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Mu Rhythm Desynchronization Detection Based on Empirical Mode Decomposition

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Abstract—**The aim of this paper is to investigate the possibility of using empirical mode decomposition (EMD) method in detecting the desynchronized mu rhythm of motor imagery EEG signal. A number of EEG studies have indentified the mu rhythm desynchronization a reliable EEG pattern for brain-computer interface. Considering the non-stationary characteristics of the motor imagery EEG, the EMD method is proposed to decompose the EEG signal into intrinsic mode functions (IMFs). By analyzing the power spectral density (PSD) of the IMFs, the characteristics one representing mu rhythm oscillations can be detected. Then by Hilbert transformation, the event-related desynchronization phenomenon can be found by the envelope of the characteristics IMF. Results demonstrate that the EMD method is an effective time-frequency analysis tool for non-stationary EEG signal.**

I. Introduction

A number of studies have shown that when the subject performs or even imagines limb movement, the mu rhythm of EEG will be desynchronized over the contralateral (ipsilateral) sensorimotor area, This phenomenon is known as event-related desynchronization of mu rhythm. Based on this phenomenon, EEG recordings during left and right motor imagery can be used as control signals for a Brain-Computer Interface (BCI), which is an EEG-based communication system to provide an alternative communication or control channel for patients with severe motor disabilities [1]-[3].

For BCI system, the most important step is the reliable EEG pattern extraction. Considering that the motor imagery EEG is non-stationary, the processing methods for pattern extraction should be selected according to this item. But the traditional processing methods for non-stationary signal, such as short time Fourier transform, wavelet transform, can not provide higher resolution both in time and frequency domain and the decomposition of signal is not adaptive. In this paper, we adopted a nonlinear, non-stationary method called the empirical mode decomposition (EMD) for pattern extraction from motor imagery EEG of left and right hand imaginary movement. The EMD method will decompose the acquired signal into a collection of intrinsic mode functions (IMFs). The IMF is a kind of complete, adaptive and almost orthogonal representation for the analyzed signal. The number of IMFs and frequencies of each IMF are inherently determined by these time scales. And the structure of each IMF is determined by the natural amplitude variations in the time series. Higher frequency oscillations are captured in the first IMF and subsequent IMFs have lower average frequencies. Therefore, EMD is a self-adaptive signal processing method that can be applied to non-linear and non-stationary process perfectly [4]-[9]. The aim of this paper is to utilize the EMD method to detect the mu rhythm desynchronization from the non-stationary motor imagery EEG during left and right hand movement imagination and some valuable results were achieved.

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I. Theory of EMD method

EMD method was firstly proposed by Norden E. Huang in 1998 [4][5]. This method was developed from the assumption that any signal consists of different simple intrinsic modes of oscillations. Each linear or non-linear mode will have the same number of extrema and zero-crossings. There is only one extremum between successive zero-crossings. Each mode should be independent of the others. In this way, each signal could be decomposed into a number of intrinsic mode functions (IMFs), each of which must satisfy the following definition:

(1) In the whole data set, the number of zero-crossings and the number of extrema must either be equal or differ at most by one.

(2) At any point, themean value of the envelope defined by local maxima and the envelope defined by the local minima is zero.

Assuming there is a time series $x(t)$, EMD has the following major steps [4]:

(1) Identify all the local maxima, and then connect all the local maxima by a cubic spline as the upper envelope.

(2) Repeat the procedure for the local minima to produce the lower envelope. The upper and lower envelopes should cover all the data between them.

(3) The mean of upper and low envelope value is designated as m_1 and the difference between the signal $x(t)$ and m_1 is the first component h_1, i.e. $x(t)-m_1=h_1$. Ideally, if h_1 is an 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 the 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. So c_1 should contain the finest scale or the shortest period component of the signal.

