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# A P300-SPELLER BASED ON EVENT-RELATED SPECTRAL PERTURBATION (ERSP)

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## ABSTRACT

A brain–computer interface (BCI) P300 speller is a novel technique that helps people spell words using the electroencephalography (EEG) without the involvement of muscle activities. However, only time domain ERP features (P300) are used for controlling of the BCI speller. In this paper, we investigated the time-frequency EEG features for the P300-based brain–computer interface speller. A signal preprocessing method integrated ensemble average, principal component analysis, and independent component analysis to remove noise and artifacts in the EEG data. A time-frequency analysis based on wavelet transform was carried out to extract event-related spectral perturbation (ERSP) and inter-trial coherence (ITC) features. Results showed that the proposed signal processing method can effectively extract EEG time-frequency features in the P300 speller, suggesting that ERSP and ITC may be useful for improving the performance of BCI P300 speller.

***Index Terms*****—** Brain-computer interface, event-related potentials, event-related spectral perturbation; inter-trial coherence, P300

## 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], with the aim of assisting, augmenting, or repairing human cognitive or sensory-motor functions, especially for those patients with severe neurological or muscular diseases. At present, electroencephalogram (EEG) is the major type of brain signal used for non-invasive BCIs. One strategy of EEG-based BCI involves the use of event related potential (ERP) that exploits the brain responses to a certain event.

The most robust feature of the ERP is a positive displacement occurring around 300 ms after infrequent stimuli, termed the P300 [2]. More precisely, a P300 response is a positive EEG defection that occurs during 200~700 ms (typically 300 ms) after stimulus onset, and is typically recorded over the central-parietal scalp. The response is evoked by attention to rare stimuli in a random series of stimulus events (i.e., the oddball paradigm). The P300 is used in the BCI P300 speller system as it appears to be closely associated with the cognitive processes [3-5]. To date, the P300 features (such as its peak latency and amplitude) have been widely utilized for designing a BCI speller [3-5].

Recently, more and more evidences have shown that, infrequent stimuli induce not only time-locked and phase-locked P300 response, but also several time-locked but non-phased locked EEG oscillatory responses, like event-related spectral perturbation (ERSP) and inter-trial coherence (ITC) [6,7]. The ERSP reflects the influence of the stimulation on the power spectrum, and can prove the evoked response theory [8]. The ITC provides a measure of phase locking (with a range of 0-1 covering from no coupling to complete phase locking) [8]. These ERSP and ITC features exhibit certain patterns in the time-frequency domain and contain relevant and complementary information with P300, and might have the potential to provide new or extra features to increase the performance of conventional P300-based speller. This study focuses on the feature extraction part in the BCI system. In this paper, we aim to develop a signal processing approach for extraction of ERSP and ITC from EEG data recorded in a P300 BCI paradigm.

## 2. MATERIALS AND METHODS

### 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. The signals (band-pass filtered from 0.1-60Hz and digitized at 240 Hz) were collected from the subject in five sessions. Each session consisted of a number of runs. In each run, the subject focused attention on a series of characters. For each character epoch in the run, 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

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columns (Fig. 1). 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 EEG 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 64×180×240 matrix (64 channels×15 blocks×12 trials×240 Hz) will be generated.

### 2.2. Data preprocessing

As it was difficult to identify the P300 in a single trial, and as there was also some noise in the signals, pre-processing of the signals was required. As the frequency of the P300 signals was usually below 30 Hz, a Butterworth filter was used as the low-pass filter with a cut-off frequency of 30 Hz. The signals were then processed using ensemble average, principal component analysis (PCA), and independent component analysis (ICA) by EEGLAB 5.02 (http://sccn.ucsd.edu/eeglab/) [8].

