Patients' EEG Analysis Based on Multi-indicator Dynamic Analysis Measure for Supporting Brain Death Determination

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Abstract. It is crucial to analyze coma and quasi-brain-death patients' EEG (electroencephalography) by using different signal processing methods, in order to provide reliable scientific references for supporting BDD (brain death determination). In this paper, we proposed the multi-indicator dynamic analysis measure which was by combining Dynamic 2T-EMD (turning tangent empirical mode decomposition) and Dynamic ApEn (approximate entropy) to comprehensively analyze offline coma and quasi-brain-death patients' EEG from dynamic EEG energy and dynamic complexity. Firstly, 60s EEG randomly selected from 36 cases of patients' EEG (coma: 19; quasi-brain-death: 17) were analyzed to show the overall dynamic energy and complexity distribution for 2 groups. Secondly, one coma patient's EEG, one quasi-brain-death patient's EEG, and one special patient's EEG which was from coma to quasi-brain-death state were processed to present individual characteristics. Results show intuitively that patients in coma state have higher dynamic EEG energy and lower complexity distribution than patients in quasi-brain-death state.

Keywords: Dynamic multi-indicator · Patient's EEG
Dynamic EEG energy · Dynamic complexity

1 Introduction

The human brain consists of medulla oblongata, pons, midbrain, cerebellum, diencephalon, and telencephalon, among which oblongata, pons and midbrain are called brainstem [1]. The concept of brain death was firstly proposed in 1959 [2]. There are three different definitions of brain death so far, which are total brain death, brainstem death and diffuse cortical death, after being constantly revised. The first BDD standard in human history was proposed in 1968, which was the complete, irreversible and permanent loss of brain and brainstem function [3].

In the clinic practice of BDD, professional physicians need to carry out a number of strict conformation tests, which might take risks such as the risk

T. Huang et al. (Eds.): ISNN 2018, LNCS 10878, pp. 824–833, 2018.
https://doi.org/10.1007/978-3-319-92537-0_93

resulted by apnea test and risk caused by taking long time during whole tests process. So it is important to use advanced signal processing methods to process EEG, in order to provide reliable and objective scientific criteria and to avoid misjudgment for supporting clinic judgment of BDD.

Some signal processing methods were applied to process EEG from different perspectives. For example, ICA (independent component analysis) was applied to remove noise and artifacts and extract weak brain activity components from EEG in the project of BDD [4]. And some complexity methods were applied to obtain statistic features of EEG signals [5]. And information fusion via fission based on EMD was used to differentiate coma and brain-death EEG [6]. Moreover, EMD based methods were applied to process EEG signals from mono-channel static EEG energy indicator [7].

In this paper, we proposed the multi-indicator dynamic analysis measure to comprehensively process patients' EEG from dynamic EEG energy and dynamic complexity aspects, which was based on by combining Dynamic 2T-EMD (turning tangent empirical mode decomposition) algorithm and Dynamic ApEn (approximate entropy) algorithm. There were 2 parts of work included. Firstly, the principle of the multi-indicator dynamic analysis measure, the Dynamic 2T-EMD algorithm and the Dynamic ApEn algorithm were briefly illustrated. Secondly, two experiment measures were conducted from both overall and individual perspectives. Specifically, from the overall perspective, 60s EEG data were selected randomly from every of 36 cases of coma and quasi-brain-death patients' EEG, and analyzed by the multi-indicator dynamic measure proposed to get the dynamic EEG energy and dynamic complexity trend characteristics for coma group and quasi-brain-death group. And from individual perspective, 60s EEG data from every of two typical EEG and one special EEG were selected randomly and processed by the measure. Here the two typical EEG were from two patients that including one coma patient and one quasi-brain-death patient, and one special EEG came from one patient who was from coma state to quasi-brain-death state. Results show obviously that the distribution of dynamic EEG energy of coma patients' EEG are higher than that of brain-death patients' EEG, and at the same time the trend of dynamic complexity of coma patient's EEG are lower than that of brain-death patient's EEG from both overall and individual perspectives, which is helpful to provide more reliable and more accurate results for supporting BDD.

