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*P*300 brainwave extraction from EEG signals: An unsupervised approach

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ABSTRACT

The *P*300 is an endogenous event-related potential (ERP) that is naturally elicited by rare and significant stimuli, arisen from the frontal, temporal and occipital lobe of the brain, although is usually measured in the parietal lobe. *P*300 signals are increasingly used in brain-computer interfaces (BCI) because the users of ERP-based BCIs need no special training. In order to detect the *P*300 signal, most studies in the field have been focused on a supervised approach, dealing with over-fitting filters and the need for later validation. In this paper we start bridging this gap by modeling an unsupervised classifier of the *P*300 presence based on a weighted score. This is carried out through the use of matched filters that weight events that are likely to represent the *P*300 wave. The optimal weights are determined through a study of the data's features. The combination of different artifact cancelation methods and the *P*300 extraction techniques provides a marked, statistically significant, improvement in accuracy at the level of the top-performing algorithms for a supervised approach presented in the literature to date. This innovation brings a notable impact in ERP-based communicators, appointing to the development of a faster and more reliable BCI technology.

1. Introduction

Brain-Computer interfaces (BCI) measure specific (intentionally and unintentionally evoked) brain activity signals, translating them into particular information (Allison, Wolpaw, & Wolpaw, 2007; Dornhege, del R. Millán, Hinterberger, McFarland, & Müller, 2007). Many factors limit the performance of these systems, like the natural noise in the brain signals measured, the limitations of recording devices and the processing methods that extract signal features and translate them into information, among others (Cinel, Poli, & Citi, 2004). Furthermore, the physical and mental state of the subject greatly influences the quality of the recorded signal. Among all, the event-related potential (ERP)-based BCIs (Farwell, 1988) are of great interest because they use waveforms with a well-known morphology and the subject needs no particular training (Hong, Guo, Liu, Gao, & Gao, 2009) in order to extract them. Furthermore, at least in principle, based on this prior-knowledge a high bit rate can be achieved (Allison et al., 2008). ERPs are composed of a response due to the primary processing of the external stimulus, and a later response evoked by the reflection of higher cognitive processing induced by the stimulus, which is defined as an endogenous ERP (Epstein & Andriola, 1983). The *P*300 is an endogenous event-related potential (ERP) that is naturally elicited by rare and significant stimuli, arisen from the frontal, temporal and occipital lobe of the brain, although is usually measured in the parietal lobe (Polich, 2007). *P*300 is contained in the 0.15 – 5 Hz frequency range whose peak often appears between 300 ms and 600 ms after related events happen. The smaller the probability of related event is, the more prominent the *P*300 will be (Citi, Poli, & Cinel, 2010).

Traditionally, two approaches are admissible to deal with any detection problem, the supervised and the non-supervised approaches. In supervised learning the detection algorithm adjusts its parameters through a learning process based on a training dataset, that is, a set of input patterns with known outcomes. Some examples include ERP or epileptic seizure detection from the EEG signals (Cinel et al., 2004; Gao, Cai, Yang, Dang, & Zhang, 2016). Most studies have been focused on a supervised approach to the ERP detection problem (Cinel et al., 2004; Donchin, Spencer, & Wijesinghe, 2000; Lotte, Congedo, Lecuyer, & Lamarche, 2007), that aims to identify the presence of *P*300s by a training stage. This approach adapts to the statistical profile of a particular user's *P*300 in an incoming and unknown EEG generated by the same user. Thus, these methods impose the requirement of a previous training stage and the risk of obtaining an over-fitted algorithm.

On the other hand, the goal for unsupervised learning is to model the underlying structure or distribution in the data in

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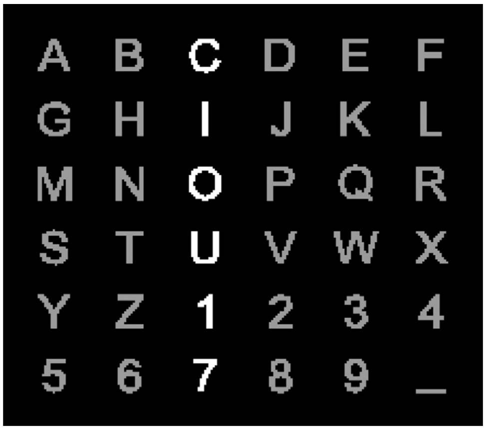

Fig. 1. Character matrix used in the Donchin Speller (Donchin, 1981).