#### *2.2.1. Ensemble average*

The ensemble average technique is typically used to process weak signals, such as EEG-P300, with a strong noise and to improve the signal-noise ratio (SNR) of the signals. The SNR was defined as $SNR = P/\delta^2$, where $P$ is the power of ideal P300 signal and $\delta^2$ is the variance of the noise. After coherence an average of $n$ trials with the same stimulus, the variance of the noise will be reduced to $\delta^2/n$, so the new SNR of P300 waveforms will become $n$ times larger.

#### *2.2.2. Principle component analysis*

PCA involves a mathematical procedure that transforms a number of possibly correlated variables into a smaller number of uncorrelated variables termed principal components. The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible. PCA is theoretically an optimal linear scheme for compressing a set of high dimensional vectors into a set of lower dimensional vectors and then reconstructing the original set.

The steps to process the EEG data by PCA are as follows. First, estimate the sample covariance matrix of the high-dimensional EEG signal after processed by coherence average. Second, calculate the eigenvalues and eigenvectors of the covariance matrix of EEG data. Third, choose P300-related principle components (for example, based on the power of a component or its similarity to P300 response). Fourth, the new low-dimensional signal can be reconstructed from a few selected principal components.

#### *2.2.3. Independent component analysis*

ICA is a statistical and computational technique for revealing hidden factors that underlie sets of random variables, measurements, or signals. ICA defines a generative model for the observed multivariate data, which is typically given as a large database of samples. In the model, the data variables are assumed to be linear mixtures of some unknown latent variables, and the mixing system is also unknown. The latent variables are assumed non-Gaussian and mutually independent, and they are termed the independent components of the observed data in the context of ICA. These independent components, also termed sources or factors, can be found by various ICA algorithm [9].

In this study, we employed the Infomax ICA algorithm based on stochastic gradient learning rules [8]. The Infomax algorithm explicitly tries to maximize the joint entropy of a nonlinear function of the separated outputs; however, it implicitly minimizes the mutual information between the separated outputs so as to make them mutually independent. Note that we assume here that the number of independent components is equal to the number of observed variables (i.e., number of principal components for PCA-processed EEG data).

### 2.3. Feature extraction

The wavelet-based time-frequency analysis is used to clarify the time course of the evoked and phase-resetting EEG contributions to the ERPs. The ERSP indicates changes in power (in dB) as a function of frequency over the time-course of the ERP. The ITC provides a measure of phase locking again as a function of frequency over the time-course of the ERP. These two measures thus allow insight into the interplay of the evoked and phase locking mechanisms as a function of time.

To determine the phase and time course of oscillatory activity, we used the complex exponential form of the sinusoidal wavelet to analysis the power spectral and the phase spectral properties. The analytical expression of the complex exponential wavelet is $\psi(t) = W(t)\exp(j2\pi t)$, where $W(t)$ is the window function. The definition of the time-frequency analysis for the signal $x$ is:

$$F(f,t) = \int x(u)W(f(u-t))\exp[-j2\pi f(u-t)]du \qquad (1)$$

where $f$ and $t$ stand for the frequency and the time, respectively.

The wavelet transform was performed for each individual trial, and the absolute values of the resulting transforms were averaged. The ERSP is delimited as follows:

$$ERSP(f,t) = \frac{1}{n}\sum \left|F_k(f,t)\right| \tag{2}$$

where $n$ is the total number of the trials. $F_k(f,t)$ is the time-frequency distribution of the kth trial. ERSP reflects the influence to the power spectrum by the stimulation. On the other hand, the definition of ITC is:

$$ITC(f,t) = \frac{1}{n}\left|\sum_{k=1}^{n} \frac{F_k(f,t)}{\left|F_k(f,t)\right|}\right|. \tag{3}$$

The degree of phase-locking was calculated by ITC, which reflects the homogeneity of the instantaneous phase across single trials. ITC values between 0 for randomly distributed phases and 1 for phases are strictly phase-locked to stimulus onset across trials [4].

