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Phase Synchrony Measurement in Motor Cortex for Classifying Single-trial EEG during Motor Imagery

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Abstract—**A motor imagery based brain-computer interface (BCI) translates the subject's motor intention into a control signal. For this BCI system, most algorithms are based on power changes of mu and beta rhythms. In this paper, we employ the measurement of phase synchrony to investigate the activities of the supplementary motor area (SMA) and primary motor area (M1) during left/right hand movement imagery. The single-trial phase locking value (PLV) features were derived from intrinsic large-scale and local-scale phase synchronies between and within SMA and M1. The classification performance suggests that phase synchrony is an additional robust feature for differentiating motor imagery states.**

Keywords—**brain-computer interface, phase synchrony, motor imagery**

I. Introduction

Motor imagery of hand movement has been widely used for producing detectable mu rhythm in Rolandic area in the EEG based brain-computer interface (BCI) systems. The electrodes over primary motor cortex (M1), as C3 and C4 electrode in the 10-20 system, have been long considered as the best positions for recording prominent change of mu (and/or beta) rhythm [1]. However, there is still no clear evidence supporting the involvement of the M1 area in the mental performance of hand (or finger) movements, even though the question has been extensively studied using functional neuroimaging methods[2], while the supplementary motor area (SMA) have been consistently found to be involved in the motor imagery [3], [4]. It is interesting to note that less attention has been paid to the role of SMA area than M1 area in the motor imagery based BCI, although there have been studies indicating the rhythmic change in SMA that could be recorded by means of EEG [5], [6]. One possible reason is that SMA activity recorded by EEG usually showed a single midline frontal focus, which can not be used, solely by itself, for differentiating the imagination of left and right hand movement. In fact, the measurement of neural coupling between SMA and M1 may largely remove the obstacle and provide additional information for BCI classification [5], [7]. However, the contribution of this feature for improving the classification rate, especially compared with conventional amplitude features of mu rhythm, has not been justified yet.

Coupling of oscillatory activity from different neural ensembles is the putative underlying mechanism of neural interaction and integration, through which neural assemblies are dynamically formed to accomplish perceptual, motor and cognitive functions [8], [9]. This kind of neural synchronization spans multiple scales from adjacent neurons to different cortical lobes. Measurement of phase coupling (or phase locking) of EEG or MEG, instead of formerly used spectral coherence, has been used for exploring the dynamics of brain networking [10], [11]. The general procedure for detecting and quantifying the phase coupling consists of following steps. Given two signals, their instantaneous phases (across different frequency bands) are estimated by convolution with a complex wavelet or by the Hilbert transform. With minor differences both approaches seem to be fundamentally equivalent [12]. The phase differences between the signals usually fluctuate around a constant value across trials or along time. It is therefore necessary to further test for synchrony in a statistical sense. An elegant way of significance testing, known as the phase locking value (PLV) [10], provides a reliable measurement of phase coupling. The PLV measurement has been recently introduced as EEG features of motor imagery in BCI applications [7]. However, an applicable and economical approach of PLV application in BCI context has not been established yet, especially with appropriate employing of physiological understanding of motor imagery.

In this study, PLV was employed to quantify the level of neural coupling during imagination of left or right hand movement, both among EEG electrodes in M1 area (local scale) and between M1 and SMA electrodes (large scale). To our best knowledge, for the first time, PLV between M1 and SMA in the band of mu rhythm was justified as additional features for the classification of left or right hand motor imagery, which contributed almost as much of information as the power of mu rhythm in M1 area.

II. Methods

A. Data Acquisition

Six right-handed volunteers (five males and one female, 22-25 years old) participated in the study. They were chosen from the subjects who could successfully fulfill online BCI control in our previous studies. The recording was made

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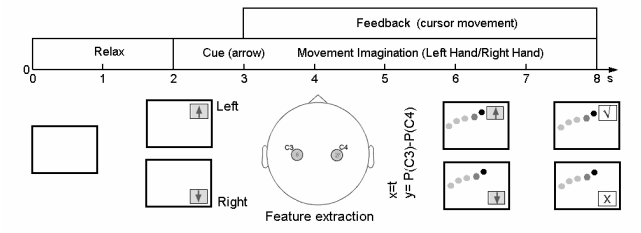

Fig.1 Online feedback paradigm of the motor imagery based brain-computer interface.

