FEATURE EXTRACTION OF HUMAN SLEEP EEG
BASED ON A PEAK FREQUENCY ANALYSIS

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Abstract: We have developed so far the automatic discrimination system of human sleep
EEG stages based on a wave-shape recognition method. These systems were able to
detect discrete stages (Stage MT, W, 1, 2, 3, 4, REM). But, more detailed information
extraction was impossible by them. Therefore, in this paper, continuous wavelet analysis
is applied to EEG signals in order to extract more precise information for the stages. A
modified wavelet transform method is proposed and an extraction method of time series
of peak frequency based on time-frequency analysis is introduced. And it is confirmed
that our method is effective through the experimental studies. Copyright © 2005 IFAC

Keywords: Wavelet analysis, Electroencephalogram, sleep stages, signal processing,
feature extraction.

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 sleep EEG stage determination systems
(Sleep Stager) based on the standard rule proposed
by the Association for Psychophysiological Study of
Sleep (APSS) (Rechtschaffen and Kales, 1968).
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 the rule” are proposed
by the committee of automatic scoring for sleep
stages of the Japanese Society of Sleep Research
(Hori, 2001). We have been also studying and
developing the sleep stagers based on these rules
(Inoue, 1997). However, these systems were
insufficient for extracting more detail information
about sleep stages.

Therefore, in this paper more detailed analysis was
tried in the time-frequency domain by using the
continuous wavelet analysis. The Gabor function was
adopted as the basis function of wavelet transform.
At first, modified wavelet transform method with
adjusting rule of damping coefficient of Gabor
function is proposed. Next, an extraction method of
time series of peak frequency is introduced. And the
characteristics of the method based on the modified
wavelet transform are compared with the methods
based on the other frequency analysis method from
view point of feature extraction of sleep stages. Our
method was applied to real EEG data signals and its
effectiveness was confirmed.

In the section 2, human sleep EEG and sleep stages
are briefly explained. Our methods are explained in
section 3, 4. And the features for sleep stages
extracted by our method are discussed in the section
5. The section 6 is devoted to our conclusions.
2. HUMAN SLEEP EEG WAVES
AND SLEEP STAGES

EEGs consist of very complicated wave patterns, and are roughly grouped into the following four patterns:

1. \(\alpha\)-waves (8~12Hz, 20~80\(\mu\)V)
2. Desynchronization of \(\alpha\)-wave; for simplicity, we will call these wave patterns as L-waves.
3. High voltage exceeding 75\(\mu\)V and slow waves (\(\delta\)-waves)
4. Special waves such as sleep spindles, K-complexes, humps, saw-toothed waves, etc.

Among them, the sleep spindle is a very important wave which specifies the sleep EEG stages. The sleep spindle has 13~14Hz frequency components and its duration is about 1.0[sec].

(1) ~ (3) is called the background EEG waves, the rough determination of sleep stages are executed based on its containing ratio. These wave patterns (\(\alpha\)-waves, L-waves and \(\delta\)-waves, K-Complex) are shown in Fig.1.

![Fig.1. Human sleep EEG patterns](image)

Sleep stages are composed of six stages: Stage W, Stage 1, Stage 2, Stage 3, Stage 4 and Stage REM. Definition of these stages are given in the reference (Rechtschaffen and Kales 1968), in detail. Each sleep stage is defined as follows:

(Stage W)
Presence of \(\alpha\)-waves and/or low voltage mixed frequency included more than 50% in one epoch.

(Stage 1)
Background waves have a relatively low voltage, mixed frequency with most activity in the 2~7Hz range. There should not be clearly defined sleep spindles and K-complexes. \(\alpha\)-waves are contained less than 50%.

(Stage 2)
Background waves have a low voltage, mixed frequency with the presence of sleep spindles and/or K-complexes. \(\delta\)-waves are contained less than 20%.

(Stage 3)
\(\delta\)-waves are contained more than 20% but less than 50%.

