Discrimination of Motor Imagery Patterns by Electroencephalogram Phase Synchronization Combined With Frequency Band Energy

Chuanwei Liu, Yunfa Fu, Jun Yang, Xin Xiong, Huiwen Sun, and Zhengtao Yu

***Abstract*—Central nerve signal evoked by thoughts can be directly used to control a robot or prosthetic devices without the involvement of the peripheral nerve and muscles. This is a new strategy of human-computer interaction. A method of electroencephalogram (EEG) phase synchronization combined with band energy was proposed to construct a feature vector for pattern recognition of brain-computer interaction based on EEG induced by motor imagery in this paper. rhythm and beta rhythm were first extracted from EEG by band pass filter and then the frequency band energy was calculated by the sliding time window; the instantaneous phase values were obtained using Hilbert transform and then the phase synchronization feature was calculated by the phase locking value (PLV) and the best time interval for extracting the phase synchronization feature was searched by the distribution of the PLV value in the time domain. Finally, discrimination of motor imagery patterns was performed by the support vector machine (SVM). The results showed that the phase synchronization feature more effective in 4 s−7 s and the correct classification rate was 91.4 %. Compared with the results achieved by a single EEG feature related to motor imagery, the correct classification rate was improved by 3.5 and 4.3 percentage points by combining phase synchronization with band energy. These indicate that the proposed method is effective and it is expected that the study provides a way to improve the performance of the online real-time brain-computer interaction control system based on EEG related to motor imagery.**

***Index Terms*—Brain-computer interaction (BCI), electroencephalogram (EEG), frequency band energy, motor imagery, phase synchronization.**

I. Introduction

DIRECT brain-computer interaction (BCI) using brain signal is a new type of human-computer interaction technology, which can directly reconstruct motor control by brain signal [1]−[4]. It can be strategically used for military purposes and also can provide auxiliary control for severely disabled patients and healthy population, thereby improving their quality of life [5]−[8]. At present, BCIs have become a major international frontier research and application hotspot, and among them, BCI based on electroencephalogram (EEG) is a very important one [9], [10]. BCI based on EEG mainly involves three aspects of research: the basic research of neuroscience closely related to the BCI, the engineering implementation method of the BCI, and the application research of the BCI. This paper mainly concerns the engineering implementation of the BCI.

The hybrid BCI, one of the engineering realization methods for BCI, refers to using two or more neural mechanisms, or BCI paradigms, in the same BCI system device. The strategy for BCI in a certain extent may improve the accuracy of identification instruction or increase the number of different types of control commands, and can bring the expertise or advantage of every BCI paradigm for communication or control into play [11], [12]. From a more generalized perspective, compared with the traditional BCI based on single mode or single feature under the experiment paradigm of single neural mechanism or a single mental activity, the combination or fusion of different types of brain signals such as EEG, near-infrared spectroscopy (NIRS), and functional magnetic resonance imaging (fMRI) [13], [14] and the combination or fusion of multi-features from the same brain signals can be called multi-modal BCI or multi-feature fusion BCI [15].

In the paper, BCI based on the fusion of multi-features of EEG related to motor imagery was studied. The key problem of the BCI is the feature extraction algorithm which directly affects the accuracy of the following pattern classification [16]. Relevant frequency band energy featuring only event-related desynchronization/synchronization (ERD/ERS) was extracted for most of the traditional BCIs based on EEG induced by motor imagery [17]−[21]; the feature vector was also constructed by the energy feature combined with movement-related potentials [20], and these methods achieved some results. However, EEG phase synchronization characterizes collaboration between the relevant brain areas during mental activities and contains some additional information besides changes in band energy, which is often neglected and rarely used as a feature to identify mental tasks [15], [22]−[24].

Therefore, the synchronization between brain areas and acti-

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vation intensity during motor imagery were simultaneously considered in the study. EEG phase synchronization combined with frequency band energy was used classifying the motor imagery patterns. It is expected that the study can provide a way of improving the performance of the online real-time BCI control system based on the multi-features fusion of EEG induced by motor imagery.

