Feature Extraction of Human EEG Sleep Stages by Using Wavelet Analysis

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Abstract

It is important to know the human's sleep process. EEG (Electroencephalogram) sleep stage is defined according to the depth of human sleep. We have been also studying and developing the sleep stagers based on APSS's rules³⁾. However, these rules are insufficient for such systems. Then, extraction of significant information from EEG signal is tried in order to supplement these rules.

Therefore, in this paper, more detailed analysis was tried in the frequency domain by using the continuous wavelet analysis. The setting method of the damping coefficient of Gabor function was proposed. Wavelet transform results show the characteristic transition phenomenon of a principal frequency component. And it is confirmed that the automatic discrimination of human EEG sleep stages based on wavelet transform can be executed in the reasonable accuracy.

1 Introduction

It is thought that EEG includes the important information about a cerebral activity situation. It was reported by Berger in 1930 that EEG changes according to sleep stage. The sleep EEG has the characteristic waveform pattern according to each sleep stage; Stage W, Stage 1-4, and Stage REM. Many studies have been carried out on the automatic human EEG sleep stage determination systems (Sleep Stager) based on the standard rule proposed by the Association for Psychophysiological Study of Sleep (APSS). Doing the development process of these systems, it becomes clear that the rule is insufficient for the automatic computing.

Therefore, "Supplemental definition and modification of a manual of standardized terminology, techniques and scoring system for sleep stages of human subjects from the view point of automatic computing" are proposed by the committee of automatic scoring for sleep stages of the Japanese Society of Sleep Research. We have been also studying and developing the sleep stagers based on these rules. However, these rules are insufficient for such systems. Then, extraction of significant information from EEG signal is tried in order to supplement these rules.

Therefore, in this paper more detailed analysis was tried in the frequency domain by using the continuous wavelet analysis.

The Gabor function was adopted the basis function of wavelet transform. The setting method of the damping coefficient of Gabor function was proposed. And some kinds of method were applied to this wavelet transformed signals. The feature extraction and pattern recognition were also performed to these processed results.

Our method was applied to real EEG data signals and its effectiveness was confirmed.

In section 2, we will explain our method. In section 3, we discuss our results. The section 4 is devoted to our conclusions.

2 Method

2.1 The continuous wavelet transform

The continuous wavelet transform is an integrating conversion with the parameters a (scaling parameter) and b (shift parameter) shown in Eq.(1). Time-frequency information is obtained by the transform. In this paper, Gabor function (Eq.(2)) is adopted as the basis

function of wavelet, because this function has relevance to frequency information.

$$(W_{\psi}f)(b,a) = \frac{1}{\sqrt{|a|}} \int f(x) \psi\left(\frac{x-b}{a}\right) dx$$

$f(x)$: signal (1)

$\psi(x)$: wavelet

$$\psi(x) = \frac{1}{2\sqrt{\pi}\sigma} \exp(-x^2/\sigma^2) \exp(jx) \quad (2)$$

Fig.1 is the result of wavelet transform of one epoch (20 seconds).

Fig.1 Wavelet transforms
Top: Energy scalogram. Bottom: EEG signal.

2.2 Modification of σ

The continuous wavelet transform can adjust the resolution of frequency and time by adjusting the value of σ (damping coefficient) in Eq.(2). Then, in this paper, the value of σ was modified as the value suitable for EEG sleep. Various Gabor functions ($a=5.0, 10.0, 15.0, \sigma=4.0, 8.0, 12.0$) are shown in Fig.2.

Fig.2 Gabor function

The horizontal axis of each graph is a time-axis. 'fre' in Fig.2 is the equivalent to the frequency of the trigonometric functions in Eq.(1) ($fre=1/a$). If σ is set to be small, the domain of a function is compressed on a time-axis and is similar to a delta function. Consequently, the influence of the signals around the target point becomes small. Moreover, a basis function of wavelet is regarded as a window function. That is, if signal and wavelet functions have the same phase and frequency component, the transformed value (integrating value) become large. On the contrary, if a difference is in a phase or frequency, the integrating value becomes small. In other words, the wavelet transform can be considered as a waveform matching method. Next, Fourier transform results of each wavelet are shown in Fig.3.