(5) After getting the first component, remove the first component from the original signal and obtain the residual r_1 as follows:

$$x(t) - c_1 = r_1 \tag{1}$$

(6) Treat r_1 as the original data and repeat the above processes. The second IMF component c_2 of $x(t)$ could 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

$$\begin{cases} r_1 - c_1 = r_2 \\ \vdots \quad \vdots \quad \vdots \\ r_{n-1} - c_n = r_n \end{cases} \tag{2}$$

The decomposition process can be stopped when r_n becomes a monotonic function or a constant from which no more IMF component can be extracted. Summing up both sides of Eq.(1) and Eq.(2) accordingly, we can obtain

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

Thus, we complete a decomposition of the signal into n-IMF components and a residual $r_n(t)$ which is the ideal trend of the signal $x(t)$. Each of the IMFs $c_1(t), c_2(t), \cdots\cdots,$ $c_n(t)$ includes different frequency bands ranging from high-to-low and it is stationary.

All IMFs obtained after the EMD admit well-behaved Hilbert transform [10]. Thus each IMF can get its analytic signal as:

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

where

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

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

$$\theta_i(t) = \arctan \frac{\hat{c}_i(t)}{c_i(t)} \tag{7}$$

Here $a_i(t)$ is named as the envelop of instantaneous-amplitude and $\theta_i(t)$ is called the instantaneous-phase.

After achieved the n-IMFs, we can detect the characteristics one representing mu rhythm oscillations according to the power spectral density (PSD). This feature IMF is put into Hilbert transform to get the envelop $a_i(t)$, further information of ERD pattern within mu rhythm can be obtained from $a_i(t)$.

II. RESULTS

A. EEG data

The raw motor imagery EEG data is from the non-stationary BCI Competition 2005 database of Austrian Graz scientific and technical university. The experiment is described as follow: The subjects were seated in an armchair and looked at a computer monitor. They were asked to keep their arms and hands relaxed and to avoid eye movements during the recordings. Each trial (8s) began with a blank screen. Two important timing cues that should be mentioned here are that at 2.0s of a trail epoch, a cue (preparation cue, lasting 1000ms) of beep fixation cross appear on the screen indicating the subject to be attention; and at 3.0s another cue (execution cue, lasting 1250ms) appeared, indicating that it was time to make the requested response (imagine a movement of the right or the left hand) according to the direction of the arrow as shown in figure 1. The experiment data were sampled at 250 Hz and filtered between 3 and 35Hz.

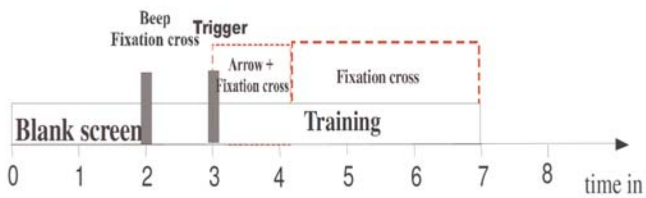


Fig. 1. The sequence of one trail epoch of the experiment

B. EMD Application

Fig.2. shows the original EEG data of one trial on electrode C3 and C4 while the subject imagines left hand movement.

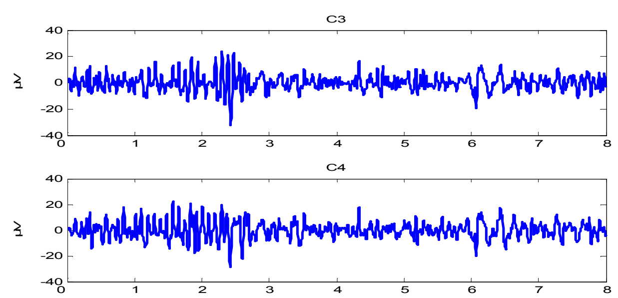


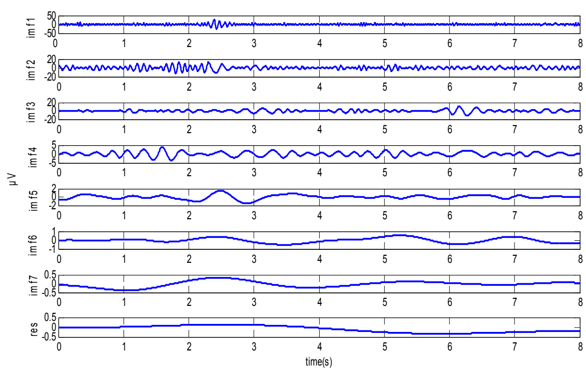
Fig. 2. The one trial EEG data (C3,C4) while imagining left hand movement

