Proceedings of 2009 APSIPA Annual Summit and Conference, Sapporo, Japan, October 4-7, 2009

Comparison of the EEG between before and during sleeping by the RCE analysis

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***Abstract*—It is crucial to practically estimate the dozing like the driver dozing, because many people cannot have enough sleeping caused by irregular hour and much stress. In the conventional study, the electroencephalogram (EEG) has been a promising indicator to driver dozing. Furthermore, it is known that frequency of the EEG is highly related to the sleep and the wake conditions. Therefore, we propose to extract frequency components of the EEG from the whole cerebral cortex, by using the rhythmic component extraction (RCE), proposed by Tanaka et al. RCE extracts a component by combining multi-channel signals with weights that are optimally sought for such that the extracted component maximally contains the power in the frequency range of interest and suppresses that in unnecessary frequencies. We found difference between the features obtained by RCE in the sleep and in the wake conditions. This implies that this method is available for analyzing the sleeping.**

I. Introduction

Modern people have been more interested in the sleeping. One reason is that there are many harmful effects by the sacrifice of the sleeping [1]. In the modern society, it is mentioned in this paper that many people have irregular hour and suffer from much stress, so that they cannot have enough of sleep. It causes driver dozing and falling asleep during the important situation. Therefore, it is necessary to reveal the mechanism of the sleeping, and to prevent from falling asleep at critical moments.

For the estimation of the dozing like the driver dozing, the questionnaires, the physical changes, the physiological changes are applied [2], [3]. The most accurate techniques are based on physiological measure like brain waves, the heart rate, the pulse rate, the respiration, the image processing for the head and the eye movements, etc. Among them, there are many studies using the image processing techniques, the electrooculogram (EOG) and the electroencephalogram (EEG). In the conventional study for estimation of the dozing, these effectiveness are shown in papers [4]–[9]. On the image processing techniques in the paper [9], images of driver especially at the retina are obtained by CCD micro camera sensitive to near infrared (IR). Although this technique is not intrusive since it does not require electrodes to be attached to the subjects, there are still problems. First is that external light sources are the main source of noise. In the driving experiment, artificial light from elements outside the road, vehicle lights, and sunlight are main sources. Furthermore, the performance of the tracker gets worse when users wear eyeglasses because different bright blobs appear in the image due to the IR reflections in the glasses. As well as, the EOG and the EEG are known to have high availability for estimation of the dozing. On the EOG studies, it is possible that the blink rate transition from wake fullness to drowsiness remains a valuable area of investigation into fatigue monitoring [3]. Furthermore, detection of the dozing by the EEG, many researchers pay attention to the frequency component such as the delta, the theta, the alpha, the beta waves by the frequency analysis (i.e., Fourier transform). For example, Yokoyama et al. suggest that the transitional EEG wave caused by the sleeping is important [10].

In the Fourier transform, rhythmic components of the EEG like the theta wave or the alpha wave is extracted for decomposing a signal to a set of frequency components. Furthermore, if we use the multi-channel signals, the principal component analysis (PCA) is useful to extract a component of which the power is very dominant [11]. Moreover, the independent component analysis (ICA) is effective to estimate statistically independent components and applicable to blind signal separation (BSS) [11]. Furthermore, Tanaka et al. pointed out if the frequency of interest is known in advance, it is more natural to directly estimate a component with respect to the frequency range mentioned in the papers [12], [13]. To estimate this component, the so-called rhythmic component extraction (RCE) method has been proposed. The extraction is made by combining multi-channel signals with weights that are optimally sought for such that the extracted component maximally contains the power in the frequency range of interest and suppresses that in unnecessary frequencies. Therefore, the frequency of interest which cannot be seen in each single channel is detectable by the RCE signal. Furthermore, the effective channel to the frequency of interest can be found by analyzing the weights of the RCE. However, no one evaluate the weights of the RCE signal. Therefore, we investigate the effectiveness of the RCE. The power spectrum of the RCE is calculated by the Fourier transform.