The paper was organized as follows: in the first section for materials and methods, EEG instantaneous phase calculated by Hilbert transform, EEG phase synchronization feature extracted by phase-locked value (PLV), and the optimal time period for extracting phase synchronization feature are introduced. Additionally, how the EEG was collected from $C3$ and $C4$ over the motor area was band pass filtered and the frequency band energy was extracted is presented. Finally, the support vector machine (SVM) is used to identify the motor imagery patterns. In the second and third sections, the results and discussion are presented, respectively, and the conclusion is given in the last section.

II. MATERIALS AND METHODS

A. Subject and Experimental Paradigm and Data Collection

The subject involved in EEG data acquisition was a woman, 25 years old, and in good health. The experiment consisted of online BCI system with feedback. The subject imagined the movement of the right or left hand to control the movement of the cursor in the screen and timing diagram was shown in Fig. 1. Each trial lasted 9 s; the subject was asked to keep quiet in the interval between 0 and 2 s; a cross cursor appeared on the screen at 2 s and at the same time a beep sound was made for cue; then the cross cursor sustained 1 s for motor imagery preparation; at 3 s, the cross cursor was replaced by the right or left arrow, and at the same time, the subject was asked to imagine the right or left hand movement in the direction of the arrow, and imagination mental activity lasted 6 s and ended at 9 s. Two kinds of tasks (the right and left hand motor imagery) were classified by the online BCI system. The coefficients of AR model at each time were extracted by using the adaptive AR model and the classification results were achieved by linear discriminant analysis and provided to the subject as the feedback signal [25].

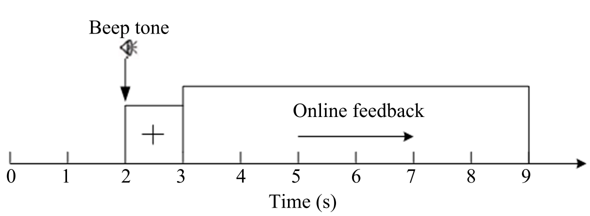


Fig. 1. Timing scheme.

The experiment consisted of 7 runs and each run had 40 trials; thus 280 trials in total. The data were acquired by the differential electrodes from $C3$, $C4$, and Cz according to the international $10-20$ lead system. The electrodes were AgCl electrode and the sampling frequency was 128 Hz. The data set contained training samples and test data of 70 trials of imagining right hand movement and 70 trials for left hand movement [25].

The second data set is the fourth brain-machine interface competition data sets 2b. It contains 3 training sets of B0X01T, B0X02T, and B0X03T, and 2 test sets of B0X04E and B0X05E. The data was collected from the experimenting the motor imagination of left hand and right hand movement [26].

B. Calculation of EEG Phase Synchronization Feature Related to Motor Imagery

The activation of motor cortex during movement may occur simultaneously in several brain areas and cooperation and integration between different brain areas may be reflected by the degree of synchronization between EEG signals collected from these areas [23], [27]$-$[30].

At present, the correlation of phase and the correlation of amplitude between signals have been known to be independent of each other. When the amplitude between signals is uncorrelated, their phases can also be synchronized [24]. The phase coupling between two signals can be measured by PLV, which is also known as phase synchronization factor. It is defined as

$$PLV = \frac{1}{N}\left|\sum_{t=1}^{N}\exp\left(j(\phi_1(t)-\phi_2(t))\right)\right| \tag{1}$$

where $\phi_1(t)$ and $\phi_2(t)$ denote the instantaneous phase value of channel 1 and 2 at time t, respectively. Range for PLV is $0-1$ and when two signal is fully synchronized, PLV is 1; when two signal is completely asynchronized, PLV is 0. PLV indicates the degree of synchronization between two channel signals rather than the phase difference between them [15].

