DOI：10.3724/SP.J.1218.2013.00045

A Two-Stage State Recognition Method for Asynchronous SSVEP-Based Brain-Computer Interface System

ZHANG Zimu，DENG Zhidong
(*State Key Laboratory of Intelligent Technology and Systems*, *Tsinghua National Laboratory for Information Science and Technology*, *Department of Computer Science and Technology*, *Tsinghua University*, *Beijing* 100084, *China*)

Abstract: A two-stage state recognition method is proposed for asynchronous SSVEP (steady-state visual evoked potential) based brain-computer interface (SBCI) system. The two-stage method is composed of the idle state (IS) detection and control state (CS) discrimination modules. Based on blind source separation and continuous wavelet transform techniques, the proposed method integrates functions of multi-electrode spatial filtering and feature extraction. In IS detection module, a method using the ensemble IS feature is proposed. In CS discrimination module, the ensemble CS feature is designed as feature vector for control intent classification. Further, performance comparisons are investigated among our IS detection module and other existing ones. Also the experimental results validate the satisfactory performance of our CS discrimination module.

Keywords: state recognition; ensemble feature model; blind source separation (BSS); continuous wavelet transform (CWT); steady-state visual evoked potential (SSVEP); brain-computer interface (BCI); electroencephalogram (EEG)

1 Introduction

Brain-computer interface (BCI), developed in recent years, is a new kind of human-machine interaction way. It does not need human beings' peripheral nerve pathway and muscle, making use of brain electronic signals to reshape communication ways with outside world[1]. BCI research is an intelligent information processing technique integrating multi-discipline knowledge such as neural science, signal processing, machine learning, and intelligent control, etc. Non-invasive scalp electroencephalogram (EEG) is predominantly adopted in BCI research due to its safety and easy operation advantages. Through the real-time analysis of EEG signals generated by brain activity, the human control intention can be identified and decoded. Thus, the human intention, originally expressed through speech or other motor functions, can be now encoded by generating EEG signals, and translated via computers.

In recent years, BCI research has been rapidly developing [2-5]. There are two control modes in BCI systems, i.e. asynchronous and synchronous modes [6]. In the former mode, computers control the input time of commands. Users need to cooperate with system, and execute operations in a certain time interval. However, human beings generally manipulate equipments in the latter mode. In other words, users prefer to operate systems according to their needs and intents. If users do not have control intent, the BCI will get into idle state. Therefore, to realize asynchronous mode, it is the first thing to reliably detect both states, i.e. idle state (IS) and control state (CS), respectively.

SSVEP is a biological response to a visual stimulus flickering at a frequency. When one gazes at a visual stimulus modulated at a frequency of larger than 4$\sim$6 Hz, the prominent spectrum value of this frequency and its harmonics can be detected from EEG signals recorded from his/her scalp over visual cortex [7-8]. SSVEP-based BCI (SBCI) sets up flashing stimuli with different frequencies in different positions on the screen, corresponding to various options or commands. Recently, the SBCI system has been developed intensively due to relatively stable performance and few training requirements [3].

In this study, adopting blind source separation (BSS) and continuous wavelet transform (CWT) techniques, a two-stage state recognition method is proposed. Using the method, the SBCI system is estab-

Suppoted by: National Natural Science Foundation of China (90820305, 60775040)
Correspondent author: DENG Zhidong, michael@tsinghua.edu.cn Submitted/Accepted/Revised dates: 2012-03-05/2012-10-12/2012-11-06

lished. Further, the proposed IS detection module is compared with other existing ones. Experimental results show the advantages of our method and also effectiveness of the CS discrimination module. Thus the method introduced in this study is promising in realizing online asynchronous mode and enhancing the recognition performance of the SBCI system.

2 Methods

2.1 A BSS algorithm for preprocessing

Assume that we have M-electrode N-point EEG signals $\boldsymbol{X}(n) \in \mathrm{R}^{M\times N}$ sampled at time instant n. Due to containing large noises, it is difficult to use directly raw EEG data to detect states. The adoption of data-driven BSS method can help to enhance the differentiation between states and solve spontaneous oscillations interference problem. Inspired by the 2nd-order blind identification algorithm [9], the preprocessing procedure is detailed as follows.

