



Analyzing patients' EEG energy for brain death determination based on Dynamic 2T-EMD

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ABSTRACT

EEG (electroencephalography) energy is an important evaluation indicator in brain death determination based on EEG analysis. In related works, the static EEG energy value can be discovered using EMD (empirical mode decomposition), MEMD (multivariate empirical mode decomposition) and 2T-EMD (turning tangent empirical mode decomposition) for EEG-based coma and quasi-brain-death analysis. However such methods are not time-varying and feasible. In this paper, we firstly propose the Dynamic 2T-EMD algorithm to evaluate the dynamic patients' EEG energy variation by the means of time window and time step method. With the time window sliding along the time axis in a time step, EEG energy of corresponding time step is computed and stored. The proposed algorithm is applied to analyze 19 cases of coma patients' EEG and 17 cases of quasi-brain-death patients' EEG. Two typical patients in coma and quasi-brain-death state and one special case who was from coma to quasi-brain-death have been taken as examples to give the algorithm performance. Results show that EEG energy in coma state are obviously higher than that in quasi-brain-death state, and even present the EEG energy change trend of every case, which can prevent loss of information and wrong analysis results caused by noise interference and provide scientific basis for doctors to evaluate patients' consciousness levels in brain death determination. The proposed algorithm will be very helpful to develop the real time brain death diagnostic system.

Keywords

EEG energy analysis; Dynamic 2T-EMD; Brain death determination

Academic Discipline And Sub-Disciplines

Signal processing; Computer Science; Neuroscience

SUBJECT CLASSIFICATION

Signal Processing; Signal Analysis

TYPE (METHOD/APPROACH)

Algorithms Analysis; Experimentation; Clinic

INTRODUCTION

Brain death is strictly defined that the complete, irreversible and permanent loss of brain and brain-stem function (Becheer et al., 1968; Wijidicks EFM et al., 2002). Based on the definition, more than 80 countries in the world have established brain death determination standards respectively. Previous researches on brain death determination were mainly concentrated in the field of clinic medicine. It is on the rise that objective scientific basis and indicators from the perspective of neuro dynamics are provided for the brain death determination. More specifically, researches of brain death determination based on EEG analysis are progressing rapidly.

Several EEG analysis algorithms such as ICA (independent component analysis) (A. Hyvarinen et al., 1997; L. Li et al., 2008; Gennady G. Knyazev et al., 2011), EMD (N. Huang et al., 1998), MEMD (N. Rehman et al., 2010), and 2T-EMD (Julien Fleureau et al., 2011) are applied to analyze coma and quasi-brain-death patients' EEG. ICA was applied in patients' EEG analysis because of its strong ability of denoising and component extraction (J. Cao et al., 2003; Z. Chen et al., 2008), but it's lack of rigorous basis for the determination of the patient whose brain activity components were not extracted. EMD based algorithms, as fully data driven algorithms, could analyze nonlinear and nonstationary signals and compute energy of signal at any time to avoid the loss of signal information. So EEG energy indicator was introduced to analyze quantitatively patients' EEG (E. Niedermeyer et al., 1991), and EMD based static algorithms such as EMD, MEMD, and 2T-EMD were all applied to process EEG and also compute EEG energy (M. Tomasz et al., 2010; Q. Shi et al., 2011). But a static EEG value was only obtained, which can't reflect dynamically patients' status.

In this paper, we firstly propose the Dynamic 2T-EMD to analyze dynamically coma and quasi-brain-death patients' EEG. The algorithm is developed by modification of the existing 2T-EMD on the time axis, using the time window and time step. With the time window sliding along the time axis, the EEG energy in corresponding to time window is computed and stored. We applied the Dynamic 2T-EMD to analyze 36 cases of patients' EEG energy, and focused on analyzing the three cases, respectively one coma patient's EEG, one quasi-brain-death patient's EEG and one patient's EEG from coma to quasi-brain-death. And then 36 cases of average EEG energy value of 6 channels for entire recording time are computed. The results show that the EEG energy in coma state is obviously higher than the EEG energy in quasi-brain-death state. More importantly, because of the non-stationarity feature of EEG, the results obtained can reflect dynamically patients' status of the whole period of measurement time and avoid the loss of information and wrong results caused by noise interference, which can provide doctors with the objective and scientific criterion for the clinical diagnosis of brain death determination. Furthermore, the developed algorithm is extremely important to the real time brain death diagnostic system.