The instantaneous phase value can be calculated by Hilbert transform or wavelets transform [31]. In this paper, we used the Hilbert transform to calculate the instantaneous phase [32]. Hilbert transform is described as

$$y(t) = \frac{1}{\pi}P\int_{-\infty}^{+\infty}\frac{x(\tau)}{t-\tau}d\tau. \tag{2}$$

The equation shows that a non-stationary signal $x(t)$ is transformed into $y(t)$ by Hilbert transform. Here P is Cauchy principal value [33], [34]. Instantaneous phase can be calculated by

$$\varphi(t) = \arctan\frac{y(t)}{x(t)}. \tag{3}$$

According to the synchronization of EEG signal between different brain areas during motor imagery, PLV of two channels pairs ($C3$-Cz and $C4$-Cz) was selected as the phase synchronization feature in the paper [35], [36]. For the PLV between $C3$ and Cz ($C3$-Cz) in the calculation, we set the instantaneous phase of the signal from $C3$ channel as φ_1, and set the instantaneous phase of the signal from Cz channel as φ_2. In the same way, for the PLV between $C4$ and Cz ($C4$-Cz), we put the instantaneous phase of the signal from $C4$ channel as φ_1, and put the instantaneous phase of the signal from Cz as φ_2. The instantaneous phases φ were calculated by (2) and (3).

C. Calculation of EEG Frequency Band Energy Feature Related to Motor Imagery

The signal energy of the specific frequency band (such as mu and beta rhythms) from contralateral sensorimotor area decreases and the signal energy from the corresponding frequency band ipsilateral sensorimotor area increases when the subject or user imagines unilateral limb movement. The above phenomenon is called event-related desynchronization (ERD) and event-related synchronization (ERS) [16]−[19], [37]. The frequency band energy feature was extracted from 8 −30 Hz (covering mu and beta rhythms) of EEG signal based on ERD/ERS.

For extracting the EEG frequency band energy feature related to motor imagery, EEG signals from $C3$ and $C4$ channels over the right and left motor cortex were chosen. EEG signals from $C3$ and $C4$ channels were filtered with an 8−30 Hz frequency band and then each sampling point of the filtered signal was squared. According to the experimental paradigm in Fig. 1, the imagination period was 3 s−9 s. Thus, the signal energy of 3 s−7 s epoch was calculated with a 1 s length and step size of the sliding time window. The sampling points were squared and summed in each time window, and divided by the total number of sampling points. Finally, the mean value placed in a logarithm operation to represent the band energy of the window. Frequency band energy feature was extracted according to

$$P_j = \lg\left(\frac{1}{n}\sum_{i-j-n+1}^{j} v_i^2\right) \tag{4}$$

where P_j is the frequency band energy of the jth time window, v_i^2 is the square of the ith sampling point, and n is the window length [38].

D. Construction of Feature Vector by Phase Synchronization Combined With Frequency Band Energy

The phase synchronization feature and the frequency band energy feature related to motor imagery were calculated in Sections I-B and I-C, respectively. Then the combined feature vector x was constructed from the two features. The energy feature of five time windows of each single trial from the $C3$ and $C4$ channels was extracted and the phase synchronization feature of corresponding $C3$-Cz and $C4$-Cz was calculated.

The combined feature vector x is of 12 dimensions according to

$$x = (FBE_{C3}, FBE_{C4}, PS_{C3\text{-}Cz}, PS_{C4\text{-}Cz}) \tag{5}$$

$$\begin{aligned} FBE_{C3} = (&FBE_{C3\text{-}TW1}, FBE_{C3\text{-}TW2}, FBE_{C3\text{-}TW3},\\ &FBE_{C3\text{-}TW4}, FBE_{C3\text{-}TW5}) \end{aligned} \tag{6}$$

$$\begin{aligned} FBE_{C4} = (&FBE_{C4\text{-}TW1}, FBE_{C4\text{-}TW2}, FBE_{C4\text{-}TW3},\\ &FBE_{C4\text{-}TW4}, FBE_{C4\text{-}TW5}) \end{aligned} \tag{7}$$

where FBE_{C3} and FBE_{C4} denote the frequency band energy (FBE) of $C3$ and $C4$ channel, respectively; $FBE_{C3\text{-}TW1}$ and $FBE_{C4\text{-}TW1}$ denote the frequency band energy in $TW1$ time window of $C3$ and $C4$ channel, respectively; $PS_{C3\text{-}Cz}$ and $PS_{C4\text{-}Cz}$ denote the phase synchronization value of $C3$-Cz and $C4$-Cz electrode pairs, respectively.