First $\boldsymbol{X}(n)$ is performed of removing direct current [10]. Then to reduce the interference of white noises, a one-point delayed correlation matrix is transformed by singular value decomposition (SVD):

$$E\left[\boldsymbol{X}(n)\boldsymbol{X}^{\mathrm{T}}(n-1)\right] = \boldsymbol{U\Sigma V}^{\mathrm{T}} \tag{1}$$

A new matrix can then be obtained:

$$\boldsymbol{Z}(n) = \boldsymbol{WX}(n) = \sqrt{\boldsymbol{\Sigma}^{-1}}\boldsymbol{U}^{\mathrm{T}}\boldsymbol{X}(n) \tag{2}$$

where $\boldsymbol{W} = \sqrt{\boldsymbol{\Sigma}^{-1}}\boldsymbol{U}^{\mathrm{T}}$ is a whitening matrix, which is the so-called whitening process.

Through typical Givens rotation algorithm, the joint diagonalization is conducted for a set of point-delayed correlation matrices $E[\boldsymbol{Z}(n)\boldsymbol{Z}^{\mathrm{T}}(n-\tau)]$ where $\tau \in \{\tau_i | i = 1, \cdots, p\}$. In this study, the value of p is user dependent during offline analysis. The diagonalization unitary matrix $\boldsymbol{Q} \in \mathrm{R}^{M\times M}$ is then obtained. Thus the multi-channel source data is given

$$\boldsymbol{S} = \boldsymbol{HX} = \boldsymbol{Q}^{\mathrm{T}}\boldsymbol{WX} \tag{3}$$

where $\boldsymbol{H}$ is a separating matrix.

Generally, hypothetically unrelated SSVEP response and spontaneous EEG oscillation mix in raw EEG data. Through such fast 2nd-order BSS procedure, both components can be separated into different channels in $\boldsymbol{S}$ robustly. Spontaneous oscillation exhibits in a relatively wide range of frequencies while SSVEP only prevails at target stimulus frequency as well as its harmonics. Thus the efficient separation of both signals can help to use these traits for state recognition and exclude spontaneous oscillation interference. Using the source data $\boldsymbol{S}$, IS feature is extracted for IS detection module as described in the next section.

2.2 Idle state detection module

The IS detection module is based on CWT technique. In a previous study, we proposed the adoption of CWT method for one-electrode SSVEP identification [11], which indicates that compared with fast Fourier transform-based method, the CWT-based one is more suitable for EEG due to the intrinsic non-stationary matching, especially for short EEG segment, thus making it perform better in the SSVEP feature extraction scheme. In this paper, we extend the method for IS detection.

CWT is capable of adjusting the window size of its wavelet function and providing a flexible way to analyze non-stationary signals like EEG [12]. In our study, the complex Morlet wavelet is used as mother wavelet due to its potential application in EEG and MEG analysis [13]. It is defined as [14]

$$\varphi(x) = \frac{1}{\sqrt{\pi f_{\mathrm{b}}}}\mathrm{e}^{2\mathrm{i}\pi f_{\mathrm{c}}x}\mathrm{e}^{-\frac{x^2}{f_{\mathrm{b}}}} \tag{4}$$

where f_{b} is the bandwidth parameter and f_{c} the wavelet center frequency. Using complex Morlet CWT, it is quite flexible to decompose sampled EEG segment into a set of time-scaled and time-shifted versions of wavelet coefficients $W(a,b)$, where a is the scale factor and b the shift one.

Define one-dimension N-point data $\boldsymbol{y}(m)$ ($m \in$[0, N-1]) as any channel component in $\boldsymbol{S}$. Complex Morlet CWT is used for $\boldsymbol{y}(m)$ to obtain stimulus frequencies corresponded wavelet coefficients. According to the relation between a and one frequency f [15], a simple equation can be obtained:

$$a = f_{\mathrm{s}} \cdot f_{\mathrm{c}}/f, \quad b = m \tag{5}$$

where f_{s} is the sampling rate. Thus using complex Morlet wavelet with only stimulus frequencies related scale factor, the calculation of CWT for $\boldsymbol{y}(m)$ can be simplified:

