DEVELOPMENT OF A SLEEP MONITORING SYSTEM WITH WEARABLE VITAL SENSOR FOR HOME USE

Takuji Suzuki[1], Kazushige Ouchi[1], Ken-Ichi Kameyama[1] and Masaya Takahashi[1,2]
[1] *Humancentric Laboratory, Corporate Research & Development Center, Toshiba Corporation, Japan*
[2] *National Institute of Occupational Safety and Health, Japan*

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Abstract: This paper describes a new sleep monitoring system for home use. The basic system consists of a wearable physiological sensor and PC software for analyzing sleep quality from user's wrist motion and heart rate variability. Different from a conventional sleep monitoring device used in a hospital, the sensor is so small and easy-to-use that a normal person can use it at home. This means that the system is useful for a sleep specialist who wants to check a patient's daily sleep pattern. The system can also be used for self-care. We have developed a wrist-watch-shaped physiological sensor that monitors user's wrist motion and pulse wave interval. We have also developed the algorithm for computing the quality of sleep from these physiological data on PC. Although sleep is a kind of brain activity and our sensor can not directly measure it, the output of our algorithm is close to medically evaluated sleep quality. We performed dozens of comparison experiments and found that its accuracy was about 73.5% on average. The value of the accuracy is enough for assessing a normal person's sleep quality.

1 INTRODUCTION

In recent years, many people have been suffering from sleep disorder caused by mental stress, irregular lifestyle or shift work. However, it is not easy to determine the quality of sleep because deep sleep is not always good sleep and shallow sleep is not always bad sleep. For example, it is natural that a person cannot sleep well because of jet lag. However, a person who is always sleepy in the daytime for a period exceeding one month might have a health problem. Therefore, it is important for a doctor to check a patient's sleep habits for several days in order to diagnose and cure his/her sleep disorder properly. Moreover, it is necessary for a person to check his/her own sleep habits and to change his/her lifestyle (self-care).

However, there is no good system to record and analyze daily sleep. For example, most medical sleep sensors, such as those employed for polysomnography (PSG), are for recording many kinds of physiological data (EEG, EMG, EOG and so on) for only one or two nights, not for recording sleep habits with natural state in daily life. It is also too difficult for a normal person to handle PSG at home because it involves the use of many electrodes for measuring the physiological data. A doctor can attempt to learn a patient's sleep habits by interviewing him or her, but this is an inherently unreliable approach. A simple and easy-to-use sleep monitoring system that can be used in the home is strongly desired in order to get objective data on sleep habits.

In order to develop such a system, we have created a wrist-watch-shaped wearable physiological sensor that monitors user's wrist motion and pulse wave intervals (Pulse-to-Pulse Intervals: PPIs). The sensor can be made small and simple because wrist motion and pulse wave can be easily measured compared to the case of using PSG. We have also developed the algorithm for computing the quality of sleep from these physiological data. The algorithm can distinguish sleep stage (wake /REM /NREM [shallow /deep]) using the relationship between autonomic nervous activity and sleep stages. Although sleep is a kind of brain activity and our sensor cannot directly measure it, the output of our algorithm is close to medically evaluated sleep quality.

In the following sections, the way of expressing sleep data, related works, our system's hardware and software, and the validation result of the sleep estimation are discussed.

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2 SLEEP DATA

Generally speaking, sleep is a kind of brain activity and its purpose is recovery from brain fatigue. Therefore, sleep state is measured mainly by EEG, and is classified into several stages. Sleep state is roughly divided into REM (rapid-eye movement) sleep and NREM (Non-REM) sleep. NREM sleep is divided into 4 stages. Stages 3 and 4 of NREM sleep are so called deep sleep, and stages 1 and 2 are shallow sleep. These stages are decided by a sleep specialist using PSG data (Rechtschaffen, 1968), and their change is shown in a graph called a hypnogram (shown in Figure 1).