1. THE DYNAMIC 2T-EMD ALGORITHM

1.1 2T-EMD algorithm

2T-EMD, belonging to EMD based static algorithms, is a fully data-driven algorithm for mono- and multivariate signals processing. Specifically, 2T-EMD could decompose a given signal s into a set of IMFs (intrinsic mode functions) $\sum_{i=1}^n IMF_i$ and a monotonic residual signal $r(n)$, shown in formula (1).

$$s = \sum_{i=1}^n IMF_i + r(n) \quad (1)$$

As 2T-EMD can decompose both mono- and multivariate signals directly, the key of 2T-EMD is the computation of signal mean trend, which is obtained by averaging two envelopes: a first envelope interpolates the even indexed barycenters which include signal borders, and a second envelope interpolates the odd indexed barycenters which also include signal borders (Julien Fleureau et al., 2011). Let s be a class C^1 function in R^D domain and differentiable with a continuous first derivative. The sifting procedure of computing the signal mean trend is briefly illustrated as below.

- (1) Defined a time series $\vec{T}(s)$ as the tangent vector to s and express as $\vec{T}(s) \rightarrow [1, \frac{ds}{dt}(t)]$.
- (2) Defined $\alpha(s)$ as the Euclidean inner products of R^{D+1} and express as $\alpha(s) \rightarrow \lim_{h \rightarrow 0} (\vec{T}_s(t-h), \vec{T}_s(t+h))$. And due to the continuity of Euclidean inner product, so $\alpha(s)$ can be expressed as $\forall t \in R, \alpha_s(t) = \lim_{h \rightarrow 0} (\vec{T}_s(t-h), \vec{T}_s(t+h))$.
- (3) Since s is a class C^1 function, we can get $\alpha(s) = \|\vec{T}_s\|^2 = 1 + \left\| \frac{ds}{dt}(t) \right\|^2$. Where $\|\cdot\|$ refers to the Euclidean norm of both R^D and R^{D+1} .
- (4) Oscillation extremum of function $s(t)$ is defined as the local minimum of function $\beta_s(t): \beta_s(t) = \left\| \frac{ds}{dt}(t) \right\|^2$.
- (5) Take two consecutive oscillation extrema, respectively $P_1 = [t_1, s(t_1)]^T$ and $P_2 = [t_2, s(t_2)]^T$, thereby $M_{P_1-P_2}$, the barycenter of the associated elementary oscillation is defined as $M_{P_1-P_2} = \left[\frac{t_1+t_2}{2}, \frac{1}{t_1-t_2} \int_{t_2}^{t_1} s(t) dt \right]^T$.
- (6) Then the signal mean vector $\vec{e}(t)$ can be obtained according to the definition above.