$$W(a,m)=\frac{\sqrt{a}}{N}\sum_{k=0}^{N-1}\boldsymbol{Y}(k)\boldsymbol{\Phi}^{*}(ak)\mathrm{e}^{\mathrm{i}\frac{2\pi}{N}mk} \tag{6}$$

where $\boldsymbol{Y}(k)$ and $\boldsymbol{\Phi}(k)$ denote the discrete Fourier transform of $\boldsymbol{y}(m)$ and discrete complex Morlet wavelet $\varphi(m)$, respectively. To make $W(a,m)$ easily interpretable, we transform it as $W(f,m)$. Define

$$\rho_f=\frac{1}{N}\sum_{m=0}^{N-1}|W(f,m)|^2 \tag{7}$$

Thus ρ_f denotes the mean energy of $W(f,m)$ at f over the temporal domain of $\boldsymbol{y}(m)$. When detecting both states, the relative significance of different SSVEP harmonics varies according to subjects. Thus it is not stable enough to recognize state only by using a single feature. Besides, the higher SSVEP harmonic information need to be used here to reduce frequency interference, especially occipital alpha disturbance problem detailed in reference [16]. As suggested in reference [17], combining single members using weighting function is considered to be a better approach. It is more reasonable to weight ρ_f at individual harmonic. Thus an ensemble feature model is built to integrate multi-harmonic features through the weighted linear combination

$$V_f=\sum_{j=1}^{N_{\mathrm{h}}}w_j\rho_{jf} \tag{8}$$

where N_{h} is the number of harmonics (here we set $N_{\mathrm{h}}=3$ in our study), and w_j the weight corresponding to ρ_{jf} with the constraint that the sum of N_{h} combination weights is equal to 1. In essence w_j denotes the relative contribution of related feature, which is trained through the learning procedure detailed in the next section. Assume there are r stimulus frequencies. Define the IS feature

$$F_{\mathrm{IS}}=\max(D_c),\quad c\in[1,M] \tag{9}$$

where c is the channel number and

$$D=\frac{\sum\limits_{j=1}^{r}(V_{f_j}-\overline{V_f})^2}{\sum\limits_{j=1}^{r}\left(-\frac{V_{f_j}}{\sum\limits_{j=1}^{r}V_{f_j}}\cdot\ln\frac{V_{f_j}}{\sum\limits_{j=1}^{r}V_{f_j}}\right)} \tag{10}$$

where f_j is one stimulus frequency and

$$\overline{V_f}=\frac{1}{r}\sum_{j=1}^{r}V_{f_j} \tag{11}$$

F_{IS} combines multi-harmonic features, working for IS detection. Defined as maximum ratio of wavelet variance to entropy for multi-channel data $\boldsymbol{S}$, the IS feature actually measures the spectrum complexity at all stimulus frequencies together with its harmonics. As we know, in CS, SSVEP is an impulse response and there exists a prominent component at the target stimulus frequency and its harmonics, whereas in IS the spectrum distribution is relatively flat. Thus high IS feature value may denote the generation of SSVEP, i.e. CS, and vice versa.

When the trained ensemble model is interrogated feeding test dataset as input, we can get output ensemble features F_{IS}, which are predictive of state. Given a threshold θ, an indicative function $I(X)$ can be defined to detect whether the EEG data X is in F_{IS}

$$I(X)=\begin{cases}1, & \text{if } F_{\mathrm{IS}}<\theta\\ 0, & \text{else}\end{cases} \tag{12}$$

where $I(X)$ = 1 denotes CS and $I(X)$ = 0 IS. Thus the prediction results depend on how the threshold is chosen. For given ensemble feature F_{IS} and a certain threshold θ, Sensitivity and Specificity measure presented in reference [16] is used to evaluate the performance of the model. We define O as the sum of both performance measures. The optimal threshold is the one that can get maximum O in training dataset

$$\theta^{*}=\underset{\theta}{\operatorname{argmax}}\,O,\quad \theta\in[\min(F_{\mathrm{IS}}),\ \max(F_{\mathrm{IS}})] \tag{13}$$

Thus it becomes a general one-dimension optimization problem with O as objective function. In our study, the exhaustive algorithm is used to obtain optimal threshold, which is incorporated with the combination weights learning scheme described in the following section.

