2014 International Joint Conference on Neural Networks (IJCNN)
July 6-11, 2014, Beijing, China

EEG Energy Analysis for Evaluating Consciousness Level Using Dynamic MEMD

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***Abstract*—Analysis of electroencephalography (EEG) energy is a useful technique in the brain signal processing. In this paper, we present a novel data analysis method based on a dynamic multivariate empirical mode decomposition (D-MEMD) algorithm to analyze EEG energy of three different conscious states such as normal awake, comatose and brain death. By using D-MEMD, we can not only denoise the original EEG data but also calculate the EEG energy of subjects in a dynamic time series. Moreover, from the result, we distinguish three consciousness levels. The results of healthy subject in normal awake, comatose patient and brain death will be shown. The analyzed results illustrate the effectiveness and performance of the proposed method in calculation of EEG energy for evaluating consciousness level.**

I. Introduction

Electroencephalography (EEG) is a recording of voltage fluctuations resulting from ionic current flows within the neurons of the brain and refers to the recording of the brain's spontaneous electrical activity over a short period of time. The healthy subject in normal awake has high brain activity. The patient in brain death state has no normal brain cells, so that their brain activity is extremely low. There are two types of patients in comatose patients, brain damage patients and no-brain-damage patients. Brain damage patients' brain cells have been destructed and their brain activity is low. However, no-brain-damage patients' brain cells are not destructed that their brain activity is as active as healthy subject [1].

For evaluating consciousness level, EEG energy analysis is used to calculate the brain activity [1]. The EEG energy analysis is important and useful in the brain signal processing. In the previous work[2], we have defined the EEG energy using the power spectrum within the frequency band multiplied by recorded EEG time. Several data-driven signal processing methods such as empirical mode decomposition (EMD) [3] and multivariate empirical mode decomposition (MEMD) [4] have been used for EEG to evaluate the brain activity [2]. In the previous study, we have proposed MEMD to calculate the energy of EEG of randomly chosen interval of one second. [1]. However, by using MEMD, it is difficult to observe EEG energy variation of subjects.

In this paper, we propose an adaptive algorithm for MEMD called dynamic MEMD (D-MEMD) to calculate and evaluate the energy of EEG recorded from the healthy subjects, comatose patients and brain deaths and observe the state changes of patients' consciousness. By using D-MEMD, we can not only denoise the original EEG data but also calculate the EEG energy of subjects with the time series. In addition to this, we observe EEG energy variation of subjects to increase the reliability and show three examples of healthy subject in normal awake, comatose patient and brain death. The analyzed results illustrate the effectiveness and performance of the proposed method in calculation of EEG energy for evaluating consciousness level.

II. Methods of Data Analysis

A. EMD and MEMD Algorithms

EMD decomposes the original signal into a finite set of amplitude- and/or frequency-modulated components, termed intrinsic mode functions (IMFs), which represent its inherent oscillatory modes [3]. More specifically, for a real-valued signal $x(t)$, the standard EMD finds a set of K IMFs $\{c_k(t)\}_{k=1}^{K}$, and a monotonic residue signal $r(t)$, so that

$$x(t) = \sum_{k=1}^{K} c_k(t) + r(t). \tag{1}$$

IMFs $c_k(t)$ are defined so as to have symmetric upper and lower envelopes, with the number of zero crossings and the number of extrema differing at most by one. The process to obtain the IMFs is called sifting algorithm. Moreover, the first complex extension of EMD was proposed in [5]. An extension of EMD to analyze complex/bivariate data which operates fully in the complex domain was first proposed in [6], termed rotation-invariant EMD (RI-EMD).

For multivariate signals, the local maxima and minima may not be defined directly because the fields of complex numbers and quaternions are not ordered [7]. Moreover, the notion of 'oscillatory modes' defining an IMF is rather confusing for multivariate signals. To deal with these problems, the multiple real-valued projections of the signal was proposed in [4]. The extrema of such projected signals are then interpolated componentwise to yield the desired multidimensional envelopes of the signal. In MEMD, we choose a suitable set of direction vectors in n-dimensional

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spaces by using: (i) uniform angular coordinates and (ii) low-discrepancy pointsets. The multivariate extension of EMD suitable for operating on general nonlinear and non-stationary n-variate time series is summarized in the following.