2 Methods

2.1 The Multi-indicator Dynamic Analysis Measure

The multi-indicator dynamic analysis measure was used to study the dynamic distribution characteristics of EEG from multi-perspective for every time window, which was conducted through a combination of different dynamic algorithms.

The key of the measure lied in dynamics and different indicators. Firstly, compared with static EEG analysis, dynamic EEG analysis has the following two advantages [8]. (i) Dynamic EEG analysis can observe changes of vital signs, and help physicians evaluate and predict patients' state trend [9]. (ii) The accuracy and reliability of results can be improved by dynamic analysis.

The brief principle is shown in Fig. 1. In Fig. 1, a segment of off-line raw EEG signals was divided into multiple time windows by introducing the time window and the time step. And as the time window and time step sliding, EEG data were analyzed by applying Dynamic 2T-EMD and Dynamic ApEn algorithms to obtain the dynamic EEG energy distribution and dynamic complexity distribution in time domain.

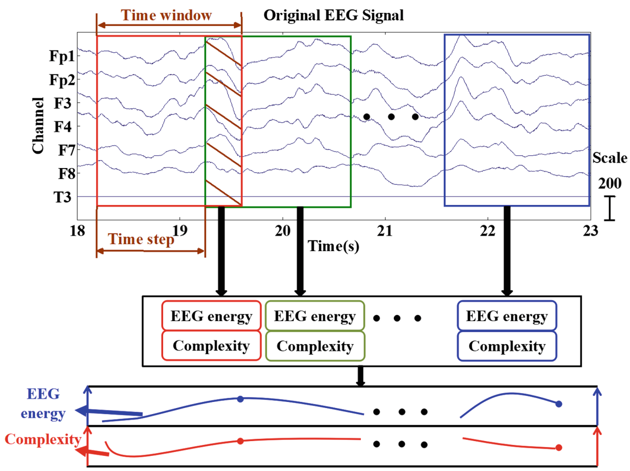

Fig. 1. The principle of multi-indicator dynamic analysis measure.

2.2 Dynamic 2T-EMD Algorithm

2T-EMD is a fully data-driven algorithm of signal processing for single and multiple channels signals. It can decompose a given signal $s(t)$ into a finite set of IMFs (Intrinsic Mode Functions) $\sum_{n=1}^{N} IMF_n$ from low frequency to high frequency and a monotonic residual signal $r(t)$, shown in (1) [10].

$$s(t) = \sum_{n=1}^{N} IMF_n + r(t) \tag{1}$$

Dynamic 2T-EMD algorithm is the extended form of 2T-EMD by introducing time window Δt and time step $\Delta\lambda$, and it's used to analyze EEG data to obtain dynamical EEG energy distribution with the time window Δt and time step $\Delta\lambda$ sliding [11]. Here EEG energy is defined as the value by multiplying power spectrum within the frequency band by corresponding recording time. Specifically, take the simple case as an example, when $\Delta t = \Delta\lambda$, for a multivariate signal with n components from T_1 to T_2

$$\{\overrightarrow{s}(k \cdot \Delta t)\}_{k=0}^{K} = \{\overrightarrow{s}(0 \cdot \Delta t), \overrightarrow{s}(1 \cdot \Delta t), \ldots, \overrightarrow{s}(K \cdot \Delta t)\} \tag{2}$$

Where T_1 is the start time of signal processing, and then

$$T_2 = T_1 + K \cdot \Delta t = T_1 + K \cdot \Delta\lambda \tag{3}$$

And K is the number of time windows in the given time from T_1 to T_2. Then after processed by Dynamic 2T-EMD, we can obtain results shown in following formula.

$$\{\overrightarrow{s}(k \cdot \Delta t)\}_{k=0}^{K} = \left\{\sum_{i=1}^{N} \overrightarrow{IMF}_i(k \cdot \Delta t) + \overrightarrow{r}_N(k \cdot \Delta t)\right\}_{k=0}^{K} \tag{4}$$

2.3 Dynamic ApEn Algorithm

The approximate entropy is defined as a similarity vector that continues to maintain a similar conditional probability over a certain threshold when the dimension increases from m to $m+1$ [12]. And its physical meaning is the probability that the time series produces a new pattern when the dimension changes. Specifically, the smaller the approximate entropy is, the lower the complexity is, the smaller the probability that the time series produces new patterns is, that is to say, it has a certain regularity and predictability [13].

