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.

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) (Rechtshaffen 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) α-waves (8~12Hz, 20~80μV)
(2) Desynchronization of α-wave; for simplicity, we will call these wave patterns as L-waves.
(3) High voltage exceeding 75μV and slow waves (δ-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 it's containing ratio. These wave patterns (α-waves, L-waves and δ-waves, K-Complex) are shown in Fig.1.

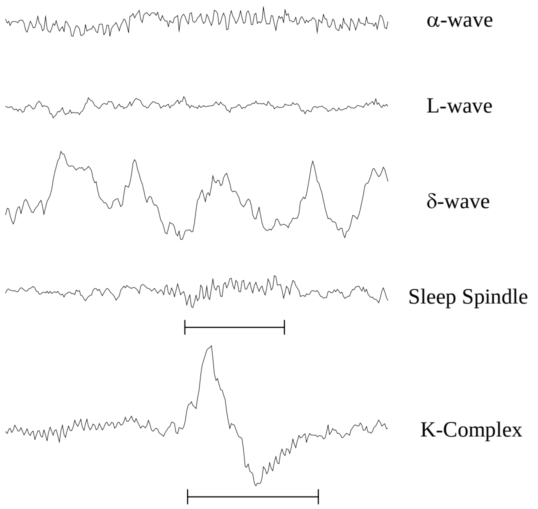


Fig.1. Human sleep EEG patterns

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 α -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. α-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. δ-waves are contained less than 20%.

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

(Stage 4)
δ-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).

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

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.

$$F(\omega, b) = \frac{1}{2\sqrt{\pi}\sigma_1} \int_{-\infty}^{\infty} e^{-(t-b)^2/\sigma_1^2} e^{-j\omega t} f(t) dt \qquad (2)$$

This will be called as method FT2.

3.2 The Ordinary Wavelet Ttransform

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.

$$(W_\psi f)(b, a) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} f(t) \psi\left(\frac{t-b}{a}\right) dt \qquad (3)$$

$$\psi(t) = \frac{1}{2\sqrt{\pi}\sigma} \exp(-t^2/\sigma^2) \exp(jt) \qquad (4)$$

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

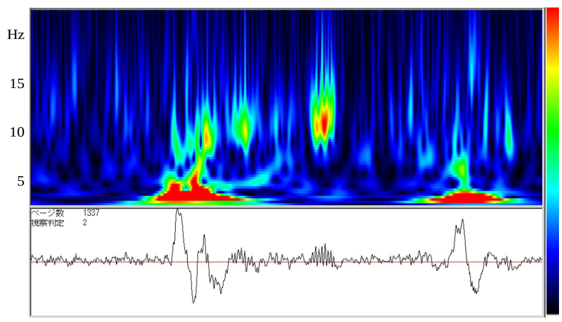


Fig.2. Ordinary wavelet transform result

3.3 Modified Wavelet Transform

The continuous wavelet transform can adjust the resolution of frequency and time by adjusting the value of σ (damping coefficient) in equation (4). Various Gabor functions (1/*a*=5.0, 10.0, 15.0, σ=4.0, 8.0, 12.0) are shown in Fig.3. The horizontal axis of each graph is a time-axis. ‘1/a’ is the equivalent to the frequency of the sinusoidal functions in equation (4). 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 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 σ 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, δ wave is defined as solitary wave, and α 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.

$$\sigma = \sigma_0 + \frac{\sigma_1}{a} \qquad (5)$$

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

$$(W_\psi f)(b,a) = \frac{1}{2\sqrt{\pi}\sqrt{|a|}(\sigma_0 + \sigma_1/a)} \cdot \int_{-\infty}^{\infty} e^{-\left(\frac{t-b}{(\sigma_0+\sigma_1/a)a}\right)^2} e^{-j\left(\frac{t-b}{a}\right)} f(t)dt \qquad (6)$$

In low frequency range ($\sigma_0 >> \sigma_1/a$), this transform becomes normal wavelet transform ($\sigma \approx \sigma_0$).
In high frequency range ($\sigma_0 << \sigma_1/a$), equation (6) becomes equation (7) ($\sigma \approx \sigma_1/a$). .

$$(W_\psi f)(b,a) \approx \frac{\sqrt{|a|}}{2\sqrt{\pi}\sigma_1} \cdot \int_{-\infty}^{\infty} e^{-\left(\frac{t-b}{\sigma_1}\right)^2} e^{-j\left(\frac{t-b}{a}\right)} f(t)dt \qquad (7)$$

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

$$(W_\psi f)(b,\omega) = \frac{1}{\sqrt{\omega}} \cdot \frac{1}{2\sqrt{\pi}\sigma_1} \cdot \int_{-\infty}^{\infty} e^{-(t-b)^2/\sigma_1^2} e^{-j\omega(t-b)} f(t)dt \qquad (8)$$

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.

