EMD-based Feature Extraction from Motor Imaginary EEG of Complex Movements

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Abstract—**In this study, we proposed and evaluated the use of the empirical mode decomposition (EMD) technique to extract feature information of the event-related (de) synchronization (ERD/ERS) phenomenon during complex motor imagination of combined body and limb action. The EEG data were separated into intrinsic mode functions (IMFs) using the EMD method and determined the characteristic IMFs by power spectral density (PSD) analysis. Thereafter, the analytic signals of the characteristic IMFs can be obtained by the Hilbert transformation, then extracting the ERD/ERS feature of each single-trial. To verify the effectiveness of this method, ten subjects were tested for distinguishing three kinds of complex motor imagery. The classification performance suggests that the proposed EMD based approach is effective for ERD/ERS feature extraction and is worth for the further application in a brain-computer interface.**

Keywords— **complex motor imagery, event-related (de) synchronization, empirical mode decomposition, intrinsic mode functions, brain-computer interface.**

I. Introduction

Since the important work of Jasper and Penfield [1], lots of research has been conducted to investigate the relationship between motor imagery and brain oscillations. However, most efforts converged to investigate the EEG patterns induced by single-motor imaginary tasks involving a restricted number of muscles. Recently, cognitive brain researchers began to investigate the complex motor imagery patterns induced by complex motor imagination of combined body and limb action [2, 3]. Research on complex motor imagery patterns had been regarded as a must for the successful application of brain-computer interfaces (BCIs) dedicated to controlling human locomotion.

A motor imagery based brain–computer interface (BCI) translates the subject's motor intention into a control signal. The frequency components that give effective discrimination between different types of motor imagery are subject-specific and variable over time [4, 5]. So ERD/ERS feature extraction methods based on traditional time-frequency analysis such as short-time Fourier transform and wavelet transform have its limitation inevitably. Because of the complexity of complex motor imagery, novel techniques for time-frequency analysis are required to better capture the ERD/ERS feature.

In this study, we introduce a novel technique called empirical mode decomposition (EMD) [7] for ERD/ERS feature extraction from complex motor imagery of combined body and limb action. The EMD method is proposed for nonlinear and non-stationary signal analysis, and it can decompose the acquired signal into a collection of intrinsic mode functions (IMFs). EMD has been identified as a self-adaptive signal processing method that can be applied to the nonlinear and non-stationary process perfectly [6]. In this work, we applied the EMD technique to better capture the ERD/ERS feature from the complex motor imagery of combined body and limb action (imaginary stand-up, or imaginary left/right-foot movement combined with homolateral hand movement). To verify the effectiveness of this method, ten subjects were tested for distinguishing these three kinds of complex motor imagery.

II. Method

A. Experimental Paradigm

The participants were instructed to perform the indicated motor imagery task without overt motor output. Each trial began with a blank screen for 2 seconds, the subject was in the 'relax' state. At the 2nd second, a fixation cross appeared at the center of the monitor, and the subject was asked to gradually focus attention to the visual cue. And at the 4th second, an arrow pointing upward, left or right indicated the imagination of stand-up, left- or right- foot movement combined with homolateral hand movement (Fig.1). At the end of imagination, a blank screen was presented for 2 seconds before next trail. The experiments were divided into 3 runs, consisting of 30 trials each. There were breaks of 3 to 5 minutes between the runs.

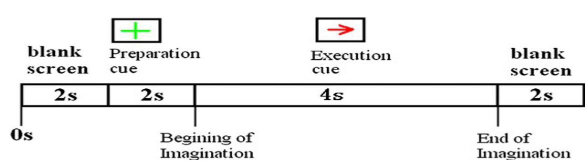

Fig.1 The time sequence of one trial epoch of the experiment

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B. Empirical mode decomposition

Empirical mode decomposition (EMD), introduced by N. E. Huang et al. [7] in 1998, is a method for nonlinear and non-stationary time series analysis. This method developed from the assumption that any signal consists of different simple intrinsic modes of oscillation. In this way, each signal could be decomposed into a number of intrinsic mode functions (IMFs), each IMF must satisfy the following definitions.

1. In the whole dataset, the number of zero-crossing sand the number of extrema must either be equal or differ at most by one.
2. At any point, the mean value of the envelope defined by local maxima and the envelope defined by the local minima is zero.

