Analyzing the EEG Energy of Quasi Brain Death using MEMD

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***Abstract*—Electroencephalography (EEG) based preliminary examination system has been proposed in the clinical brain death determination. This paper presents a novel data analysis algorithm based on multivariate empirical mode decomposition (MEMD) to calculate and evaluate the energy of EEG recorded from the comatose patients and brain deaths. MEMD is an extended approach of empirical mode decomposition (EMD), in which it overcomes the problem of the decomposed number and frequency, and enable to extract brain activity features from multi-channel EEG simultaneously. Comparison with the previous study by used EMD, not only the performance of computation complexity but also the accuracy of data analysis is improved.**

I. Introduction

The concept of brain death, first appeared in 1960's, is defined as the irreversible and complete loss of all brain activity including involuntary activity necessary to sustain life due to total necrosis of cerebral neurons following loss of blood flow and oxygenation [1]. Based on this definition, for example, the Japanese established the criterion including following major items to diagnose the brain death: 1) Deep coma: unresponsive to external visual, auditory and tactile stimuli and be incapable of communication; 2) Pupil test: no pupils' response to light and pupils dilate to 4 *mm*; 3) Brain stem reflexes test: absence of reflex such as cough reflex, corneal reflex, painful stimuli; 4) Apnea test: patient's loss of spontaneous respiration after disconnecting the ventilator; 5) EEG confirmatory test: persistence of brain dysfunction, six hours with a confirmatory EEG, flat EEG at level of 2 μ*V/mm*. In the standard process of brain death diagnosis, it involves certain risk and takes a long time (e.g., the need of removing the respiratory machine and 30 minutes' EEG confirmatory test).

For supporting the diagnosis of brain death, we have proposed an EEG preliminary examination system as a reliable yet safety and rapid way for the determination of brain death [2]. That is, after above items 1)- 3) have been verified, and an EEG preliminary examination along with real-time recorded data analysis method is applied to detect the brain wave activity at the bedside of patient. On the condition of positive examined result, we suggest to stop the brain death diagnosis process and spend more time on the medical care. Otherwise, the rest tests will be carried out as in the standard diagnosis procedure.

In the preliminary examination system [2], [3], several EEG data analysis algorithms such as independent component analysis (ICA)[3] and approximate entropy (ApEn) [2], [4] have been proposed to evaluate the state of comatose patients and quasi brain death patients.

Empirical mode decomposition (EMD) [5] is a fully data-driven approach that decomposes a signal into oscillations inherent to the data, referred to as intrinsic mode functions (IMFs). Applied EMD to evaluate the differences of EEG energy between comatose patients and quasi brain deaths since the power of brain activities from comatose patient is usually higher than that of non-activity components from quasi brain death [6]. However, EMD has a shortcoming in channel by channel EEG decomposition.

This paper presents a novel data analysis algorithm based on multivariate empirical mode decomposition (MEMD) to calculate and evaluate the energy of EEG recorded from patients. MEMD is an extensions approach of EMD, in which the main advantage is that enable to extract brain activity features from multi-channel EEG simultaneously, and also the number of features extraction are marched. The experimental results illustrate that the MEMD is effective in extracting the underlying data, and show good performance on the classification of comatose patient and brain death groups.

II. Method of EEG Data Analysis

A. Existing EMD Algorithm

EMD decomposes the original signal into a finite set of amplitude- and/or frequency-modulated components, termed IMFs, which represent its inherent oscillatory modes [5]. More specifically, for a real-valued signal $x(k)$, the standard EMD finds a set of N IMFs $\{c_i(k)\}_{i=1}^{N}$, and a monotonic residue signal $r(k)$, so that

$$x(k) = \sum_{i=1}^{n} c_i(k) + r(k). \qquad (1)$$

IMFs $c_i(k)$ 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.

The first complex extension of EMD was proposed in [7]. An extension of EMD to analyze complex/bivariate data which operates fully in the complex domain was first proposed in [8], termed rotation-invariant EMD (RI-EMD). An algorithm which gives more accurate values of the local mean is the bivariate EMD (BEMD) [9], where the envelopes corresponding to multiple directions in the complex plane are generated, and then averaged to obtain the local mean. An extension of EMD to trivariate signals has been recently proposed in [10]; the estimation of the local mean and envelopes of a trivariate signal is performed by taking projections along multiple directions in three-dimensional spaces.

