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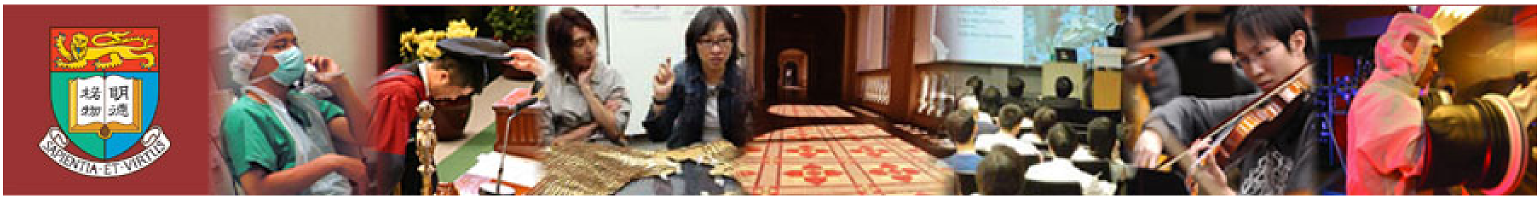

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Single-trial Detection of Visual Evoked Potentials by Common Spatial Patterns and Wavelet Filtering for Brain-computer Interface

Yiheng Tu, Gan Huang, Yeung Sam Hung, Li Hu, Yong Hu, and Zhiguo Zhang

Abstract— **Event-related potentials (ERPs) are widely used in brain-computer interface (BCI) systems as input signals conveying a subject's intention. A fast and reliable single-trial ERP detection method can be used to develop a BCI system with both high speed and high accuracy. However, most of single-trial ERP detection methods are developed for offline EEG analysis and thus have a high computational complexity and need manual operations. Therefore, they are not applicable to practical BCI systems, which require a low-complexity and automatic ERP detection method. This work presents a joint spatial-time-frequency filter that combines common spatial patterns (CSP) and wavelet filtering (WF) for improving the signal-to-noise (SNR) of visual evoked potentials (VEP), which can lead to a single-trial ERP-based BCI.**

I. Introduction

Brain-computer interface (BCI) is an emerging technology which can build the pathway between human brain and external devices without any muscle activities thus it allows people who are severely or completely paralyzed to re-establish communication with outside world [1]. Various meaningful cognitive or sensory related features, such as P300 event-related potential (ERP) [2], steady state visual evoked potential (SSVEP) [3], flash onset and offset visual evoked potential (FVEP) [4] can be extracted from electroencephalography (EEG) and served as control signals for a BCI.

Chromatic transient visual evoked potential (CTVEP) was first proposed in [5], where "chromatic" means that stimuli are in equiluminant chromatic modulation, "transient" means that temporal presentation is long enough to give discrete deflections or components in VEP waveforms. CTVEP can be elicited when chromatic visual stimuli are presented at low frequency (<4Hz) and perceived within the visual field. Unlike SSVEP-based and FVEP-based BCI, CTVEP-based BCI can minimize the risk of evoking epileptic seizures and reduce fatigue because it is driven by low-frequency stimuli without luminance variation [6].

However, the low-amplitude ERPs are usually buried in a high amount of background ongoing EEG and other non-cortical artifacts, and hence the signal-to-noise (SNR) is very low. Conventionally, across-trial averaging is commonly performed to detect reliable ERPs for improving the accuracy of ERP-based BCI systems, but it inevitably increases the response time of BCI systems. Recent signal processing research for ERP-based BCI has focused on minimizing the number of trials required for reliable detection of ERP, moving towards the goal of single-trial ERP detection [7]. A fast and reliable single-trial ERP detection method is highly desirable in BCI research, as it can lead to a BCI system with both quick response and high accuracy.

Generally, spatial domain, spectral domain or joint domain can be used to improve SNR of observed single-trial responses. Spectral filter is used to improve the quality of EEG signals by removing unrelated signals and noise beyond the frequencies of interest, while the spatial filter can remove noise by using their spatial distribution across different electrodes.