1.2 Dynamic 2T-EMD algorithm

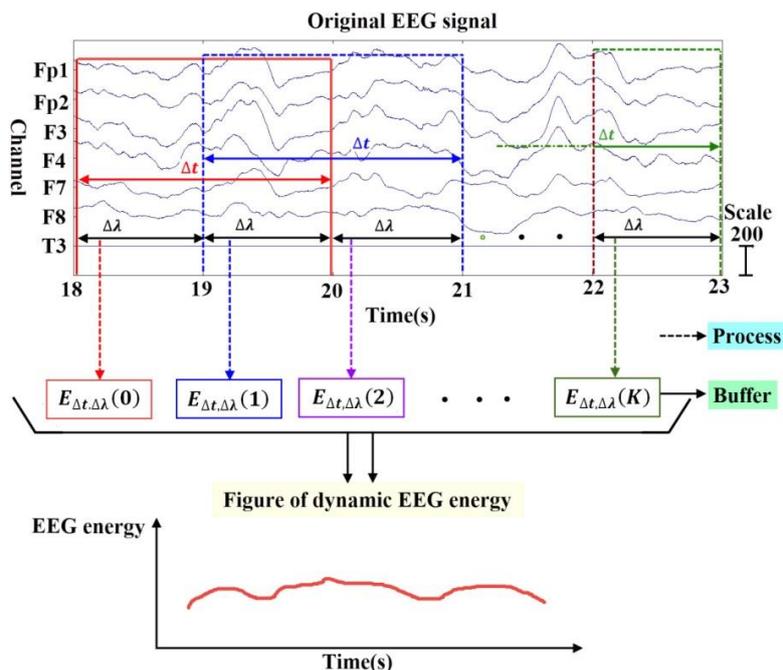


Fig. 1 Schematic diagram of Dynamic 2T-EMD

Dynamic 2T-EMD is developed by extending 2T-EMD based on 2T-EMD that is with excellent static EEG energy computational performance. As is shown in Figure 1, In the Dynamic 2T-EMD algorithm, a time window that the width is Δt and a time step with the width $\Delta \lambda$ are introduced, where Δt and $\Delta \lambda$ are controllable parameters. With the time window sliding along the time axis in a time step, a time step of EEG is processed and value is stored, then repeat the steps above. And finally we obtain a collection of ordered data. More specifically, for a multivariate signal with n components $\{\vec{s}(k \cdot \Delta t)\}_{k=0}^K = \{\vec{s}(0 \cdot \Delta t), \vec{s}(1 \cdot \Delta t), \dots, \vec{s}(K \cdot \Delta t)\}$ from T_1 to T_2 , where $T_2 = T_1 + K \cdot \Delta t$. The decomposition process of Dynamic 2T-EMD and the flow chart of decomposition process for Dynamic 2T-EMD are respectively as shown in Figure 1 and Figure 2.

- (1) Initialize the number of iteration $j = 1$, the number of IMF $i = 1$, and the number of time step $k = 0$; and set $\vec{r}_i(k \cdot \Delta t) = \{\vec{s}(k \cdot \Delta t)\}_{k=0}^K$, $\vec{h}_{i,j-1}(k \cdot \Delta t) = \vec{r}_i(k \cdot \Delta t)$.
- (2) Compute the barycenter $M_{(i,j-1)P_{k_x}-P_{k_{x+1}}}(k \cdot \Delta t)$ of random consecutive oscillation extrema P_{k_x} and $P_{k_{x+1}}$ in the period of $k \cdot \Delta t$, that is $M_{(i,j-1)P_{k_x}-P_{k_{x+1}}}(k \cdot \Delta t) = \left[\frac{k_x \cdot \Delta t + k_{x+1} \cdot \Delta t}{2}, \frac{1}{k_{x+1} \cdot \Delta t - k_x \cdot \Delta t} \int_{k_x \cdot \Delta t}^{k_{x+1} \cdot \Delta t} \vec{h}_{i,j-1}(t) dt \right]^T$.
- (3) Obtain the signal mean trend $\vec{e}_{i,j-1}(k \cdot \Delta t)$ by interpolating between oscillation barycenters of $\vec{h}_{i,j-1}(k \cdot \Delta t)$.
- (4) Subtracting $\vec{e}_{i,j-1}(k \cdot \Delta t)$ from the given signals $\vec{h}_{i,j-1}(k \cdot \Delta t)$, we define $\vec{h}_{i,j}(k \cdot \Delta t) = \vec{h}_{i,j-1}(k \cdot \Delta t) - \vec{e}_{i,j-1}(k \cdot \Delta t)$. If $\vec{h}_{i,j}(k \cdot \Delta t)$ obey the sifting stop criteria, defining $\overline{IMF}_i(k \cdot \Delta t) = \vec{h}_{i,j}(k \cdot \Delta t)$, otherwise repeat the iteration steps from (2) to (4). It is worth noting that the stop criteria is using the Cauchy-like criteria, more precisely, let $d_{i,j}$ be the $i - th$ IMF computed at the $j - th$ iteration of the sifting process, then the sifting criteria is for instance 90% of values $\left\| \frac{d_{i,j+1}(t) - d_{i,j}(t)}{d_{i,j}(t)} \right\|$ are lower than 10^{-2} .
- (5) Define $\vec{r}_i(k \cdot \Delta t) = \vec{r}_i(k \cdot \Delta t) - \overline{IMF}_i(k \cdot \Delta t)$, if the result signal is monotonous, we can get the decomposition result of signal during $k \cdot \Delta t$, that is $\vec{s}(k \cdot \Delta t) = \sum_{i=1}^N \overline{IMF}_i(k \cdot \Delta t) + \vec{r}_N(k \cdot \Delta t)$, otherwise repeat steps from (2) to (5).
- (6) Determine whether the elapsed time $k \cdot \Delta t$ exceeds the end time T_2 , if it does, the process goes to end and the final decomposition result $\{\vec{s}(k \cdot \Delta t)\}_{k=0}^K = \left\{ \sum_{i=1}^N \overline{IMF}_i(k \cdot \Delta t) + \vec{r}_N(k \cdot \Delta t) \right\}_{k=0}^K$; If it doesn't, moving the time window and repeat steps from (2) to (6).

