

## Time-locked and phase-locked features of P300 event-related potentials (ERPs) for brain–computer interface speller

Dong Ming<sup>a,b</sup>, Xingwei An<sup>a</sup>, Youyuan Xi<sup>a</sup>, Yong Hu<sup>b,\*</sup>, Baikun Wan<sup>a</sup>, Hongzhi Qi<sup>a</sup>, Longlong Cheng<sup>a</sup>, Zhaojun Xue<sup>a</sup>

<sup>a</sup> Department of Biomedical Engineering, College of Precision Instruments and Optoelectronics Engineering, Tianjin University, Tianjin, PR China

<sup>b</sup> Department of Orthopaedics and Traumatology, Li Ka Shing Faculty of Medicine, University of Hong Kong, Hong Kong, China

### ARTICLE INFO

#### Article history:

Received 30 August 2009

Received in revised form 26 July 2010

Accepted 2 August 2010

Available online 26 August 2010

#### Keywords:

Brain–computer interface

Evoked response potentials

Phase reset

Event-related spectral perturbation

Inter-trial coherence

### ABSTRACT

The brain–computer interface P300 speller is aimed to help those patients unable to activate muscles to spell words by utilizing their brain activity. However, a problem associated with the use of this brain–computer interface paradigm is the generation mechanics of P300 related to responses to visual stimuli. Herein, we investigated the event-related potential (ERP) response for the P300-based brain–computer interface speller. A signal preprocessing method integrated coherent average, principal component analysis (PCA) and independent component analysis (ICA) to reduce the dimensions and noise in the raw data. The time–frequency analysis was based on wavelet and two characteristic parameters of event-related spectral perturbation (ERSP) and inter-trial coherence (ITC) were computed to indicate the evoked response (time-locked) and phase reset (phase-locked) activity, respectively. Results demonstrated that the proposed method was valid for the time-locked and phase-locked feature extraction and both the evoked response and phase reset contributed to the genesis of the P300 signal. These electrophysiological responses characteristics of ERPs would be used for BCI P300 speller design and its signal processing strategies.

© 2010 Elsevier Ltd. All rights reserved.

### 1. Introduction

A brain–computer interface (BCI) provides alternative communication and control channels to convey messages and commands from the brain to the external world [1], especially for those patients with severe neurological or muscular diseases. At present, electroencephalogram (EEG) is the major brainwave signal used by non-invasive BCIs. One strategy of EEG-based BCI involves the use of event related potential (ERP) that exploits the electrophysiological responses to a certain event.

The most robust feature of the ERP is a positive displacement occurring around 300 ms after stimulus, termed the P300 or P3 [2]. The P300 was first utilized in BCI as a speller [3]. A major technical problem in the P300-based BCI speller is the robustness of the classification of the response from background noise to improve the BCI system performance. Furthermore, it remains controversial whether ERPs are generated by evoked response or by phase reset with the outward stimulus [4]. ERP is traditionally considered to reflect transient, fixed latency, and fixed polarity evoked responses to a stimulus [5–8]. In other words, the ERP has a time-

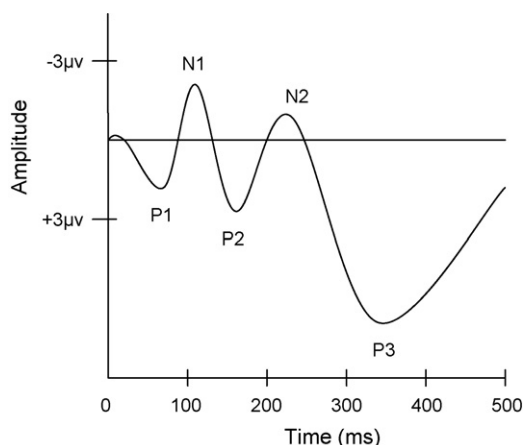
locked relation with stimulation. Another competing view suggests that at least part of the ERP is generated by a reorganization of ongoing oscillations in the EEG; i.e., a portion of ongoing EEG to a phase-locked relationship with stimulation. Non-additive processes typical for a phase reset were recently shown to be involved in the generation of the ERP [9], with the conclusion that phase resetting existed in the human EEG, while phase concentration or phase locking was observed in the alpha range EEG [10].

Importantly, many of arguments used to test the prediction of the evoked and phase reset model have been argued for predictive validation [11]. For example, a predictor of the phase reset model is empirical evidence for phase concentration in the absence of a power increase. While a reset of phase will not lead to a power change, the superposition of an evoked response on background EEG activity must lead to a power change. It was also suggested that both phase and amplitude dynamics should be considered, as both the evoked activity and phase reset of ongoing EEG activity contribute substantially to the different auditory Go and NoGo ERP components [12]. In this previous study [12], phase locking mainly contributed to the exogenous ERP components, while evoked activity related to the cognitive processing mainly contributed to the endogenous ERP components.

The aim of the present study was to investigate both the evoked response (termed time-locked) and phase reset (termed phase-locked) activities that contribute to the genesis of the P300 signal

\* Corresponding author at: Duchess of Kent Children's Hospital, The University of Hong Kong, Hong Kong, China. Tel.: +852 2817 7111; fax: +852 2855 0684.

E-mail address: [yhud@hkusua.hku.hk](mailto:yhud@hkusua.hku.hk) (Y. Hu).