1) Choose a suitable pointset for sampling on an $(n-1)$ sphere.
2) Calculate a projection, denoted by $\{p^{\theta_k}(t)\}_{t=1}^{T}$, of the input signal $\{\mathbf{v}(t)\}_{t=1}^{T}$ along the direction vector $\mathbf{x}^{\theta_k}$, for all k (the whole set of direction vectors), giving $\{p^{\theta_k}(t)\}_{k=1}^{K}$ as the set of projections.
3) Find the time instants $\{t_i^{\theta_k}\}$ corresponding to the maxima of the set of projected signals $\{p^{\theta_k}(t)\}_{k=1}^{K}$.
4) Interpolate $[t_i^{\theta_k}, \mathbf{v}(t_i^{\theta_k})]$ to obtain multivariate envelope curves $\{\mathbf{e}^{\theta_k}(t)\}_{k=1}^{K}$.
5) For a set of K direction vectors, the mean $\mathbf{m}(t)$ of the envelope curves is calculated as

$$\mathbf{m}(t) = \frac{1}{K}\sum_{k=1}^{K}\mathbf{e}^{\theta_k}(t). \tag{2}$$

6) Extract the 'detail' $d(t)$ using $d(t) = x(t) - m(t)$. If the 'detail' $d(t)$ fulfills the stoppage criterion for a multivariate IMF, apply the above procedure to $x(t) - d(t)$, otherwise apply it to $d(t)$.

The stoppage criterion for multivariate IMFs is similar to the standard one in EMD, which requires IMFs to be designed in such a way that the number of extrema and the zero crossings differ at most by one for S consecutive iterations of the sifting algorithm. The optimal empirical value of S has been observed to be in the range of 2–3 [8].

B. D-MEMD Algorithm

The D-MEMD is an adaptive algorithm of the MEMD. We have defined the EEG energy using the power spectrum within the frequency band multiplied by recorded EEG time [2]. To observe EEG energy variation of subjects, we extend MEMD in the temporal domain along time-coordinate of EEG signal. Supposing a multivariate EEG data series $\mathbf{v}(t)$ consisting of N segments (epochs) $\{\mathbf{v}_n(t)\}_{n=1}^{N}$, the MEMD can be carried out through each segment.

The Dynamic MEMD is defined as the MEMD applied to all segments such that

$$\begin{aligned}\mathbf{v}(t) &= [\mathbf{v}_1(t), \ldots, \mathbf{v}_N(t)] \\ &= \left[\sum_{k=1}^{K_1} c_{k,1}(t) + r_1(t), \ldots, \sum_{k=1}^{K_N} c_{k,n}(t) + r_N(t)\right]\end{aligned} \tag{3}$$

where $\mathbf{r}_N(t)$ are residue signals and $\{\mathbf{c}_{k,n}(t)\}_{k=1}^{K_n}$ are IMF components with K_n $(n = 1, \ldots, N)$ being the number of IMFs for the segmented nth signal $\mathbf{v}_n(t)$.

Consequently, in our experiment, we remove the residue signal $\mathbf{r}_N(t)$ and Q IMFs from $\{\mathbf{c}_{k,n}(t)\}_{k=1}^{K_n}$ which is not expected, and combine the $(N-Q)$ IMFs to be the denoised signal. We have defined the EEG energy using the power spectrum within the frequency band multiplied by recorded EEG time. Thus we change the denoised signal from time domain to frequency domain by Fast Fourier Transformation and integrate it to compute the EEG energy.