More specifically, compute the time series $\overrightarrow{x}(n) = \{x(1), x(2)..., x(N)\}$, $(n = 1, 2, ..., N)$ to obtain the ApEn($\overrightarrow{x}(n)$, m, r) of the sequence, where m is the length of the series of vectors, r is threshold. And m-dimensional vectors $\overrightarrow{v}(k) = \{x(k), x(k+1), ..., x(k+m-1)\}$ is firstly constructed from $\overrightarrow{x}(n)$, and then use $\overrightarrow{v}(i)$ and $\overrightarrow{v}(j)$ $(i, j \leq N-m+1)$ to represent $\overrightarrow{x}(n)$. The distance between $\overrightarrow{v}(i)$ and $\overrightarrow{v}(j)$ can be represent as shown below, where d is the maximum norm.

$$d[\overrightarrow{v}(i), \overrightarrow{v}(j)] = max_{k=1,2,...m}[|x(i+k-1) - x(j+k-1)|] \tag{5}$$

Given a threshold r, $B^{m,r}(i)$ is defined as the number of $\overrightarrow{v}(i)$ and $\overrightarrow{v}(j)$ in the threshold for each $i \leq N-m+1$. Then we define $C^{m,r}(i)$ as the conditional probability that $\overrightarrow{v}(i)$ and $\overrightarrow{v}(j)$ are similar at the threshold.

$$C^{m,r}(i) = \frac{B^{m,r}(i)}{N-m+1} \tag{6}$$

Where $i \leq N-m+1$, and $\phi^{m,r}$, the average of $C^{m,r}(i)$, which is also the entropy average is expressed as below.

$$\phi^{m,r} = \frac{1}{N-m+1} \sum_{i=1}^{N-m+1} \log C^{m,r}(i) \tag{7}$$

Then $ApEn(\overrightarrow{x}(n), m, r)$ can be expressed as below.

$$ApEn(\overrightarrow{x}(n), m, r) = \phi^{m,r} - \phi^{m+1,r} \tag{8}$$

Dynamic ApEn algorithm is the extension of existing ApEn algorithm by introducing a running window Δt, which can reflect the dynamic complexity change of the whole recording time and avoid the loss of detail information.

2.4 The EEG Recording

The EEG data we used in the paper were recorded in EEG preliminary examination in a Chinese hospital from June 2004 to March 2006, with the permission of patients' families [14]. During the EEG recording, patient was lying on the bed in the ICU. And the EEG data was detected by the portable NEUROSCAN ESI-64 system and a laptop computer. Six exploring electrodes (Fp1, Fp2, F3, F4, F7, F8) as well as one ground electrode (GND) were placed on the forehead, and two reference electrodes (A1, A2) were placed on earlobes. And the sampling frequency was 1000 Hz and the electrode resistance was lower than 8 $K\Omega$. The placement of electrodes was shown in Fig. 2. In this paper, the EEG of 35 coma and quasi-brain-death patients (male: 21; female: 14) with a total of 36 cases of EEG (coma: 19; quasi-brain-death: 17), in which there were one case of EEG in coma and one case of EEG in quasi-brain-death included in the same special patient whose state was from coma in the first EEG recording process to quasi-brain-death state in the second EEG recording process after 10 h. And since the recording time for each case of EEG was different, 60s EEG data were selected randomly from 36 cases of EEG to process in order to unify the time of EEG being processed in the dynamic analysis.

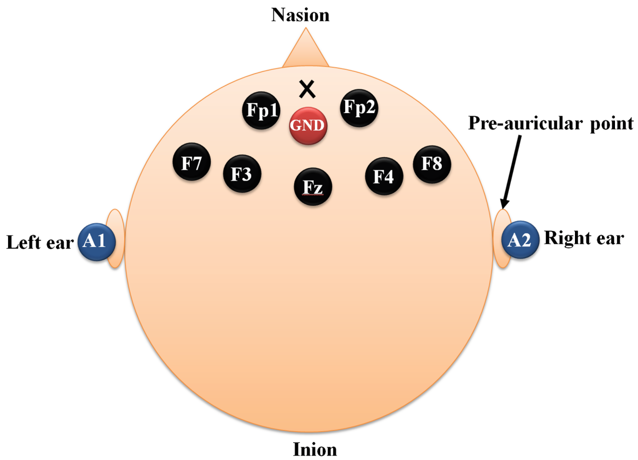

Fig. 2. The placement of 9 electrodes.