In this work, we propose a joint spatial-time-frequency filtering techniques, which combines common spatial patterns (CSP) [8] and wavelet filtering (WF) [9] to improve the SNR of single-trial CTVEPs. CSP is a mathematical tool for separating a multivariate signal into a set of additive components which have maximum differences in variance between two classes. Compared with independent component analysis (ICA), CSP makes use of prior information about the classes so that the decomposed components are ranked according to their discriminative power. Hence, CSP can avoid the difficult problem of selecting event-related independent components for reconstruction in ICA, which relies heavily on operator's experience. CSP is followed by the WF-based time-frequency analysis, which is designed for characterizing and manipulating signals whose statistics vary in time, such as transient signals. Compared with short-time Fourier transform (STFT) using a fixed window and thus having a limited time-frequency resolution, wavelet is a more sophisticated technique which offers the optimal compromise between time and frequency resolution therefore it is more suitable for exploring event-related modulations of the EEG spectrum in a wide range of frequencies. When applied to CTVEPs, the proposed CSP+WF method provides a significant improvement of SNR and enhance the classification accuracy notably.

II. Method

A. Data acquisition and pre-processing

Eight subjects (four males and four females, 21-25 years) participated in the experiment. All participants were given written informed consent and the local ethics committee approved the experimental procedure.

Subjects were seated at a comfortable chair and

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experiments were done in a dim, unshielded office laboratory with reasonable activities to simulate real-life situation. EEG signals were recorded non-invasively and binocularly with 12 AN/AgCl electrodes using a NeuroScan Quik-cap electrode (Compumedics NeuroScan, EI Paso, TX, USA) placement system. Nine electrodes in the visual cortex were used to collect data and they were kept at impedance of less than 5 kΩ and monitored under built-in impedance measurement module. During experiment, EEG signals were continuously recorded and filtered (0.05-200Hz) with a sampling rate of 1kHz. Continuous EEG data were band-pass filtered between 1 and 30Hz.

Four time-encoded (0-1-1-0, 1-1-0-0, 0-1-0-1, 1-0-1-0) isoluminant red-green circular sinusoidal gratings with 2 cpd of spatial frequency were used to elicit CTVEP (Figure. 1). A visual stimulus was turned on for 50ms and turned off for 200ms to denote a code of "1", while one silent cycle with duration of 250ms denoted a code of "0". Consequently, the duration of one 4-bit code was 1 s.

In the experiment, subjects were instructed to gaze at the fixation after the first notification sound, minimizing eye blinking and to rest after the second notification sound. Visual stimuli were delivered in trains of three identical trials, and one trial consisted of stimuli representing a 4-bit code. Four types of 4-bit codes were randomly delivered at the center of the screen and in total twenty trains (five trains per type) were collected. Therefore, we had 60 trials and each trial contained two "1-bit" and two "0-bit".

B. Common Spatial Patterns

The proposed single-trial CTVEP detection consists of two consecutive stages: CSP-based spatial filtering and wavelet-based time-frequency filtering.

To apply CSP for detecting single-trial CTVEPs, EEG waveforms in response to visual stimuli (1-bit) and those recorded when stimuli were absent (0-bit) will be regarded as two classes. Denote $X_1^i \in R^{n \times t}$ as the raw data of i^{th} 1-bit in training session, where n is the number of channels and t is the number of samples in time (in this work, n is equal to 9 and t is equal to 250). Similarly, we have X_0^i which denote the raw data of i^{th} 0-bit in training session. By solving the generalized eigenvalue equation

$$X_1^i (X_1^i)^T w = \lambda X_0^i (X_0^i)^T w \tag{1}$$

the generalized eigenvector w is found to maximize the difference in variance between two classes. In this work, two components with the most discriminative power (i.e. CTVEP-related components) were automatically selected by calculating the correlation coefficients between the averaged 1-bit waveform and the EEG trials reconstructed form the selected components. Leave one out cross validation (LOOCV) is used throughout the CSP, wavelet filtering and classification. The LOOCV strategy was done for each subject by using one trial as the test sample and the remaining (60-1) trials from the same subjects as the training set. This procedure is therefore repeated 250 times, and averages and standard deviations can be calculated.

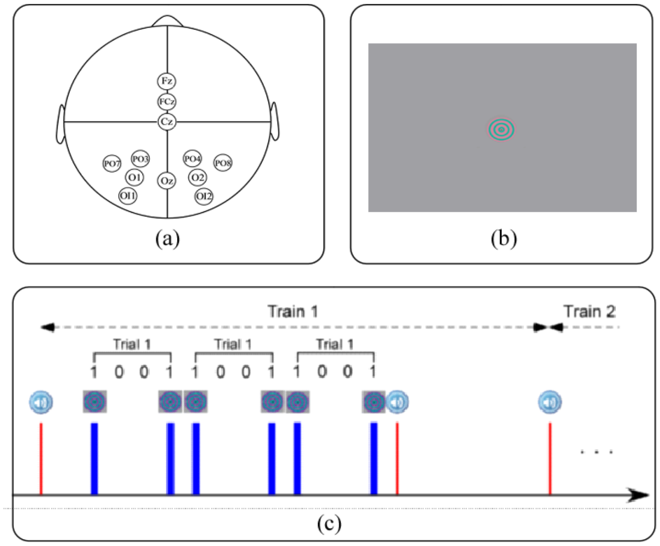

Figure. 1 Experimental setup. (a) Channel layout used in the experiments; (b) The location of stimulus; (c) The paradigm of the experiment.