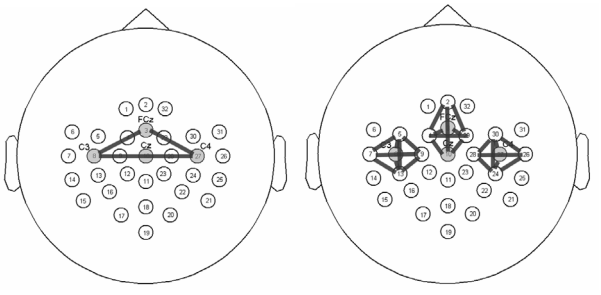

Fig. 2 (a) Large-scale electrode pairs between the SMA area and left/right M1 areas. (b) Local-scale electrode pairs located over SMA and M1 areas.

using a BioSemi ActiveTwo system. 32 EEG channels were measured at positions involving the primary motor area (M1, C3 and C4) and the supplementary motor area (SMA, FCz) (see Fig.2). Signals were sampled at 256Hz and preprocessed by a 50Hz notch filter and a 4-35Hz band-pass filter.

B. Online Feedback Paradigm

Fig. 1 shows the paradigm of online BCI control with visual feedback, which is similar to that described in [17]. The "left hand" and "right hand" movement imagination were designated to control one dimensional cursor movement, up and down, respectively. The subject sat comfortably in an armchair, opposite to a computer screen for displaying the visual feedback. The duration of each trial was 8 seconds. During the first 2 seconds, while the screen was blank, the subject was in the "relax" state. At second 2, a visual cue (arrow) was presented in the screen, indicating the imagery task to be performed. The arrow pointing upward and downward indicated the imagination of the left hand and the right hand movement respectively. At second 3, a cursor started to move from the left side to the right side of the screen. The vertical position of the cursor was determined by the power difference of mu rhythm between left and right primary motor areas (C3 and C4 electrodes), which was caused by characteristic contralateral distribution of event-related desynchronization (ERD) during left/right hand imagery [13]. At second 8, a true or false mark appeared to indicate the final result of the trial and the subject was asked to relax and wait for the next task. The experiment consisted of 4 sessions and each session consisted of 60 trials. The dataset comprising 240 trials (120 trials per class) was used for the following study of phase synchrony.

C. Measuring Synchrony during Motor Imagery

1) Single-trial phase locking value

Given $s_x(t)$ and $s_y(t)$ the signals over two electrodes x and y, and $\Phi_x(t)$ and $\Phi_y(t)$ their corresponding instantaneous phases, phase locking means

$$\phi_x(t) - \phi_y(t) = \text{constant} . \tag{1}$$

In scalp EEG signals with low signal-to-noise ratio, the true synchrony is always buried in a considerable background noise. For measuring phase synchrony with EEG signals, two steps are needed: the first is to estimate instantaneous phase of each signal and the second is to provide a statistical criteria to quantify the degree of phase-locking [10].

The instantaneous phase can be obtained by means of the analytic signal. For arbitrary signal $s(t)$, the analytic signal $z(t)$ is a complex function defined as

$$z(t) = s(t) + j\hat{s}(t) = A(t)e^{j\phi(t)}$$
$$\hat{s}(t) = \frac{1}{\pi}\int_{-\infty}^{\infty}\frac{s(\tau)}{t-\tau}d\tau \tag{2}$$

where $\hat{s}(t)$ is the Hilbert transform of $s(t)$. The instantaneous phase of $s(t)$ can be determined as follows

$$\phi(t) = \arctan(\hat{s}(t)/s(t)) . \tag{3}$$

The difference of instantaneous phases corresponding to $s_x(t)$ and $s_y(t)$ are defined as $\Delta\Phi(t)=\Phi_x(t)-\Phi_y(t)$, then a single-trial phase locking value is defined for each individual trial as

$$\text{PLV} = \left|\left\langle e^{j\Delta\phi(t)}\right\rangle_t\right| \tag{4}$$

where $\langle\cdot\rangle_t$ is the operator of averaging over time. In the case of completed synchronized signals, $\Delta\Phi(t)$ is a constant and PLV=1. If the signals are unsynchronized, then $\Delta\Phi(t)$ follows a uniform distribution and PLV=0.