order to extract relevant information. In EEG processing, prior-knowledge of the processes involved in the data generation can be very useful to determine an effective time series model. In the aim of addressing the need of further data optimization and removing the hazard of over-fitted parameters during the design, we present a novel approach that avoids the traditional supervised model by looking for specific features in the data, instead of similar features previously found in a training stage. In this paper we theoretically model and design an algorithm that processes the raw signal and extracts the $P300$ features through a matched filter (Borjesson, Pahlm, & Sornmo, 1892). The structure of the algorithm is shown in Fig. 2. This well-known methodology constitutes an important building block in many detection schemes as a part of the field of time series analysis (Gao et al., 2015; Sörnmo & Laguna, 2005). In addition, an artifact-free signal is required to be obtained in order to avoid type I&II errors in the classifier decision. Therefore, an automatic artifact cancelation stage is designed and implemented as a preprocessing step. By achieving the overall system allows us to substantially reduce the computational load, as well as to discard noisy data recordings in the training stage, instead of those relevant for stimulus detection (Lotte et al., 2007). An unsupervised $P300$ detection algorithm is a significant step forward, easing its implementation in different fields such as BCI spellers for locked-in syndrome patients or ERP-based polygraphs (Fazel-Rezai et al., 2012; Pfister & Foerster, 2014) among many others (Farwell, 1995). In fact, $P300$-based Guilty-Knowledge Tests are already been suggested as an alternative approach for conventional polygraphy (Abootalebi, Moradi, & Khalilzadeh, 2009; Farwell & Donchin, 1991), grounded in feature extraction algorithms (Wang, Chang, & Zhang, 2016).

1.1. Materials

To evaluate the proposed method, data from a Donchin ERP-based speller is investigated (Donchin, 1981; Donchin et al., 2000). In this speller, users are presented with a 6 by 6 character matrix whose rows and columns are randomly highlighted without replacement for a short period (0.1 s) and one at a time. Users focus their attention on the character they want to input, having the flash of the row and column containing the desired character as target stimuli (see Fig. 1). This task is performed approximately 20 times for every single letter, subjects are required to count how many times their desired character flashed. Each of the 12 subjects of this study spells 20 letters. During the recordings, subjects were seated with the neck supported by a C-shaped pillow to minimize muscular artifacts as shown in Goldberger et al. (2000). The eyes were at approximately 80 cm form a 22-inch LCD screen with 60Hz refresh rate. The 12 participants had their brain and ocular activity recorded through a BioSemi ActiveTwo EEG system (Citi et al., 2010), with 64 electroencephalography (EEG) electrodes that are located in standardized positions following the 10–20 International System. Furthermore, 4 electrooculography (EOG) electrodes, positioned in vertical and horizontal pairs around the eyes, are also placed, as well as one last pair in the earlobes for referencing.

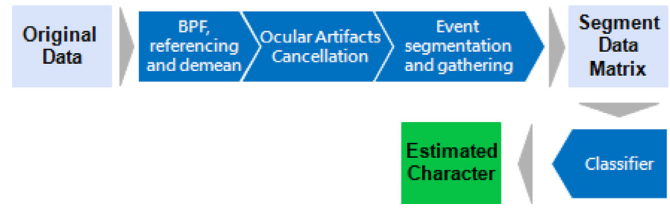

Fig. 2. General structure of the algorithm.

2. Data preprocessing

Before applying the classification algorithm some preprocessing is performed including noise-artifact removal, filtering, segmentation and feature extraction in terms of relevant feature vectors for ERP detection.

2.1. Band-Pass Filtering, referencing and demean

Band-Pass Filtering is applied to remove most of the undesired frequency components contained in the signal (Rakotomanonjy & Guige, 2008) that was sampled at $F_s = 2048$ Hz. A FIR Band-Pass Filter with $N = 1800$ coefficients and pass band frequencies at 0.15 Hz and 5 Hz is applied, keeping a trade-off between the transition band and delay, as suggested in Ghaderi, Kim, and Kirchner (2014). This filtering process reduces the power line interference (50 Hz), most of the background white noise and several artifacts, such as the muscular artifact (50–100 Hz) and the one created by the reaction of the sweat at the electrodes surface ($>$ 0.4 Hz) (Sörnmo & Laguna, 2005).

However, there are some noisy signals that are not possible to be removed with filtering, because their frequency spectrum overlaps the one of the $P300$. These signals are the ocular artifacts, composed by eye movements and blinks. We use the 4 EOG electrodes to collect data from these artifacts in order to cancel them in a further stage of preprocessing (Fortgens & Bruin, 1983). In order to enhance the SNR in the blinks, we subtract the mean of the EOG signals and then subtract one of the vertical EOG channels from the other. Furthermore, by adding the horizontal EOG channel, we obtain a channel with an improved eye movement signal. Finally, the addition of both new signals conform a high-SNR signal of the ocular artifacts that are used to perform an efficient blink cancelation.

2.2. Artifact cancelation

Artifact cancelation is a key task to be performed to obtain artifact-free data composed of only brain activity sources (Barlow, 1986). The effect can be observed in Fig. 3. An automatic artifact cancelation method is applied to each one of the 64 EEG channels separately. It is worth mentioning that the purpose of our artifact cancelation stage is not suited to cancel the saccadic spike potential (SP) because their shape does not resemble the $P300$ waveform, thus their presence will not contaminate the results. In addition, the SP artifact is specially present in the frontal and temporal lobe (Keren, Yuval-Greenberg, & Deouell, 2010) and not in the parietal lobe, where our main analysis were performed.