B. The Proposed n-Variate EMD Algorithm[11]

For multivariate signals, the local maxima and minima may not be defined directly because the fields of complex numbers and quaternions are not ordered [10]. 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 is proposed in [11]. 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 spaces by using: (i) uniform angular coordinates and (ii) low-discrepancy pointsets.

The problem of finding a suitable set of direction vectors that the calculation of the local mean in an n-dimensional space depends on can be treated as that of finding a uniform sampling scheme on an n sphere. For the generation of a pointset on an $(n-1)$ sphere, consider the n sphere with centre point C and radius R, given by

$$R = \sum_{j=1}^{n+1}(x_j - C_j)^2. \tag{2}$$

A coordinate system in an n-dimensional Euclidean space can then be defined to serve as a pointset on an $(n-1)$ sphere. Let $\{\theta_1, \theta_2, \cdots, \theta_{n-1}\}$ be the $(n-1)$ angular coordinates, then an n-dimensional coordinate system having $\{x_i\}_{i=1}^{n}$ as the n coordinates on a unit $(n-1)$ sphere is given by

$$x_n = sin(\theta_1) \times \cdots \times sin(\theta_{n-2}) \times sin(\theta_{n-1}). \tag{3}$$

Discrepancy can be regarded as a quantitative measure for the irregularity (non-uniformity) of a distribution, and may be used for the generation of the so-called 'low discrepancy pointset', leading to a more uniform distribution on the n sphere. A convenient method for generating multidimensional 'low-discrepancy' sequences involves the family of Halton and Hammersley sequences. Let $x_1, x_2, \cdots, x_n$ be the first n prime numbers, then the ith sample of a one-dimensional Halton sequence, denoted by r_i^x is given by

$$r_i^x = \frac{a_0}{x} + \frac{a_1}{x}^2 + \frac{a_2}{x}^3 + \cdots + \frac{a_s}{x}^{s+1}, \tag{4}$$

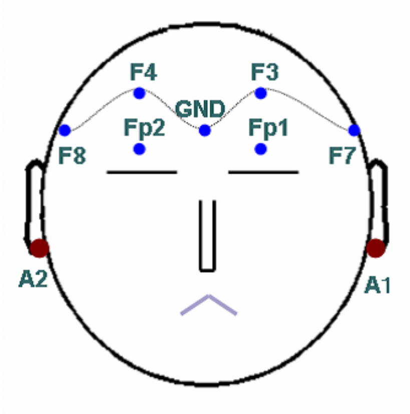


Fig. 1: The layout of six exploring electrodes.