2) Measuring multi-scale phase synchrony

In the study of human brain synchrony, two scales of phase synchrony can be distinguished: short-range (local-scale) synchrony and long-range (large scale) synchrony [9], [10]. Local-scale synchrony is found between adjacent areas corresponding to a single sensory modality, i.e., electrodes are in the same region, while large-scale synchrony occurs between a bit widely separated brain regions. Since SMA, left M1 and right M1 areas are considered as primary cortical regions involved in the task of hand movement imagery[2],[3], we investigated the characteristic of local-scale and large-scale synchronies within and between these regions.

As illustrated in Fig.2(a), three electrodes representing SMA and left/right M1 areas were employed in the investigation of large-scale synchrony. Phase locking value was calculated on three pairs of electrodes, i.e., FCz-C3, FCz-C4, and C3-C4. As shown in Fig.2(b), within each

region, four neighboring electrodes of FCz, C3 and C4 were combined to form a five-electrode group respectively for the measurement of local-scale synchrony. Phase locking value was obtained by averaging over all ten combinations of electrode pairs from five electrodes. Thus, the single-trial PLV was defined as

$$\mathrm{PLV}_{\text{Local-scale}} = \frac{1}{10}\sum_{k=1}^{10}\left|\left\langle e^{j\Delta\phi(t,k)}\right\rangle_t\right|$$

$$\mathrm{PLV}_{\text{Large-scale}} = \left|\left\langle e^{j\Delta\phi(t)}\right\rangle_t\right| \qquad (5)$$

where t was the time window corresponding to the imagery period (2-8s). The statistical PLV was obtained through averaging over all trials in each class. Subject-specific band-pass filter was designed to preprocess the EEG data in order to only focus on the mu rhythm (e.g. 8-12Hz). The electrode POz was selected as the reference electrode through comparison, which is far from the motor cortex and supposed to retain imagery related components and reduce the other background activities.

D. Phase Synchrony for Classifying single-trial EEG

The method of phase synchronization has already been applied for classifying single-trial EEG during motor imagery [7]. However, without considering the motor imagery related scalp regions based on the physiological background, high dimensional PLV features were calculated between or within different scalp regions and resulted in an intricate observation. For single-trial EEG classification based on phase synchrony, our specific configuration over SMA and M1 has the advantages of convenient electrode preparation, easy data processing, and robust performance due to a low feature dimension.

For single-trial classification, three local-scale PLV features and three large-scale PLV features were derived according to Eq. (5) . Linear classifiers were used to classify local-scale features and large-scale features respectively. A linear classifier was defined by a normal vector **w** and an offset b as:

$$y = \mathrm{sign}(\mathbf{w}^{\mathrm{T}}\mathbf{x} + b), \qquad (6)$$

where **x** was the feature vector. **w** and b were determined by Fisher discriminant analysis. To investigate the independency between two scales, feature combination was adopted to expect a performance gain. Cross-validation was used to estimate the classification accuracy.

III. RESULTS

Mean statistical PLV over all the subjects was displayed in Fig.3. It presents a significant contralateral dominance during hand movement imagery. Large-scale PLV over C3-FCz has a higher value during right hand imagery than left hand, and besides, the same result can be observed within the left M1 area. On the contrary, the higher PLV is corresponding to left hand imagery over C4-FCz and within the right M1 area. In contrast to C3-FCz and C4-FCz, PLV shows a low synchrony