3 Results and Discussion

There were 2 parts in this section. Firstly, in order to give an overall dynamic distribution results for coma group and quasi-brain-death group, we selected randomly 60s EEG data from every of 36 cases of coma and quasi-brain-death EEG, and analyzed by the multi-indicator dynamic measure proposed. Secondly, two typical cases of EEG from two different patients who were in coma and quasi-brain-death state respectively, and one special patient whose EEG was from coma state to quasi-brain-death state were processed to give the 3 cases of individual dynamic distributions.

3.1 Results and Discussion for 2 Groups

In this part, 19 cases of EEG data for coma group and 17 cased of EEG data for quasi-brain-death group were analyzed by the multi-indicator dynamic measure based on Dynamic 2T-EMD and Dynamic ApEn. Here the time window of both Dynamic 2T-EMD and Dynamic ApEn were set to 1 s and no overlap among time windows. Then we took mean value of every second for channels averaged for coma group and quasi-brain-death group respectively due to the two group were not balanced. As shown in Fig. 3, it is obviously observed that the range of mean dynamic EEG energy for channels averaged for coma group is 2.3×10^4–4.5×10^4, is higher than that for quasi-brain-death group which is 4.0×10^3–4.7×10^3, and at the same time the mean dynamic complexity distribution for channels averaged for coma group is lower than that of quasi-brain-death group, in which the range of dynamic complexity for coma group and quasi-brain-death group are 0.328–0.5 and 0.999–1.101 respectively. Moreover, the overall mean value and standard deviation of EEG energy for coma group and quasi-brain-death group are $2.9 \times 10^4 \pm 3.6 \times 10^3$ and $4.4 \times 10^3 \pm 2.0 \times 10^2$, respectively; and that of ApEn for coma and quasi-brain-death group are 0.4048 ± 0.0390, 1.0499 ± 0.0219, separately. That can be observed there exists larger individual differences.

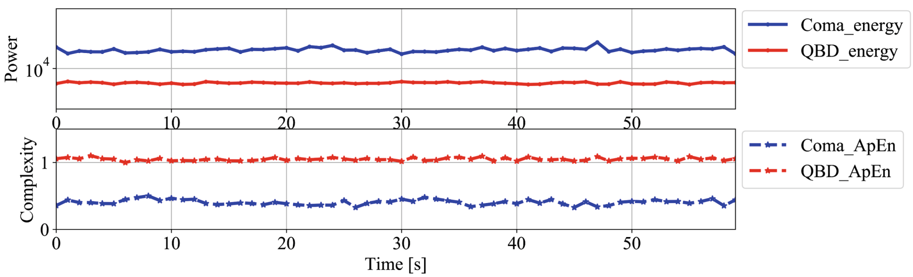

Fig. 3. Dynamic mean EEG and complexity distribution of average channel for coma group and quasi-brain-death group.

And as shown in Fig. 4, we also analyzed the dynamic EEG energy distribution for every channel (Fp1, Fp2, F3, F4, F7 and F8) for both coma group and quasi-brain-death group. The mean dynamic EEG energy and dynamic ApEn distributions characteristics for every channel for coma and quasi-brain-death group are consistent with the distributions of average channels for 2 groups, in which the fluctuation range of dynamic EEG energy for 2 groups at 6 channels are 2.4×10^4–5.5×10^4, 2.2×10^4–4.8×10^4, 2.6×10^4–4.9×10^4, 2.2×10^4–4.1×10^4, 1.8×10^4–4.0×10^4 and 1.7×10^4–3.3×10^4 respectively, while that for quasi-brain-death group are 3.3×10^3–4.6×10^3, 3.7×10^3–5.0×10^3, 3.9×10^3–5.3×10^3, 4.4×10^3–5.4×10^3, 3.6×10^3–5.7×10^3 and 4.2×10^3–6.2×10^3 respectively, no more than 1.0×10^4, and the fluctuation range of dynamic complexity for coma group at 6 channels are 0.2696–0.4806, 0.2986–0.5209, 0.2859–0.4769, 0.3466–0.5360, 0.3031–0.5044 and 0.3455–0.5594 respectively, no more than 0.6, and the fluctuation range of dynamic complexity for quasi-brain-death group at 6 channels are 0.9874–1.1473 and 0.9645–1.1330, 1.0138–1.1479, 1.0348–1.1754, 0.9731–1.1245 and 0.8802–1.0338 respectively.