where base-x representation of i is given by

$$i = a_0 + a_1 \times x + a_2 \times x^2 + \cdots + a_s \times x^s. \tag{5}$$

Starting from $i = 0$, the ith sample of the Halton sequence then becomes

$$(r_i^{x_1}, r_i^{x_2}, r_i^{x_3}, \cdots, r_i^{x_n}). \tag{6}$$

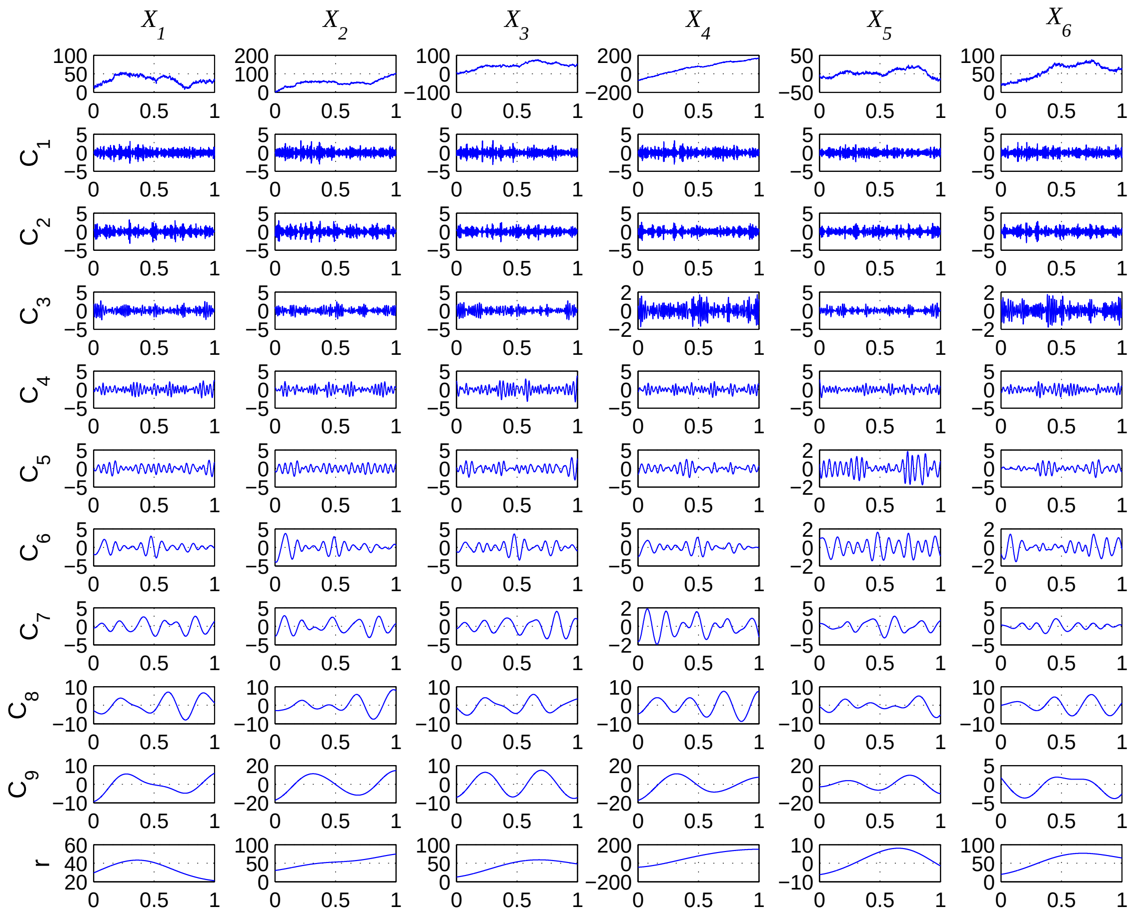
Consider a sequence of n-dimensional vectors $\{\mathbf{v}(t)\}_{t=1}^{T} = \{v_1(t), v_2(t), \cdots, v_n(t)\}$ which represents a multivariate signal with n-components, and $\mathbf{x}^{\theta_k} = \{x_1^k, x_2^k, \cdots, x_n^k\}$ denoting a set of direction vectors along the directions given by angles $\theta_k = \{\theta_1^k, \theta_2^k, \cdots, \theta_{n-1}^k\}$ on an $(n-1)$ sphere. Then, the proposed 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

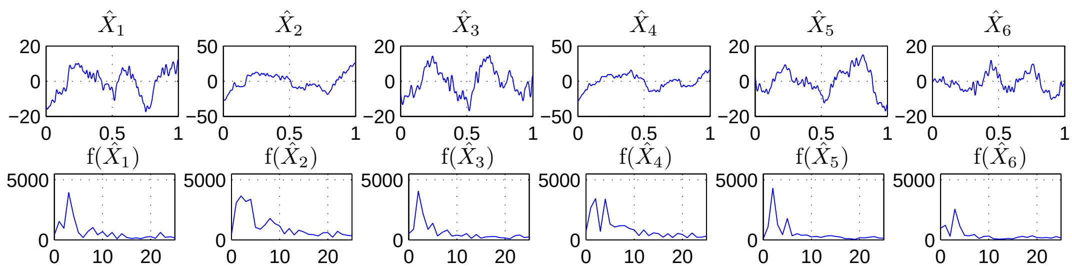
$$\mathbf{m}(t) = \frac{1}{K}\sum_{k=1}^{K}\mathbf{e}^{\theta_k}(t). \tag{7}$$

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 [12]. In the MEMD, we apply



(a) Decomposed IMFs for multi-channel EEG.