## 3. RESULTS AND DISCUSSION

The EEG data of each electrode was separated after stimulation for 1 s. At sampling rate of 240 Hz, a 180×240 data matrix (15 blocks×12 trials×240 Hz) was generated. Data from the row and column trial including the focused character were respectively averaged across all 15 blocks. The averaged row and column data were connected end to end. Then for each electrode there were a 1×480 vector (1×240 for row: 1×240 for column), and for each character there were a 64×480 matrix.

The EEG data processed by PCA and ICA can be seen in Fig. 2. The signal dimension is successfully reduced from 64 to 2 (two principal components) by PCA method. Then, two independent components are transformed from these two principal components by ICA method, as shown in Fig. 2. According to the prior knowledge (such as latency and shape) of P300, the second component is considered to reflect the P300. Furthermore, from the component we can easily determine the time domain properties of the P300. However, we can only observe the time delay of the P300 signals from the time analysis, without any information on the genesis of the P300 signals.

The EEG signals, which have already been processed by PCA and ICA, are then analyzed. As we know there is only one component in each EEG signal, then there will be one set of ERSP and ITC results for the signals without the P300 and one set of results for the signals with the P300. The ERSP and ITC values of 20 respective signals without P300 and with P300 can be seen in Fig. 3, in which the difference between signals with P300 and signals without P300 is obvious. ERSP reflects the influence on the power spectrum by the stimulation, while ITC reflects the homogeneity of the instantaneous phase across single trials. In Fig. 3 (a), both the ERSP and the ITC obviously show the P300 components in these trials, while such P300-related components cannot be seen in Fig. 3 (b). Thus, overall the above analysis suggests that both phase resetting and evoked activity contribute to the genesis of the P300 component.

## 4. CONCLUSION

In this paper, we developed a signal processing approach to analyze time-frequency features of EEG data in a P300 BCI speller. By analysis of event-related EEG responses in the time-frequency domain via computing the ERSP and ITC of the P300, we determined that both time-locked and phase-locked features existed in EEG responses recorded in the BCI P300 speller. The joint analysis of ERSP and ITC demonstrated the validity of our proposed feature extraction method. This study may be useful for not only improving the BCI P300 speller design and its signal processing strategies but also extracting and analyzing other visual and auditory or somatosensory evoked potentials.

## 5. ACKNOWLEDGMENTS

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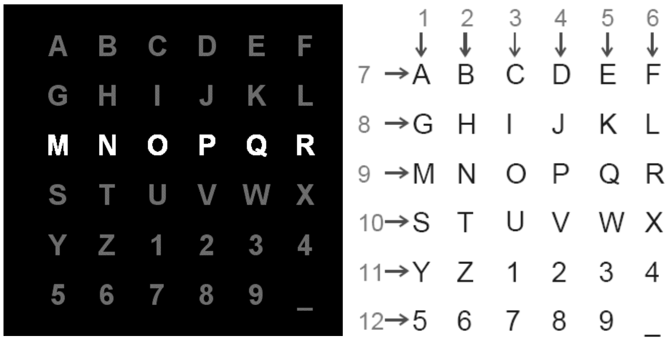


Fig. 1. User display and the assignment of Stimulus Code for this paradigm. In this example, the users' task is to spell the word 'SEND' (one character at a time). For each character, all rows and columns in the matrix were intensified a number of times (e.g., the third row in this example) as described in the text. The right panel illustrates the assignment of the variable Stimulus Code to different row/column intensifications (from [10]).