II. Rhythmic component extraction

RCE is a method to extract a particular EEG component that concentrates the energy in a certain frequency range. These frequencies are corresponding to the delta, the theta wave and so on. It is expressed as

$$\hat{x}[k] = \sum_{i=0}^{M} w_i x_i[k]. \tag{1}$$

Observed signal $x_i[k](k = 0, ..., N-1)$ is based on the channel $i(i = 1, ..., M)$. w_i is the weight and it is determined to maximize the power of specific frequency component, whereas the power of the other frequency component is minimized (2). $\Omega_1 \subset [0, \pi]$ is frequency component we want to extract, and $\Omega_2 \subset [0, \pi]$ is the other frequency component we want to suppress, when the Fourier transform is computed for $x_i[k]$. Therefore, the cost function defined as

$$J_1[w] = \frac{\int_{\Omega_1} |\hat{X}(e^{-j\omega})|^2 d\omega}{\int_{\Omega_2} |\hat{X}(e^{-j\omega})|^2 d\omega} \tag{2}$$

is maximized. Furthermore, define $X \in \mathbb{R}^{M \times N}$ as $[X]_{ik} = x_i[k]$, and matrices W_1 and W_2 as

$$[W_1]_{l,m} = \Re \int_{\Omega_1} e^{-j\omega(l-m)} d\omega, \tag{3}$$

$$[W_2]_{l,m} = \Re \int_{\Omega_2} e^{-j\omega(l-m)} d\omega, \tag{4}$$

respectively, where $l, m = 0, ..., N-1$ and $\Re$ takes the real part of the complex value. Then, $J_1[w]$ can be described in the matrix-vector form as

$$J_1[w] = \frac{w^T X W_1 X^T w}{w^T X W_2 X^T w}. \tag{5}$$

III. Adaptation and regularization of RCE

Adaptation of RCE can be made by using frame processing [13]. Let $x_i[n]$ be the observed signal in the ith channel with time index n. In this case, the time index can be either finite or infinite. In a way similar to (1), a rhythmic component is extracted as follows;

$$\hat{x}[k] = \sum_{i=0}^{M} w_i^{(n)} x_i[k], \tag{6}$$

where $w_i^{(n)}$ is the weight for the nth sample. The weight, $w_i^{(n)}$, is obtained by replacing sample matrix X. $X^{(n)}$ is defined by;

$$[X^{(n)}]_{ik} = a[k] x_i[n + k - d], \tag{7}$$

where $a[k], k = 0, ..., N-1$, is an appropriate window function with a length of N and d is a time delay. We can obtain the weight at time index n, $w^{(n)}$, by maximization of $J_1[w]$ at time index n. Note that it is highly possible that the rhythmic components extracted in the $n-1$th frame and in the nth frame significantly differ from each other. However, this analysis is batch-type algorithm, which causes discontinuity in the weight coefficients or the extracted signal over time. Therefore, a regularization method that takes into consideration the correlation between the signals extracted in the previous frame and to be extracted in the current frame to avoid the discontinuity effect, is needed.

Let $w^{(n-1)}$ and $w^{(n)}$ be the weight coefficients in the $n-1$th and the nth frames, respectively. Notice that $w^{(n-1)}$ has already been obtained and $w^{(n)}$ is an unknown vector to be determined. Then, the correlation of rhythmic components extracted in the previous and current frames is described as;

$$r^{(n)} = w^{(n)T} X^{(n)} P_1 P_0^T X^{(n-1)T} w^{(n-1)}, \tag{8}$$

where P_1 and P_0 are the matrices of size $l \times (l-1)$ that take the part overlapping between $X^{(n)}$ and $X^{(n-1)}$. In the case of a one-sample shift of frames, with zero matrix $0_{l \times (l-1)}$, they are described as

$$P_0 = \begin{bmatrix} 0_{l \times (l-1)} \\ I_{l-1} \end{bmatrix}, P_1 = \begin{bmatrix} I_{l-1} \\ 0_{l \times (l-1)} \end{bmatrix}. \tag{9}$$

Under the assumption that a rhythmic signal from a brain varies slowly with time, we should estimate the w in such a way that $|r^{(n)}|$ remains large while adapting. Therefore, $|r^{(n)}|^2$ is used for regularized the cost function.