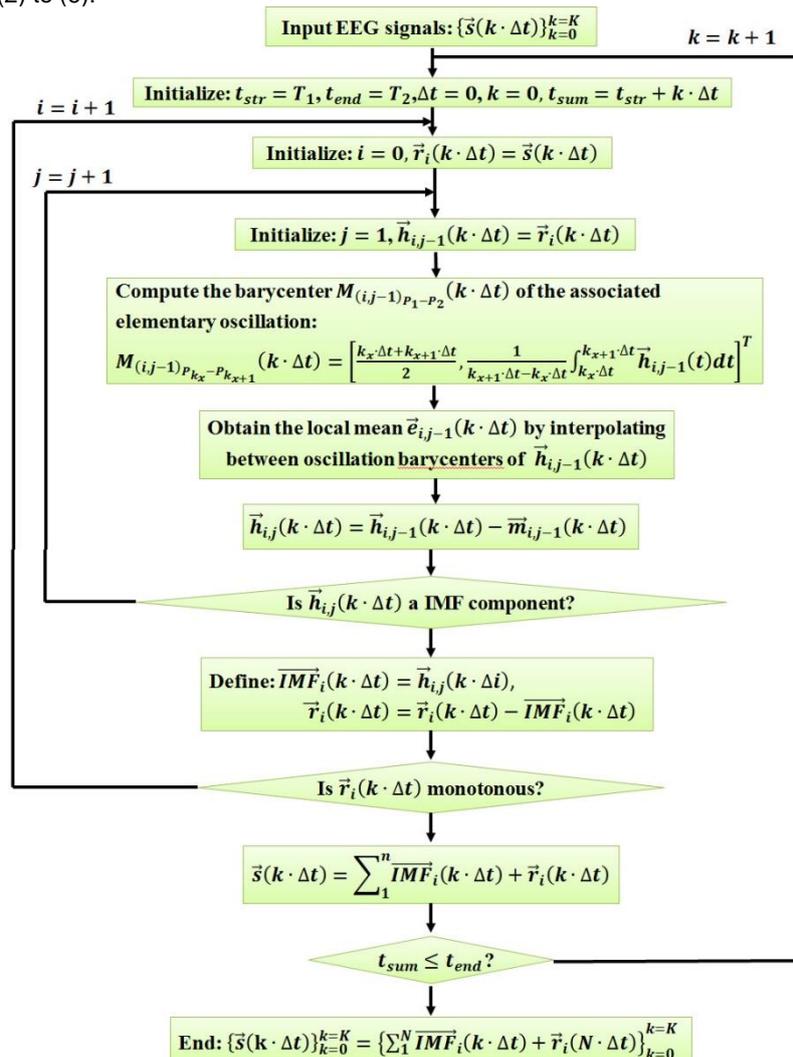


Fig. 2 Flow chart of Dynamic 2T-EMD

2. EXPERIMENTS AND RESULTS

2.1 Experiments

In this paper, we apply Dynamic 2T-EMD to process 36 cases of coma and quasi-brain-death patients' EEG (19 coma, 17 quasi-brain-death). The 36 cases of patients' EEG was recorded from 35 patients (male:20, female:15), with age ranging from 17 to 85 years old. It is noted that 36 cases of patients' EEG were recorded in EEG preliminary examination in a Chinese hospital in Shanghai from June 2004 to March 2006, with the permission of patients' families. Considering the specificity of patients' symptoms, the measure of placing the high-purity electrodes on the forehead to record EEG was used in the EEG preliminary examination (J. Cao et al., 2006). The portable electroencephalograph with NEUROSCAN ESI-64 system was applied, where 7 electrodes were placed on the forehead of patients, respectively 6 exploring electrodes (Fp1, Fp2, F3, F4, F7, F8) and 1 ground electrode (GND), and 2 electrodes (A1, A2) as reference electrodes were placed on earlobes. The sampling rate of EEG was 1000Hz and the electrode resistance was lower than 8k Ω , shown in Figure 3. Moreover, EEG energy is defined as that the power spectrum within the frequency band multiplied by recorded EEG time. When there are obvious periodic rhythms in the EEG signal, that is to say, there exists brain activity, the corresponding EEG energy is higher.

