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Automatic Estimation of Sleep Level for Nap Based on Conditional Probability of Sleep Stages and An Exponential Smoothing Method

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***Abstract*—An automatic sleep level estimation method was developed for monitoring and regulation of day time nap sleep. The recorded nap data is separated into continuous 5-second segments. Features are extracted from EEGs, EOGs and EMG. A parameter of sleep level is defined which is estimated based on the conditional probability of sleep stages. An exponential smoothing method is applied for the estimated sleep level. There were totally 12 healthy subjects, with an averaged age of 22 yeas old, participated into the experimental work. Comparing with sleep stage determination, the presented sleep level estimation method showed better performance for nap sleep interpretation. Real time monitoring and regulation of nap is realizable based on the developed technique.**

***Index Terms*—Sleep level estimation, Sleep stage, Conditional probability, Nap regulation.**

I. Introduction

With the rapid development of modern society, the effects of irregular life and high pressures are harmful to human mental and physical health. In the developed country, about 1/5 persons have sleep problems and 1/3 elders are suffered by sleep disorders. The lack of enough sleep may damage the concentration, reduce work efficiency, lead to mis-operation and serious accident [1].

Besides the essential function of long term overnight sleep, the day time nap has considerable relaxation function for our health. There are mainly two types of nap: compensatory nap and prophylactic nap. About two hours of compensatory nap can compensate the insufficient amount of night time sleep. The prophylactic nap is for mode refreshing from pressure, tiredness, etc. The proper latency is suggested by 20-30 minutes [2]. However, it may cause sleep inertia when the sleeping time is too long and subject falling into deep sleep.

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Sleep stages are mainly adopted for sleep evaluation. In the international criteria, sleep stages are defined based on the characteristics of physiological signals [3]. Automatic technique of sleep stage scoring had been investigated and developed [4]-[7] as assisting tool for visual inspection. However, there are differences between overnight sleep and daytime nap, including external factors (sleep circumstance of light, temperature, sound, etc.) and internal factors (personal status, sleep habit, ect.). Due to the differences of above sleep factors, the automatic technique developed for overnight sleep may not suitable for day time nap.

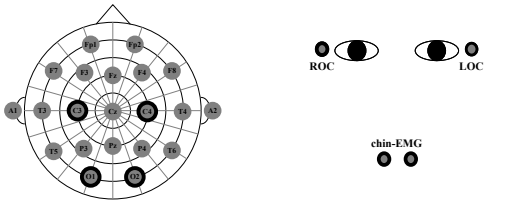
In this study, the automatic sleep level estimation method is investigated for prophylactic nap. The ultimate purpose is for nap regulation which can ensure the positive function and avoid negative effect. The physiological features for stage awake, stage 1 and stage 2 are analyzed. A parameter of sleep level is defined. The automatic estimation is realized based on the conditional probability of sleep stages. An exponential smoothing method is applied for estimated sleep level. Based on the developed technique, continuous changing of sleep level can be observed for nap monitoring and evaluation purposes.

II. Method

A. Data acquisition

Totally, 12 healthy subjects were participated. The average age was 22 years old. The sleep data was recorded based on PSG (Polysomnography) measurement. All the data were recorded in the Department of Advanced Control Systems, Saga University Japan. Detail explanation was done for all the subjects before recordings and informed consent was obtained.

The subject was placed in a supine position on a comfortable chair. EEGs were measured according to the International 10-20 System [8]. The 4 EEG (Electroencephalograph) channels of C3-A2, O1-A2, C4-A1, O2-A1, 2 EOG (Electrooculograph) channels of LOC-A1, ROC-A1, and 1 EMG



(a) 4 EEG recording channels (b) 2 EOG and 1 EMG recording channels

Fig. 1. Recording positions of EEG, EOG and EMG

(Electromyograph) channel of chin-EMG were mainly for physiological signal analysis as in Fig. 1. The recording was done with the time constant of 0.3 s, the high cut filter of 70 Hz and a sensitivity of 0.5 cm/50 μV. The sampling rate was 100 Hz for all the channels. The long EEG record was divided into consecutive segments of 5-second long each for analysis. Sleep stage was inspected for the recorded data by clinical neurologist.