EMD method was separately applied on the one trail EEG data as shown in Fig.2, Fig.3 gives the decomposed results. Fig.3 (a) is seven IMFs and one residue decomposed from the first channel data (C3) in Fig.2. And Fig.3 (b) is seven IMFs and one residue decomposed from the second channel data (C4) in Fig.2. Here, it should be pointed that the number of the IMF decomposed from the data in C3 may be different from the data in C4, but it will not affect our analysis results, because the required characteristics is distributed in the first several IMFs,

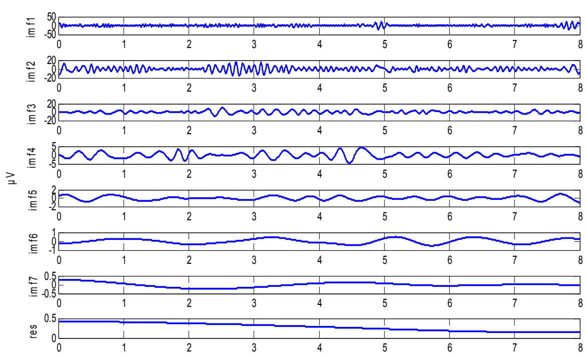
To find out the characteristic IMF of mu rhythm, frequency spectrum analysis by periodogram was adopted. Considering the fluctuations of periodogram for single trail EEG data, we calculated the mean power spectral density of 5 trails on the corresponding IMFs of C3 and C4. Fig.4 and Fig5 separately gave the mean PSD of the first 4 IMFs according to the trails on electrode C3 and C4. The characteristics IMFs of mu rhythm on electrode C3 and C4 are all locating at the second IMF (imf2), and the mean PSD peak value of imf2 on C3 is greater than imf2 on C4. This means that the energy of mu rhythm on C4 is suppressed more than that on C3, i.e. the mu-ERD phenomenon is more obvious on C4 than on C3 during imaginary left hand movement.

According to the same approach, EMD method was applied to the motor imagery EEG of right hand movement. Fig.6 gives the PSD distribution of characteristics IMF of mu rhythm on electrode C3 and C4. It is obvious the energy of mu rhythm on C4 is more than the mu rhythm on C3, i.e. the mu-ERD phenomenon is more obvious on C3 during imaginary left hand movement.

To further investigate the ERD pattern of mu rhythm, the Hilbert transform is used on the characteristic IMF. Fig. 7(a) and Fig. 7(b) separately gives out the Hilbert envelop of the characteristic IMF on electrode C3 and C4 during imaginary left hand movement or right hand movement. Fig. 7 (a) demonstrated that during imaginary left hand movement, the mu-ERD phenomenon exists on both C3 and C4, but C4 is more obvious. Contrarily, the mu-ERD is more obvious on C3 during imaginary right hand movement (see Fig. 7 (b)).



(a)



(b)

Fig. 3. The EMD decomposed results of Fig.2: (a) IMFs of EEG on C3; (b) IMFs of EEG on C4.