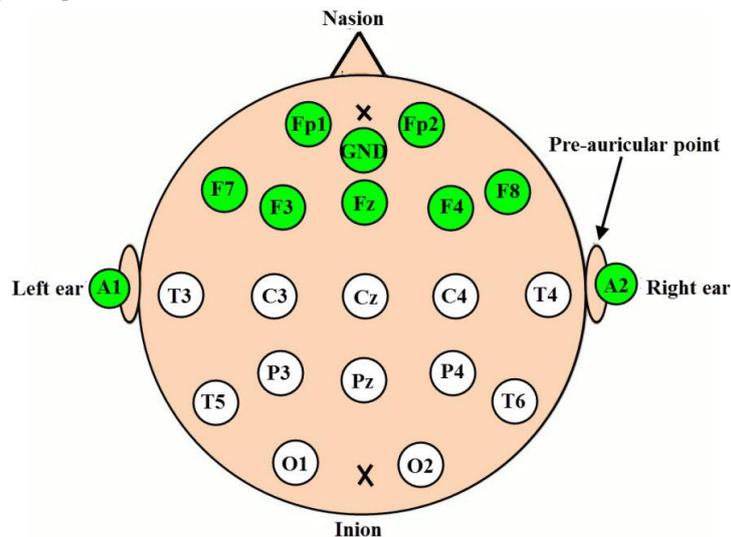


Fig. 3 The placement of electrodes

In the following section, we firstly analyze two typical patients' EEG that are from different patients, respectively one coma patient and one quasi-brain-death patient, by Dynamic 2T-EMD. Secondly, we concentrate on the special patient who was from coma to quasi-brain-death. Finally, we summary the average EEG energy of 6 channels in the whole recording time period for 36 cases of patients' EEG by Dynamic 2T-EMD.

2.2 Results

2.2.1 Result analysis of one coma patient's EEG and one quasi-brain-death patient's EEG

We analyze one coma patient's EEG with a record duration of 909s and one quasi-brain-death patient's EEG with a record duration of 1088s. As is shown in Figure 4 and Figure 5. We select EEG energy curve for the first 50s to observe. The results illustrate that the dynamic EEG energy of each channel for coma patient's EEG is higher than 1×10^4 , and the variation range is $1.71 \times 10^4 \sim 1.98 \times 10^5$, while the dynamic EEG energy for quasi-brain-death patient's EEG is far lower than 1×10^4 with changing range from $1.23 \times 10^3 \sim 6.06 \times 10^3$. Then we compute the average dynamic EEG energy of 6 channels for the two cases, as is shown in Figure 6 and Figure 7, and the average dynamic EEG energy of coma patient's EEG is obviously higher than that of quasi-brain-death at any time.

