Ballistocardiography for Nonintrusive Sleep Structure Estimation

Kwang Suk Park, *Senior Member*, Su Hwan Hwang, Da Woon Jung, Hee Nam Yoon, and Won Kyu Lee.

Abstract— Based on the its nonintrusive characteristics, ballistocardiography(BCG) has applied in the estimation of sleep structure without attaching any sensors to the subject's body. Loadcell or polyvinylidenefluoride (PVDF) film sensors are installed on the mattress for the monitoring of BCG. BCG peak was detected and heart rate variability parameters are derived. Parameters representing sleep structure and quality are estimated using these parameters. Sleep efficiency, four stages of sleep structure and sleep onset latency are estimated and results are compared with the results derived from polysomnographic recording.

I. Introduction

We spent almost one third of our life time in sleep. Sleep is not just resting period escaping from physical and mental loads, but the recuperative period to restore physical and physiological strength for ordinary daily activities. To evaluate the sleep structure and sleep efficiency for patients with sleep related problems and diseases, polysomnography is widely used as the clinical standard. For polysomnographic recording we need the attaching tens of sensors and electrodes on body surfaces for the measurement of multiple channel of biological signals including EEG, EOG, EMG, respiration, pulse oximetry, blood pressure and body position. This difficulty and inconvenience of monitoring sleep based on polysomnography limits the use of the method only within specialized sleep laboratory and for the diagnosis of sleep related diseases. If we can monitor sleep nonintrusively without attaching any sensors directly to body surface, it will greatly increase the convenience for the sleep monitoring and widen the application to evaluate the sleep quality in ordinary our daily lives at home.

Sleep is structured with 4-5 cycles sleep stage variation consisted of light sleep, deep sleep and REM sleep. This variation is closely related with the autonomic rhythm of the body during sleep. Since heart rate is also affected by the autonomic nervous system, we are expected to derive information on sleep structure by analyzing the heart rate variation. Heart rate variability parameters which are derived in time and frequency domain as well as in nonlinear domain can be used as a tool to evaluate the balance between sympathetic and parasympathetic rhythms controlled by autonomic nervous system. Several studies reported the results of successful estimation of sleep stages based on the characteristics of heart rate affecting by autonomic nervous system. These studies are mostly done with the ECG whose clear R-peak provides the increased accuracy in the derivation of heart rate. Since ECG generally need electrodes attached to the body surface, it does not fully eliminate the constraints required for non-intrusive measurement. In contrast to ECG, BCG has its own characteristic of non-intrusiveness and we can collect the signal without attaching any sensor directly on body surface. In addition, if BCG is used with ECG, we can drive R-J interval which is closely related with the blood pressure[1]. Based on these characteristics of BCG, we have tried to evaluate the sleep structure by the sleep efficiency, four-level of sleep structure and sleep onset latency.

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II. Methods

A. Subjects

Ten normal subjects (eight males, two females; mean age 38.7 ± 14.6 years) and ten patients with OSA (eight males, two females; mean age 44.2 ± 16.5 years) participated. Of the OSA patients, three had mild symptoms, three had moderate symptoms, and four had severe symptoms

B. BCG measurements

BCG has measured with two kinds of sensors separately for each experiments as in Figure 1. Loadcells are used by installing under the four legs of the bed[2]. And polyvinylidenefluoride (PVDF) film, another type of sensor, is used by installing it on the mattress.

C. BCG peak detection

BCG peaks have detected by the developed algorithm. Measured BCG was bandpass filtered with 0.5~35Hz. Time with the maximum value in amplitude within 1/5 of beat interval from maximum positive slope is detected as the peak.

III. Sleep Parameter Estimation

A. Nocturnal awakening and sleep efficiency

While heart rate is affected both by multiple external stimuli and internal rhythm during the daytime activities, internal rhythm caused by autonomous system is dominating during sleep in contrast to weakened external stimuli during the sleep. This mechanism suggests the possibility for the detection of

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nocturnal sleep awakening based on heart rate variation. For each of 30sec epoch whether the subject is awake or in sleep is determined following rules[3].