We define rank-1 matrix;

$$C^{(n-1)} = P_1 P_0^T X^{(n-1)T} w^{(n-1)} w^{(n-1)T} X^{(n-1)} P_0 P_1^T, \tag{10}$$

and find the w that maximizes the new cost function given as;

$$J_2[w] = \frac{w^T X^{(n)} (W_1 + \epsilon C^{(n-1)}) X^{(n)T} w}{w^T X^{(n)} W_2 X^{(n)T} w}, \tag{11}$$

where ϵ is a regularization coefficient. When $\epsilon = 0$, $J_2[w]$ coincides with $J_1[w]$. The EEG analysis examples are shown in the papers [12], [13].

IV. Experimental procedure

In the experiment, we investigate the difference of the EEG between the waking and the sleeping. We pay attention to only 1 subject. The reason is that the other subjects cannot sleep in the laboratory. We measure the EEG before sleeping and just after falling asleep. There are multiple stages in the sleeping [11], so we focus on the stage I which is the stage of drowsiness because the purpose of this paper is to prevent from falling asleep at critical moments. The EEG is measured by the NEUROSCAN system, which is the cup type electroencephalograph. There are 32 channels (including reference electrodes A1 and A2) according to the international 10/20 system, and sampling frequency is 1000 Hz. After the attachment of the electroencephalograph, we measure the EEG for 1 minute. We define the data as before the sleeping in this study. After that, the subject keeps relaxing and sleeps. For determination that the subject sleeps, we drum on the table every 4 minutes (see Fig. 1). If he notices, the subject can moves his fingers in small motions, and it is defined that the subject is not sleeping. If he does not notice, the subject cannot move fingers. When it happens the EEG is measured for 1 minute. We define the data as during the sleeping.

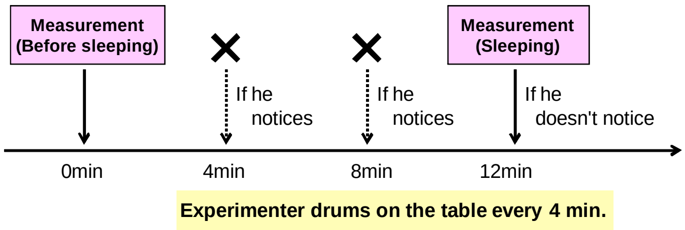

Fig. 1. The experimental procedure in the experiment 1.

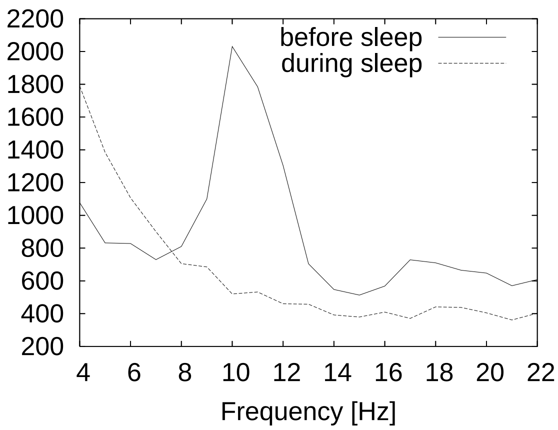

Fig. 2. Fourier spectra before and during sleeping at FP1.

V. RESULTS AND DISCUSSIONS

In this section, we show experimental results. At the first, we try to analyze the frequency component in before and during the sleeping by the Fourier transform. Then, we indicate the effectiveness of the RCE. Next, the important frequency range, determined by the frequency analysis, is extracted by the RCE. In the RCE analysis, the extracted signal is composed using weights corresponding to each channel. These weights indicate the importance of each channel for the specific frequency range of interest. Therefore, the analysis of the weight variation can represent the effectiveness of the RCE, too.