2.3 Weights learning and threshold estimation

In our learning scheme, a training algorithm is designed to simultaneously obtain the combination weights and optimal threshold. First, the whole experimental data are divided into training and test samples respectively. After single harmonic feature values are obtained using training dataset, the weights learning and the threshold estimation procedure are conducted. The parameters trained here will be used in (12) for IS detection module in the test datasets.

Inspired by the expectation-maximization algorithm [18], which is a robust method adapted to learn parameters using incomplete data corresponding to the unknown weights here, we give the weights learning and threshold estimation scheme:

Step1 For each stimulus frequency, calculate N_h values of ρ_{jf} ($j = 1, \cdots, N_\mathrm{h}$) according to (7) independently using the same training samples.

Step2 Assign weights $w_j^1 \in [0,1]$ randomly. Compute V_f according to (8) and F_IS using (9).

Step3 Determine optimal threshold θ^1 through the above threshold optimization procedure.

Step4 Set each ρ_{jf} to V_f and evaluate the performance of single harmonic IS features with θ^1 on the training dataset. These performance evaluations are further used to obtain w_j^2 by (14).

Step5 Calculate F_IS^2 using w_j^2. Find the current optimal threshold θ^2 via the threshold optimization procedure.

The scheme above can be iterated to get convergent values. In Step4, a transformation is conducted to convert performance evaluations respectively obtained into weights:

$$w_j^{i+1} = O_j^i \Big/ \sum_{n=1}^{N_\mathrm{h}} O_n^i \tag{14}$$

where O_j^i and w_j^i are the evaluated performance and the weight of the j-th harmonic feature respectively in the i-th iteration. Here in our study only three rounds of iterations are used. Through this iteration procedure, the overall performance of the IS detection module is improved by decreasing the relative significance of single F_IS features with worse performance and increasing that of the ones that works better. Meanwhile, the combination weights are learned and the detection threshold is estimated. Then the obtained parameters are used for IS detection in the test dataset.

2.4 Control state discrimination module

When CS is determined, the target stimulus needs to be identified. For this purpose, the CS discrimination module is presented using the obtained values in the first stage. First, the channel corresponding to F_IS in $\boldsymbol{S}$ is obtained,

$$l = \underset{c}{\mathrm{argmax}}(D_c), \quad c \in [1, M] \tag{15}$$

For the l-th channel, define the ensemble CS feature vector using V_f

$$\boldsymbol{F}_\mathrm{CS} = [V_{f_1}, \cdots, V_{f_r}]^\mathrm{T} \tag{16}$$

In the second stage, SVM [19] is employed to perform real-time CS discrimination. As a supervised learning machine, SVM can achieve remarkable generalization performance based on statistical learning theory [20]. In our SBCI, for each EEG trial data, taking $\boldsymbol{F}_\mathrm{CS}$ as input feature vector, the SVM model is used to decode users' intention into a corresponding command to realize EEG control of human intention.

2.5 Overview of the proposed method

The block diagram of our method is shown in Fig.1. The two parts divided by the dash dot line compose the two-stage state recognition structure, i.e. IS detection and CS discrimination modules. If the CS is detected through the first stage, the target stimulus will be identified in the second stage and then transformed into the predefined command.

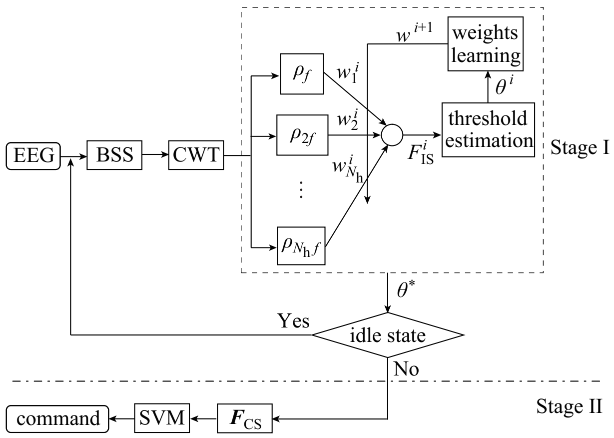

Fig.1 Framework of our two-stage state recognition method

3 Experimental results

3.1 Experimental setup

In our experiment, there are four stimulus sources on a LCD screen (60 Hz refresh rate, 1024×768 resolution) with four frequencies, i.e. 15, 12, 10 and 8.57 Hz, respectively. Users can choose to focus on any stimulus according to their intents.