- If the body movements are dominated so that BCG cannot be measured more than 15 sec, the epoch is estimated as the "awake" epoch.
- If the heart rate is higher than the threshold based on the average of last three minutes consecutively for more than 15sec, this epoch is also considered as the awake epoch.
- So, if the heart rate is lower than threshold more than 15sec out of 30sec epoch, or period of higher heart rate is not consecutive for 15 sec, epochs are considered as "sleep".

Based on the awakening epochs, sleep efficiency is calculated as in (1).

$$\text{Sleep efficiency} = \text{time in sleep} / \text{time in bed} \quad (1)$$

Estimated results are compared with the results obtained by standard clinical polysomnography.

B. REM sleep detection

During the REM sleep, which is the period of dreaming sleep, fluctuation of biological rhythms are increased and become irregular due to the increased sympathetic tone while parasympathetic tone is decreased[12]. This change can be detected by heart rate variability parameters. We have compared mean heart rate, standard deviation of the heart rate, alpha value of detrended fluctuation analysis(DFA) of heart rate calculated for each epoch with the moving threshold calculated from smoothed value of each parameter over ten epochs. If all of these three parameters score higher values than each of corresponding thresholds, we regarded the epoch as the REM epoch.[2]

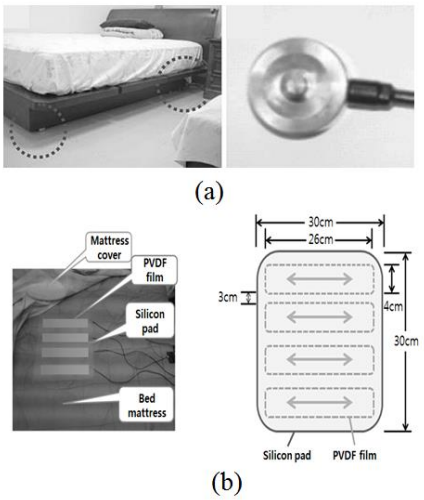

Figure 1. BCG measurements. (a) with loadcells under the bed, (b) with PVDF film on the mattress.

C. Slow wave sleep detection

During the slow wave sleep, which is the deepest sleep stage, slow waves of lower frequencies are dominating in EEG caused by the increased parasympathetic tone and decreased sympathetic tone. This effect is also reflected in heart rate variation and it shows slower and more regular pattern compared with the other sleep stages. Among 20 possible heart rate variability parameters, we have selected four parameters reflecting the changes of autonomic tone by preliminary analysis. These parameters are the alpha value of DFA, low frequency to high frequency ratio(LF/HF), standard deviation of heart interval(SDANN) and correlation of heart rate series with its shifted version(rRR). If all of these four parameters scored lower values than threshold calculated from ten epoch average of these parameters, we regarded the epoch as a period of slow wave sleep.

D. Sleep onset latency

Heart rate is also in the middle of the baroreflex control for the blood pressure by decreasing the heart rate in response to the increased blood pressure. This baroreflex control is more activated upon sleep to maintain blood pressure in lowered level.[4,5,6] Upon this concept, we estimated sleep onset latency which means the elapsed time from time in bed to the time of first any stage of sleep epoch.

We have used BCG to estimate blood pressure equivalent parameter, R-J interval, together with ECG in this case. R-J interval, similarly with pulse arrival time(PAT) calculated from ECG and PPG, is negatively correlated with blood pressure variation. So if we can detect the time when the correlation changes between heart beat interval from ECG (or from BCG) and R-J interval, we can detect the time the subject fall in sleep and estimate the sleep onset latency. First epoch whose correlation fall into negative range is detected as the first sleep epoch and estimated sleep onset latency was compared with the reference[7].

IV. Results

Estimated sleep parameters are compared with the results derived from polysomnographic recording for 20 subjects.