According to the definition of EEG energy, the higher energy indicates that there are obvious periodic rhythms in patient's EEG, that is to say, the patient has brain activity in the coma state. While quasi-brain-death patient has almost no brain activity, and as there exists random noise in EEG, there is lower EEG energy in quasi-brain-death patient.

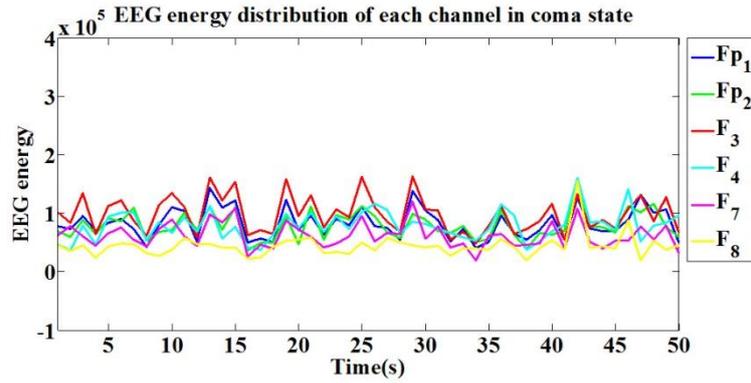


Fig. 4 EEG energy distribution of each channel in coma state

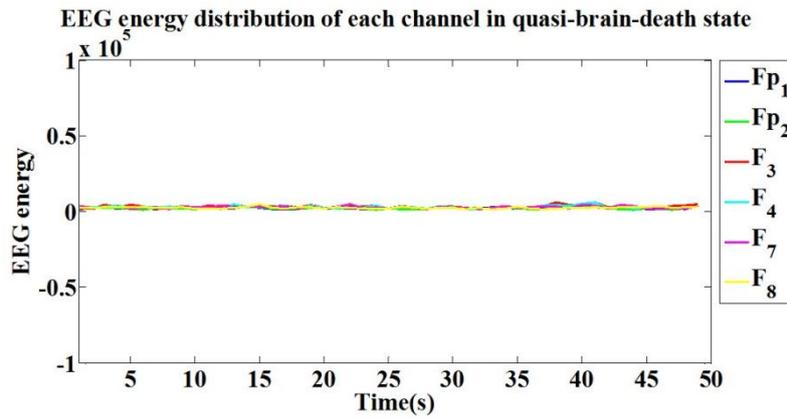


Fig. 5 EEG energy distribution of each channel in quasi-brain-death state

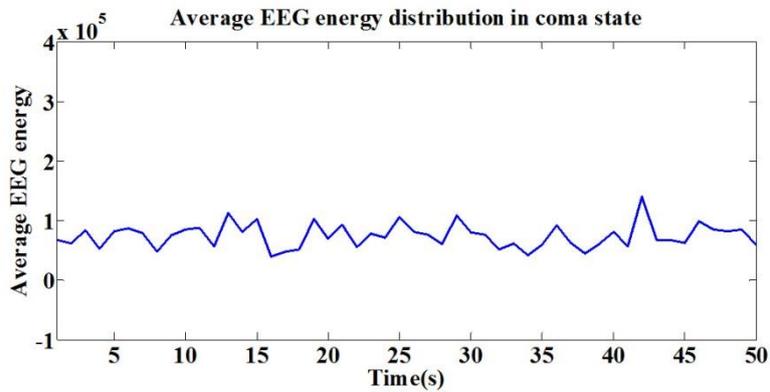


Fig. 6 Average EEG energy distribution in coma state

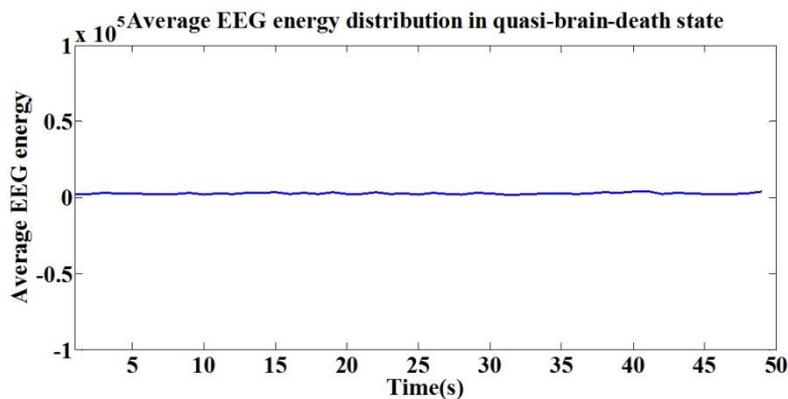


Fig. 7 Average EEG energy distribution in quasi-brain-death state

2.2.2 Result analysis of the patient's EEG from coma to quasi-brain-death state

Then we process the patient's EEG from coma to quasi-brain-death state. The patient lost cognitive and motor functions, the pupil dilated to 4mm that only had a weak visual response, and a respiratory machine was used. And the patient lost consciousness unexpectedly some time in October 2005. The first EEG examination was taken