B. Feature calculation

In order to estimate the continuous changing in terms of sleep level during the 20-30 minutes of nap, the features of sleep stage awake, stage 1 and stage 2 are taken into account. Here, two parameters are extracted from EEG by,

$$R_{s1} = max(\frac{S_{z1}(O1)}{S_T(O1)}), (\frac{S_{z1}(O2)}{S_T(O2)}), \quad (1)$$

$$R_{s2} = max(\frac{S_{z2}(C3)}{S_T(C3)}), (\frac{S_{z2}(C4)}{S_T(C4)}), \quad (2)$$

where S is the amount of powerspectrum of certain frequency, $z1$ and $z2$ are corresponding to the frequency bands of α rhythm (8-13 Hz) and θ rhythm (2-7 Hz). The ratio of R_{z1} and R_{z2} is taking the maximum value between left and right hemisphere. Additionally, parameters of eye movement ($z3$: 2-10 Hz) in EOG channels and EMG activity ($z4$: 50-100 Hz) in chin-EMG channel are calculated. A set of training data is adopted to obtain the probability density function of features for stage awake, stage 1 and stage 2. The parameter distribution is approximately evaluated using histograms with Cauchy distribution as,

$$f(y|\zeta) = \frac{b}{\pi((y-a)^2 + b^2}, \quad (3)$$

where a is the location and b is the scale of Cauchy distribution. a is determined by media and b is determined by quartile.

C. Conditional probability

The conditional probability of segment k is calculated based on the Bayesian rule [9],

$$P_{k|k}(\zeta^j|y_k) = \frac{f(y_k|\zeta^i)P_{k|k-1}(\zeta^i)}{\sum_{j=0}^{2} f(y_k|\zeta^j)P_{k|k-1}(\zeta^j)}, \quad (4)$$

where, $f(y_k|\zeta^i)$ is the joint probability of parameters $Y_k = (y_k^1, y_k^2, ..., y_k^m)$ for sleep stage ζ^i, $P_{k|k-1}(\zeta^i)$ is the prior probability. The conditional probability indicates the possibility of the occurrence of the sleep stage ζ^j in the current segment k. The transition between sleep stages for day time nap if quite different from overnight sleep. Here, the calculation of conditional probability is simplified where the prior probability is supposed to be same for three sleep stages.

D. Sleep level estimation

The sleep level is defined as a variable which indicating the continuous changing of sleep depth during nap [10]. The definition of sleep level is given by,

$$X_{k|k} = e_w P_{k|k}(\zeta^w|y_k) + e_1 P_{k|k}(\zeta^1|y_k) + e_2 P_{k|k}(\zeta^2|y_k), \quad (5)$$

where X_k is sleep level for current data segment k. It is obtained based on the conditional probabilities for stage awake, stage 1 and stage 2 by (4). There are coefficients defined for each sleep stage in Eq. 4, e_w is 0, e_1 is 1 and e_2 is 2.

Exponential weighted average method is adopted as,

$$X'_{k+1|k+1} = \varepsilon \bullet X_{k|k} + (1-\varepsilon) \bullet X'_{k-1|k-1}, \quad (6)$$

where, ε is smoothing factor, $X_{k|k}$ is the actual estimated sleep level for time k, $X_{k+1|k+1}$ is the smoothing sleep level for next time $k+1$, and $X_{k-1|k-1}$ is the smoothing sleep level for previous time $k-1$.

III. Results

A. Probability density function of parameters for sleep stages

The sleep recording of one subject was adopted as training data. There were totally 6 parameters calculated from EEGs, EOGs and EMG data. According to the visual inspection of stage awake, stage 1 and stage 2, the parameter values were grouped by sleep stages. The probability density function of each parameter for certain sleep stage were obtained. In Fig. 2, the distributions of parameters were given for stage awake, stage 1 and stage 2. The horizontal axis is parameter value and vertical axis is the probability density.

In the ratio of $z1$ (8-13 Hz) in EEGs, the distribution of stage awake was near to 60%. α activity is the main characteristic of stage awake when the subject closed eyes and relaxed. With the sleep changing to light sleep stage, the amount of α activity was depressed to 20%. In the ratio of $z2$ (2-7 Hz), the distribution of light sleep stage 1 and stage 2 were about 40% to 50% while 20% to 30% for stage awake. The characteristics of α activity and θ activity were consistent with defined sleep stages in R&K criteria. The amount of $z3$ (2-10 Hz) in EOGs and the amount of $z4$ (25-100 Hz) in chin-EMG were adopted as the additional features. The combination of those selected parameters was utilized for calculating the conditional probability of sleep stages.