E. Classification Method for EEG induced by Motor Imagery

Support vector machine (SVM) based on structural risk minimization principle and statistical theory is often used to verify the effect of the feature extraction algorithm. The core of SVM is to construct the optimal hyper plane so that the classification error of the unknown sample is minimized [39].

For the linear separable training sample $\{(x_1, y_1), \ldots, (x_n, y_n)\}$, x_i is the feature vector and $y_i = \{-1, 1\}$ is the class label. The optimal classification plane should accurately classify two kinds of samples and the classification spacing is the biggest, thus it should satisfy the following constraint equation

$$\begin{cases} (x_i w) + b \geq 1, & \text{if } y_i = 1 \\ (x_i w) + b \leq 1, & \text{if } y_i = -1 \end{cases} \tag{8}$$

where w is the projection vector of classification plane and b is the classification threshold. The classification function is

$$f(x) = \mathrm{sgn}(wx + b). \tag{9}$$

Aiming at the nonlinear inseparable problem, the appropriate kernel function was chosen for the classification hyper plane to perform the nonlinear transform, change it into the linear separable problem, and map the original space to a high dimensional space. The corresponding discriminant function is [39]

$$f(x) = \mathrm{sgn}\left[\sum_{i=1}^{n} \alpha_i y_i K(x_i x) + b\right] \tag{10}$$

where n is the number of vectors, α_i is Lagrange multiplier, and $K(x_i x)$ is kernel function [40].

In this paper, the radial basis kernel function was chosen as the kernel function of SVM and the feature vector constructed by phase synchronization combined with frequency band energy was used to classify the test data.

III. Results

A. Phase Synchronization and Frequency Band Energy Feature of EEG Related to Motor Imagery

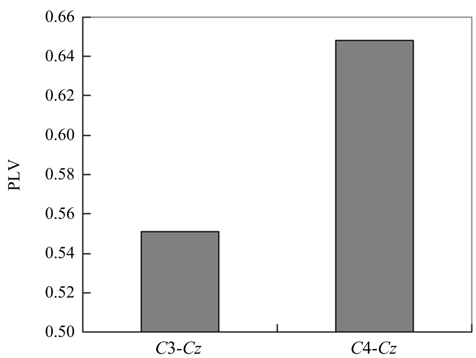
Figs. 2 (a) and 2 (b) show the average PLV of two channels pairs of $C4$-Cz and $C3$-Cz under two kinds of imagination tasks. $C4$-Cz and $C3$-Cz are signs that indicate a relationship between two channels of $C4$ and Cz (or $C3$ and Cz). According to (1), we put the instantaneous phase of the signal from $C4$ channel as φ_1, and put the instantaneous phase of the signal from Cz channel as φ_2. Finally, we calculated the mean value of PLV, and the PLV of $C3$-Cz was calculated in the same way in Fig. 2. For the acquisition of original signal, the way of Bipolar derivations was used, and the recording data was the difference of the two EEG from two electrodes. For the PLV, both $C4$-Cz and $C3$-Cz were based on the instantaneous phase of the Cz channel. So, the Cz can be regarded as the reference signal.

When the subject imagined her left hand movement, the PLV of $C4$-Cz was higher than that of $C3$-Cz, or the degree of synchronization between $C4$ and Cz was higher. Compared with the PLV of $C4$-Cz, when the subject imagined her right hand movement, the PLV of $C3$-Cz was higher, or the degree of synchronization between $C3$ and Cz was higher. Figs. 2 (c) and 2 (d) show the frequency band energy of $C3$ and $C4$ under the two kinds of imagination tasks.