An IMF represents a simple oscillatory mode as a counter part to the simple harmonic function, but it is much more general: instead of constant amplitude and frequency in a simple harmonic component, an IMF can have variable amplitude and frequency along the time axis. With this definition, any time series $x(t)$ can be decomposed as follows:

1. Identify all the local maxima, and then get the upper envelope by interpolating between maxima.
2. Identify all the local minima, similarly get the lower envelope.
3. The mean of the upper and lower envelope values is designated as m_1 and the difference between the signal $x(t)$ and m_1 is the first component h_1 i.e. $x(t)-m_1=h_1$. If h_1 satisfies all the requirements of IMF, then h_1 is the first IMF component of $x(t)$.
4. If h_1 is not an IMF, treat h_1 as the original signal and repeat steps 1-3 until h_1 is an IMF. Then, it is designated as $c_1=h_1$ the first IMF component from the original data.
5. After getting the first component, remove the first component from the original signaland obtain the residue r_1 as follows:
$$x(t)-c_1=r_1 \tag{1}$$
6. Treat r_1 as the original signal and repeat the above processes. The second IMF component c_2 of $x(t)$ will be obtained.
7. Repeat the process as described above n times. Then, all the IMFs of the signal $x(t)$ can be obtained, which are given by

$$\begin{cases} x(t)-c_1=r_1 \\ r_1-c_2=r_2 \\ \quad\cdots \\ r_{n-1}-c_n=r_n \end{cases} \tag{1}$$

The decomposition process can be stopped when r_n becomes a monotonic function or a constant from which no more IMF components can be extracted. Summing up both sides of equations (2) accordingly, we obtain

$$x(t)=\sum_{i=1}^{n}c_i(t)+r_n(t) \tag{3}$$

Thus, one can achieve a decomposition of the signal into n-empirical modes and a residue $r_n(t)$, which is the mean trend of $x(t)$.

The complex motor imagery involves several cortical sensorimotor areas, its mode is more complex. Therefore, we use wavelet package transformation to decompose the complex motor imagination potential to obtain the sub-bands covering the alpha-rhythm and beta-rhythm, then reconstructing the alpha-rhythm component x_α and beta-rhythm component x_β of the signal by inverse wavelet package transformation, avoiding the model mixture phenomenon induced by direct application of the EMD.

Thereafter, All IMFs of x_α and x_β can be obtained by the EMD, and they admit a well-behaved Hilbert transformation. Thus, the analytic signal of each IMF can be obtained as

$$z_i=c_i+j\hat{c}_i=B(t)e^{j\Psi(t)} \tag{4}$$

Where

$$\hat{c}_i=\frac{1}{\pi}\int_{-\infty}^{+\infty}\frac{c_i(\tau)}{t-\tau}d\tau \tag{5}$$

$$B(t)=\sqrt{c_i^2(t)+\hat{c}_i^2(t)} \tag{6}$$

Here, $B(t)$ is the envelope of the instantaneous amplitude and $\Psi(t)$ is the instantaneous phase.

After obtaining the n-IMFs, we can detect the characteristic IMFs c_α and c_β representing alpha-rhythm oscillations and beta-rhythm oscillations respectively using the distribution of power spectral density (PSD).

The analytic signal of each characteristic IMF can be obtained by the Hilbert transformation. $B_\alpha(t)$ and $B_\beta(t)$ represent the Hilbert envelope of the characteristic IMF c_α and

c_β respectively. Therefore, referring to the quantitative principles for ERD/ERS patterns presented by Pfurtscheller, the ERD/ERS coefficient under the characteristic oscillatory mode can be given by

$$C_{ERD/ERS} = \frac{B_A - B_R}{B_R} \times 100\% \tag{7}$$

III. Results and discussion

Firstly we can obtain the alpha-rhythm component by wavelet package transformation and inverse wavelet package transformation from the EEG data of a single trial at electrode C4 while the participant performed mental task of combined left-foot movement with homolateral hand movement. Thereafter, all IMFs of alpha-rhythm component at electrode C4 can be obtained by applying EMD method. Thereafter, in order to find out the characteristic IMF of alpha rhythm, power spectrum analysis was carried out on these IMFs. Fig.2 shows the PSD distributions of the first four IMFs. It can be seen that the characteristic IMF of alpha rhythm at electrode C4 is located at the second one (imf2). According to the same processes presented above, we can obtain the characteristic IMF of alpha-rhythm component at electrodes C3. Similarly, we can also obtain the characteristic IMFs of beta-rhythm component.

