
Results: Covert spatial attention modulates the temporal patterning of TVEPs in such a way that a brief ST-segment, from a single synthesized sensor, is sufficient for a Mahalanobis-Taguchi (MT) system to decode subject's intention.
Comparison with existing method(s): In contrast to previous VEP-based approaches, stimulus-related information and user's intention are being decoded from transient ST-signals via exploiting aspects of brain response in the temporal domain.
Conclusions: We demonstrated that in the TVEP signals there is sufficient discriminative information, coming in the form of a temporal code. We were able to introduce an efficient scheme that can fully exploit this information for the benefit of online classification. The measured performance brings high expectations for incorporating these ideas in BCI-control.

1. Introduction

BCI systems provide a novel communication mode, by predicting the user's thoughts and goals from recorded brain activity (Wolpaw et al., 2002; Graimann et al., 2010). While originally stemmed from clinical needs, there is nowadays a growing tendency to utilize them in applications that go beyond supporting physically impaired patients. *Gaming* (Pires et al., 2011b; Kaplan et al., 2013; Marshall et al., 2013) and interactions in multimedia-rich environments (Pohlmeyer et al., 2011; Uscumlic et al., 2013) are definitely among the most exciting fields of BCI applications.

Electroencephalography (EEG) remains by far the most popular approach to building BCI systems with reasonable reaction time. The existing EEG-based BCI designs rely on a variety of different EEG signal features, such as slow cortical potentials (Birbaumer et al.,

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2000), mu rhythms (Wolpaw et al., 1991), P300 potentials (Pires et al., 2011a; Fazel-Rezai et al., 2012) and visual evoked potentials (VEPs) (Bin et al., 2009).

VEPs are the brain's response to visual stimulation and they are considered indicators of the visual information processing in the occipital cortex. The associated BCIs are considered as "naive" communication modes, in contrast to the rest of systems that operate with signals reflecting thoughts and intentions. Steady-state VEPs (SSVEPs), generated by a high-speed blinking light, are conventionally employed (Kelly et al., 2005; Wang et al., 2006). Several visual targets are flickering at different frequencies (higher than 1 Hz) and the spectral analysis of the recorded signals results to a readout providing the identity of the target that the user is gazing at (Zhu et al., 2010; Hwang et al., 2012). Brain activity is modulated by the stimulus rate of the gazed target. As a modification of this approach, the time-modulated VEPs (t-VEPs) were introduced (Bin et al., 2009). In t-VEPs the encoding of target location lies in the particular temporal sequence of a series of flashed stimuli. On average, a stimulus rate below 4 Hz is employed and the decoding stage is based on time-locked signal averaging. Based on the sequence resulting in the stronger averaged response, the attended target is identified. Motivated by the need to alleviate the discomfort induced by the flickering stimuli when directly gazed in SSVEP-based BCIs, the authors of (Yoshimura and Itakura, 2008, 2009) introduced the use of transient VEPs (TVEPs) in a way that flickering stimuli do not coincide with the gazed target. A small-sized set of single trial responses (~20) is necessary for averaging (to restore the brain response) and performing the relevant peak measurements. This necessity arises due to the low signal-to-noise ratio (SNR) and drastically limits the information transfer rate of the overall BCI system.

In both (t-VEP and TVEP) BCI approaches the decoding starts with averaging multiple ST-responses; however, only in the former approach this step is unavoidable. TVEP-based BCI systems may benefit from signal-trial analysis so as to implement prediction of user's gaze target at faster rates (>1 Hz). Moreover, they might offer an enriched communication channel by incorporating covert spatial attention as additional encoding parameter. This particular hypothesis was motivated by recent studies in neuroscience, where the spatial selective attention has been shown to influence the early processing stages of transient visual responses (Poghosyan and Ioannides, 2008; Mishra et al., 2012).