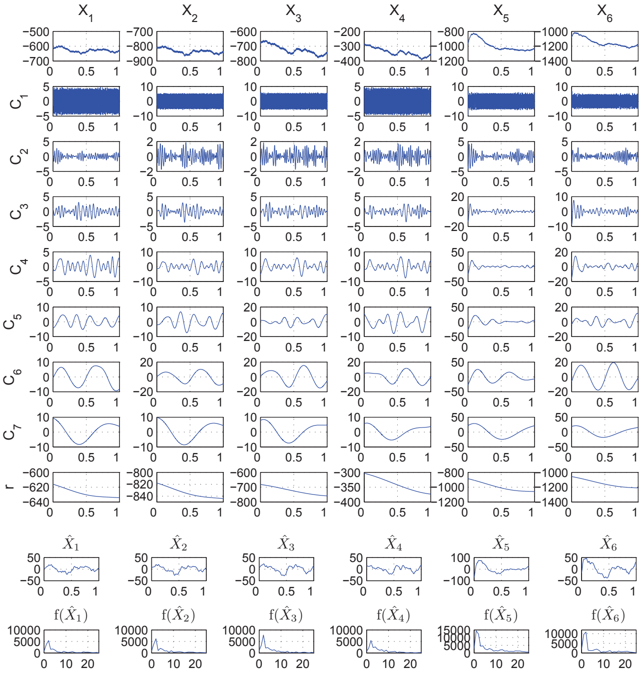


Fig. 1. Results for a static EEG energy analysis using MEMD.

III. Experiments and Results

A. EEG Experiment

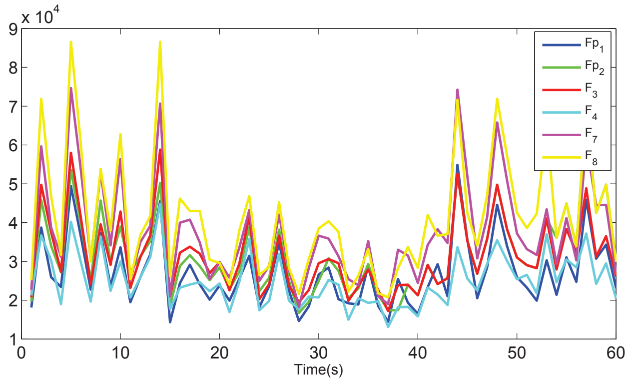
A portable EEG system (NEUROSCAN ESI) was used to record the healthy subject's brain activity in normal awake. In the EEG recording, only nine electrodes are chosen to apply to subject. Among these electrodes, six exploring electrodes (Fp1, Fp2, F3, F4, F7 and F8) as well as GND were placed on the forehead, and two electrodes (A1, A2) as the reference were placed on the earlobes based on the standardized 10-20 system. The sampling rate of EEG was 1000 Hz and the resistances of the electrodes were set to less than 10 kΩ.

The comatose patients and brain deaths' EEG preliminary examination was carried out in a hospital in Shanghai. With the permission of the patients' families, a total of 35 comatose and quasi brain death patients with the age ranging from 18 to 85 years had been examined by using EEG from June 2004 to March 2006. In this paper, we present the experimental results for 21 comatose patients, 15 quasi brain deaths and 8 healthy subjects in normal awake.

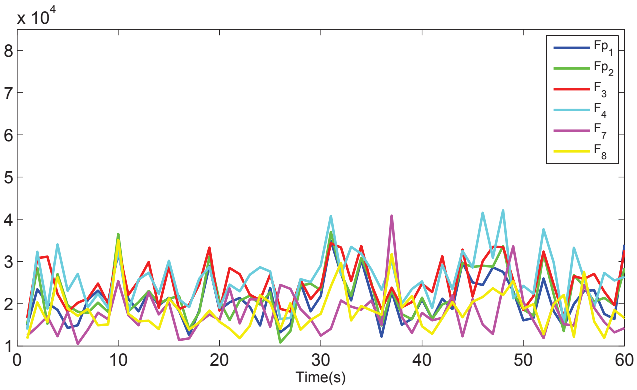
We have defined the EEG energy using the power spectrum within the frequency band multiplied by recorded EEG time. This definition can be also used to calculate the other signals energy generated by artificial data. Using the formula of energy, we can calculate and evaluate the energy of healthy subjects, comatose patients and brain deaths.