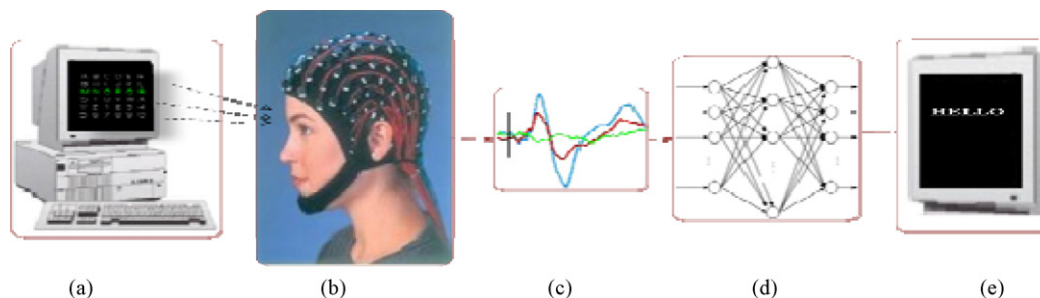
**Fig. 1.** Main components of event-related potentials, including exogenous components and endogenous components. The P1, N1, P2, N2, and P3 (also termed P300) are the main components.

in brain–computer interface speller. Two characteristic parameters of event-related spectral perturbation (ERSP) and inter-trial coherence (ITC) around 300 ms of the signal were applied to indicate the evoked response and phase reset activity, respectively.

## 2. Materials and methods

ERP waveform consists of a sequence of positive and negative voltage deflections [13], labeled as P1, N1, P2, N2, and P3 (also termed P300) as shown in Fig. 1. The initial peak (P1) is an obligatory sensory response that is elicited by visual stimuli without cognitive processes. The P1 wave is strongly influenced by stimulus parameters such as luminance. The early sensory responses are called exogenous components to indicate their dependence on external rather than internal factors. By contrast, the P300 wave depends entirely on the task performed by the subject, and is not directly influenced by the physical properties of the eliciting stimulus. The P300 wave is therefore termed an endogenous component to indicate its dependence on internal rather than external factors.

P300 as a constituent of the ERP is considered a potential BCI control signal [14]. P300 is a positive EEG deflection that occurs during 200–700 ms (typically 300 ms) after stimulus onset, and is typically recorded over the central-parietal scalp [15]. The response is evoked by attention to rare stimuli in a random series of stimulus events (i.e., the oddball paradigm). P300 was used in the BCI P300 speller system because it appears to be closely associated with the cognitive processes. The system consists of stimulus, data acquisition, feature extraction, pattern recognition, and result display (Fig. 2). This study focuses on the feature extraction part.



**Fig. 2.** Major components of the system. These components include (a) the stimulus, where the subject responds to different stimulus in their EEG, (b) data acquisition, (c) data processing for extraction of the features of the signals, and (d) pattern recognition. The results are then displayed on a monitor.

### 2.1. Stimuli and data acquisition

We used the EEG dataset from Dataset IIb (P300 speller paradigm) obtained from the BCI Competition 2003 data bank [16]. The signals (band-pass filtered from 0.1 to 60 Hz and digitized at 240 Hz) of 64 channels according to the standard electrode position nomenclature of American electroencephalographic society were collected from the subject in three sessions [16]. The first two sessions are used to train the classifier. And the third session is used as the test session. In this study, we only use the first two sessions to extract the P300 feature. Each session consisted of a number of runs. In each run, the subject focused attention on a series of characters. And, totally there are 42 characters to be focused on.

For each character epoch, user display was as follows: the matrix was displayed for a 2.5-s period, and during this time each character had the same intensity (i.e., the matrix was blank). Subsequently, each row and column in the matrix was randomly intensified for 100 ms (i.e., resulting in 12 different stimuli of six rows and six columns (Fig. 3)). After intensification of a row/column, the matrix was blank for 75 ms. Row/column intensifications were block randomized in blocks of 12. The sets of 12 intensifications were repeated 15 times for each character epoch (i.e., any specific row/column was intensified 15 times, resulting in 180 total intensifications for each character epoch). Each character epoch was followed by a 2.5-s period during which time the matrix was blank. This period informed the user that this character was completed and to focus on the next character in the word that was displayed on the top of the screen (the current character was shown in parentheses).

We analyze the signals acquired from the stimulation to 1 s after. For each character, it contains 15 blocks. And each block contains 12 trials (i.e. the stimulation of 6 rows and 6 columns). The sample rate is 240 Hz with 64 channels. So for each character, a  $64 \times 180 \times 240$  matrix (64 channels  $\times$  15 blocks  $\times$  12 trials  $\times$  240 Hz) will be generated.

### 2.2. Data preprocessing and feature extraction

This process can be separated into two parts: preprocessing and feature extraction. For preprocessing, the coherence average, principal component analysis (PCA), and independent component analysis (ICA) were used to reduce dimensions and improve signal to noise ratio (SNR). The time–frequency features were then extracted and analyzed.

#### 2.2.1. Data preprocessing

It would be difficult to identify the P300 in a single trial without pre-processing. In this study, a Butterworth filter was used as the low-pass filter with a cut-off frequency of 30 Hz. The signals were then processed using coherence average, PCA and ICA by the analysis tool EEGLAB 5.02 (<http://sccn.ucsd.edu/eeglab/>).

Download English Version:

<https://daneshyari.com/en/article/558226>

Download Persian Version:

<https://daneshyari.com/article/558226>

[Daneshyari.com](https://daneshyari.com)