EEG data are measured using a whole-head BioSemi ActiveTwo system (highpass, 3 Hz; sampled at 256 Hz). Due to the physiological mechanism that maximum SSVEP amplitude is evoked over occipital area, the used electrodes are P3, Pz, P4, PO3, PO4, O1, Oz and O2 (10/20 sites).

Ten subjects with normal vision capability, aged from 20 to 30, served as paid volunteers after giving informed consent. Seven of them were naive to EEG experiments prior to this study. In the experimental process, the subjects were seated in an armchair in a lab room. Each trial lasted 2 s and subjects had 0.3 s interval between trials. In CS, each subject did 50 trials for focusing on each stimulus, while in IS the subjects could see any places without watching the screen or close their eyes or even make casual conversation, and each also did 50 trials. For every 2 s trial, the EEG data from all subjects were analyzed. The accuracy results were used for evaluating the performance of our method and other ones. Besides, the accuracy was obtained by 10-fold cross validation to avoid randomness.

3.2 Experimental results

Here we randomly take one subject's experimental result for detailed analysis below. The distribution of all the IS feature values is shown in Fig.2. It is obvious that mostly, the IS feature values in IS are rather smaller than that in CS, denoting that compared with CS, the stimulus frequencies related spectrum complexity is relatively higher in IS. Hence effective IS detection can be achieved using the learned optimal threshold. By employing a set of IS feature values as detection threshold, a receiver operating characteristic (ROC) curve is shown in Fig.3. Further, comparison is shown between our method and the PCC_0 one that Ren *et al.* proposed [16], which only uses dual polar and the principal component analysis (PCA) based method. As seen in Fig.3, the change of ROC curves denotes that different thresholds greatly affect Sensitivity and Specificity. More importantly, compared with the PCC_0, our method achieved more satisfactory performance.

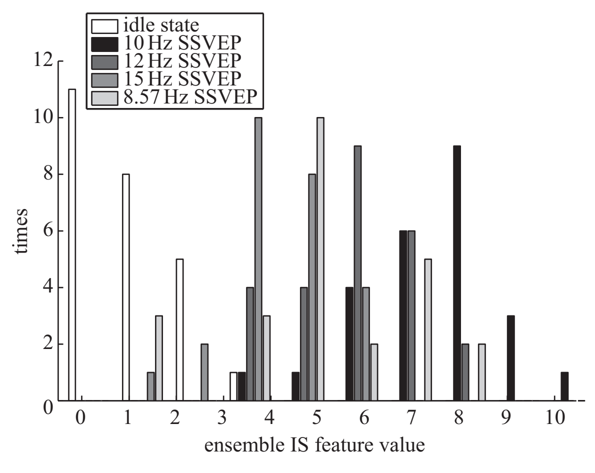

Fig.2 Distribution of the ensemble IS feature values of training samples for subject 1

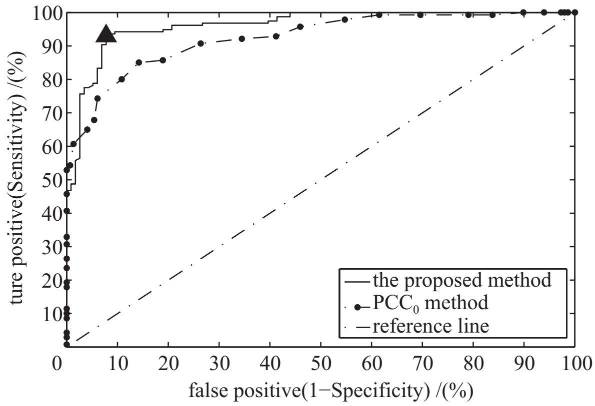

Fig.3 ROC curves based on the IS feature values for subject 1. The black upward-pointing triangle marker denotes the position where the sum of Sensitivity and Specificity reaches maximum. Hence the corresponding IS feature value is chosen as the learned optimal threshold θ^*

We compared our method with the one proposed by Wang *et al.* [21], which used multiple electrodes and considered alpha waves interference. Tab.1 lists the Sensitivity and Specificity for both methods respectively. It is illustrated that although our method attains slightly lower Specificity, the Sensitivity is improved greatly.