(Stage 4)
\(\delta\)-waves are contained more than 50%.

(Stage REM)
Background waves have a relatively low voltage, mixed frequency with the presence of rapid eye movements (REMs); sleep spindles and K-complexes are absent. Level of EMG is the lowest level of the record in sleeping period.

3. FREQUENCY ANALYSIS

3.1 Fourier transform

Fourier transform is expressed as equation (1).

\[
F(\omega) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-j\omega t} f(t) dt
\]

(1)

In actual data processing, the data length is limited, and FFT is used generally. This will be called as method FT1.

On the other hand, the short time Fourier transform with the Gabor window is shown as the following equation.

\[
F(\omega, b) = \frac{1}{2\sqrt{\pi} \sigma} \int_{-\infty}^{\infty} e^{-(t-b)^2/2\sigma^2} e^{-j\omega t} f(t) dt
\]

(2)

This will be called as method FT2.

3.2 The Ordinary Wavelet Transform

The continuous wavelet transform is an integrating conversion with the parameters \(a\) (scaling parameter) and \(b\) (shift parameter) shown in equation (3). Time-frequency information is obtained by the transform. In this paper, Gabor function (equation (4)) is adopted as the basis function of the wavelet, because this function has relevance to frequency information.

\[
(W_{\psi,f})(b,a) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} f(t) \psi^* \left(\frac{t-b}{a}\right) dt
\]

(3)

\[
\psi(t) = \frac{1}{2\sqrt{\pi} \sigma} \exp(-t^2/2\sigma^2) \exp(jt)
\]

(4)

This will be called as method OWT. Fig.2 is the result of wavelet transform of one epoch (20 seconds).

![Fig.2. Ordinary wavelet transform result](image)
3.3 Modified Wavelet Transform

The continuous wavelet transform can adjust the resolution of frequency and time by adjusting the value of $\sigma$ (damping coefficient) in equation (4). Various Gabor functions ($1/\omega=5.0, 10.0, 15.0, \sigma=4.0, 8.0, 12.0$) are shown in Fig.3. The horizontal axis of each graph is a time-axis. ‘$1/\omega$’ is the equivalent to the frequency of the sinusoidal functions in equation (4). If $\sigma$ 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 there is a difference in a phase or frequency, the integrating value becomes small. In other words, the wavelet transform can be considered as a waveform matching method.

Usually, damping coefficient $\sigma$ is set to be constant. This means that the number of waves included in the basis function is constant. But, for the EEG wave patterns, $\delta$ wave is defined as solitary wave, and $\alpha$ wave is defined as consecutive wave. Therefore, in this study, it is modified as equation (5) in order to have the frequency resolution corresponding to sleep EEG frequency components (shown in Fig.4), although orthonormality is lost theoretically.

$$\sigma = \sigma_0 + \frac{\sigma_1}{a}$$  \hspace{1cm} (5)

The next expression is obtained by substituting equation (4) and (5) for equation (3).

$$\left(W_{\psi'}f\right)(b,a) = \frac{1}{2\sqrt{\pi} \sqrt{a} (\sigma_0 + \sigma_1 / a)} \cdot \int_{-\infty}^{\infty} e^{-\frac{(t-b)^2}{\sigma_0}} e^{-\frac{t^2}{\sigma_1}} f(t) dt$$  \hspace{1cm} (6)

In low frequency range ($\sigma_0 >> \sigma_1 / a$), this transform becomes normal wavelet transform ($\sigma = \sigma_0$).