C. Wavelet filtering

CSP will be followed by the WF method (Figure. 2) as follows: (1) single-trial VEP waveforms are transformed into time-frequency representations using continuous wavelet transform (CWT); (2) a specific region on the time-frequency domain corresponding to the VEP is identified from the time-frequency representation of the VEP waveform averaged across all trials; (3) single-trial VEP waveforms can be reconstructed from the wavelet coefficients within the VEP-related time-frequency region using inverse CWT (ICWT).

1) Continuous wavelet transform (CWT)

Unlike the windowed Fourier transform, the CWT is able to construct a time-frequency representation of EEG or ERP signals that offers an optimal compromise for time and frequency resolution by adapting the window width as a function of estimated frequency, CWT can present a time-domain EEG signal into time-frequency domain and offers the optimal compromise between time and frequency resolution. The CWT of a VEP waveform $x(t)$ is defined as:

$$W(\tau, a) = \frac{1}{\sqrt{|a|}} \int_t x(t) \cdot \psi^* \left(\frac{1}{a}(t-\tau)\right) dt \tag{2}$$

$$\psi(t) = \frac{1}{\sqrt{\pi f_0}} e^{2i\pi f_0 t} e^{-\frac{t^2}{f_b}} \tag{3}$$

where a is the scaling factor defined as the ratio between frequency f and central frequency f_0 . $\psi(t)$ is the morlet wavelet acting as mother wavelet with central frequency f_0 and bandwidth f_b . In this study, f_b is set to be 0.1, while f_0 is selected by an empirical function

$$f_0 = 8.8 \cdot P_{LF} - 3.43 \tag{4}$$

where P_{LF} is the power ratio of low-frequency (<10Hz) components in the VEP waveform $x(t)$.

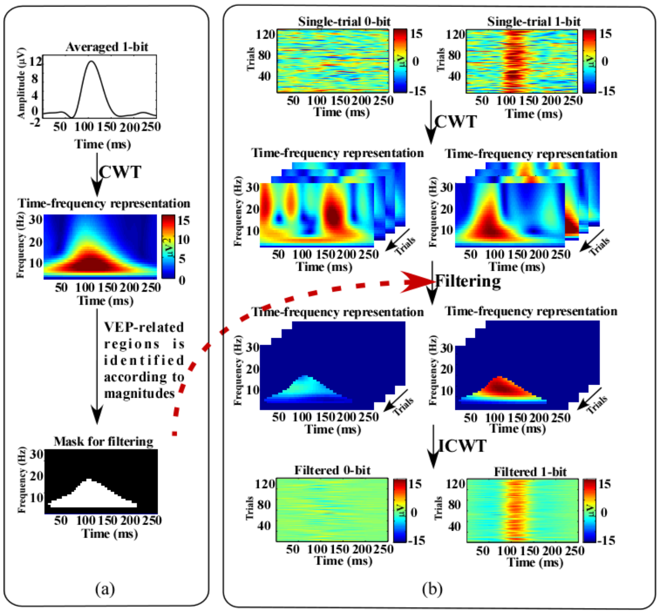

Figure. 2 Procedure of wavelet filtering. (a) Building the mask from training set. The white corresponding to the VEP is identified and can be used to filter the single-trial VEP of test sample; (b) Filtering the single-trial data of test sample.

2) *Wavelet filtering mask*

A binary time-frequency mask M_f is generated by creating a matrix whose time-frequency pixels are set to 1 when cumulative distribution function (CDF) of normalized power spectrum is larger than a threshold (= 0.55*max(CDF)) while others are set to be 0. The selected threshold was set jest before the inflection point, with the objective of keeping the greater part of 1-bit while removing as much noise as possible. Thus, the mask can identify the distribution of CTVEPs elicited by circulars' flickering from averaged templates. This mask is used to filter the 1-bit as well as 0-bit of each single-trial. After filtering, the time-frequency representation is achieved by:

$$WF_i(\tau, a) = M_f \cdot W_i(\tau, a) \tag{5}$$

where W_i is the time-frequency representation of single-bit input obtained by CWT and WF_i is the filtered time-frequency representation.