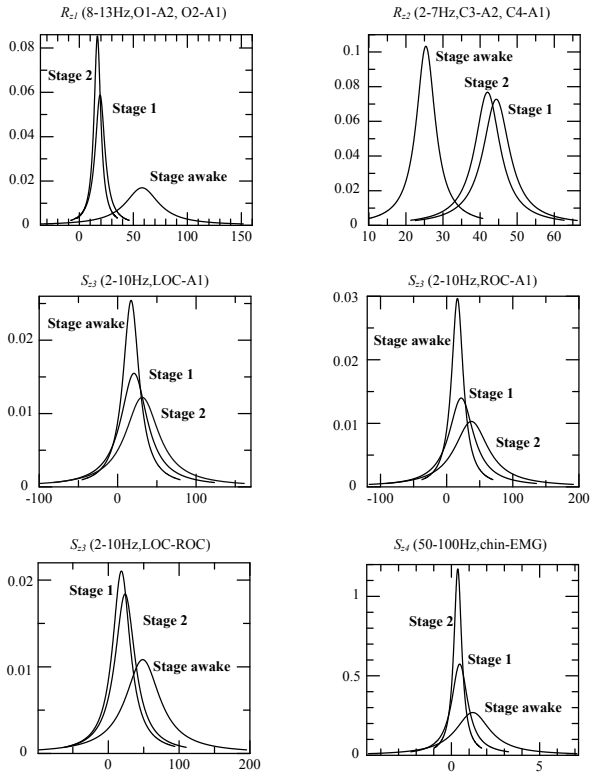


Fig. 2. Probability density functions of parameters for stage awake, stage 1 and stage 2.The parameters are calculated within a certain frequency band in the corresponding channels.

B. Sleep level estimation based on conditional probability

The conditional probability was calculated by (4) for each 5-second segment data. The sleep level was estimated based on the conditional probability of stage awake, stage 1 and stage 2 by (5). In Fig. 3 (a-1) to (a-3), the recorded raw nap data of EEGs were illustrated. (a-1) was inspected as stage awake where EEGs (O1-A2, O2-A1) showed predominant rhythmic α activity when the subjects were falling to sleep with the eyes closed. (a-2) was determined as stage 1 and (a-3) is stage 2, where the amount of α activity was decrease and θ activity becomes apparent.

Based on the conditional probability of three sleep stages, the obtained sleep level and smoothed sleep level for each 5-second segment were shown in Fig. 3 (b-1) and (b-2). The visual inspection of sleep stage awake, stage 1 and stage 2 was illustrated in Fig. 3 (c). The three dotted lines were corresponding to the segment data in Fig. 3(a-1) to (a-3) respectively. Due to the dominant α activity, the estimated sleep level for nap data in Fig. 3(a-1) is 0. The sleep level estimated for data in Fig. 3(a-2) and (a-3) was 1.0 and 1.8 respectively. The initially obtained sleep level in Fig. 3 (b-1) was fluctuated frequently. The estimated sleep level was smoothed by exponential weighted average method in (6) where ε was set to 0.3. The final results was illustrated in Fig. 3 (b-2). Comparing with the visual inspection, the obtained sleep level after smoothing was satisfied which reflected the transition within and between the sleep stages.

IV. Discussion

A. Sleep level and sleep stage

Sleep stage scoring is conventional technique which is widely applied in clinics for overnight sleep interpretation. Criteria and techniques on sleep stages had been developing to meet the clinical requirements. However, the sleep stage determination for 20-30 second segment is not enough for nap regulation. The detail changing within and between sleep stages is necessary for nap monitoring and evaluation purposes. In this study, we are trying to develop a parameter having the comparable meaning with sleep stages. Here, a variable of sleep level based on the conditional probability of sleep stage is proposed. From the time resolution, sleep stage is determined for every 20-30 minutes while the presented sleep level is for 5-second segment. From the sleep depth resolution, sleep stage is a discrete variable including stage awake, stage 1 and stage 2. The presented sleep level can be considered as a continuous variable where the coefficient of e_w, e_1 and e_2 are defined comparable with the sleep stages. However, the estimated sleep level fluctuated due to the discontinuous characteristics of physiological data. An exponential smoothing method was adopted. The final obtained results showed that the detail changing within and between sleep stages can be derived.