In high frequency range ($\sigma_0 << \sigma_1 / a$), equation (6) becomes equation (7) ($\sigma \approx \sigma_1 / a$).

$$\left(W_{\psi'}f\right)(b,a) \approx \frac{\sqrt{\omega}}{2\sqrt{\pi} \sigma_1} \cdot \int_{-\infty}^{\infty} e^{-\frac{(t-b)^2}{\sigma_0}} e^{-\frac{t^2}{\sigma_1}} f(t) dt$$  \hspace{1cm} (7)

The next expression is obtained by assuming $\omega = 1/a$.

$$\left(W_{\psi'}f\right)(b,a) = \frac{1}{\sqrt{\omega}} \cdot \frac{1}{2\sqrt{\pi} \sigma_1} \cdot \int_{-\infty}^{\infty} e^{-\frac{(t-b)^2}{\sigma_0}} e^{-\frac{t^2}{\sigma_1}} f(t) dt$$  \hspace{1cm} (8)

This is a kind of short time Fourier transform with Gabor window.

In a word, this transform has the intermediate character between a short time Fourier transform and ordinary wavelet transforms. This will be called as method MWT.

Fig.4 shows the EEG wave patterns and the corresponding wavelet adopted in this study. Fig.5 is the result of modified wavelet transform of one epoch (20 seconds). When Fig.2 and Fig.5 are compared, it is confirmed that the frequency resolution is improved in the beta wave band in Fig.5. Fig.6 shows the result of wavelet transform of one night. One vertical line in Fig.6 is the averaging value of the one epoch (20 seconds) in Fig.5.

Where, 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 the amount of calculation. For $\sigma_0$, $\sigma_1$, these values are set to be 8.0 and 1.0 respectively.
4. TIME SERIES OF PEAK FREQUENCY

In order to obtain time series of peak frequency, the following processing is done to the wavelet transform result.

Step 1: Emphasizing high frequency component (EHFC). (Multiplying $\sqrt{2\pi f}$ to original wavelet transform)

Step 2: 2D smoothing filtering in time-frequency space. (9×9 mask)

Step 3: Detection of three peak frequencies with largest power every 1 epoch. (1 epoch: 20 seconds) (see Fig. 8)

Step 4: Median filtering in each time series of peak frequency.

Schematic diagram of these procedures are shown in Fig.7.

Fig.9 shows the wavelet transform results (after Step 1) by each method (FT1, FT2, OWT, MWT). The results of extracted peak frequency time series are shown in Fig.10. It shows that the second peak frequency time series (blue line in middle figure) changes corresponding to sleep stages. In the case of the subject (JPSG08), a consecutive frequency change is observed in $\beta$ wave band. In the case of the subject (JSSR009), a consecutive frequency change is observed in $\theta$ wave band. Although the frequency band of the second peak is different depending on each subject, there are strong correlation between the time series and sleep stages.

Table 1 shows the second peak frequency detection results. The number of pages in which the second peaks is able to be detected in EFMC is more than the number in usual Fourier or wavelet transform. Therefore, Step 1 is introduced in this study.
Fig. 10. Detection result of peak frequency.
1st peak: black line, 2nd peak: blue line,
3rd peak: red line in upper figure.

Table 1. The second peak frequency detection results
Number of pages in which the second peak is
able to be detected.

<table>
<thead>
<tr>
<th>Subject A_Data</th>
<th>JPSG08</th>
<th>JSSR004</th>
<th>JSSR009</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total page</td>
<td>1500</td>
<td>1455</td>
<td>1500</td>
</tr>
<tr>
<td>FT1 Normal</td>
<td>1315</td>
<td>751</td>
<td>792</td>
</tr>
<tr>
<td></td>
<td>EHFC</td>
<td>1468</td>
<td>1223</td>
</tr>
<tr>
<td>FT2 Normal</td>
<td>1489</td>
<td>1414</td>
<td>1445</td>
</tr>
<tr>
<td></td>
<td>EHFC</td>
<td>1492</td>
<td>1447</td>
</tr>
<tr>
<td>OWT Normal</td>
<td>1033</td>
<td>421</td>
<td>496</td>
</tr>
<tr>
<td></td>
<td>EHFC</td>
<td>1277</td>
<td>930</td>
</tr>
<tr>
<td>MWT Normal</td>
<td>1234</td>
<td>647</td>
<td>624</td>
</tr>
<tr>
<td></td>
<td>EHFC</td>
<td>1427</td>
<td>1122</td>
</tr>
</tbody>
</table>

Table 2. The number of discontinuous page.