Tab.1 Performance of idle state detection module (%)

subject	**the proposed method**		**Wang et al.'s method**	
	Sensitivity	Specificity	Sensitivity	Specificity
1	92.8	90.8	70.6	96.6
2	91.1	95.1	92.1	97.6
3	91.4	90.5	92.2	100
4	98	95.4	85.2	98.4
5	74.5	78.1	71.7	95.7
6	98.1	97.8	80	100
7	90.7	87.3	91.6	95
8	96.8	94	85	100
9	77.2	82.4	70	92.8
10	82.6	79.6	70.8	91.8
average	89.3	89.1	80.9	96.8

Tab.2 shows the performance of the CS discrimination module. It is readily observed that the mean accuracy is 97.1%. Thus as for the second stage, the results verify the low inter-user variation and satisfactory performance.

Tab.2 Performance of control state discrimination module (%)

subject	**SSVEP classification accuracy**
1	100
2	97.5
3	99
4	99.3
5	97.3
6	100
7	97.1
8	99.2
9	85.8
10	96
average	97.1

4 Discussion

SSVEP is a quite weak response compared with spontaneous EEG signals. Thus in the PCA based PCC_0 method, the extracted primary component may contain large noise. Further, spontaneous oscillation interference isn't considered, so it is difficult for the approach to achieve satisfactory performance as shown in Fig.3.

In our experiment, the stimulus frequencies coincided with the occipital alpha band. Thus the frequency interference may occur. In our method, the problem can be effectively solved due to robust BSS procedure as well as the higher SSVEP harmonics information incorporated into the ensemble feature model. Hence compared with Wang *et al.*'s approach, our method provides a better way in excluding the spontaneous oscillation interference not limited to alpha disturbance.

In formula (1), the one-point delayed correlation matrix is used for SVD, because the self-similarity of large approximate white noise can be reduced through taking time delay into account. Meanwhile in CS, the SSVEP response can be enhanced and extracted using BSS. Further to make reaction time short enough, the time delay should not be much long. By assessing different delay lengths, the one-point delay is chosen to achieve effective performance.

Mostly, users prefer to accurate detection in their IS. They are more tolerant when their CS is wrongly detected as IS. For this case, we can change the threshold estimation strategy. The detection threshold should be adjusted to attain Specificity of above one floor lever and acceptable Sensitivity as high as possible.

In the proposed method, the adoption of CWT improves the effectiveness of extracting ensemble feature. The calculation of wavelet coefficients with stimulus frequencies doesn't take high computational complexity. Besides, our method makes full use of multi-electrode EEG to obtain significant recognition information, which integrates functions of spatial filtering and feature extraction. Especially for short segment, greater performance can be achieved through our method than the unipolar or bipolar based ones. Further, better effect may be obtained by using more electrodes. With the real-time calculation and space complexity in mind, only eight fixed electrodes were used in our method.

5 Conclusions

In this paper, using BSS and CWT techniques, a two-stage state recognition method is proposed for our SBCI system. In IS detection stage, the ensemble IS feature turned out to be a satisfactory index for detecting idle and control states. Through the CS discrimination stage with the $\boldsymbol{F}_{\mathrm{CS}}$ input, users' control intention can be decoded into corresponding control commands with high classification performance. The experimental results validated the effectiveness and satisfactory advantages of the proposed method over other ones. Therefore, it is promising that our approach can be further modified and improved to realize online asynchronous SBCI system.

References

[1] Wolpaw J R, Birbaumer N, McFarland D J, et al. Brain-computer interfaces for communication and control[J]. Clinical Neurophysiology, 2002, 113(6): 767-791.

[2] Scherer R, Mueller G R, Neuper C, et al. An asynchronously controlled EEG-based virtual keyboard: Improvement of the spelling rat[J]. IEEE Transactions on Biomedical Engineering, 2004, 51(6): 979-984.