After obtaining the characteristic IMFs of alpha-rhythm and beta-rhythm at electrode C3and C4 during each kind of complex motor imagery, the analytic signal of each characteristic IMF can be obtained by the Hilbert transformation. Thereafter, the Hilbert envelope under alpha and beta rhythm of every single trial can be obtained respectively. It can be seen from Fig.3 (a) that the existence of ERD feature at both C3and C4 channel under alpha-rhythm during the motor imagery of the left-foot movement combined with homolateral hand movement. But the ERD feature at C4 is more obvious, it shows the contralateral dominance. Fig.3 (b) shows the beta-rhythm ERD feature and there is no obvious difference between C3 and C4. Fig.4 (a) shows the alpha-rhythm ERD feature of C3 and C4 channel during the motor imagery of the right-foot movement combined with homolateral hand movement. It can be seen that the ERD feature at C3 is stronger, and it shows the contralateral dominance. Fig.4 (b) shows the beta-rhythm ERD feature, and it also shows the contralateral dominance. Fig.5 (a) shows the alpha-rhythm ERD feature of C3 and C4 channel during the motor imagery of standing up. There is no remarkable difference between C3 and C4. Fig.5 (b) shows the ERD feature of C3 and C4 channel under beta-rhythm. It can be seen the ERD feature at C4 is relatively weak, and the ERD feature at C3 is stronger.

After getting the energy change feature, the ERD/ERS coefficient of each characteristic oscillatory mode under three kinds of complex motor imagery can be obtained according the equation (7). In our research, the ERD/ERS coefficient corresponding to typical time intervals of each trial (from 4.0 s to 8.0 s) were adopted as the input data of the classifier. In order to assess the ability of the EMD-based technique for ERD/ERS feature extraction, the traditional method based on band pass filter was introduced for comparison. Table 1 presents the classification results of ten subjects. It can be seen that the average accuracy is 73.71% while adopting the traditional method to extract ERD/ERS feature. It is relatively lower with respect to the recognition result while adopting the EMD based method, and the average accuracy is 79.09%. Obviously, EMD-based technique has better classification results than traditional band pass based approach.

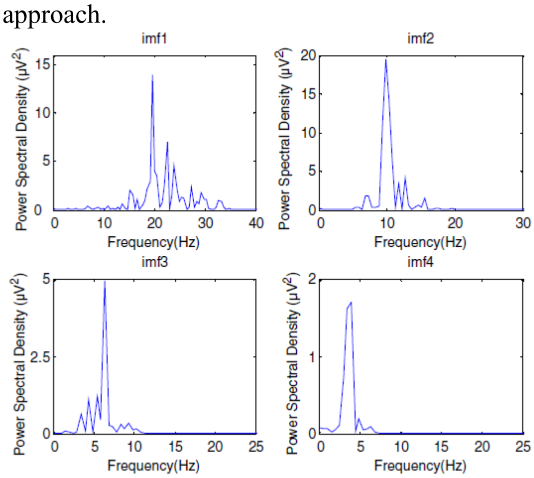

Fig.2 The PSD distribution of the first four IMFs

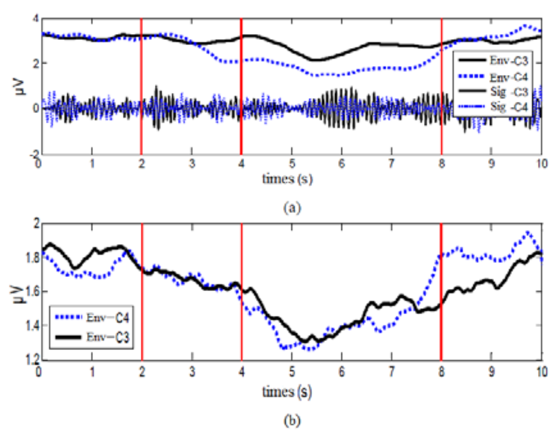

Fig.3 Hilbert envelope at C3 and C4 during the motor imagery of the left-foot movement combined with homolateral hand movement. (a) alpha rhythm (b) beta rhythm