3) *Inverse continuous wavelet transform (ICWT)*

In the last step, we reconstruct the signal into time domain using ICWT:

$$y_i(t) = \int_\tau \int_a \frac{1}{a^2} WF_i(\tau, a) \frac{1}{\sqrt{|a|}} \psi\left(\frac{1}{a}(t-\tau)\right) d\tau\, da \tag{6}$$

where $y_i(t)$ is the filtered and reconstructed single-trial VEP waveform.

In order to show the performance of proposed method, we estimated the SNR of single-trial CTVEPs before and after each stage (CSP and WF) as:

$$\hat{SNR} = 10 \log_{10}[(\hat{\sigma}_X^2 - \hat{\sigma}_N^2) / \hat{\sigma}_N^2] \tag{7}$$

where $\hat{\sigma}_X^2$ is the power of single-trial CTVEP waveform and $\hat{\sigma}_N^2$ is the power of noise (estimated as the difference between single-trial CTVEP waveform and the average across all trials).

III. Results

A. Improvement on SNR

When applied to the 9-channel CTVEP recordings, the proposed CSP+WF method showed significant improvement on SNR (t-test, p<0.05).

Figure. 3 showed the single-trial CTVEPs of "1-bit" and "0-bit" in each processing stage. The CSP filter decreased the fluctuations of 0-bit and increased the pattern of 1-bit. However, noises still existed even when CSP was used. Then the WF method further removed the components which were not related to CTVEP responses. Therefore, the single-trial CTVEPs with minimum noisy components were obtained.

Figure. 4 (a) showed the averaged SNRs in each processing stage, and they were compared using t-test. Our proposed CSP+WF method can significantly increase the SNR. (CSP vs. Raw: p=0.0002; CSP+WF vs. Raw: p=0.000005; CSP+WF vs. CSP: p=0.0002; t-test).

B. Classification accuracy

The classification accuracy was estimated under the LOOCV strategy for each subject by using one trial as the test sample and the remaining (60-1) trials from the same subjects as the training set to build the template. Linear discriminant analysis (LDA), naïve bayes (NB) and support vector machine (SVM) were used and compared.

The correlation coefficients between single-trial CTVEPs in the test sample and four different templates obtained from training set were calculated and compared. Single-trial CTVEPs could be classified into one of four categories corresponding to the template with the maximum correlation coefficient with the trial under test. By evaluating the classification accuracy, we can estimate the performance of proposed method when being used at BCI system to translate CTVEPs into corresponding commands.

Figure. 4 (b) showed the averaged classification accuracy and Table 1 showed the classification accuracies of 8 subjects using different VEP detection methods. When using CSP+WF, the accuracy can be as high as almost 90%. It can also be observed that the CSP and CSP+WF methods can significantly improve the classification accuracy (CSP vs. Raw: p=0.0309; CSP+WF vs. Raw: p=0.0048; CSP+WF vs. CSP: p=0.0177; t-test).

IV. Discussion

In this study, a spatial-time-frequency VEP detection methods which combined CSP-based spatial filtering and CWT-based time-frequency filtering were developed and applied to CTVEP recordings. The proposed method is designed for BCI systems to improve the SNR and thus increase the classification accuracy. Three main founding are observed from the experimental results. First, we show that the two classes in CTVEPs can be successfully separated by CSP with correct patterns of waveform. However, the SNR after