B. Result for a Subject Using MEMD

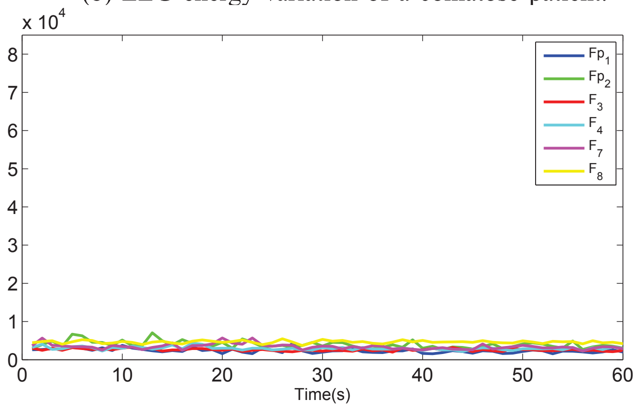
In the previous study, we have defined the EEG energy using the power spectrum within the frequency band multiplied by recorded EEG time. Here we give an example of a



(a) EEG energy variation of a healthy subject.



(b) EEG energy variation of a comatose patient.



(c) EEG energy variation of a brain death.

Fig. 2. Results for a dynamic EEG energy analysis using D-MEMD.

subject using MEMD to calculate a static EEG energy. This subject's EEG recording last over 500 seconds.

As shown in Fig. 1, the decomposing condition of channel Fp1, Fp2, F3, F4, F7 and F8 expressed as X_1, X_2, X_3, X_4, X_5 and X_6 in the time range one second is selected randomly. By applying the MEMD method described in Section II-A, we obtain 7 IMF components (C_1 to C_7) within different frequency from high to low. Since the IMF components C_1 to C_2 that with high frequency scales refer to electrical interference or other noise from environment that contains in the recorded EEG. The residual component r is not the typical useful components considered, either. The desired components from C_3 to C_7 are combined to form the denoised EEG signal, and changed into frequency

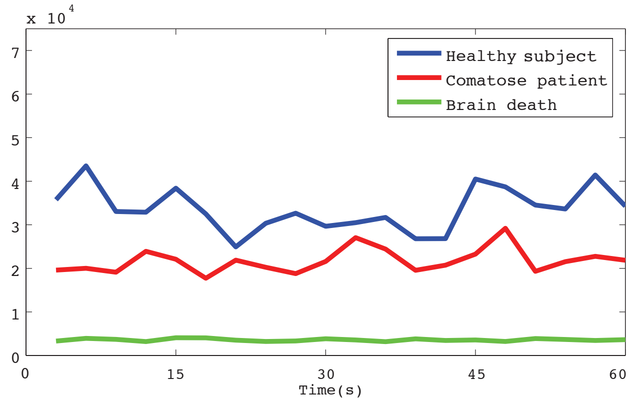


Fig. 3. Comparison of dynamic EEG energy for a healthy subject, comatose patient and brain death.

domain by fast Fourier transform (FFT) (Fig. 1). And then we integrate the denoised signal and calculate the energy of EEG data. The average energy of every channels of this second is 6.05×10^4.

C. Result for Healthy Subject, Comatose Patient and Brain Death Using D-MEMD

Furthermore, let us show dynamic EEG energy of healthy subject, comatose patient and brain death by using D-MEMD. By applying the D-MEMD method described in the Section II-B, with the change of time, the number of IMF components will change in theory. In our experiments, 5 lower frequency IMF components are combined to form the denoised EEG signal. Therefore, the number of IMF components change will not affect the result of experiments. The example for healthy subject's EEG examination was performed in August 2013. The EEG recording last over 500 seconds. By applying D-MEMD algorithms described in Section II-B, we obtain EEG energy variation of healthy subject (Fig. 2-a) in 60 seconds. EEG energy of each channel are between 1.43×10^4 and 8.65×10^4.

The comatose case is concerned with a male patient. The EEG recording lasted 380 seconds. By the same way of healthy subject to analysis the EEG data of this patient by D-MEMD, we obtain the EEG energy variation of comatose patient in 60 seconds (Fig. 2-b). This patient's EEG energy of each channel is between 1.05×10^4 to 4.2×10^4 (Fig. 2-b) that reflects a high intensity of brain activity.

With the same analysis for brain death, we still analyzed 60 seconds EEG data by using D-MEMD as an example. Fig. 2-c shows each channel's EEG energy. This patient's maximum value of 6 channels' EEG energy is only 7.03×10^3, the value is extremely low. The analysis result indicate that this patient' physiological brain activity is extremely low.

