Selecting EEG components using time series analysis in brain death diagnosis

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Abstract In diagnosis of brain death for human organ transplant, EEG (electroencephalogram) must be flat to conclude the patient's brain death but it has been reported that the flat EEG test is sometimes difficult due to artifacts such as the contamination from the power supply and ECG (electrocardiogram, the signal from the heartbeat). ICA (independent component analysis) is an effective signal processing method that can separate such artifacts from the EEG signals. Applying ICA to EEG channels, we obtain several separated components among which some correspond to the brain activities while others contain artifacts. This paper aims at automatic selection of the separated components based on time series analysis. In the flat EEG test in brain death diagnosis, such automatic component selection is helpful.

Keywords Brain death diagnosis · Signal processing · Independent component analysis · Time series analysis · Wayland test

Introduction

Diagnosis of brain death for human organ transplant is among the most important social issues in many countries. Brain death is defined as the irreversible loss of the brain functions and many countries have their own legal criteria of brain death for organ transplant (Wijdicks 1995, 2002; Taylor 1997). For example, Japanese legal criterion of brain death consists of the following five items: (i) coma test, (ii) pupil test, (iii) brainstem reflex test, (iv) apnea test, and (v) flat EEG (electroencephalogram) test. In the flat EEG test, there must be no electrical activity above 2 μ V but it has been reported that the EEG signals of patients in brain death sometimes show electrical activities above 2 μ V because of artifacts including the contamination from the power supply and ECG (electrocardiogram, the signal from the heartbeat). Hori et al. (2000, 2001) proposed to apply ICA (independent component analysis) to the flat EEG test and showed that ICA can efficiently remove the ECG signal and other kinds of noises from the EEG signals of patients in brain death. Furthermore, Cao (2006), Cao and Chen (2008), and Chen et al. (2008) proposed the use of frequency-based and complexity-based statistics in quantitative EEG analysis for diagnosis of brain death. Applying ICA to EEG channels, we obtain several separated components among which some correspond to the brain activities while others contain artifacts. The purpose of this paper is to introduce automatic selection of the separated components into ones from the brain activities and ones from artifacts using time series analysis. Specifically, we intend to select the separated EEG components using the Wayland test which is a method of time series analysis for deciding whether given time series data is deterministic or stochastic. In the flat EEG test in brain

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death diagnosis employing ICA, such automatic component selection is helpful.

The rest of the paper is organized as follows. The former half of “Methods” introduces the ICA algorithm applied to the EEG data in “Results”. The latter half of “Methods” introduces the concept and the procedure of the Wayland test. “Results” applies ICA and the Wayland test to the actual EEG data of the patients in coma or brain death recorded in the Shanghai Huashan Hospital affiliated to the Fudan University. “Discussion” discusses the results obtained in “Results”.

Methods

Independent component analysis

Independent component analysis (ICA) is a method of multi-channel signal processing that can separate multi-channel observed signals to independent source components by a linear transform. Although it resembles principal component analysis (PCA) in that it separates multi-channel signals by a linear transform, it outperforms PCA in signal separation capability mainly because it exploits statistical independence of the source signals and does not restrict its linear transform to an orthogonal one. ICA is well established and widely used as a preprocessing in EEG analysis such as noise elimination and extraction of components related to the brain activities.

We denote the n -channel source signals and the m -channel observed signals by

$$s(t) = (s_1(t), \dots, s_n(t))^T,$$

$$x(t) = (x_1(t), \dots, x_m(t))^T$$

where T denotes the vector transpose. The source signals are all supposed to be zero-mean and statistically independent to each other. The observed signals are assumed to be linear mixtures of the source signals,

$$x(t) = As(t)$$

where the mixing matrix A is an $m \times n$ real matrix. An ICA algorithm finds the demixing matrix W which recovers the independent source signals as

$$y(t) = Wx(t)$$

without using any knowledge on the mixing matrix A or the probability distributions of the source signals. The demixed signals

$$y(t) = (y_1(t), \dots, y_n(t))^T$$

are statistically independent to each other and the matrix WA is a permutation matrix with amplitudes. In application

to the EEG signals of patients in coma or brain death, the source signals $s_i(t)$ are either the signals from the brain activities or artifacts including the contamination from the power supply and the ECG signal. We use relatively simple ICA model and algorithm in this paper because our main focus is application of the Wayland test for EEG component selection. For advanced and rather complicated ICA model and algorithm for diagnosis of brain death, see Cao and Chen (2008). Also we consider the case of $n = m$ which is simple but enough for our purpose in this paper.