(b) Denoised EEG signal in time and frequency domains.

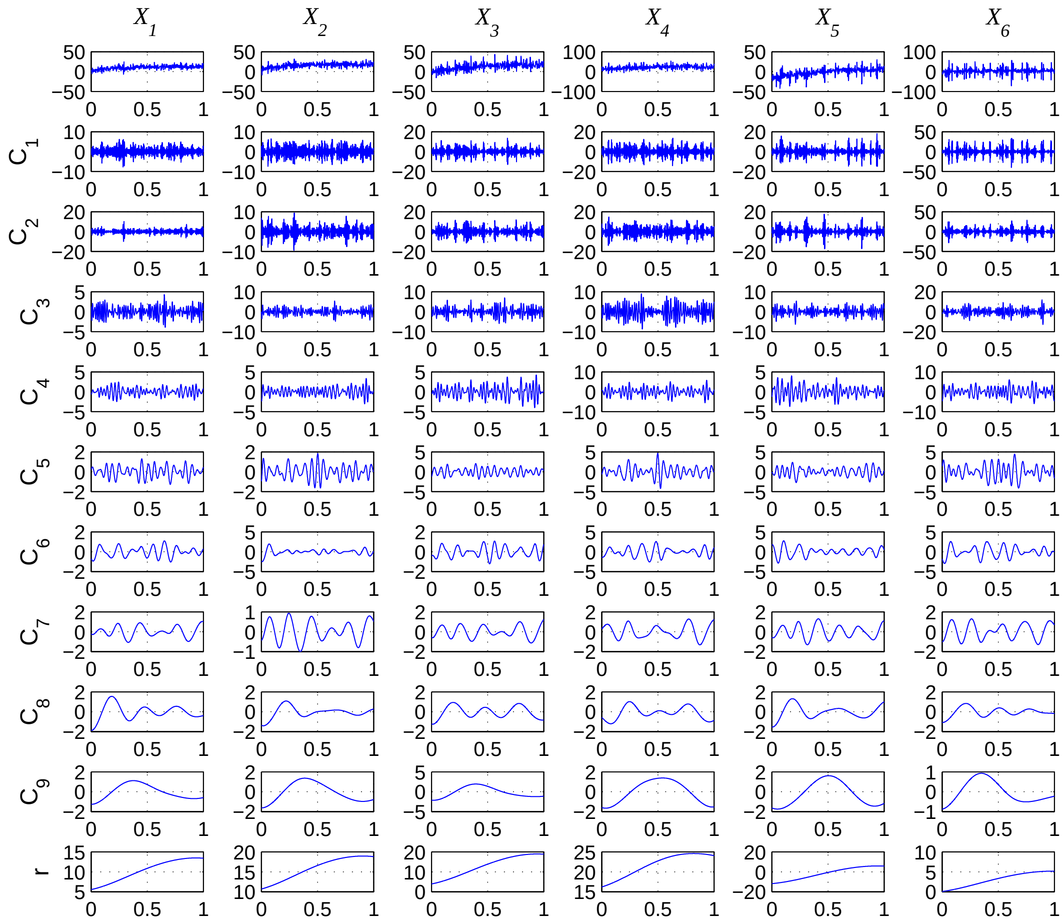
Fig. 2: An example for comatose patient used MEMD.

this criterion to all projections of the input signal and stop the sifting process once the stopping condition is met for all projections.

III. Experiments and Results

The EEG preliminary examination was carried out in a hospital in Shanghai. A portable EEG system (NEUROSCAN ESI) was used to record the patient's brain activity. The EEG data was directly recorded at the bedside of the patients in the intensive care unit (ICU). In the EEG recording, only nine electrodes are chosen to apply to patients. 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 (Fig. 1). The sampling rate of EEG was 1000 Hz and the resistances of the electrodes were set to less than 10 kΩ.