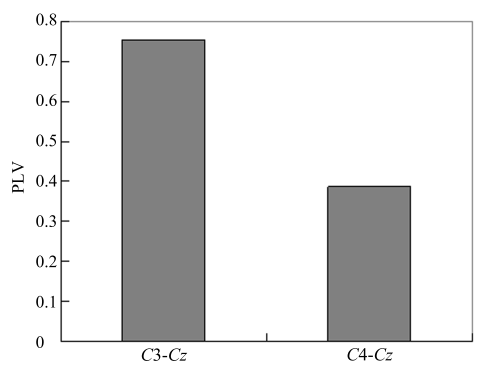
Figs. 3 (a) and 3 (b) showed PLV distribution in time domain during motor imagery tasks. The solid line indicated the PLV distribution in the time domain during motor imagery involving the right hand and the dotted indicated the PLV distribution in the time domain during motor imagery involving the left hand. Each curve was the average PLV across 70 single trials during corresponding motor imagery. According to the experimental timing in Fig. 1, motor imagery started at 3 and Fig. 3 showed the phase synchronization between different brain areas was different in time domain. Fig. 3 also showed the significant differences of phase synchronization in the interval of 4 s to 7 s between two imagination tasks.

B. Recognition of Motor Imagery Patterns

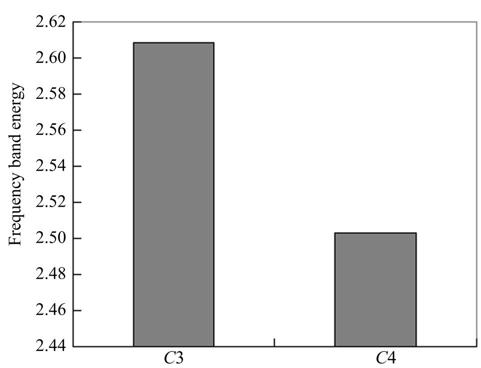
EEG signals were acquired from 3 channels ($C3$, Cz, $C4$) in the experiment. The phase synchronization feature of $C3$-Cz and $C4$-Cz channels pair was extracted and the frequency band energy features of $C3$ and $C4$ channels were calculated. From the analysis of Fig. 3, the difference of phase synchronization between imaginary left and right hand movements was significant in the interval of 4 s−7 s. In this paper, phase synchronization combined with frequency band energy feature were calculated in the intervals of 1 s−9 s, 2 s−7 s, 3 s−8 s, 4 s−7 s, and 4 s−8 s respectively and the correct recognition



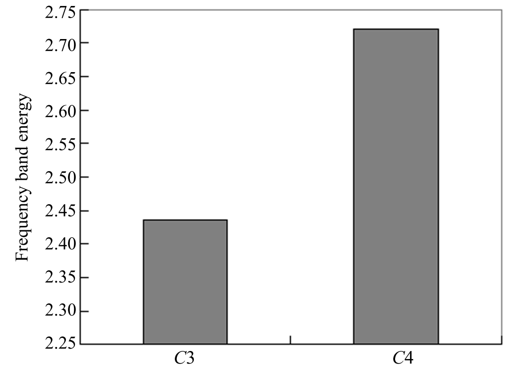
(a) Imagination of left hand movement



(b) Imagination of right hand movement

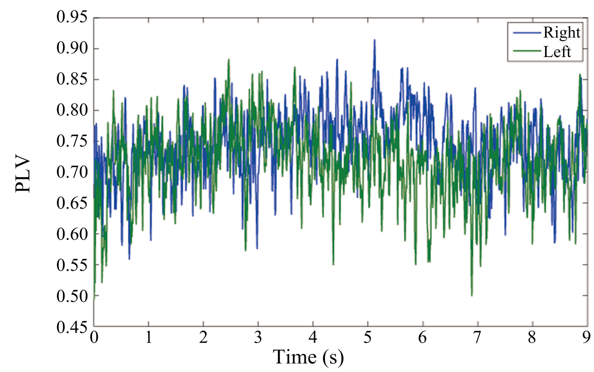


(c) Imagination of left hand movement

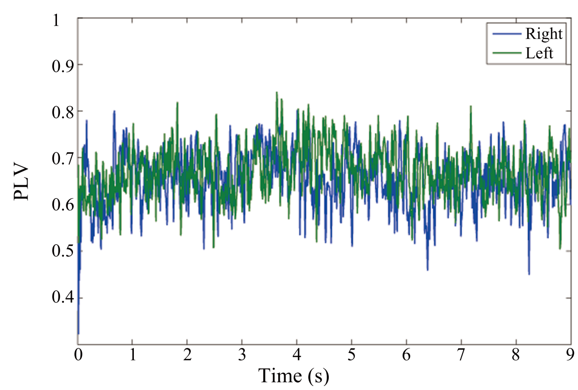


(d) Imagination of right hand movement

Fig. 2. The average PLV and the frequency band energy during motor imagery. (a) and (b) The average PLV of two channels pairs of $C3$-Cz and $C4$-Cz under two kinds of imagination tasks. (c) and (d) The frequency band energy of $C3$ and $C4$ under two kinds of imagination tasks.