B. Nap regulation

Short term prophylactic nap is effective for mode refreshment and relaxation. However, sleep inertia is one of the problems. The monitoring and regulation for nap latency would be helpful to avoid falling into deep sleep and sleep inertia. In this study, the sleep evaluation technique for nap is investigated. Within the short term of nap sleep, light sleep stages are the main subject for analysis. Stage awake is usually identified by alpha activity. Stage 1 is a transitional stage. Stage 2 is suggested not to be longer than 3 minutes in prophylactic nap. The current study was focused on the sleep level estimation. The physiological features were selected based on criteria on sleep stage. However, the parameter especially for light sleep need to be investigated by considering the sleep factors in day time nap. Furthermore, the prediction technique is necessary for realizing the real time monitor and regulation for nap. In the future work, we would investigate on the real time monitoring and regulation by developing prediction method based on current estimation method. In addition, the experimental devices and conditions including comfortable sleep data recording and proper regulation techniques waking up the subjects before falling into deep sleep would be developed to improve the application performance of presented techniques.

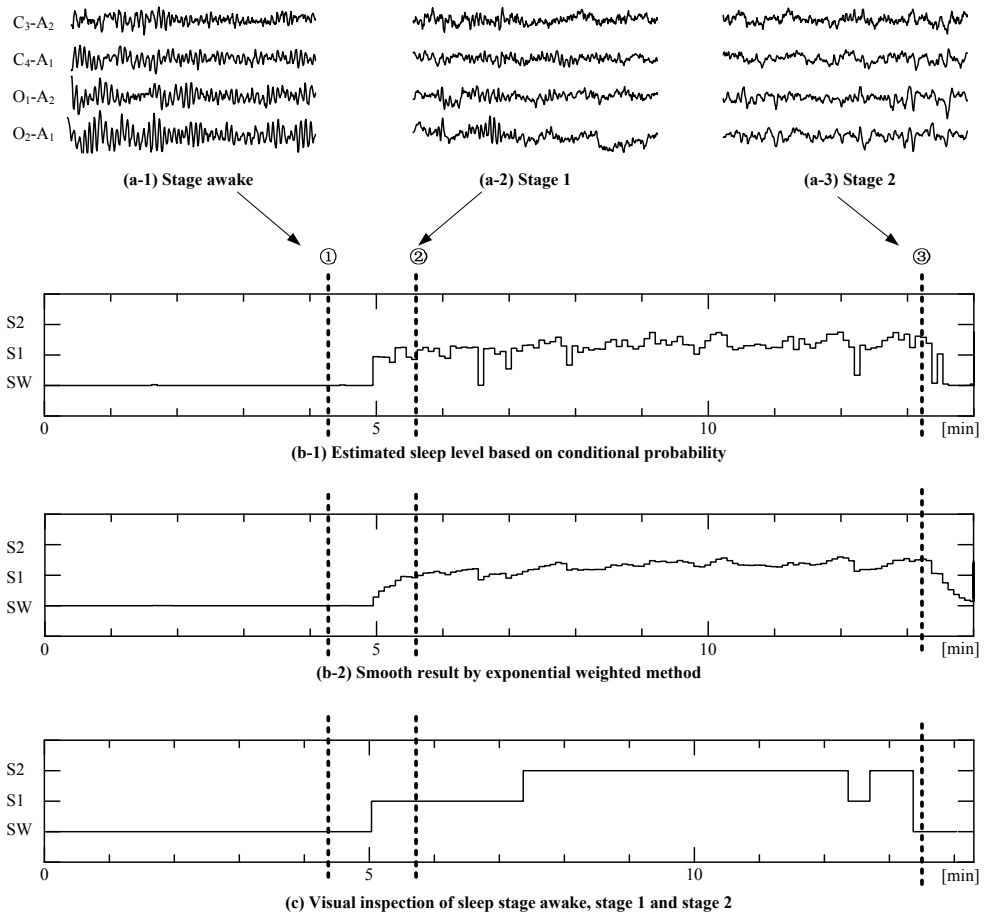


Fig. 3. Feature values and estimated sleep level

V. Conclusion

In this study, the automatic sleep level estimation method is investigated for day time nap. The sleep level is estimated based on the conditional probability of sleep stages. An exponential smoothing method is adopted to smooth the estimated sleep level. The obtained results are helpful to observe the continuous sleep level changing. It can be an assistant and objective tool for nap sleep monitoring and regulation.

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