3.2 Results and Discussion for 3 Cases

In this part, we selected 60s EEG data from the coma patient's EEG with recording time of 937 s as well as 60s EEG data from the brain-death patient's EEG with recording duration of 905 s. As is shown in Fig. 5, it is intuitively observed the dynamic change of EEG energy and ApEn for the two typical cases. The range of dynamic EEG energy of the coma patient's EEG is 3.5×10^4–1.1×10^5, while it's 1.8×10^3–4.1×10^3 for the brain-death patient's EEG. At the same time, the results show that the ApEn of coma patient's EEG fluctuate in the range of 0.0128–0.1764, and no more than 1, while the ApEn of brain-death patient's EEG changes in the range of 0.6194–1.4176. Moreover, the special patient' EEG whose state was from coma to quasi-brain-death state was processed, in which 60s EEG data from coma EEG segment and 60s EEG data from quasi-brain-death segment were selected to analyzed by the measure proposed. It is shown that for the same patient, the EEG energy and complexity distribution characteristics for coma state and quasi-brain-death state are consistent with that for coma group and quasi-brain-death group. And the distribution range of EEG energy for the special patient' EEG decrese from 1.7×10^4–4.1×10^4 to 2.4×10^3–5.8×10^3, at the same time the fluctuate range of comlexity increse from 0.0725–0.3045 to 0.9304–1.3178. As shown in Fig. 6.

The more obvious the brain activity is, The higher the EEG energy is. And the lower the ApEn is, the lower of the complexity is, then the smaller the probability that the sequence generate the new pattern is, that is to say, it has a certain regularity and predictability. So it can be infer that there exists brain activity for coma group while there is almost no brain activity for quasi-brain-death group since the dynamic EEG energy distribution for coma group is obviously higher than that for quasi-brain-death group. Moreover, And it can be also infer that there exists the brain activity rhythm in EEG for coma group while there are almost disorder noise in EEG for quasi-brain-death group as