D. Comparison of EEG Energy for Healthy Subject, Comatose Patient and Brain death

Fig. 5 shows the Comparison of total EEG energy for healthy subject, comatose and brain death by simple moving average for 3 seconds. First, we averaged each channel's EEG energy of these 3 subjects. Moreover, by using simple moving average, we averaged 3 seconds' EEG energy of each

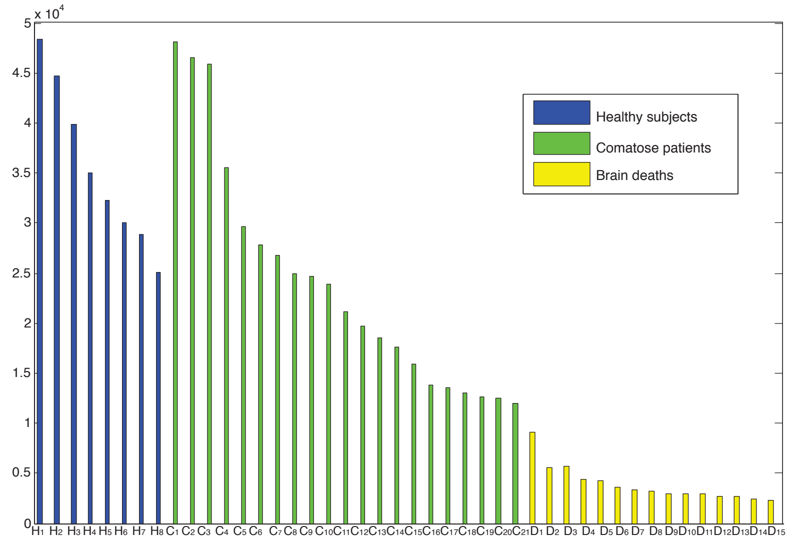


Fig. 4. The EEG energy of 8 healthy subject, 21 comatose patients and 15 brain deaths.

kind of subject to compare the value of EEG energy. Comparing the value of them, we obtain that healthy subject's maximum EEG energy is 4.35×10^4, and the minimum is 2.3×10^4. Contrary to healthy subject's EEG energy, brain deaths reflected no EEG energy over 4.1×10^3. Comatose patient's EEG energy is between 1.71×10^4 and 2.3×10^5. In brief, EEG energy of healthy subject is almost higher than comatose patient, and EEG energy of comatose patient is higher than brain death. The results illustrated the effectiveness and performance of D-MEMD in calculation of EEG energy for evaluating consciousness level.

Furthermore, we analyze 8 healthy subjects, 21 comatose patients and 15 brain deaths' EEG data with 5 seconds by using D-MEMD and obtain the average value of 5 seconds' EEG energy. The EEG energy of all subjects is shown in Fig. 6. The EEG energy of healthy subject is between 2.51×10^4 and 4.78×10^5, the EEG energy of comatose is between 1.20×10^4 and 4.81×10^5, the EEG energy of brain death is under 1.00×10^4. From the result, the EEG energy of healthy subject and comatose patients is higher than brain death. However we find the brain activity of comatose patients whose EEG energy is close to the brain deaths' are not high. We speculate that they are brain damage. However another part of comatose patients' EEG energy is close to, even more than the healthy subject's. These patients still have high brain activity.

IV. Conclusions

In this paper, we focus on a novel data analysis method based on D-MEMD to calculate and evaluate the energy of EEG recorded from the healthy subjects, comatose patients and brain deaths and observe the state changes of patients' consciousness. By using D-MEMD, we can not only denoised the original EEG data but also calculate the EEG energy of subjects with the time series. In addition to this, we recorded EEG energy variation of subjects and compared them. The result is that EEG energy of healthy subjects is extremely high and show a high brain activity. EEG energy of brain death is extremely low and demonstrate that brain death has no brain activity. In comatose patients, a part of patients' EEG energy is close to the brain deaths'. We speculate that they are brain damage. another part of comatose patients' EEG energy is close to, even more than the healthy subjects'. They are no-brain-damage and still have high brain activity. The analyzed results illustrate the effectiveness and performance of the proposed method in calculation of EEG energy for evaluating consciousness level and increase the reliability.

Acknowledgment

This work was partly supported by KAKENHI (25420417).

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