(a)



(b)

Fig. 3. PLV distribution in time domain during motor imagery tasks. (a) PLV distribution in time domain for $C3$-Cz channel pair during two kinds of imagination tasks. (b) PLV distribution in time domain for $C4$-Cz channel pair during two kinds of imagination tasks.

rate by SVM was 80.7 %, 85 %, 87.8 %, 91.4 %, and 89.2 % respectively, as shown in Table I.

TABLE I
THE CORRECT IDENTIFICATION RATE BY PHASE SYNCHRONIZATION FEATURE FOR DIFFERENT TIME INTERVAL

Time interval (s)	Identification rate (%)
1−9	80.7
2−7	85.0
3−8	87.8
4−7	91.4
4−8	89.2

Table II shows the classification accuracy before and after the phase synchronization feature (PSF) combined with the frequency band energy feature (FBEF). Here the frequency band energy E1 was extracted by the method proposed in Section II-C and the frequency band energy E2 was the average of the square of the sampling point in the time windows mentioned in Section II-C, but without the logarithmic operation.

TABLE II
CLASSIFICATION ACCURACY BEFORE AND AFTER PHASE SYNCHRONIZATION COMBINED WITH BAND ENERGY (%)

	Feature	Accuracy
Single feature	FBEF E1	87.90
	FBEF E2	85.00
Fusion feature	FBEF E1+ PSF	91.40
	FBEF E2+ PSF	89.30

Table III shows the classification accuracy of the 4th brain-computer interface competition data sets 2b. In the table, 1T, 2T, and 3T are the training sets, and 4E and 5E are the test sets. The training set 2T may have some error, which leads to the unsatisfactory classification accuracy. The accuracy of the other two groups is satisfactory, and they demonstrate the efficiency of the method in classifying left and right hand motor imagination.

TABLE III
THE CLASSIFICATION ACCURACY BASED ON ELECTROENCEPHALOGRAM PHASE SYNCHRONIZATION COMBINED WITH FREQUENCY BAND ENERGY FOR THE 4TH BRAIN-COMPUTER INTERFACE COMPETITION DATA SETS 2B (%)

Classification	1T	2T	3T
4E	91.25	53.75	92.50
5E	87.50	51.88	88.75

IV. DISCUSSION

The more natural and intuitive realization method than the commonly reported traditional one of driving devices to move by thoughts is the brain-computer interaction control interface based on EEG induced by motor imagery. It is expected to achieve human-machine integration control or brain-machine fusion control based on the BCI [41]. However, the identification accuracy and stability of this kind of brain-computer interaction is far from the requirements of practical application, and a single EEG energy feature related to motor imagery was mainly used for the traditional identification methods. By contrast, BCI based on the fusion of multiple features, entails finding other neural signal features characterizing motor imagery mental activity to increase the correct recognition rate and improve the stability of the BCI.

The difference of activation in motor areas during different motor imagery tasks was used for BCI based on the ERD/ERS related to motor imagery [16]−[19]; the time characteristics of brain processing was used for BCI based on the features of movement-related potentials evoked by motor imagery and the processing may involve the differences of movement preparation, execution, and termination [42]−[45]. However, the brain areas collaboratively work as a network system during real or imaginary movement. The collaboration between the brain areas can be characterized by EEG phase synchronization and thus BCI based on EEG phase synchronization can be constructed [15], [23], [24], [36]. Compared with the existing researches [18], [20], [22], the new idea and characteristic of this study lies in EEG phase synchronization combined with frequency band energy in order to improve the classification accuracy and stability of motor imagery patterns.