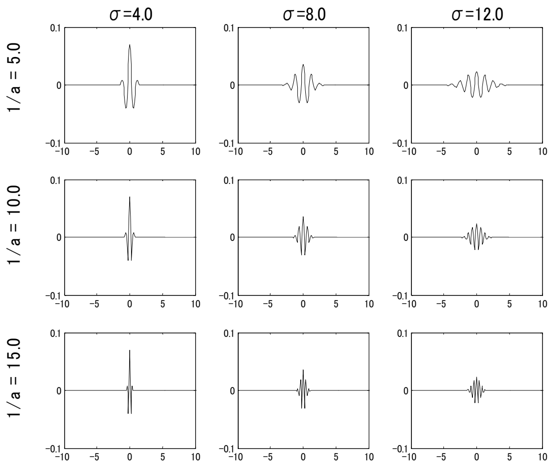


Fig.3. Gabor function

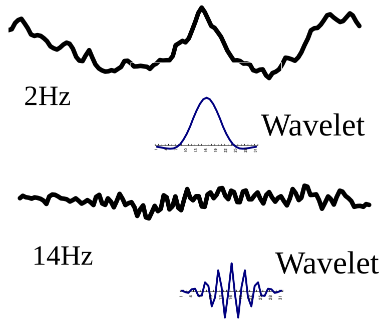


Fig.4. EEG waves and the corresponding wavelet

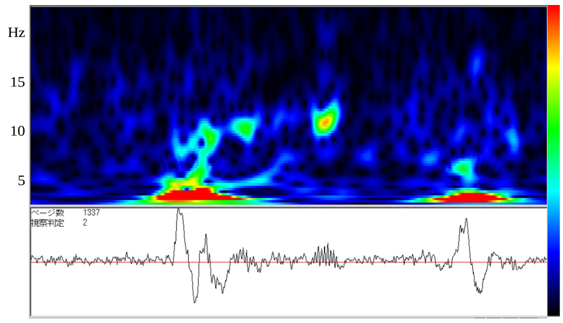


Fig.5. Modified wavelet transform result

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 σ_0, σ_1, these values are set to be 8.0 and 1.0 respectively.

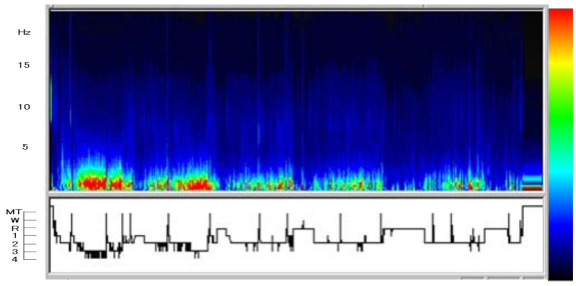


Fig.6. Wavelet transform result of one night. (MWT)

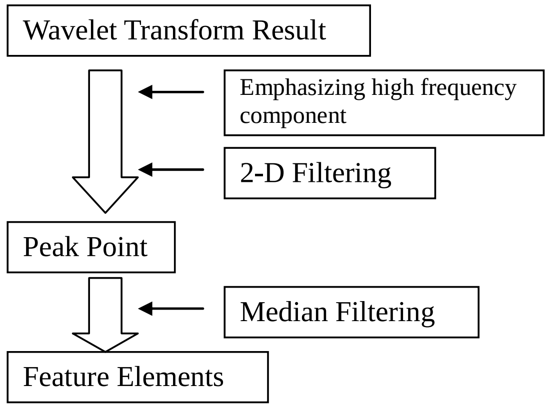


Fig.7. Schematic diagram of extraction method of peak frequency.

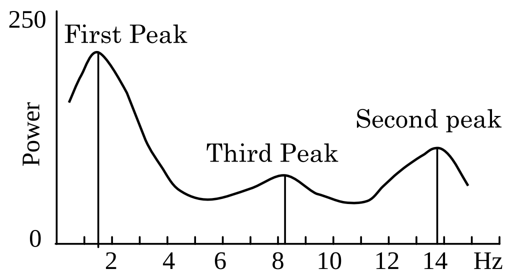


Fig.8. Detection of three peak points

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.