In “Results”, we apply to the EEG data of patients in coma or brain death the natural gradient algorithm (Amari et al. 1996) with an automatic detection mechanism of sub- and super-Gaussian sources (Lee et al. 1999),

$$\dot{W} = (I - K \tanh(y)y^T - yy^T)W, \quad (1)$$

where

$$\tanh(y) = (\tanh(y_1), \dots, \tanh(y_n))^T,$$

$$K = \text{diag}(k_1, \dots, k_n),$$

$$k_i = \text{sign}(E[\text{sech}^2(y_i)]E[y_i^2] - E[\tanh(y_i)y_i]).$$

As illustrated in Fig. 1, six electrodes (Fp1, Fp2, F3, F4, C3 and C4) are placed at the scalp of the patients in the recording of the EEG data used in this study. Then the ICA algorithm is applied to the EEG data of six channels to produce six independent components. We refer to the signals before separation by ICA as “channels” and the separated signals as “components”.

Fig. 1 Placement of electrodes

Wayland test

Based on the stream of works by Kaplan and Glass (1983) and Sugihara and May (1990), Wayland et al. (1993) introduced the Wayland test which is a method for deciding whether given time series data is deterministic or stochastic. It provides a quantitative measure of determinism that can distinguish time series data from the viewpoint of determinism. In the Wayland test, given single channel time series data is considered to be generated from a higher dimensional attractor. The attractor is reconstructed based on Takens' embedding theorem (Takens 1981) and the translation error is calculated from the reconstructed attractor as explained in the following.

Let $z(t)$ be given single channel time series data and

$$\xi(t) = (z(t), z(t+\tau), \dots, z(t+(D-1)\tau))$$

the reconstructed attractor in the D -dimensional state space where τ is a delay time. The delay time τ is chosen so that the auto correlation of the time series

$$\rho(\tau) = \frac{E[(z(t) - \mu)(z(t+\tau) - \mu)]}{\sigma^2}$$

takes its first local minimum when searching from $\tau = 0$ to $\tau = \infty$ where μ and σ are the mean and the variance of the time series respectively. Consider a point $\xi_0(t)$ randomly sampled from the reconstructed attractor and its K nearest points on the attractor $\xi_k(t)$ ($k = 1, \dots, K$). Let $v_k(t)$ denote

the displacement of $\xi_k(t)$ along the time evolution of T steps,

$$v_k(t) = \xi_k(t+T) - \xi_k(t) \quad (k = 0, \dots, K).$$

The variance of the displacements,

$$E_{trans} = \frac{1}{K+1} \sum_{k=0}^K \frac{|v_k(t) - \langle v(t) \rangle|^2}{|\langle v(t) \rangle|^2},$$

$$\langle v(t) \rangle = \frac{1}{K+1} \sum_{k=0}^K v_k(t),$$

is called “translation error” and used for deciding whether the given time series data is deterministic or stochastic. The above procedure is repeated M times for randomly sampled $\xi_0(t)$ and the median is used as the result to make the estimate of the translation error robust. The translation error is calculated changing the embedding dimension D from a small value to larger ones. For deterministic time series data, the displacements are expected to be concentrated on their center to make the variance small. The translation error E_{trans} will decrease as the embedding dimension D approaches the dimension of the generating attractor. On the other hand, for stochastic time series data, the displacements will be scattered to make the variance large. The translation error E_{trans} stays at larger values not depending on the embedding dimension D .

The signals from the brain activities are thought to be deterministic. For example, Ikeguchi et al. (1990) and

Fig. 2 EEG attractors and Wayland test

Gallez and Babloyantz (1991) obtained results on the Lyapunov exponent of human EEG that suggest the signals from the brain activities are deterministic. The contamination from the power supply is basically a sine wave which is apparently deterministic while other kinds of noises are stochastic. Figure 2 displays the reconstructed attractors for $D = 3$ of EEG channels of a patient in coma and a patient in brain death. From Fig. 2, it is easy to see that the EEG channel of the patient in coma is more deterministic than one of the patient in brain death, that is, the left reconstructed attractor gives a smaller value of the translation error than the right one. The EEG channels of the patient in brain death are mainly environmental noises while ones of the patient in coma are mainly the signals from the brain activities. This explains the difference illustrated in Fig. 2.