with a record duration of 900s, and the EEG recorded was in coma state. After about 10h on the same day, the patient's condition appeared worse and was found to have completely lost reaction to external visual, auditory and tactile simulation. Then the diagnosis was made as a quasi-brain-death case by two physicians. The EEG examination was taken for the second time, and the recorded time is 1153s (Q. Shi et al., 2011). We select the last 50s of EEG in coma state and the beginning 50s of EEG in quasi-brain-death to analyze.

As is shown in Figure 8 and Figure 9, the analysis results illustrate intuitively that EEG energy trend from coma to quasi-brain-death state. In the state of coma, the average EEG energy varies within the range of $2.02 \times 10^4 \sim 5.59 \times 10^4$, while in the state of quasi-brain-death the EEG energy is varies in the range of $2.26 \times 10^3 \sim 4.82 \times 10^3$, lower than 1×10^4 . EEG energy in coma state is obviously higher than that in quasi-brain-death state in the whole dynamic EEG energy distribution curve.

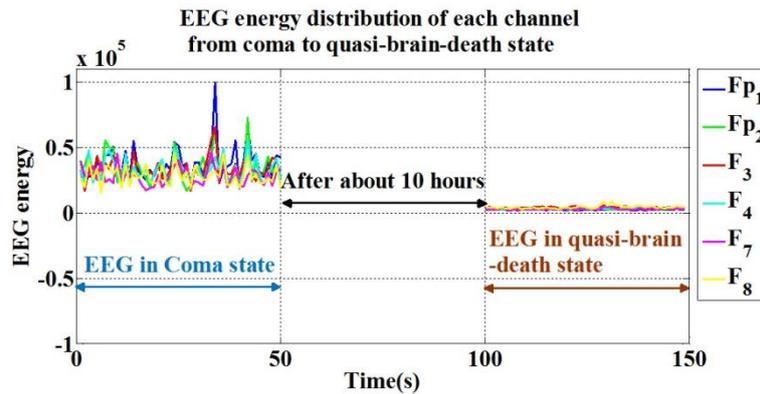


Fig. 8 EEG energy distribution of each channel from coma to quasi-brain-death state