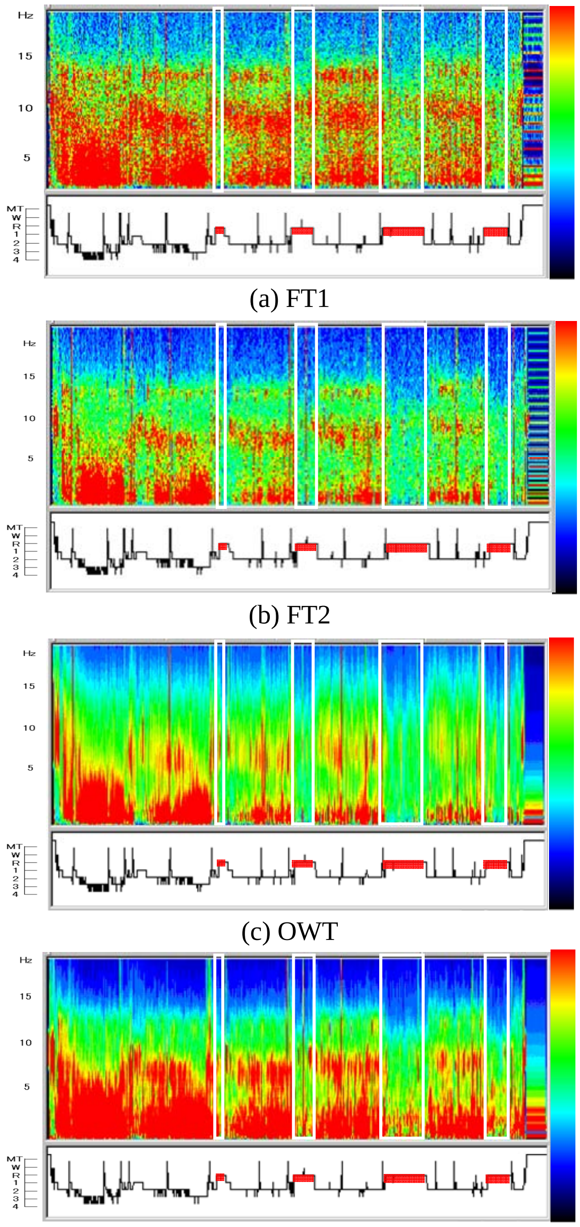
Step 1: Emphasizing high frequency component (EHFC). (Multiplying $\sqrt{2\pi f}$ to original wavelet transform)

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.



(a) FT1

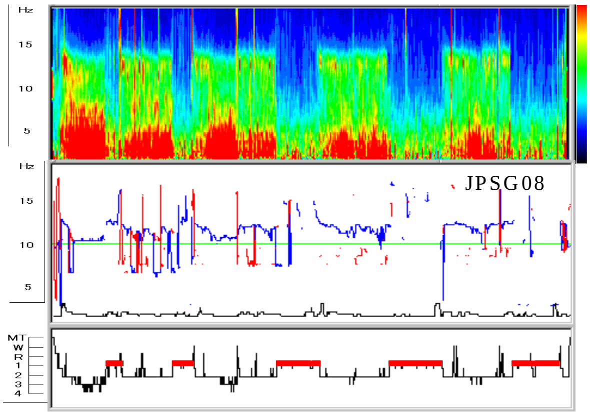
(b) FT2

(c) OWT

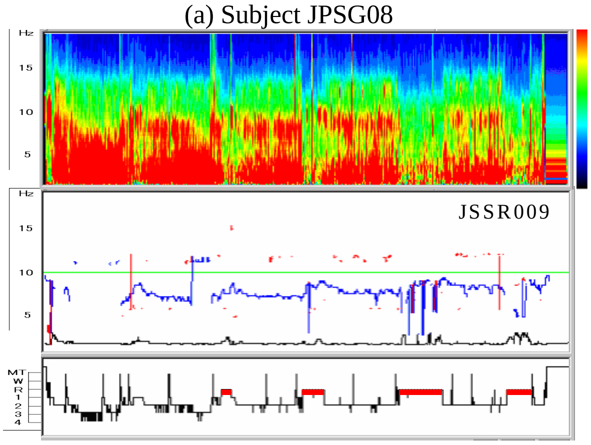
(d) MWT

Fig.9. Wavelet transform result (EHFC).
Subject JSSR009.
Rectangle with white edge shows the period of Stage REM.

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 β wave band. In the case of the subject (JSSR009), a consecutive frequency change is observed in θ 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.



(a) Subject JPSG08



(b) Subject JSSR009

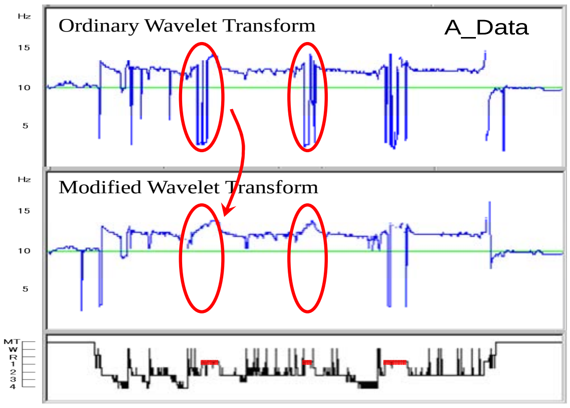
Fig.10. Detection result of peak frequency.
1st peak: black line, 2nd peak: blue line,
3rd peak: red line in upper figure.