A doctor mainly uses a hypnogram for evaluating a person's sleep quality. For example, the doctor checks the quantity of deep sleep if a patient complains about oppressive drowsiness in the daytime. If the patient frequently wakes up in the night and experiences difficulty in breathing, he/she might be suffering from sleep apnea syndrome. If REM sleep always occurs soon after falling asleep, there might be a problem concerning the patient's nervous system. From the viewpoint of healthcare, it is important to check the balance of deep sleep, REM sleep or sleep cycle. Therefore, a sleep monitoring system for home use can also show the result of one night's data in a graph similar to a hypnogram.

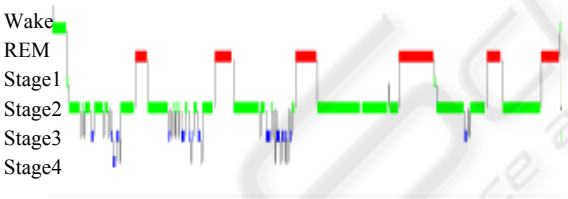


Figure 1: Sleep hypnogram.

There are many studies on the relationship between physiological parameters and sleep stages. For example, Baharav et al. stated that autonomic nervous activity level derived from heart rate variability (HRV) during sleep changes in response to the sleep stages (Baharav, 1995). A value of LF/HF shows the activity of the sympathetic nerve. During a REM sleep, a value of LF/HF and the variability of that are large, and the value of LF/HF decreases during a NREM sleep, particularly in the case of deep sleep (Slow Wave Sleep). Since the brain stem controls both the cerebrum and the autonomic nervous system, it may be possible to estimate the sleep stage using HRV.

3 RELATED WORKS

A number of trials have been conducted with a view to developing sleep monitors for home use. For example, body/wrist motion has been used for wake/sleep identification. The amount of activity (number of subtle wrist motions per minute) measured from acceleration sensors is often used for monitoring wake/sleep rhythms (Sadeh, 1989) although the sleep stages (ex. REM sleep / NREM sleep) cannot be determined from the data.

More recently, researchers have focused on measuring heart/pulse rate and analyzing its variability: HRV (Watanabe, 2004, Michimori, 2003 and Wakuda, 2007). The sleep stages can be calculated from HRV if the indices of HRV are properly mapped for the sleep stages.

However, there are two problems in this approach. One is that body/wrist motion often disturbs heart/pulse sensing and the HRV value can not be calculate correctly. The other is that the level of autonomic nervous activity differs according to age, sex and body/mental condition. For example, the autonomic nervous system of the young is generally more active than that of the old. Sleep stages cannot be classified using static thresholds.

Our sensor measures both pulse wave interval and wrist motion. The wrist motion data are used not only for counting the amount of activity, but also for detecting errors in HRV data. This solves the first problem mentioned above.

For the second problem, we employ a statistical method for deciding sleep stages (Suzuki, 2007). We assume that there are several stages in a certain period of sleeping time since the sleep stage cyclically repeats about every 90 minutes. It means that the data of autonomic nervous activity can be classified into several groups if we have any 90-120 minute dataset. In this way, the thresholds for dividing sleep stages are changed flexibly along with the dataset.

4 THE OVERVIEW OF THE SYSTEM

4.1 Wearable Physiological Sensor

Figure 2 shows our wearable physiological sensor. The size of the sensor is 50mm*60mm*13mm and the weight is only 35g. A rechargeable battery is used as an electrical power source. It is possible to measure physiological data for over 40 hours after

full charge. The sensor incorporates a photoelectric pulse wave sensor and a 3-axis accelerometer. Besides, it has an external pulse wave sensor. Therefore, pulse waves can be measured on the user's wrist or on his/her finger, depending on his/her preference. The front panel serves as a wrist-watch displaying date and time, and as a sensor displaying time and the amount of activity. The sensor has only two buttons; namely, one is a light switch, and the other is a switch to start/end sensing.

Figure 2: Wearable physiological sensor.

The sensor measures pulse waves and accelerations on a user's wrist and stores the computed pulse-to-pulse intervals (PPIs) and the amount of activity in a flash memory (4MiB). Both analog and digital filters are used to remove the fluctuations of the amplitude and the basal line of pulse waveform, which makes PPIs more precise. As the size of the data measured in one night (7 hours) is 256 KiB, the sensor can store almost 2 weeks' data in the flash memory.
The sampling rate of the pulse wave and 3-axis accelerations is 64Hz. However, the resolution of the PPI is 0.1 ms by using linear interpolation to detect pulse peak.