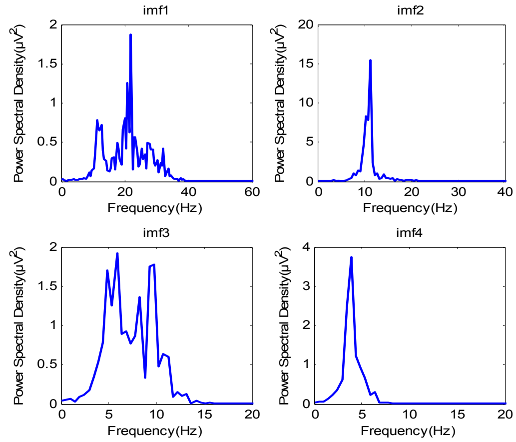


Fig.4 The mean PSD distribution of IMFs from motor imagery EEG of left hand movement on C3

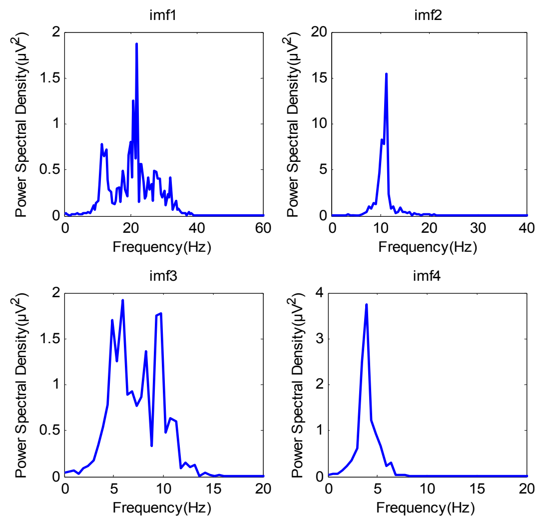


Fig.5 The mean PSD distribution of IMFs from motor imagery EEG of left hand movement on C4

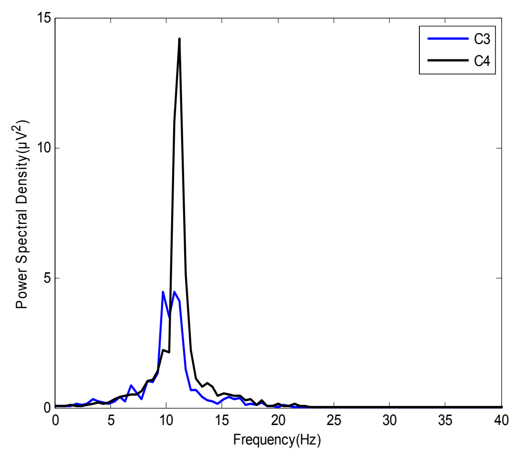
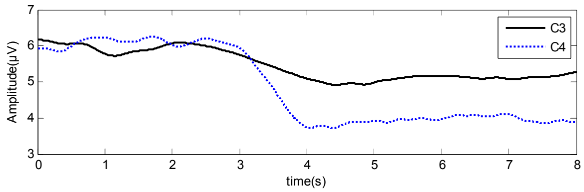
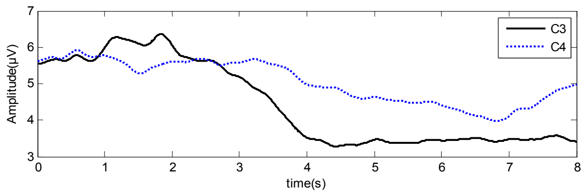


Fig.6 Comparing the PSD distribution of the imf2 on C3 with C4.



(a)



(b)

Fig.7 The Hilbert envelop of mu-rhythm IMF on electrode C3 and C4. (a) imaginary left hand movement (b) imaginary right hand movement

III. CONCLUSION

This study discussed the desynchronized mu rhythm detection from the non-stationary EEG data by using EMD method. The results demonstrated that the mu rhythm can be detected by the decomposed IMFs component from the non-stationary EEG data, and the ERD/ERS phenomenon of the mu rhythm changes during left and right hand movement imagination can be analyzed by the Hilbert envelop of the characteristics IMFs. In conclusion, the EMD method can be a valuable method for studying the pattern extraction of motor imagery EEG. Its powerful predominance for nonlinear and non-stationary data analysis makes it worth for further application in studying the characteristic extraction of motor imagery EEG and BCI implementation

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