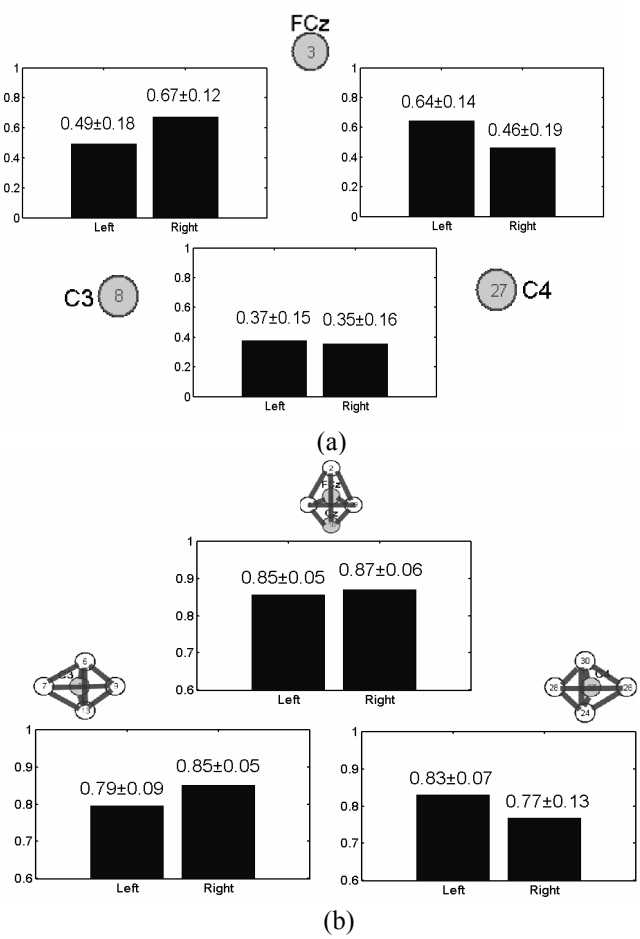

Fig. 3 (a) Average large-scale PLV and (b) average local-scale PLV corresponding to left and right hand movement imagery.

level between left and right hemispheres (C3-C4) and there exists no significant difference between left and right hand imagery. This observation is consistent with the notion in [14]. Local-scale synchrony within SMA area also shows no obvious difference between left and right hand imagery. It suggests that SMA may be activated under both imagery conditions, synchronized with the contralateral M1 area. Although local-scale synchrony is greatly influenced by volume conduction and the separation between "conduction synchrony" and "true synchrony" is difficult, the contralateral appearance can be distinctly observed during hand movement imagery and demonstrates the existence of local-scale true synchrony within M1 areas.

Table I lists the synchrony based classification results of all the subjects. Average accuracy derived from large-scale and local-scale synchrony was 84.70% and 77.08% respectively. For subjects KYX and ZD, significant difference existed between two scales. It may be caused by the spurious synchrony due to volume conduction, where the true synchrony was drowned. The combination of two-scale synchronies reached an average performance gain of 2.3%. To some extent, this result reflected the independency between these two-scale neural networks during motor imagery.

TABLE I
CLASSIFICATION ACCURACIES CORRESPONDING TO LARGE-SCALE AND LOCAL-SCALE SYNCHRONIES

Subjects	Large-scale	Local-scale	Combined
CSH	93.21±0.48	93.70±0.55	96.61±0.28
WW	91.93±0.80	92.50±0.60	94.19±0.54
KYX	87.02±0.51	61.03±1.14	87.05±0.47
FL	86.76±0.65	82.52±1.65	90.97±1.28
ZD	80.77±0.75	61.33±0.89	81.28±0.96
JCH	70.37±0.68	71.41±1.19	72.03±1.15
Mean	84.70	77.08	87.02

TABLE II
CLASSIFICATION ACCURACIES CORRESPONDING TO LARGE-SCALE SYNCHRONY AND POWER FEATURES

Subjects	Large-scale	Power Features	Combined
CSH	93.21±0.48	97.89±0.28	99.33±0.15
WW	91.93±0.80	98.12±0.35	99.43±0.13
KYX	87.02±0.51	91.41±0.42	97.84±0.22
FL	86.76±0.65	96.75±0.46	98.07±0.65
ZD	80.77±0.75	93.32±0.46	94.88±0.76
JCH	70.37±0.68	85.40±0.41	87.25±0.74
Mean	84.70	93.82	96.13

Most current algorithms for classifying single-trial EEG during motor imagery are based on the feature derived from power analysis on mu and beta rhythms (e.g. AR and CSP algorithms) [15]-[17]. A convenient method we developed here was to take the power magnitudes over C3 and C4 as the features. As illustrated in Table II, the averaged accuracy derived from the power features was 93.82%. The combination of large-scale synchrony and power features led to an improved performance of 96.13%. This result suggests that phase synchrony, especially the large-scale synchrony, can be an additional feature for the classification of different motor imagery states and its performance for differentiating left/right hand imagery is almost as good as widely used mu rhythm power.

IV. CONCLUSION

SMA has long been recognized to play an important role in the planning of movement [2], [3], while its value in motor imagery based BCI application was rarely explored [5]. In our study, SMA activation during motor imagery was proved through measuring large-scale synchrony between SMA and M1. Furthermore, the classification based on phase synchrony justified the intrinsic activation of SMA and coupling of oscillatory activity between SMA and M1 areas during hand movement imagery. In the method of power based feature extraction, SMA also played an important role although it is activated almost the same during both hand imagery states. Particularly, FCz electrode in SMA area was selected as the reference electrode, which was supposed to augment the difference between the synchronized and the unsynchronized M1 sides. In our future work, an online BCI system based on phase synchrony features in motor cortex will be tested, following the direction of this study.