[3] Wang Y J, Wang R P, Gao X R, et al. A practical VEP-based brain-computer interface[J]. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 2006, 14(2): 234-239.

[4] Li Y, Gao X R, Liu H S, et al. Classification of single-trial electroencephalogram during finger movement[J]. IEEE Transactions on Biomedical Engineering, 2004, 51(6): 1019-1025.

[5] Berger T W, Chapin J K, Gerhardt G A, et al. International assessment of research and development in brain-computer interfaces: Report of the World Technology Evaluation Center[R]. Berlin, Germany: Springer, 2007.

[6] Borisoff J F, Mason S G, Birch G E. Brain interface research for asynchronous control applications[J]. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 2006, 14(2): 160-164.

[7] Kastner S, Pinsk M A. Visual attention as a multilevel selection process[J]. Cognitive, Affective, & Behavioral Neuroscience, 2004, 4(4): 483-500.

[8] Regan D. Human brain electrophysiology: Evoked potentials and evoked magnetic fields in science and medicine[M]. New York, USA: Elsevier Science Ltd, 1989.

[9] Belouchrani A, Abed-Meraim K, Cardoso J F, et al. A blind source separation technique using second-order statistics[J]. IEEE Transactions on Signal Processing, 1997, 45(2): 434-444.

[10] Peters B O, Pfurtscheller G, Flyvbjerg H. Automatic differentiation of multichannel EEG signals[J]. IEEE Transactions on Biomedical Engineering, 2011, 48(1): 111-116.

[11] Zhang Z M, Li X Q, Deng Z D. A CWT-based SSVEP classification method for brain-computer interface system[C]//IEEE International Conference on Intelligent Control and Information Processing, Part 2. Piscataway, NJ, USA: IEEE, 2010: 43-48.

[12] Samar V J, Bopardikar A, Rao R, et al. Wavelet analysis of neuroelectric waveforms: A conceptual tutorial[J]. Brain and Language, 1999, 66(1): 7-60.

[13] Tallon-Baudry C, Bertrand O, Delpuech C, et al. Stimulus specificity of phase-locked and non-phase-locked 40 Hz visual responses in human[J]. Journal of Neuroscience, 1996, 16(13): 4240-4249.

[14] Goupillaud P, Grossmann A, Morlet J. Cycle-octave and related transforms in seismic signal analysis[J]. Geoexploration, 1984, 23(1): 85-102.

[15] Wang S Y, Aziz T Z, Stein J F, et al. Time-frequency analysis of transient neuromuscular events: Dynamic changes in activity of the subthalamic nucleus and forearm muscles related to the intermittent resting tremor[J]. Journal of Neuroscience Methods, 2005, 145(1/2): 151-158.

[16] Ren R, Bin G Y, Gao X R. Idle state detection in SSVEP-based brain-computer interfaces[C]//2nd International Conference on Bioinformatics and Biomedical Engineering. Piscataway, NJ, USA: IEEE, 2008: 2012-2015.

[17] Freund Y. Boosting a weak learning algorithm by majority[J]. Information and Computation, 1995, 121(2): 256-285.

[18] Dempster A P, Laird N M, Rubin D B. Maximum likelihood from incomplete data via the EM algorithm[J]. Journal of the Royal Statistical Society: Series B (Methodological), 1977, 39(1): 1-38.

[19] Cortes C, Vapnik V. Support-vector network[J]. Machine Learning, 1995, 20(3): 273-297.

[20] Vapnik V N. The nature of statistical learning theory[M]. New York, USA: Springer-Verlag, 1995.

[21] Wang N Y, Qian T Y, Zhuo Q, et al. Discrimination between idle and work states in BCI based on SSVEP[C]//IEEE International Conference on Advanced Computer Control, vol.4. Piscataway, NJ, USA: IEEE, 2010: 355-358.

About Authors:

ZHANG Zimu (1984–), male, Ph.D. candidate. His research interests include neural science, signal processing, BCI, and robot control.

DENG Zhidong (1966–), male, Professor. His research interests include computational intelligence, BCI, complex network theory, computational biology, virtual reality, wireless sensor network, and robotics.