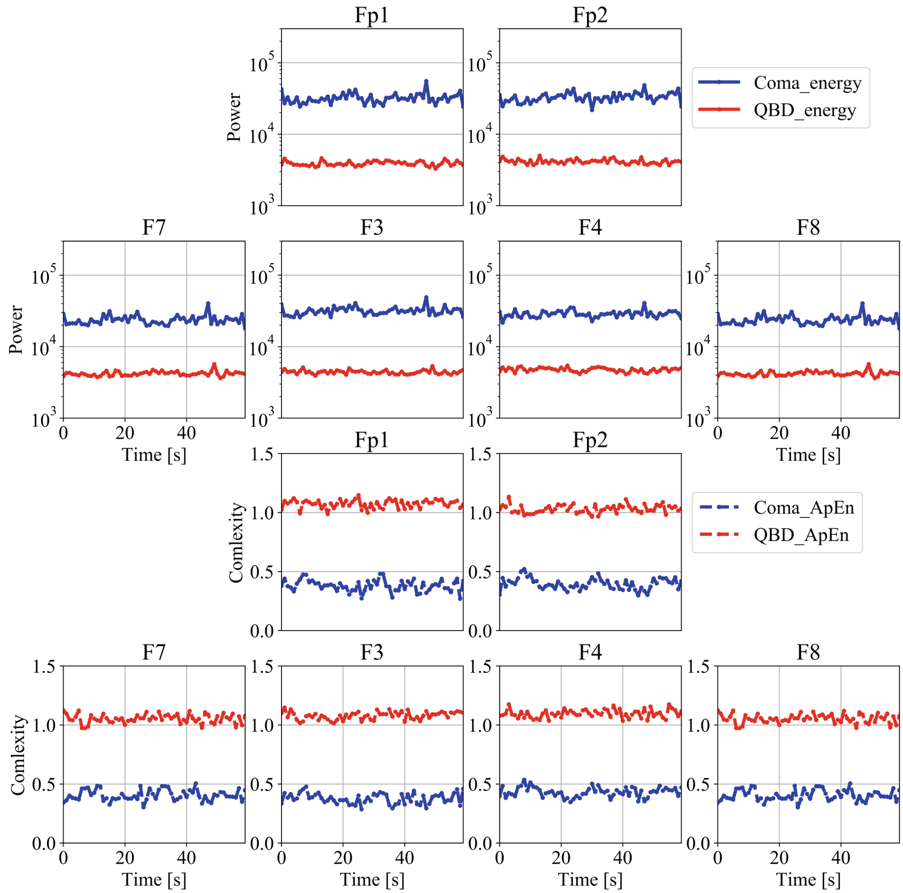

Fig. 4. Dynamic mean EEG energy and complexity of 6 channels for coma group and quasi-brain-death group.

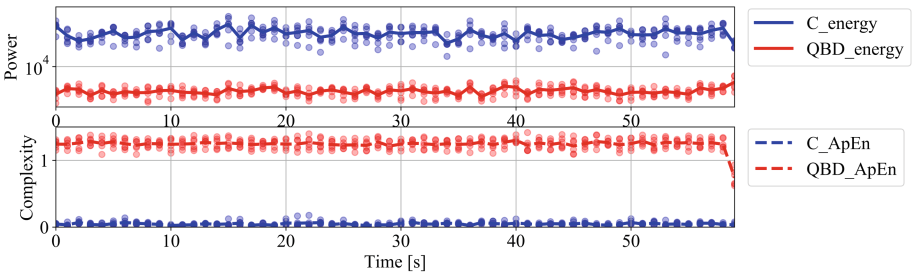

Fig. 5. Dynamic EEG energy and complexity distribution of average channel for one coma patient and one quasi-brain-death patient.

the dynamic ApEn distribution for coma group is lower than that for quasi-brain-death group. And dynamic distribution can provide more accurate and reliable results compared with static values. Furthermore, since the BDD is a serious issue, it is necessary to use different methods to improve the accuracy of results. For example, measures of synchronization for EEG has been widely used to analyzed real EEG [15], and especially applied in Alzheimer's disease EEG analysis [16]. This can be used as another EEG processing methods for supporting BDD in the future.

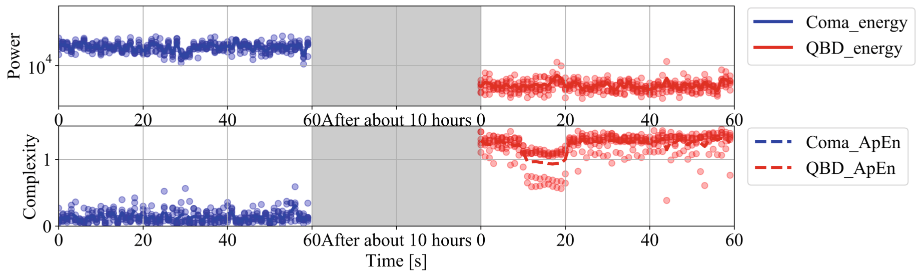

Fig. 6. Dynamic EEG energy and complexity distribution of average channel for the patient who was from coma to quasi-brain-death state.

4 Conclusion

In this paper, The multi-indicator dynamic analysis measure was proposed, which was by combining Dynamic 2T-EMD algorithm and Dynamic ApEn algorithm to comprehensively analyze patients' EEG signals from dynamic EEG energy and dynamic complexity indicators. And 36 cases of coma and quasi-brain-death patients' EEG were analyzed to show the overall dynamic distribution characteristics for coma group and quasi-brain-death group. Then 3 patients' EEG including one coma patient's EEG, one quasi-brain-death patient's EEG and one patient' EEG from which was from coma to quasi-brain-death state were processed from individual perspective. Results show intuitively that patients in coma state have higher EEG energy and lower complexity at the same time than patients in brain-death state from dynamic aspect. And this work can provide more accurate and reliable results for supporting BDD and also helpful to develop real-time EEG preliminary examination systems.