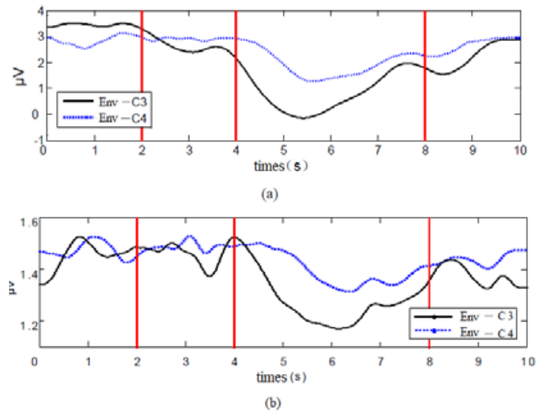

Fig.4 Hilbert envelope at C3 and C4 during the motor imagery of the right-foot movement combined with homolateral hand movement. (a) alpha rhythm (b) beta rhythm

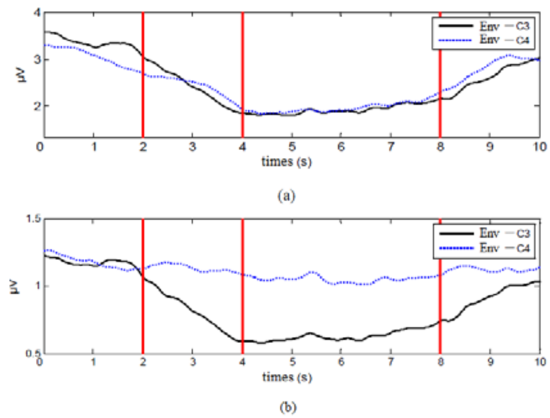

Fig.5 Hilbert envelope at C3 and C4 during the motor imagery of stand-up. (a) alpha rhythm (b) beta rhythm

Table 1 Classification accuracies of three complex mental tasks

Subjects	band pass	EMD	Improved
LXH	83.63	87.69	4.06
ZPF	71.06	73.24	2.18
GCW	61.09	65.72	4.63
WK	75.23	81.20	5.97
JJN	79.58	84.77	5.19
LWZ	71.36	78.64	7.28
ZYH	76.59	81.33	4.74
XQJ	78.91	84.40	5.49
LYW	61.09	69.39	8.3
ZK	78.56	84.56	6
Mean	73.71	79.09	5.38

IV. Conclusions

In this study, EMD based approach was applied to extract ERD/ERS feature as the input for classification during the complex motor imagery of combined with body and limb action. The result demonstrates that this method is an effective technique for ERD/ERS feature extraction. From the classification result, this EMD based method performs better than the traditional band pass filter based approach. In conclusion, the EMD method can be a valuable method for differentiating complex motor imaginary states of combined body and limb action. Its powerful predominance for non-linear and non-stationary data analysis makes it worth for further application in feature extraction for BCI.

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References

1. Jasper H H, Penfield W. (1949) Electrocorticograms in man: effect of the voluntary movement upon the electrical activity of the precentralgyrus. Arch Psychiat Z Neurol 183: 163–174
2. Omar F N, Kim D N and Michael V. (2005) Influence of directional orientations during gait initiation and stepping on movement-related cortical potentials Behav. Brain Res 161: 141–154.
3. Kim D N, Alvaro F C, Omar F N. (2006) EEG based BCI-towards a better control. IEEE Trans Neural System Rehabil Eng 14: 202–204.
4. Guger C, Ramoser H, Pfurtscheller G. (2000) Real time EEG analysis with subject specific spatial patterns for abrain–computer interface. IEEE Trans Rehabil Eng 8: 447–456.
5. Kavitha P T, Cuntai G, Chiew T L et al. (2011) Adaptive tracking of discriminative frequency components in electroencephalograms for a robust brain-computer interface. J Neural Eng 8: 1-15.
6. Yeh C L, Chang H C, Wu C H et al. (2010) Extraction of single-trial cortical beta oscillatory activities in EEG signals using empirical mode decomposition. BioMedical Engineering OnLine. pp 9-25.
7. Huang N E, Shen Z, Long S R. (1999) A new view of nonlinear water waves: the Hilbert spectrum Annu. Rev. Fluid Mech. 31 417–457
8. Pfurtscheller G, Brunner C, Schlogl A et al. (2006) Mu rhythm (de)synchronization and EEG single-trial classification of different motor imagery tasks. NeuroImage 31: 153–159.