When the EEG data is measured, impedance levels of each channel are lower than 5 kΩ or sometimes a little higher than it. Before the RCE analysis, we applied DTFT to detect the variation of the frequency component. The window size is set as $N = 1000$. In Fig. 2, the vertical axis indicates the power spectrum and the abscissa axis indicates the frequency. Compared with the power spectra of before and during the sleeping, the alpha wave component (8–13 Hz) decreased during the sleeping. On the other hand, the theta wave component (4–7 Hz) increased. These features are also confirmed at the other channels. These results suggest that the alpha and theta wave components are promising candidates in revealing the sleeping stage I. In the paper [11], the resemble features that appearance of rhythmical 4–6 cycles/s theta activity and brisk alpha dropout are also mentioned.

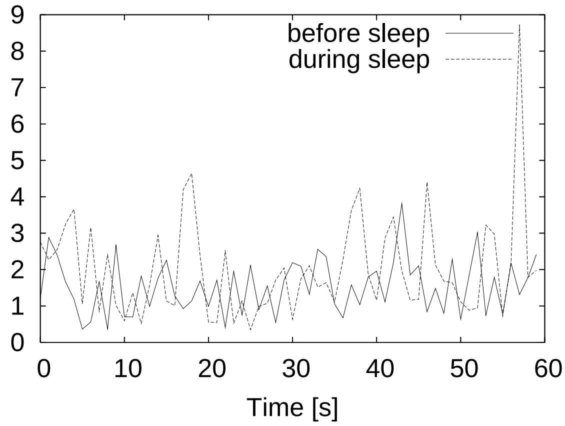

Fig. 3. Power spectrum of the theta component.

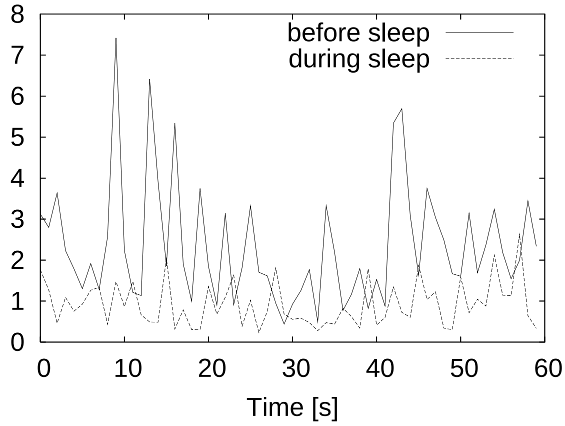

Fig. 4. Power spectrum of the alpha component.

Therefore, we extract the theta and the alpha wave components by the RCE. To extract the theta wave component from the RCE, Ω_1 is set to the range corresponding to 4–7 Hz. In the case of the alpha wave component, the range corresponds to 8–13 Hz. The RCE signals are extracted from all 30 channels per 1 second. The sampling rate is down-sampled to 500 Hz, and $\epsilon = 1000$. Moreover, to investigate the variation of the frequency component of the RCE signals, DTFT was applied per 1 second. The band powers of the theta wave and the alpha wave are shown in Fig. 3–4. The abscissa axis means the time range and the vertical axis means the bands power. Time range is set as 60 seconds. From the RCE analysis, there was no difference in the theta wave component between before and during the sleeping. On the contrary, the power of the alpha wave during the sleeping is lower than that before the sleeping.