The amount of activity is calculated as the number that the scalar of the 3-axis acceleration is larger than 0.01 G, which is the same as Actigram (Cole, 1992).

The stored PPIs and amount of activity data are sent to PC via USB.

We evaluated the performance. Firstly, the correlation coefficient between the amount of activity counted by the sensor worn on the left forearm and that measured by an actigraph (Micromini-Motionlogger Actigraph, Ambulatory Monitoring Inc.) worn on the right forearm during sleep was 0.95 (average of 3 healthy subjects). Figure 3 shows an example of the result.

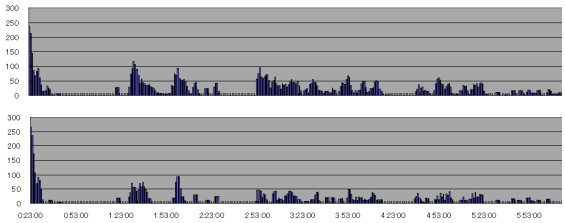


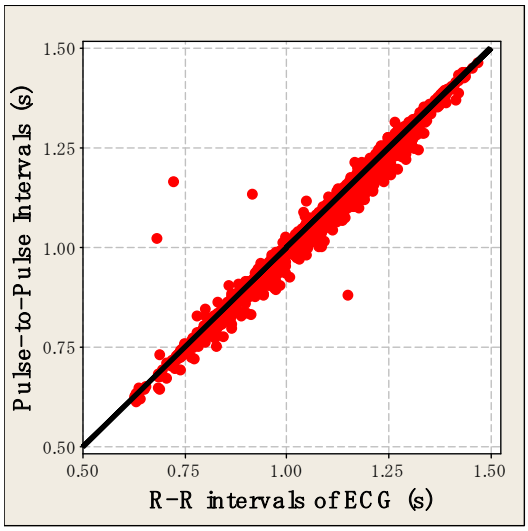
Figure 3: Actigram during sleep. Upper graph shows the result measured by Actigraph and lower graph shows that measured by our sensor.

Besides, the correlation coefficient between the PPIs computed by the pulse wave measured by the sensor and the R-R intervals computed by a simultaneously measured electrocardiogram during sleep was evaluated. Single-channel ECG was measured by CM5 lead using PSG (Polymate AP1124, TEAC Corporation, sampling rate: 1 kHz) simultaneously with the PPI measured by our sensor. R-R intervals were computed using commercially available R-R interval analysis software for the PSG (NoruPro Light Systems, Japan). The correlation coefficient is 0.96 (average of 3 healthy subjects). Figure 4(a) shows the correlation plot, and (b) shows the Bland & Altman plot between R-R intervals of ECG and PPIs.

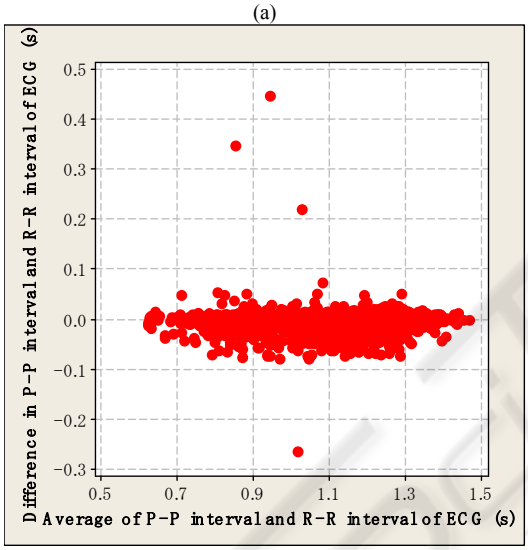
These values are accurate enough to use the sensor as a medical device.