<table>
<thead>
<tr>
<th>Subject A_Data</th>
<th>JPSG08</th>
<th>JSSR004</th>
<th>JSSR009</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total page</td>
<td>1500</td>
<td>1455</td>
<td>1500</td>
</tr>
<tr>
<td>FT1 Normal</td>
<td>2</td>
<td>6</td>
<td>20</td>
</tr>
<tr>
<td></td>
<td>EHFC</td>
<td>8</td>
<td>37</td>
</tr>
<tr>
<td>FT2 Normal</td>
<td>42</td>
<td>219</td>
<td>165</td>
</tr>
<tr>
<td></td>
<td>EHFC</td>
<td>79</td>
<td>177</td>
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<tr>
<td>OWT Normal</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>EHFC</td>
<td>20</td>
<td>28</td>
</tr>
<tr>
<td>MWT Normal</td>
<td>2</td>
<td>13</td>
<td>14</td>
</tr>
<tr>
<td></td>
<td>EHFC</td>
<td>14</td>
<td>45</td>
</tr>
</tbody>
</table>

Table 2 shows the number of discontinuous page
defined as the following. The difference of detected
second peak frequency between the page and the
previous page is 3Hz or more. Table 1 and Table 2
suggest that the following result. Method FT2 is able
to detect a number of the second peak. But extraction
of the information from the peak frequency by
method FT2 is not easy, since the time series is not
continuous. On the other hand, the wavelet methods
cannot detect a lot of second peaks compared with
the Fourier transform method. However, it is thought
that the feature extraction is easy, because the
detected time series is continuous.

Fig. 11 shows the discontinuity of the detected peak
frequency. This figure shows that MWT is the better
method than OWT in which the target frequency
band is $\beta$ wave band. On the other hand, OWT is the
better method than MWT in which the target
frequency band is $\theta$ wave band. This suggests that
the adjustment defined by equation (5) should be
improved.

5. FEATURE EXTRACTION OF
SLEEP EEG STAGES

In this section, the relation between the second peak
frequency detected by the previous mentioned
method and the sleep stages is investigated.

Fig. 12 shows the average frequencies in each sleep
cycle. It is confirmed that the second peak frequency
becomes low along with the change from Stage 2 to
Stage 3, and the average of peak frequency becomes high by repeating the sleep cycle.

Table 3 shows the average of the slope derived by the minimum mean square method. This table shows that the second peak frequency tends to increase by repeating the sleep cycle even in the same stage.

Table 4 shows the difference of the averaged peak frequency between Stage 2 and Stage 3. If the difference is large, transition state from Stage 2 to Stage 3 is able to be analyzed in more detail. In such sense, it seems that the MWT method is the best method among the above mentioned methods (FT1, FT2, OWT, MWT).

6. CONCLUSIONS

In this paper, at first, modified wavelet transform method is introduced. Next, an extraction method of time series of peak frequency is proposed. And the characteristics of the method based on MWT are compared with the methods based on the other frequency analysis method (FT1, FT2, OWT) from view point of feature extraction of sleep stages. It is confirmed that the time series of the second peak frequency extracted by the proposed method have some information which is related to the sleep stages. It is also confirmed by our method that the second peak frequency increases by repeating the sleep cycle even in same stage. These results show that our method is effective for analysis of sleep stages.

The $\sigma$ adjustment method defined by equation (5) should be improved as mentioned in section 4. But, since the fluctuation of peak frequency was extracted as time series information, it becomes possible that more precise information about sleep stages is extracted by using such a time change parameter like the velocity and the acceleration, etc. These studies are under consideration.

REFERENCES