REFERENCES

[1] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, "Brain-computer interfaces for communication and control," *Clin. Neurophysiol.*, vol. 113, pp. 767-791, 2002.

[2] P. Dechent, K.-D. Merboldt, and J. Frahm, "Is the human primary motor cortex involved in motor imagery?" *Cognitive Brain Res.*, vol. 19, pp. 138-144, 2004.

[3] P. E. Roland, B. Larsen, N. A. Lassen, and E. Skinhoj, "Supplementary motor area and other cortical areas in organization of voluntary movements in man," *J. Neurophysiol.*, vol. 43, pp. 118-136, 1980.

[4] M.-P. Deiber, V. Ibanez, M. Honda, N. Sadato, R. Raman, and M. Hallett, "Cerebral Processes Related to Visuomotor Imagery and Generation of Simple Finger Movements Studied with Positron Emission Tomography," *NeuroImage*, vol. 7, pp. 73-85, 1998.

[5] A. Spiegler, B. Graimann, and G. Pfurtscheller, "Phase coupling between different motor areas during tongue-movement imagery," *Neurosci. Lett.*, vol. 369, pp. 50-54, 2004.

[6] L. Leocani, C. Toro, P. Manganotti, P. Zhuang, and M. Hallett, "Event-related coherence and event-related desynchronization/synchronization in the 10 Hz and 20 Hz EEG during self-paced movements," *Electroencephalogr. Clin. Neurophysiol.*, vol. 104, pp. 199-206, 1997.

[7] E. Gysels and P. Celka, "Phase synchronization for the recognition of mental tasks in a brain-computer interface," *IEEE Trans. Neural. Syst. Rehabil. Eng.*, vol. 12, pp. 406-15, 2004.

[8] W. Singer, "Neuronal synchrony: a versatile code for the definition of relations?" *Neuron*, vol. 24, pp. 49-65, 1999.

[9] F. Varela, J.-P. Lachaux, E. Rodriguez, and J. Martinerie, "The brainweb: phase synchronization and large-scale integration," *Nat. Rev. Neurosci.*, vol. 2, pp. 229-239, 2001.

[10] J.-P. Lachaux, E. Rodriguez, J. Martinerie, and F. J. Varela, "Measuring phase synchrony in brain signals," *Hum. Brain Mapp.*, vol. 8, pp. 194-208, 1999.

[11] B. Hong, S. Acharya, Y. Ku, S. Gao, and N. Thakor, "Measurement of dynamic coupling of independent EEG components from cognitive tasks," *Int. J. Bioelectromagnetism*, vol. In press, 2006.

[12] M. Le Van Quyen, J. Foucher, J.-P. Lachaux, E. Rodriguez, A. Lutz, J. Martinerie, and F. J. Varela, "Comparison of Hilbert transform and wavelet methods for the analysis of neuronal synchrony," *J. Neurosci. Meth.*, vol. 111, pp. 83-98, 2001.

[13] G. Pfurtscheller, and F. H. Lopes da Silva, "Event-related EEG/MEG synchronization and desynchronization: basic principles," *Clin. Neurophysiol.*, vol.110, pp.1842-1857, 1999.

[14] W.Storm Van Leeuwen, G. Wieneke, P. Spoelstra, and H. Versteeg, "Lack of bilateral coherence of mu rhythm," *Electroencephalogr. Clin. Neurophysiol.* , vol. 44, pp. 140-146, 1978.

[15] G. Pfurtscheller, C. Neuper, A. Schlogl, and K. Lugger, "Separability of EEG signals recorded during right and left motor imagery using adaptive autoregressive parameters," *IEEE Trans. Rehab. Eng.*, vol.6, no.3, pp.316-325, 1998.

[16] H. Ramoser, J. M. Gerking, and G. Pfurtscheller, "Optimal spatial filtering of single trial EEG during imagined hand movement," *IEEE Trans. Rehab. Eng.*, vol. 8, no.4, pp.441-446, 2000.

[17] J. R. Wolpaw, D. J. McFarland, T. M. Vaughan, and G. Schalk, "The Wadsworth center brain-computer interface (BCI) research and development program," *IEEE Trans. Rehab. Eng.*, vol. 11, no. 2, pp. 204-207, 2003.