A. Sleep efficiency estimation

Figure 2 shows some example epochs which are detected as awake epoch or sleep epoch. Table 1 show the detection results for the awakening epochs based on heart rate variation. When sleep efficiency has calculated by (1) with the detected awake epochs, sleep efficiency has estimated with $1.08 \pm 0.83\%$ of absolute error for normal subjects and with $1.44 \pm 0.94\%$ of absolute error for subjects having apnea while their sleep efficiency shows $91.0 \pm 0.94\%$ in average.

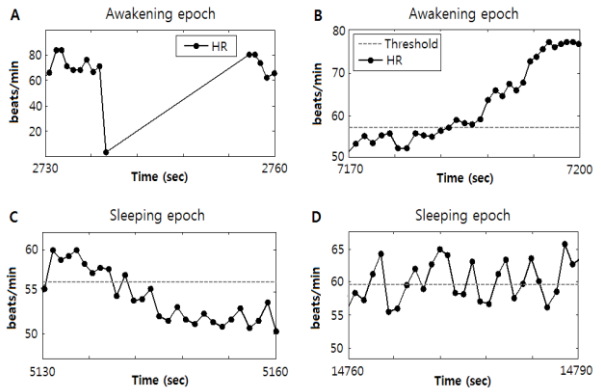

Figure 2 Example epochs detected as awake or sleep

TABLE I. ACCURACY OF AWAKENING EPOCH DETCTION

	Sensitivity	Specificity	Accuracy	Kappa
Normal	85.3±6.6	98.4±1.3	97.4±1.9	0.83±0.08
OSA	85.2±9.7	97.7±1.2	96.5±2.0	0.81±0.09

B. *REM sleep detection*

By comparing fluctuation of three heart rate parameters with smoothed version of each parameter as in Figure 3, REM sleep has estimated with the accuracy of 92.1±1.4% and kappa value of 0.72±0.04 for five normal subjects.

C. *Sleep efficiency estimation*

For the remaining epochs not estimated for REM epoch, we applied the algorithm to separate slow wave sleep from light sleep. The result shows 89.4± 4.2% in total detection accuracy and 0.48±0.08 in kappa value for slow wave sleep detection. Remaining epochs after awake, REM and slow wave sleep detection were considered as light sleep epochs, and the result for light sleep detection was 76.2± 3.4% in accuracy and 0.53±0.21in kappa value.

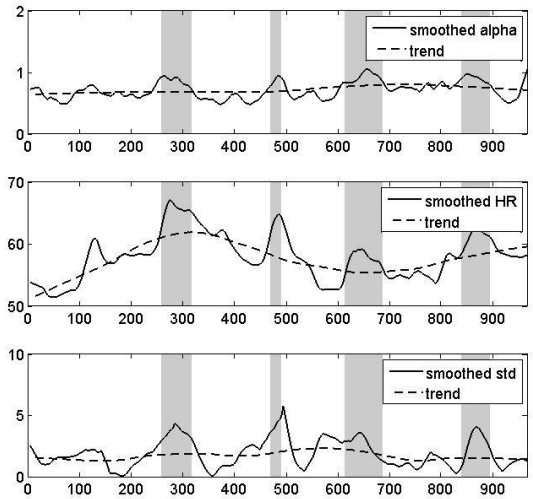

Figure 3 Results of REM sleep detection

D. *Result for four-level sleep stage estimation*

Table II show the summed results combing previous three sleep stage estimation algorithms for four-level sleep stage estimation. The result shows 77.1±3.3% in accuracy and 0.58±0.06 in kappa value. Figure 4 shows one example of estimated hypnogram which shows estimation kappa value 0.64 compared with the corresponding hypnogram derived from polysomnography.