With the permission of the patients' families, a total of 35 comatose and quasi brain death patients with the age ranging



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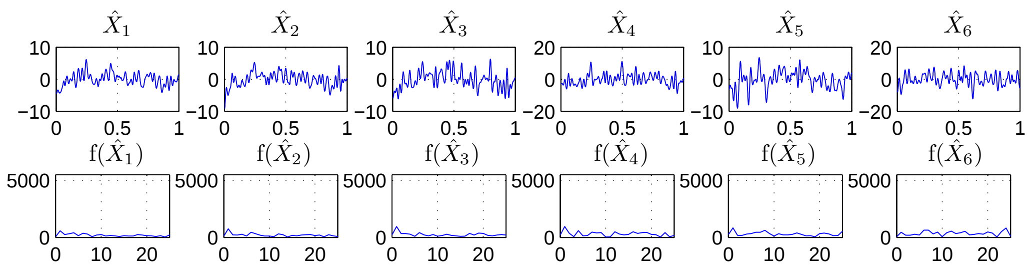

(b) Denoised EEG signal in time and frequency domains.

Fig. 3: An example for quasi brain death patient used MEMD.

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 20 comatose patients, 14 quasi brain deaths and one case a patient changed from comatose state to quasi brain death state. In the following sections, we will present two typical clinical cases, the first case appeared in a comatose state and another appeared a quasi brain death state. Then we present a summary of average power of all patients' physiological brain activities.

A. A Patient in a Comatose State

This case is concerned with an 18-year-old male patient. The EEG examination was performed in June 2004 with a comatose state. His pupil dilated to 2 *mm*, and a respiratory machine was used. The EEG recording lasted 38 seconds.

As showed in Fig. 2(a), 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 1s is selected randomly. By applying the MEMD method described in Section II, we obtain 9 IMF components (C1 to C9) within different frequency from