Considering these premises and with our recently documented success of Mahalanobis-Taguchi (MT) strategy in enhancing brain response estimates (Liparas et al., 2013) as starting point, we attempted single-trial classification of TVEP signals, elicited by pattern stimuli (checkerboard), as a means to brain activity decoding. The data come from a previous study (Tzelepi et al., 2008), in which TVEPs had been incorporated in a virtual-reality paradigm in which the user (acting as a driver) had to avoid, by executing a saccade, the obstacles that had the form of approaching reversing checkerboards (see Fig. 1). The incorporation of pattern stimuli led to robust and consistent visual evoked responses.

Currently, exerting control in a BCI context is almost synonymous to classifying EEG responses (Lotte et al., 2007). Among the related literature, the technique of common spatial patterns (CSP) (Ramoser et al., 2000; Lotte and Guan, 2011) is the most popular, particularly in the case of motor imagery (Pfurtscheller and Neuper, 2001). The CSP algorithm aims, mainly, at spatial discrimination (Blankertz et al., 2008). Patterns of instantaneous multichannel activation are derived during an optimization step, which maximizes class-separability and weights appropriately the contribution of each EEG-sensor during the subsequent decision making. The spatial encoding of stimulus-related information has been recently studied (Tzovara et al., 2012) in a visual-stimulation setting. Finally, the stimulus encoding in the frequency domain has been exploited in SSVEPs-based BCI-design using variants of canonical correlation analysis (Lin et al., 2006; Zhang et al., 2013, 2014).

In the current work, we adopted a different viewpoint and utilized a methodology that exploits potentially discriminating information coming in the form of a temporal code. The motivation stemmed from the fact that transient evoked responses are often modeled as short-lasting, band-specific, signal patterns appearing in well known, topographically-defined locations. With this in mind, we introduced an approach that involves two stages. In the first stage (exploratory analysis for *feature selection*) we specified the channel and detected the optimal temporal window, during which two given types of visual responses (differing in the spatial location of visual stimulus) and two different mental states (attentive/passive viewing) were having the largest deviation from each other. In the second stage (*classification stage*) we extracted the selected features (consecutive signal values from the selected channel at the latencies of optimal temporal window) from all single trials and then we applied machine learning methodologies (including training and testing). The latter stage provided performance measurements that revealed the benefits of incorporating the principles of the particular experimental design and single-trial analysis methodology in BCI-control.

The rest of the paper is structured as follows. In Section 2, after a brief description of the data and their preprocessing, the necessary theoretical background for presenting the performed exploratory study and describing the suggested MT-system is provided. In Section 3, the results are presented analytically, including a systematic comparison with standard classification approaches. Finally, in Section 4 the implications of the study and the potentiality of a TVEP-based MT-system as a module in BCI are discussed.

2. Methods

2.1. Experimental data and preprocessing

The data used in this study had served for the design of a BCI system and did not correspond to an actual BCI implementation (recording during BCI gaming is not a well-controlled condition and data can be corrupted in many unpredictable ways).

We analyzed data recorded from 6 subjects (2 males). All volunteers had normal or corrected-to-normal vision, were seated in front of a visual display and performed the following task (see Fig. 1). A fixation cross appeared in the middle of the screen indicating the beginning of the trial (baseline period). Two seconds later, a checkerboard pattern appeared either on the left, or on the right, pseudo-randomly. Four seconds later, the central fixation cross went off and subjects had to make a saccade toward the opposite side of the checkerboard (antisaccade). A rest period of 5 s then followed before the beginning of the next trial. We further recorded each subject using the same stimuli but this time he/she was instructed not to perform the saccade and view passively the stimuli on the screen. In the manuscript we refer to the first as "attentive" condition, and to the second as "passive" condition. Furthermore, the time instant of pattern onset (i.e. the time-lag associated with the appearance of checkerboard stimulus) is denoted as 0-time. Before the actual EEG recording session, each participant underwent a training session during which a few stimuli were delivered to them and they had to either ignore them or respond by producing the corresponding antisaccade, according to the scenario of a passive or attentive recording condition, respectively. That preparatory session helped the subjects to get accustomed to the tasks and taught them how to exploit the rest period at the end of each trial for blinking.