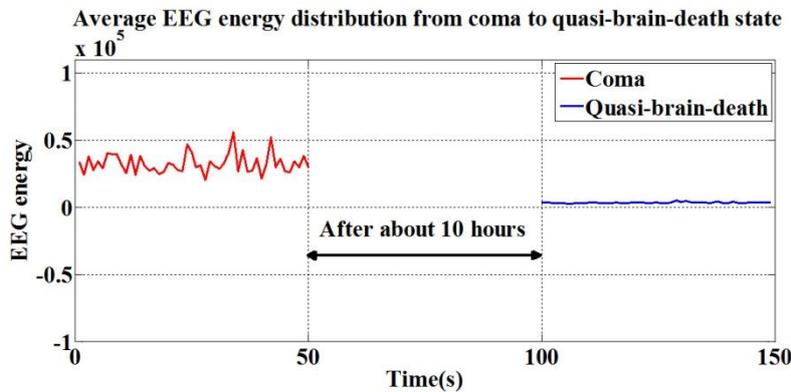


Fig. 9 Average EEG energy distribution in quasi-brain-death state

2.2.3 Summary of average EEG energy of patients' EEG

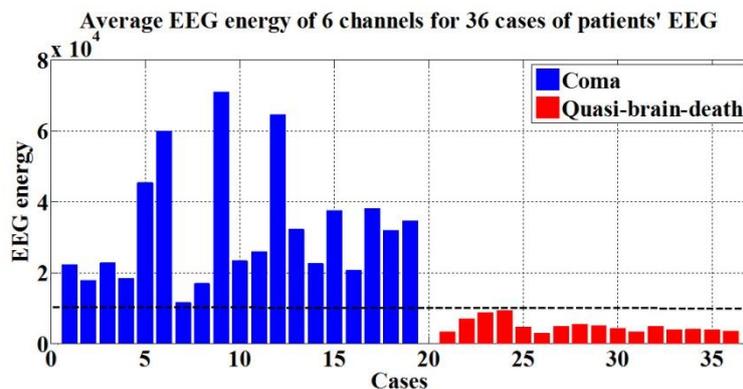


Fig. 10 Average EEG energy of 6 channels for 36 cases of patients' EEG



We apply Dynamic 2T-EMD to obtain the average EEG energy of 6 channels in the entire recording time for all 36 cases of patients' EEG, which can prevent the information loss and wrong static results caused by some artificial factors or interference noises of equipment in EEG examination. As is shown in Figure 10, it is obviously shown that the average EEG energy of coma patients' EEG is higher than 1×10^4 , and it indicates that there exists brain activity. While the average EEG energy of quasi-brain-death patients' EEG is lower than 1×10^4 , which explain there almost no brain activity apart from some kinds of noises.

3. CONCLUSION

In this paper, we have proposed the Dynamic 2T-EMD by extending 2T-EMD to analyze dynamically EEG energy. It's the algorithm by introducing two parameters of the time window Δt and the time step $\Delta \lambda$. With the time window sliding along the time axis, the EEG in the corresponding time step is analyzed and the EEG energy is computed. Then we apply Dynamic 2T-EMD to analyze 36 cases of coma and quasi-brain-death patients' EEG. We showed two examples for two typical patients' EEG including one coma patient's EEG and one quasi-brain-death patient's EEG, and a special patient's EEG that the patient was from coma state to quasi-brain-death state to analyze by Dynamic 2T-EMD, and finally we summary average EEG energy of 36 cases of patients' EEG for corresponding recording time. The results present dynamic EEG energy distribution in coma and quasi-brain-death state, and also illustrate that EEG energy in coma state is higher than that in quasi-brain-death state from perspective of dynamic EEG energy. And the results can prevent information loss and wrong static EEG energy resulted by noise interference and provide doctors scientific basis to evaluate patients' consciousness level. More importantly, The proposed algorithm is extremely important to the real time brain death diagnostic system.

In the future work, we will focus on developing the real time brain death diagnostic system by connecting the EEG measurement system to the EEG analysis system to realize real time analysis of EEG.

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Author' biography with Photo



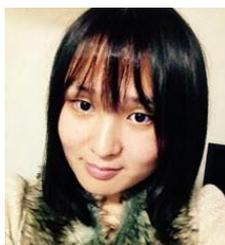
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