Fig.3 Power spectrum of Gabor function

As shown in Fig.3, the peak frequency coincides with parameter $fre=1/a$ which defines Gabor function.

Thus, wavelet with arbitrary frequency component can be obtained by adjusting parameter a . In Fig.3, the shape of power spectrum becomes sharp as σ becomes large. Hence, high-resolution of frequency is expected.

Usually, σ is set to be constant. But, in this study, it is modified as Eq.(3) in order to have the frequency resolution corresponding to sleep EEG frequency components, although orthonormality is lost theoretically.

$$\sigma = 1/a + \sigma_0 \quad (3)$$

Based on Eq.(3), the resolution of time has been improved in low frequency, and the resolution of frequency has been improved in high frequency. The validity of Eq.(3) will be shown as follows.

The Gabor functions (2Hz and 12Hz) are shown in Fig.4 and 5.

Fig.4 Gabor function ($\sigma=2\text{Hz}$)

Fig.5 Gabor function ($\sigma=12\text{Hz}$)

Next, slow waves and Gabor function ($\sigma=2\text{Hz}$) is shown in Fig.6. Sleep spindle and Gabor function ($\sigma=12\text{Hz}$) is Fig.7.

Fig.6 Slow waves and Gabor function

Fig.7 Sleep spindle and Gabor function

EEG sleep waveforms such as high amplitude slow waves are defined as one wave. However, the EEG sleep waveform of high frequency, such as sleep spindles and alpha

waves, is defined as two or more successive waves. The Gabor function and the EEG sleep waveform are similar. The wavelet function becomes more suitable for sleep EEG pattern by introducing modified σ in Eq.(3). The number of waves is changed according to the frequency (ex. Slow wave: 1 wave, Sleep Spindle: 5 waves). That is, the suitable window length is obtained according to each EEG signal.

2.3 Wavelet analysis

Fig.8 is the result of wavelet transform of one epoch (20 seconds).

Fig.8 Wavelet transforms.

Top: Energy scalogram. Bottom: EEG signal.

Fig.9 is the result of wavelet transform of one night. One vertical line in Fig.9 is the averaging value of the one epoch (20 seconds) in Fig. 8.

Fig.9 Wavelet transform value sum of one epoch (20 seconds)

Top: Energy scalogram. Bottom: Sleep process.

From now on, feature extraction method and pattern recognition method will be explained.

2.4 The feature extraction based on the peak of wavelet transform

The feature extraction procedure is shown in Fig. 10. First, a space filter (a smoothing filter) is applied to wavelet transformed value. Next, three peaks are detected in descending order of power, as shown in Fig.11. Next, a Median filter is applied to the frequency component corresponding to three peak points. These feature elements of peak points are plotted in Fig.12. Also, the result, which is detected the peak points with usual constant σ , is shown in Fig.13. The third peak cannot detect in Fig.13. The validity of modified σ is confirmed by this fact.

Fig.10 Feature extraction procedure

Fig.11 Detection three Peak points

Fig.12 Three peak points with modified σ
(a)first peak (b)second peak
(c)third peak(d)sleep process

Fig.13 Three peak points usual constant σ
(a)first peak (b)second peak
(c)third peak(d)sleep process

2.5 Pattern recognition

Stage discrimination is executed in each epoch (20 seconds) based on Bayes decision rule shown in Eq.(4)

$$\begin{aligned} \omega_i^* &= \text{Arg Max}_i \log \Pr(\omega_i | X) \\ &= \text{Arg Max}_i \log \Pr(\omega_i) \Pr(X | \omega_i) \end{aligned} \quad (4)$$

where, $\Pr(\omega_i | x)$ is a posteriori probability of class ω_i given x and x is a feature vector, which has 16 elements. It is assumed that $\Pr(x | \omega_i)$ ($i=1, \dots, N$) are the Gaussians. The EEG signals (C3-A2) with sampling frequency 500Hz are used for analysis. Before analysis, down sampling (from 500Hz to 50Hz) is executed to reduce calculation amount. The features vector used the 16 elements (1,2, $\dots$ 16Hz) for stage pattern recognition. The typical EEG sleep stages (Stage W, REM, 1-4) were trained by the data of 50 series, respectively, and pattern recognition of the sleep data was carried out. The average value of the feature vector is shown in Fig.14.