TABLE II. ACCURACY OF FOUR-LEVEL SLEEP STAGE ESTIMATION

		No. of epochs from polysomnography				
		REM	Wake	Light	Deep	Total
Estimated no. of epochs.	REM	287	299	1	3	590
	Wake	186	2350	109	158	2803
	Light	5	56	109	4	174
	Deep	0	140	29	599	768
	Total	478	2845	248	764	4335

E. *Sleep onset latency*

Sleep onset latency was estimated for ten subjects based on the correlation between R-R interval from ECG and R-J interval. As the baroreflex control increases upon sleep, decrease in R-J interval which is compatible with the increase in blood pressure causes the increase of the heart beat interval. Figure 5 show the example of correlation variation around sleep onset. First epoch showing negative correlation is selected as the sleep onset time and the result shows mean absolute error of 0.25 ± 0.35 min in sleep latency estimation for ten subjects.

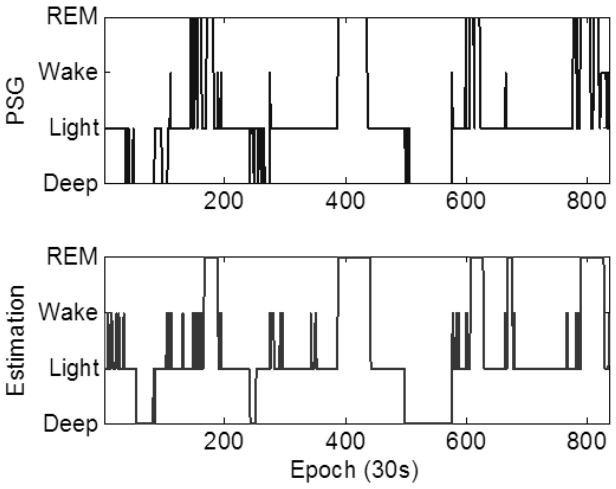

Figure 4 Comparison of estimated hypnogram with the result from polysomnogram

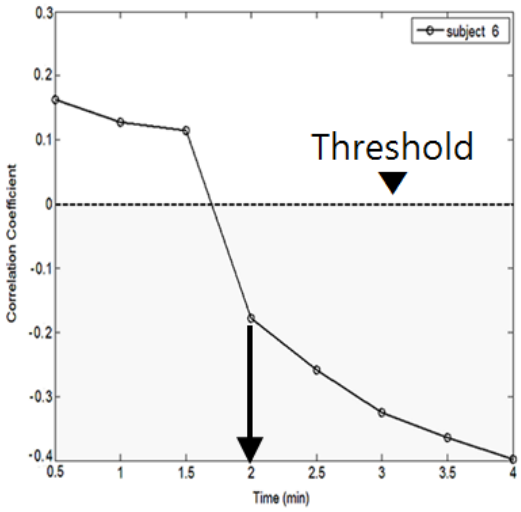

Figure 5 Change in correlation between R-R interval and R-J interval around sleep onset.

V. DISCUSSION

Since heart rate is affected by the sympathetic and parasympathetic rhythms as sleep itself did during sleep, sleep structure estimation based on heart dynamics is easily agreeable. As ECG is the most widely using physiological signal in clinical and research domain, sleep structure estimation using ECG performed in earlier stage than the work done with BCG[8.9]. ECG shows higher SNR and sharper peaks with extended signal bandwidth and it allows increased temporal resolution and shows higher accuracy in equivalent studies. But the use of ECG as a signal for this purpose is constrained by the way that electrodes are attached directly on body surface. Attaching electrodes makes sleep less comfortable and limits the repetitive uses of the method over long period of nights. In this point of view, BCG has great advantage of not attaching sensors directly to the body. Even though the quality of the measured signal is not better than the ECG, the error of most estimated heart rate variability parameters are within acceptable range[10]. So, we can replace the role of ECG with BCG in many applications which is based on heart rate variability with additional advantage of non-intrusiveness of not attaching sensors to the body. When long time of data is required for every day monitoring, BCG is quite suitable. And for the application of ubiquitous healthcare, which extends the role of diagnosis and therapy out of hospital into our daily active life, BCG can take a right role for the non-intrusive monitoring[11]. BCG can appropriately be used for the monitoring of subject's physical and physiological states while they are doing their ordinary activities without concerning the measurement of their signals.

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