Figs. 2 (a) and 2 (b) show that the PLV between contralateral primary motor area and parietal area was higher during the subject imagining unilateral limb movement. This meant that the degree of synchronization between them was higher, and coordination between them increased. Figs. 2 (c) and 2 (d) show that the energy of the EEG signal from the contralateral primary motor area decreased during the subject imagining unilateral limb movement (corresponding brain function may be the activation of contralateral motor area which play an important regulation role in limb movement), and the energy of the EEG signal from the ipsilateral primary motor area increased (corresponding brain function may be the activation of ipsilateral motor area decreased or inhibited). This once again verified ERD/ERS phenomenon during motor imagery [17]−[19]. In addition, comparing Figs. 2 (a) and 2 (b) with Figs. 2 (c) and 2 (d) show that a lower energy and a higher the degree of synchronization indicate that the degree of collaboration between the brain areas and brain activation has a certain correlation.

Furthermore, Fig. 3 shows that phase synchronization feature between corresponding brain areas had significant differences in the interval of 4 s−7 s under different imaginary movement modes. This may provide the evidence for extracting the phase synchronization feature. In Table I, the correct recognition rate based on phase synchronization in different time intervals confirmed that the appropriate time of extracting phase synchronization feature was 4 s−7 s.

The classification results were compared between the single EEG energy feature and fusion feature with phase synchronization feature in Table II based on the above-mentioned research of the EEG phase synchronization feature related to motor imagery. Table II shows that the classification accuracy was improved as the phase synchronization combined with the frequency band energy and the maximum classification rate was 91.4 %, and two fusion features had an increase by 3.5 % and 4.3 %, respectively. This indicates that the EEG phase synchronization feature related to motor imagery may contain some additional information besides changes in band energy.

Compared with the studies of Palaniappan *et al.* [46] and Wang *et al.* [47], this study differed from their experiment paradigm in the data acquisition and data processing method. In the study of Palaniappan *et al.*, EEG signals were recorded from four subjects while they were thinking of four different mental tasks. Their method uses spectral power and power difference in four bands: delta and theta, beta, alpha, and gamma. Spectral powers in the four bands are computed using the energy of Elliptic FIR filter output. The mental tasks are detected by a neural network classifier. In Wang's research, a power projection based feature extraction method was used to classify the EEGs by combining the information accumulative posterior Bayesian approach. The method improves the classification accuracy by maximizing the average projection energy difference of the two types of signals. In our paper, the additional phase synchronization feature was extracted, the appropriate time of extracting phase synchronization feature was searched in the study, and the energy features of five time windows were calculated from the $C3$ and $C4$ channels. The above analysis and the results of Tables I−III show that more reliable classification results were achieved by the phase synchronization feature in a specific time (4 s−7 s). However, the current deficiency of the method can use a little longer time for processing EEG signal than the existing research because two features need to be extracted and combined. The optimization of the algorithm will be needed for the online system.

V. CONCLUSIONS

In addition to the hybrid BCI method, the method of multimodal BCI or multiple features fusion BCI can be also used to improve the performance of the BCI system based on EEG induced by motor imagery. Being different from the traditional BCI based on the single feature of EEG related to motor imagery, Hilbert transform was used to calculate the EEG instantaneous phase, and the phase locking value (PLV) was employed to extract the EEG phase synchronization feature. The study showed that the PLV between the contralateral primary motor area and the parietal area was higher and their collaboration increased during the subject imaging unilateral limb movement. Furthermore, this may also indicate that collaboration between brain areas and activation of the brain area has certain relevance. By the analysis, the appropriate time of extracting the phase synchronization feature was 4 s−7 s and the energy feature of the five time windows were extracted from the $C3$ and $C4$ channels. Additionally, the classification accuracy and stability were improved by combining the two features, and the maximum recognition accuracy was 91.4 %. This indicates that the classification accuracy and stability of motor imagery patterns can be improved by the phase synchronization feature in a specific period of time.

Our future works will be focused on: 1) optimization of the method to reduce the time of processing EEG and reasonably apply it to the online system for improving the performance of the whole system; 2) further research of controllability and observability of subject/user's mental activity in order to improve the stability and reliability of identification of motor imagery patterns.

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