Fig.14 Power spectrums on each sleep stage

The feature of alpha wave zone (8 to 13 Hz) in Stage W, the feature of sleep spindle zone (12 to 16 Hz) in Stage 2, the feature of high amplitude slow waves range (0.5 to 2 Hz) in Stage 3 and 4 correspond to the standard EEG sleep stage discrimination rule by Rechtschaffen and Kales. Also, all power spectrums are low in Stage REM.

The 16 features elements are used for pattern recognition of EEG sleep stages in this paper. Two ways to take the training data for pattern recognition were considered.

- (1) Training data include the test data
- (2) Training data does not include the test data

The coincident rates in the two training methods are shown in Fig.21.

3 Results

3.1 Wavelet analysis results

Five sets of data (5 subjects) were processed. The three results of them are shown in Fig.15 and Fig.16 and Fig.17. A wavelet analysis is shown above and a doctor's result is shown below. These figures suggest the following facts.

- (1) There is little power over all frequency range in stage REM.
- (2) α (8 to 13Hz) frequency component is gradually increasing and decreasing before stage REM and after stage REM, respectively.
- (3) The phenomenon of (2) is observed in all subjects, although the frequency component is different among subjects.

Fig.15 Wavelet analysis (subject A)
Top: Energy scalogram. Bottom: Sleep process.

Fig.16 Wavelet analysis (subject B)
Top: Energy scalogram. Bottom: Sleep process.

Fig.17 Wavelet analysis (subject C)
Top: Energy scalogram. Bottom: Sleep process.

3.2 The feature extraction results based on the peak of wavelet transform

Five sets of data (5 subjects) were processed. The three results of them are shown in Fig.18 and Fig.19 and Fig.20. A processed result is shown above and a doctor's result is shown below. These suggest the following facts.

- (1) The second and third peaks in α frequency range are not detected in stage REM.
- (2) The second peak is gradually increasing and decreasing before stage REM and after stage REM, respectively.
- (3) The phenomenon of (2) is observed in all subjects, although the frequency component is different among subjects.

Fig.18 The peak points (subject A)

Fig.19 The peak points (subject B)

Fig.20 The peak points (subject C)

3.3 Pattern recognition results

Five sets of data (5 subjects) were processed. The coincident rates between the discrimination results by this system and doctor's scores are shown in table.1.

Table.1 The coincident rates between the discrimination results by this system and doctor's scores (Training pattern is (1))

	W	R	1	2	3	4	Total
JSSR004	100	90.7	49.5	83.4	96.1	0.0	79.3
JSSR009	95.6	90.8	67.8	75.9	93.2	96.4	79.7
A_DATA	100	95.2	58.3	82.9	83.8	80.6	79.2
JPSG_08	86.9	94.8	45.7	77.9	100	0.0	81.7
JPSG_10	70.3	91.4	53.7	79.3	100	100	76.1
Ave.	90.6	92.6	55.0	79.9	94.6	55.4	79.2

On the average, about 80% of accuracy was acquired. Moreover, Stage REM can be discriminated 90%, without EMG and EOG. Even if it is not applied that the 3 minutes rule for Stage 2, about 80% of accuracy was obtained.

Fig.21 The coincident rates of pattern recognition

For the pattern recognition results, an overall coincident rate is about 80% in case of self-recognition (training data include the test data). And it is about 70% in case that training data does not include the test data.

4 Conclusions

Wavelet transform results show the characteristic transition phenomenon of a principal frequency component. And it is confirmed that the automatic discrimination of human EEG sleep stages based on wavelet transform can be executed in the reasonable accuracy, even if information from EMG and EOG was not used and 3 minutes rule is not applied. This fact suggests that an extraction of detailed information of EEG sleep stages is possible from only EEG signals. These quantitative estimations will be studied on feature investigations.

References

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