Results

The EEG data used in this study was recorded in the Shanghai Huashan Hospital affiliated to the Fudan University. The data acquisition was carried out in the ICU (intensive care unit) using a portable EEG recording system (NEUROSCAN ESI-32). Six electrodes (Fp1, Fp2, F3, F4, C3, C4) out of the international standard 10-20

system were placed at the scalp of the patients. The sampling rate of the EEG data was 1,000 Hz. Out of all the EEG data recorded from 36 patients in coma or brain death, we analyze seven 10 s portions of EEG recordings of the following six patients:

- Patient A: 18-year-old male patient in coma
- Patient B: 19-year-old female patient in brain death
- Patient C: 48-year-old male patient who transitioned from coma to brain death
- Patient D: 56-year-old female patient in brain death
- Patient E: 26-year-old female patient in brain death
- Patient F: 22-year-old male patient in brain death

First, we apply the ICA algorithm (1) (Amari et al. 1996; Lee et al. 1999) to the EEG channels of all the portions to separate them to independent EEG components. Next, we carry out the Wayland test for all the EEG channels and the separated EEG components changing the embedding dimension from $D = 2$ to $D = 10$. We set the parameters of the Wayland test as $K = 4$, $\tau = 50$, $T = 10$ and $M = 30$, that is, the number of the nearest points is 4, the delay time for embedding is 50 ms, the time evolution of 10 ms is used to calculate the displacements, and the median is taken from 30 trials of the calculation procedure.

Fig. 3 Wayland test of Patient A in coma

Fig. 4 Wayland test of Patient B in brain death

Fig. 5 Wayland test of Patient C in coma

Fig. 6 Wayland test of Patient C in brain death

Fig. 7 Wayland test of Patient D in brain death

Fig. 8 Wayland test of Patient E in brain death

Figures 3 and 4 display the results for Patient A in coma and Patient B in brain death respectively. Patient C transitioned from coma to brain death. Figures 5 and 6 display the results for Patient C in coma and in brain death respectively. Figures 7, 8 and 9 display the results for Patient D, E and F all in brain death respectively. Comparing the Wayland test of the EEG components in Figs. 3 and 4, we find that the translation error E_{trans} decreases to fall below 1.0 for all the components of Patient A in coma while it stays above 1.0 for Patient B in brain death excepting the second component. Magnifying the second component, we see that it corresponds to the contamination from the power supply for which the translation error stays around 0.5. The above observation holds generally for the EEG components of other patients in coma or brain death described in Figs. 5, 6, 7, 8 and 9. The translation error decreases to fall below 1.0 for Patient C in coma (Fig. 5) while it stays around or above 1.0 for the patients in brain death (Figs. 6, 7, 8, 9) excepting the components of the contamination from the power supply. On the other hand, for the EEG channels, the translation error does not show such clear difference for patients in coma or brain death. For example, in Figs. 7 and 8, the translation error of the EEG channels stays around or below 1.0 for patients in brain death.

Discussion

Our observation in the previous section and related consideration are summarized in the following three points.

- In the Wayland test of the EEG components of patients in coma, the translation error decreases to fall below 1.0 for all the components. This is explained by supposing that all the EEG components of patients in coma are related to the brain activities and the signals from the brain activities are deterministic.
- In the Wayland test of the EEG components of patients in brain death, the translation error stays around or above 1.0 excepting the component of the contamination from the power supply. The components for which the translation error stays around or above 1.0 are stochastic noises and that most components are stochastic noises suggests that the patient is in brain death.
- In the Wayland test of the EEG components of patients in brain death, the component for which the translation error is far smaller than others corresponds to the contamination from the power supply. This is because the contamination from the power supply is basically a sine wave which is deterministic. This component

Fig. 9 Wayland test of Patient F in brain death

should be eliminated in the flat EEG test in diagnosis of brain death.

Also we observe that, for the EEG channels, the translation error sometimes takes smaller values for patients in brain death as in Figs. 7 and 8. This is mainly because the deterministic signal from the power supply contaminates the EEG channels to make their translation errors smaller. Accordingly, the Wayland test of the EEG channels does not always show clear contrast for patients in coma or brain death therefore the Wayland test of the EEG components is more reliable in diagnosis of brain death. In conclusion, we find that the Wayland test of the EEG components is useful in brain death diagnosis for selecting components such as (i) the components related to the brain activities, (ii) the components of stochastic noises, and (iii) the component of the contamination from the power supply which should be eliminated in diagnosis of brain death. The Wayland test of the EEG components also provides a suitable means to verify that certain components are stochastic noises and are not signals from the brain activities.

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