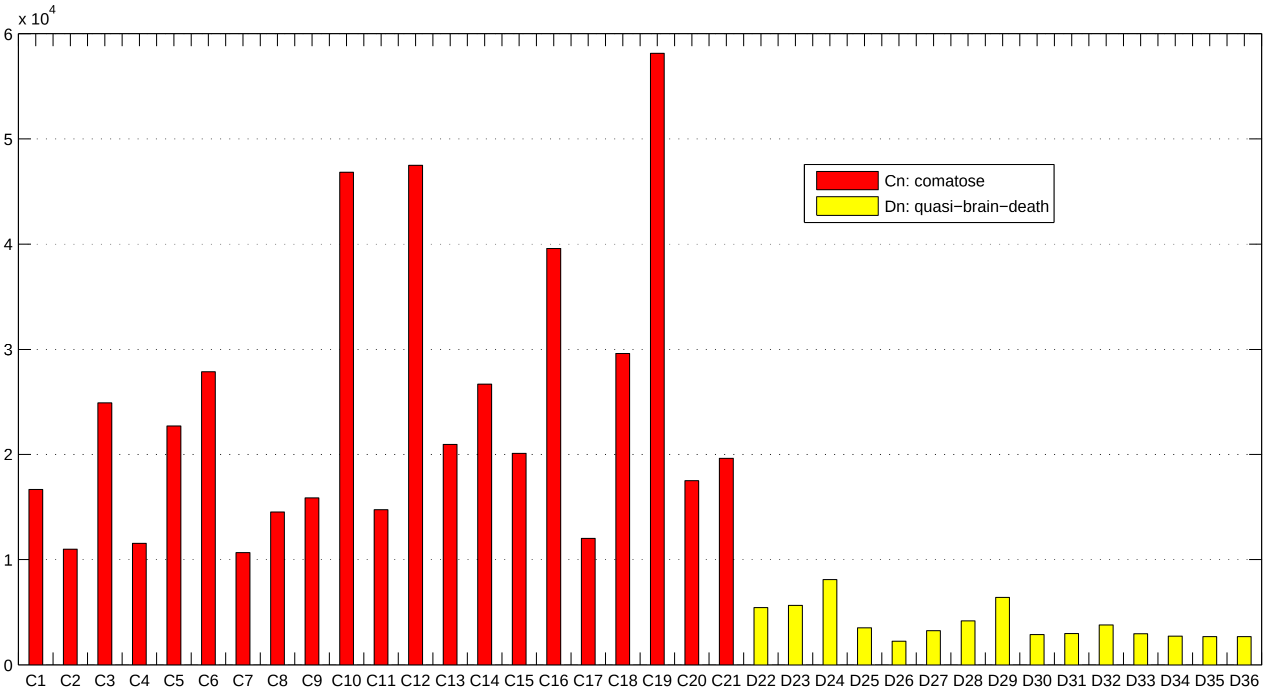

Fig. 4: The EEG energy of with a comatose state and a quasi brain death state

high to low. In the ordinary EMD analysis, each channel can be decomposed by 8-11 IMF components with a uncertain quantity, and only one channel can be analysised by the EMD at the same time. However, in the MEMD analysis, the IMF components of each channel has the same quantity, and we can obtain all the IMF components of each channel by MEMD analysis at the same time. Each IMF carries a single frequency mode, illustrating the alignment of common scales within different channels. Therefore, generally in our experiment, the IMF components from C1 to C3 that within the same 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 C4 to C9 are combined to form the denoised EEG signal, and changed into frequency domain by fast Fourier transform (FFT). As showed in Fig. 2(b), the upper line gives each channel's denoised EEG signal in time domain, and the lower line display the denoised EEG signal of each channel in their frequency domain. With y-coordinate in the scope from 0 to 5000 in the frequency domain, we find the value of power spectra at 2-10Hz is very high. This patient's maximum value of 6 channels in power spectra was between 3439 to 4295 that reflects a high intensity of brain activity. The analysis result indicated the patient still had strong physiological brain activity, and in fact, the patient was in a comatose state. With the aid of further therapy, this patient regained consciousness.

B. A Patient in a Quasi Brain Death State

The second is a 36-year-old male patient (Patient 23). With the family's consent, the EEG examination was performed in June 2005 when the patient had no brain-stem reflexes and the pupil had dilated to 4.5 mm(quasi brain death state). The EEG recording lasted 902 seconds. The time range 1s was selected randomly. We obtained MEMD result of 9 IMF components of each channel.

As showed in Fig. 3(a), with the same analysis of the first patient, the IMF components from C1 to C3 that within the same 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 C4 to C9 are combined to form the denoised EEG signal, and changed into frequency domain by fast Fourier transform (FFT). Fig. 3 is showed each channel's denoised EEG signal in their time domain and frequency domain. Comparing to the first patient's denoised EEG signal, we can not distinguish the comatose patient from the quasi brain death patient in their time domain. But from the power spectrum in frequency domain(the lower line of Fig. 3(b)), with y-coordinate in the same scope from 0 to 5000, this patient's maximum value of 6 channels' power spectra is only between 581.3 to 954.4, contrary to the first patient's power spectrum(the lower line of fig.2(b)), the value is in a low range. The analysis result indicate that this patient' physiological brain activity is extremely low.

C. The EEG Power Spectrum of Each patient

Brain activities show their power in spectral pattern. We integrate the power spectra with all channels in 0-20Hz in frequency domain, and we define the result value of this the power of physiological brain activity. Fig. 4 show the average power of physiological brain activity of 35 patients in 36 cases with 6 channels in one second. In Fig. 4, from case C1 to case C21, the maximum average power of physiological brain activity goes up over 6.00×10^4, and their minimum average power is above 1.00×10^4. It probably illustrates that the brain activities really exist. Contrary to this, (D22-D36) cases reflected no spectral power over 9.00×10^3. From Fig. 4, we can distinguish the patient in the comatose state from the quasi brain death state clearly.

IV. Conclusions

In this paper, we proposed an EEG data analysis approach based on multivariate empirical mode decomposition for evaluating the EEG energy recorded from the comatose and quasi brain death patients. By used MEMD, it enables to extract brain activity features from multi-channel EEG simultaneously, which is important to calculate the EEG energy in a same platform of all patients. It is obviously that the EEG energy from comatose patients is much higher than that of quasi brain deaths since the brain of comatose patients is activity. This data analyzed result is completely identical to the result achieved from clinical brain death determination. In the future studies, more patients' EEG data collection and blind testing are necessary.

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