Acknowledgments. This work was partly supported by KAKENHI (25420417, 15H04002 and 17K00326).

References

1. Chen, Z., et al.: Brian Death: Modern Thanatology. Chinese Science Press, Beijing (2008)
2. Mollaret, P., Goulon, M.: Le Coma dpass. Revue Neurol. **101**, 5–15 (1959)
3. Becheer, H.K., et al.: Report of the Ad hoc committee of the Harvard medical school to examine the definition of brain death: a definition of irreversible coma. JAMA **205**, 337–340 (1968)
4. Cao, J.: Analysis of the quasi-brain-death EEG data based on a robust ICA approach. In: Gabrys, B., Howlett, R.J., Jain, L.C. (eds.) KES 2006. LNCS (LNAI), vol. 4253, pp. 1240–1247. Springer, Heidelberg (2006). https://doi.org/10.1007/11893011_157
5. Chen, Z., Cao, J., Cao, Y., et al.: Qualitative evaluation and quantitative EEG analysis in brain death diagnosis for adults: an empirical study. Cogn. Neurodyn. **2**(3), 257–271 (2008)
6. Li, L., Saito, Y., Looney, D., et al.: Data fusion via fission for the analysis of brain death. In: Evolving Intelligence Systems: Methodology and Applications, pp. 279–320. Springer, Heidelberg (2008)
7. Shi, Q., Cao, J., Tanaka, T., Wang, R., Zhu, H.: EEG data analysis based on EMD for coma and quasi-brain-death patient. J. Exp. Theor. Artif. Intell. **23**, 97–110 (2011)
8. Ni, L., Cao, J., Wang, R.: Analyzing EEG of quasi-brain-death based on dynamic sample entropy measures. Comput. Math. Methods Med. (2013)
9. Zhang, T., Xu, K.: Multifractal analysis of intracranial EEG in epilepticus rats. In: Lu, B.-L., Zhang, L., Kwok, J. (eds.) ICONIP 2011. LNCS, vol. 7062, pp. 345–351. Springer, Heidelberg (2011). https://doi.org/10.1007/978-3-642-24955-6_42
10. Fleureau, J., Nunes, J.-C., Kachenoura, A., Albera, L., Senhadji, L.: Turning tangent empirical mode decomposition: a framework for mono- and multivariate signals. IEEE Trans. Sig. Process. **59**, 1309–1316 (2011)
11. Miao, Y., Wang, D., Cui, G., Zhu, L., Cao, J.: Analyzing patients' EEG energy for brain death determination based on Dynamic 2T-EMD. Int. J. Comput. Technol. **16**, 717–720 (2017)
12. Pincus, S.M.: Approximate entropy (ApEn) as a measure of system complexity. Proc. Natl. Acad. Sci. **88**, 110–117 (1991)
13. Ni, L.: Decision support for brain death diagnosis based on EEG signal processing on complexity and power feature. East China University of Science and Technology, China (2016)
14. Cao, J., Chen, Z.: Advanced EEG signal processing in brain death diagnosis. In: Mandic, D., Golz, M., Kuh, A., Obradovic, D., Tanaka, T. (eds.) Signal Processing Techniques for Knowledge Extraction and Information Fusion, pp. 275–298. Springer, Boston (2008). https://doi.org/10.1007/978-0-387-74367-7_15
15. Jalili, M., Barzegaran, E., Knyazeva, M.G.: Synchronization of EEG: bivariate and multivariate measures. IEEE Trans. Neural Syst. Rehabil. Eng. **22**(2), 212–221 (2014). A Publication of the IEEE Engineering in Medicine & Biology Society
16. Knyazeva, M.G., Jalili, M., Brioschi, A., et al.: Topography of EEG multivariate phase synchronization in early Alzheimer's disease. Neurobiol. Aging **31**(7), 1132–1144 (2010)