4.2 PC Software

Figure 5 shows the flow of the algorithm for computing sleep stages from the data of PPIs and the amount of activity.
We employ Cole's algorithm for wake/sleep identification from the amount of activity data (Cole, 1992). This algorithm cannot determine wake/sleep in real time, but its accuracy is about 90%. At the same time, the indices of autonomic nervous activity are derived from frequency analysis of the variability of PPIs. Firstly, sampled PPIs' dataset in a minute is interpolated at even intervals by cubic spline interpolation by the minute. Next, Fast Fourier Transformation (FFT) is executed for the even-interval PPIs to get the frequency spectrum. In the frequency domain, the integral value of the power from 0.04Hz to 0.15Hz is called LF (low frequency), which shows both sympathetic and parasympathetic nervous activities. The integral value of the power from 0.15Hz to 0.4Hz is called HF (high frequency), which shows parasympathetic nervous activity. Therefore, we can get the balance



(a)



(b)

Figure 4: Correlation plot (a) and Bland & Altman plot (b) between R-R intervals of ECG and PPIs.

of sympathetic and parasympathetic nervous activity, which is related to sleep stages as we mentioned above. In order to classify the sleep stages from the dataset of LF and HF values, the k-means clustering method is adopted. Firstly, REM/NREM sleep is divided from 2-hour data set, and then, shallow/deep sleep is divided from its NREM dataset.

We developed sleep analysis software on Windows XP/Vista using this algorithm. The program was coded and compiled by Visual Basic Ver.6 (Microsoft Corp.).

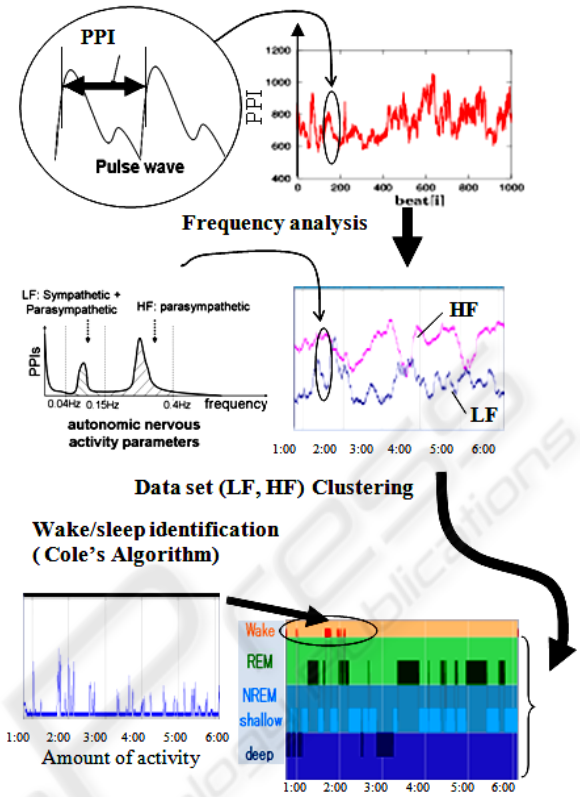


Figure 5: Algorithm for computing sleep stages.

Figure 6 and 7 are the picture image of the software. Figure 6 is one night's data, which shows pulse rate, variability of pulse rate, LF and HF trends, amount of activity and the simplified hypnogram.

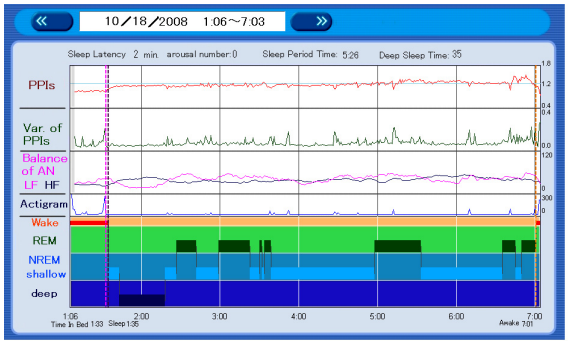


Figure 6: Result of one night's data.

Figure 7 is a summary of a 2-week hypnogram showing sleep habits. This is the most useful function for sleep care, which cannot be implemented in the conventional sleep monitoring systems.