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

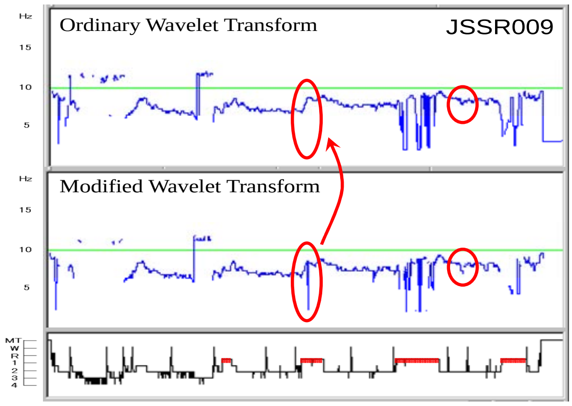
Subject		A_Data	JPSG08	JSSR004	JSSR009
Total page		1500	1455	1500	1527
FT1	Normal	1315	751	792	596
	EHFC	1468	1223	1211	1374
FT2	Normal	1489	1414	1445	1446
	EHFC	1492	1447	1492	1519
OWT	Normal	1033	421	496	495
	EHFC	1277	930	1336	1172
MWT	Normal	1234	647	624	588
	EHFC	1427	1122	1323	1208

Table 2. The number of discontinuous page.

Subject		A_Data	JPSG08	JSSR004	JSSR009
Total page		1500	1455	1500	1527
FT1	Normal	2	6	20	2
	EHFC	8	37	15	33
FT2	Normal	42	219	165	45
	EHFC	79	177	105	85
OWT	Normal	0	0	0	0
	EHFC	20	28	23	18
MWT	Normal	2	13	14	0
	EHFC	14	45	63	23



(a) Subject A_Data



(a) Subject JSSR009

Fig.11. Discontinuity of the detected peak frequency.

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 β wave band. On the other hand, OWT is the better method than MWT in which the target frequency band is θ wave band. This suggests that the adjustment defined by equation (5) should be improved.

5. FEATURE EXTRACTION OF SLEEP EEG STAGES

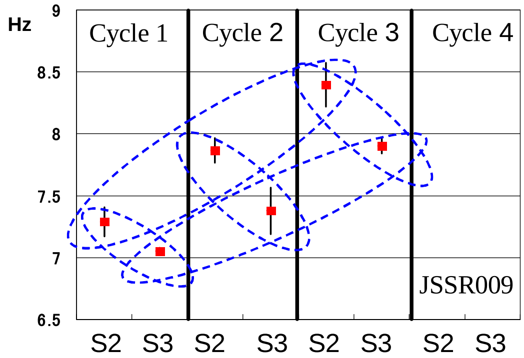
In this section, the relation between the second peak frequency detected by the previous mentioned method and the sleep stages is investigated.

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

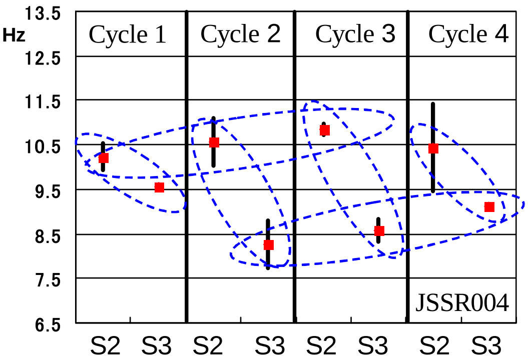
Stage 3, and the average of peak frequency becomes high by repeating the sleep cycle.

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).



(a) Subject A_Data



(a) Subject JSSR009

Fig.12. Average frequency in each sleep cycle (S2: Stage 2, S3:Stage 3)

Table 3. Average of the slope

Subject		A_Data	JPSG08	JSSR004	JSSR009
FT1	Stage2	0.136	0.262	0.177	0.567
	Stage3	0.187	0.347	0.024	0.434
FT2	Stage2	0.090	0.212	0.133	0.558
	Stage3	0.116	0.342	-0.178	0.451
OWT	Stage2	0.925	0.341	0.198	0.531
	Stage3	0.685	-0.231	0.268	0.416
MWT	Stage2	0.178	0.289	0.088	0.545
	Stage3	0.181	0.354	0.035	0.400

Table 4. Difference of the averaged peak frequency between Stage 2 and Stage 3.

Subject	A_Data	JPSG08	JSSR004	JSSR009
FT1	0.323	0.515	1.495	0.369
FT2	0.226	0.480	**1.712**	0.256
OWT	**0.501**	**0.711**	1.290	**0.477**
MWT	**0.610**	**0.900**	**1.700**	**0.418**

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 σ 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

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