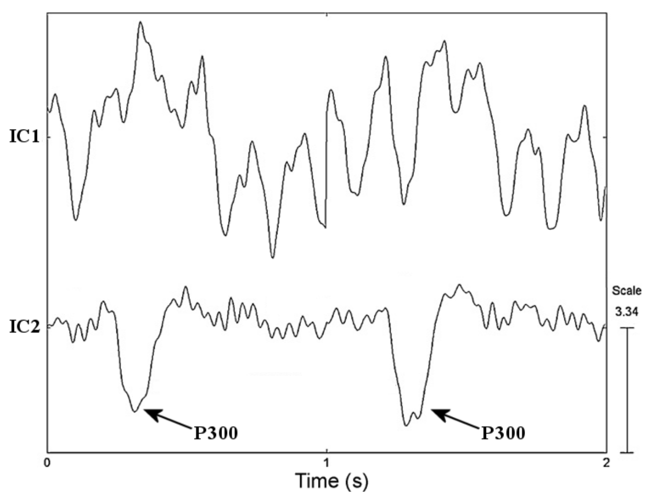


Fig. 2. EEG components processed by PCA and ICA, which include the P300 responses when a word is spelt. Two components were retained after the PCA and ICA operations. According to the prior knowledge (for example, the latency of P300 peak and the shape of P300), the second component is considered to contain the P300 component and is used for subsequent analysis (redraw from [10]).


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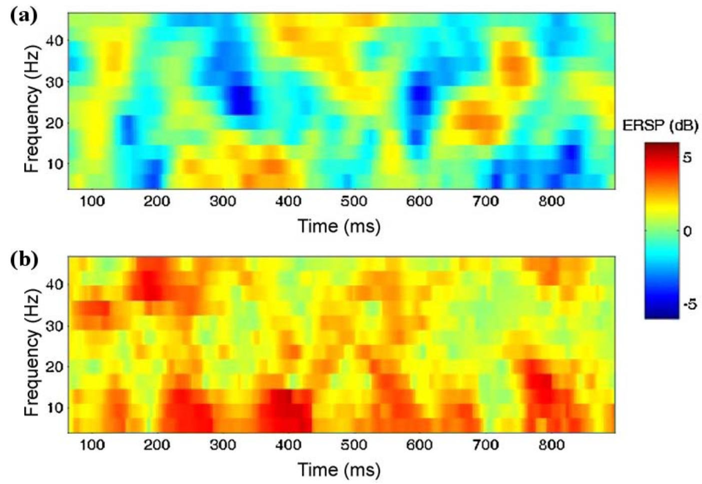


Fig. 3. The ERSP (in dB) of 20 averaged epochs processed by PCA and ICA. (a) ERSP of the epochs with P300; the ERSP towards 300ms are larger than for the other period. (b) ERSP of the epochs without P300; there were no differences towards different time and frequency and the ERSP values were random and low.

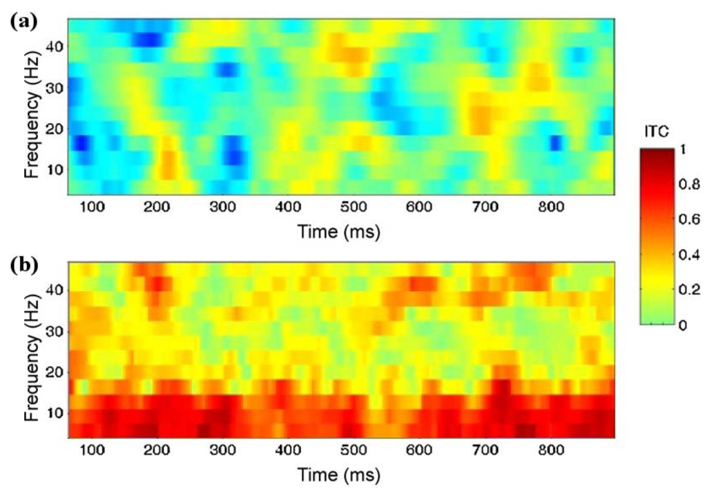


Fig. 4. The ITC of 20 averaged epochs processed by PCA and ICA. (a) ITC of the epochs with P300; the ITC towards 300ms are larger than for the other period. (b) ITC of the epochs without P300; there were no differences towards different time and frequency and the ITC values were random and low.