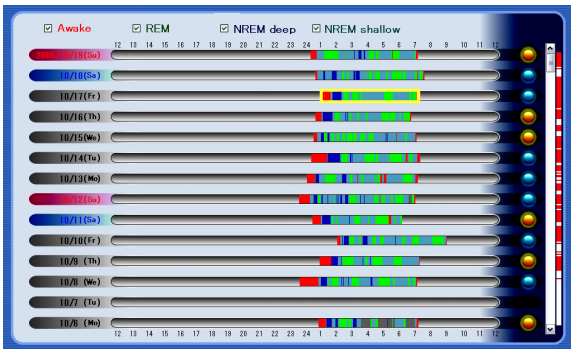


Figure 7: Result of summary of a 2-week hypnogram.

5 VALIDATION OF THE SLEEP ESTIMATION

Correlation between the sleep stage estimated by the proposed method using our wearable physiological sensor and the sleep stage estimated using PSG by sleep specialists was evaluated. EEG, EOG, chin EMG, ECG, respiration and SpO2 by PSG (Polymate AP1000, TEAC Corporation, Sampling rate: 250Hz), the pulse wave and acceleration by our sensor was recorded simultaneously in a night (8 hours). The test was held in two cites (Showa University East Hospital, Tokyo, Japan and The Institute for Science of Labour, Kawasaki, Japan). 45 normal healthy subjects (30 males and 15 females, 19-72 years old) are measured. All subjects had informed consent.

The sleep stages of PSG were distinguished manually by sleep specialists (doctor, clinical laboratory technologist, or sleep researcher) who belong to those cite based on Rechtschaffen & Kales method (Rechtschaffen, 1968) by the minute. Our sensor also estimated the sleep stages also by the minute.

We defined coincidence ratio as an evaluation function to compare the estimation result by our sensor with the result by PSG.

The coincidence ratio is defined as a correlation coefficient of moving average of sleep stages (20-minutes time window) between the stages estimated by this method and those from PSG. Table 1 shows the result of the comparison.

Table 1: Result of the comparison.

	coincidence ratio				
	SWS	REM	NREM	WAKE	ALL
average	0.740	0.712	0.697	0.799	0.735
SD	0.079	0.067	0.080	0.100	0.052

Figure 8 shows an example of the estimation results.

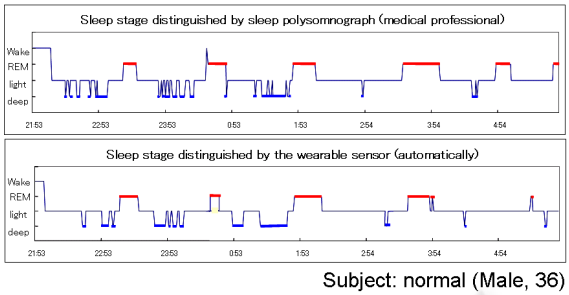


Figure 8: An example of the estimation results (upper: sleep stage distinguished by medical professionals using PSG, lower: sleep stage distinguished automatically by the sensor).

6 DISCUSSIONS

"Beat-to-beat" pulse interval detection is necessary to obtain autonomic nervous activity. Our algorithm has enough ability to get "beat-to-beat" pulse intervals. However, this algorithm is applicable for healthy subjects, except for cardiac disease, peripheral blood circulation disorder.

The coincidence ratio of our sleep stage estimating algorithm is 0.735. Although it is a rather low value, PSG results also varied depending on the examiner (variance is about 20%), and therefore it seems to be acceptable for home healthcare use. However, it is also applicable for healthy subjects, except for autonomic nerve disorder, cardiac disease.

7 CONCLUSIONS

Measurement of sleep habits is a promising new medical field. However, there are no systems suitable for it. This is because current sleep monitoring systems cannot satisfy the needs for accurate analysis of sleep and convenience in use. In order to provide a solution, we developed a small and easy-to-use sensor device. We also developed an algorithm for analyzing sleep stages. We confirmed sufficient accuracy in the detection of PPIs by comparison with R-R Intervals by ECG, and that in the estimation of the sleep stage by comparison with the result of PSG. The software can display the sleep data of one night and the summary of a 2-week hypnogram. This function is useful not only for a doctor analyzing a patient's sleep habits, but also for a user analyzing his/her sleep.

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