From these results, the power of the alpha wave component is possible to be larger than that during the sleeping. Furthermore, there may be specific channels which greatly affect the RCE signal. For investigation of weights, the time average of the weight for each channel is calculated. The weights extracted by the RCE are transformed to absolute value. In

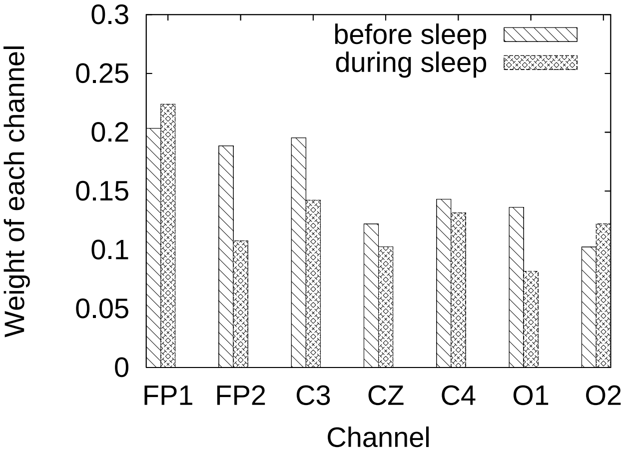

Fig. 5. Weight of each channel in the theta wave component.

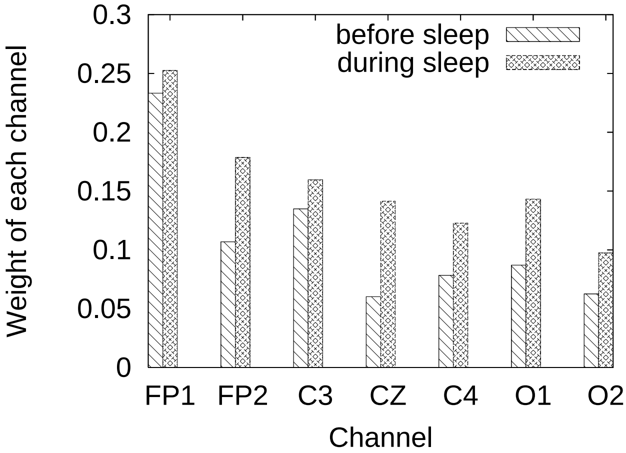

Fig. 6. Weight of each channel in the alpha wave component.

Fig. 5–6, the time average of the 7 channels weight (FP1,..., O2) are shown. Furthermore, Fig. 5 declare in the case of the theta wave component, and Fig. 6 indicate in the case of the alpha wave component. From Fig. 5, the weights of FP2, C3, CZ, C4, and O1 decreased, and the weights of FP1 and O2 increased. In the previous analysis, the power of the theta wave component from all channels by the RCE was not different by the sleep and the wake conditions. However, analysis of the weights intends that the theta wave appears in different channels depending on the sleep and the wake conditions. Moreover, from Fig. 6, the weights of FP2, C3, CZ, C4, and O1 indicate the opposite change. These results mean that the power of the alpha range shows relative increase among channels during the sleeping. On the contrary, the power of the theta range shows relative decrease.

From this result, it is confirmed that the weights change by the sleep and the wake conditions. These results represent the effectiveness of the RCE because the relative power of the frequency of interest among channels can be revealed by weight analysis. As these results, the relative power of the specific channel may be different by the sleep and the wake conditions. These differences by the RCE analysis can be confirmed. In the future work is to evaluate the time variation of the weight of the channel. Moreover, it is necessary to analyze the other frequency bands like the delta and beta wave, and the other subjects.

VI. Conclusions

In order to compare the sleep and the wake conditions, the RCE for the multi-channel EEG data is applied. Analyzing the frequency component, the power of the alpha and the theta wave components indicate the different changes depending on the sleep and the wake conditions. Therefore, we extract the alpha wave component and the theta wave component from 30 channels by the RCE. As the result, it is confirmed that the alpha power of the RCE signal is lower than before the sleeping, on the contrary the theta power is not different change. Furthermore, it is confirmed that weights change depending on the sleep and the wake conditions, in the case of the alpha and the theta wave extraction by the RCE. Therefore, the availability of the analyzing the weights in the RCE signal are indicated. In the future works, we will focus on the other frequency bands, and try to analyze the other subjects.

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