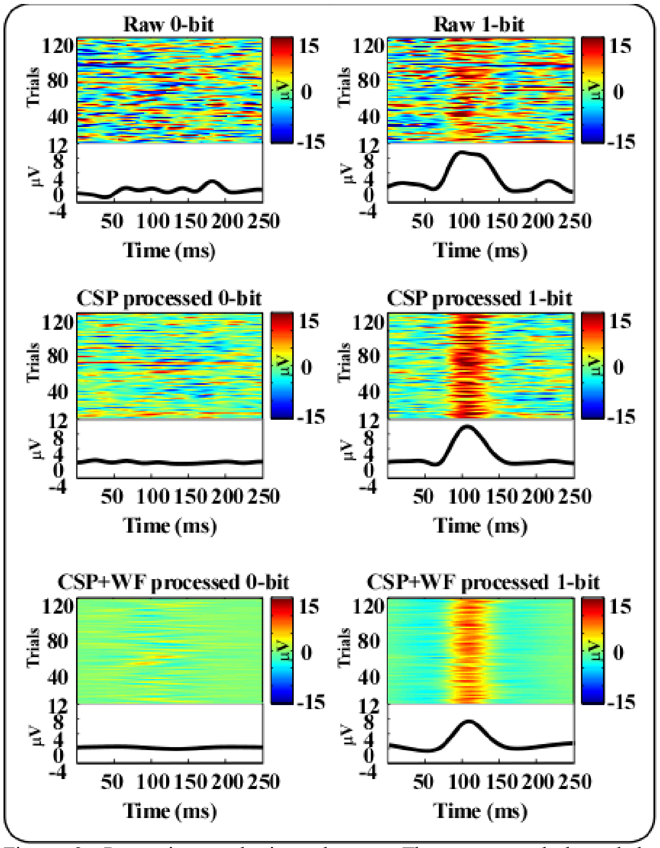

Figure. 3 Processing results in each stage. The upper panel showed the single-trial "1-bit" and "0-bit" waveforms. The lower panel showed the averaged waveform.

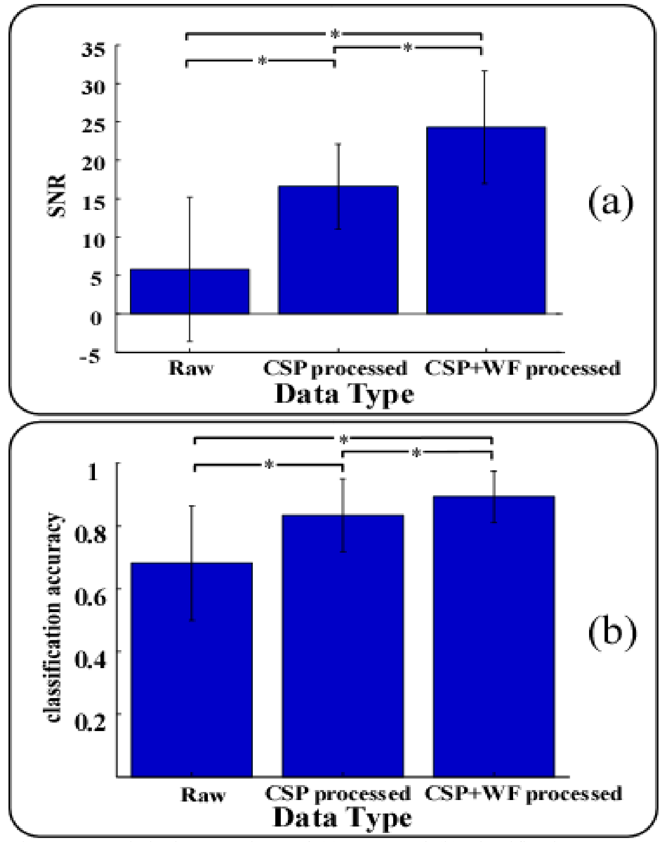

Figure. 4 Statistical comparison of (a) SNR and (b) classification accuracy (averaged across trials) obtained at different processing stages across all subjects. Error bars represent the standard deviation across subjects. *p<0.05 (t-test).

CSP are still relatively low which may be caused by the large-scale frequency contribution from the unrelated visual stimulus. For this reason, time-frequency filtering which is able to capture the unique time-frequency characteristics of VEPs, is needed. Second, after removing noises by CSP+WF, the SNR of CTVEPs can be significantly enhanced both in average and single-trials. The time-frequency filter model is generated by thresholding the time-frequency representation of averaged "1-bit". Each subject will have a trained time-frequency filter model to capture his VEP characteristics to achieve the highest SNR. Third, the classification accuracy can achieve almost 90% which is quite good for single-trial BCI system. In our work, four types of 4-bit codes were tested, and consequently they can be translated into four corresponding commands for a BCI system.

Many signal-processing techniques can effectively improve the SNR of ERPs, but their high computational complexity impedes their practical applications in BCI systems. The proposed VEP detection methods can process the data within a short time (<100ms for one trial, configuration: *Intel Core i7-2600 CPU @ 3.40GHz, 8GB RAM*), which makes a good compromise between time and performance.

TABLE. 1 CLASSIFICATION ACCURACY FOR EACH PROCESSING STAGE

Subject / Data type	1	2	3	4	5	6	7	8	Mean	Std
Raw	0.659	0.765	0.452	0.544	0.513	0.920	0.941	0.657	0.682	0.183
CSP processed	0.933	0.800	0.617	0.867	**0.917**	0.933	0.933	0.683	0.835	0.117
CSP+WF processed	**0.983**	**0.833**	**0.733**	**0.917**	0.900	**0.950**	**0.950**	**0.833**	**0.894**	**0.083**

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