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Physiol. Meas. **30** (2009) 1327–1340 doi:10.1088/0967-3334/30/12/003

REM sleep estimation only using respiratory dynamics

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Received 1 March 2009, accepted for publication 2 October 2009
Published 28 October 2009
Online at stacks.iop.org/PM/30/1327

Abstract

Polysomnography (PSG) is currently considered the gold standard for assessing sleep quality. However, the numerous sensors that must be attached to the subject can disturb sleep and limit monitoring to within hospitals and sleep clinics. If data could be obtained without such constraints, sleep monitoring would be more convenient and could be extended to ordinary homes. During rapid-eye-movement (REM) sleep, respiration rate and variability are known to be greater than in other sleep stages. Hence, we calculated the average rate and variability of respiration in an epoch (30 s) by applying appropriate smoothing algorithms. Increased and irregular respiratory patterns during REM sleep were extracted using adaptive and linear thresholds. When both parameters simultaneously showed higher values than the thresholds, the epochs were assumed to belong to REM sleep. Thermocouples and piezoelectric-type belts were used to acquire respiratory signals. Thirteen healthy adults and nine obstructive sleep apnea (OSA) patients participated in this study. Kappa statistics showed a substantial agreement ($\kappa > 0.60$) between the standard and respiration-based methods. One-way ANOVA analysis showed no significant difference between the techniques for total REM sleep. This approach can also be applied to the non-intrusive measurement of respiration signals, making it possible to automatically detect REM sleep without disturbing the subject.

Keywords: REM sleep, respiratory physiology, sleep stage estimation, automatic detection

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1. Introduction

Polysomnography (PSG) is currently the conventional method used to evaluate sleep structure and sleep quality. In Rechtschaffen and Kales' criteria (1968), sleep is classified into six stages: wakefulness, rapid-eye-movement (REM) sleep and stages 1–4. To determine the sleep stages, at least three kinds of electrophysiological signals must be assessed: electroencephalograms (EEG), electrooculograms (EOG) and electromyograms (EMG). Electrodes and sensors are attached directly to the body to obtain the necessary measurements, which can affect sleep quality and sleep structure. Moreover, specialists are needed to attach the electrodes and sensors at precise spots on the body and check for special events during sleep. These constraints limit sleep monitoring to hospitals and sleep clinics and largely prevent sleep monitoring outside of hospitals. If data could be obtained in a less intrusive manner, sleep monitoring would become more convenient and perhaps be performed in an ordinary home. To be able to continuously monitor patients' sleep patterns and observe responses to treatments is an important issue. Thus, many researchers have tried to non-intrusively obtain sleep recordings from patients for a whole night of sleep (Johnson *et al* 2007, Watanabe and Watanabe 2004, Chen *et al* 2008).

Since various unconstrained methods have been introduced to obtain cardiopulmonary signals in home healthcare environments, automatic detection of REM sleep with cardiopulmonary data is likely to contribute to progress in sleep medicine and improve health management at home. The static charge-sensitive bed (SCSB) is a well-known contact-free measurement system used to measure heart rates and respiratory fluctuations (Alihanka *et al* 1981, Kirjavainen *et al* 1996). Kirjavainen *et al* (1996) suggested respiration and body movements as useful indicators of different sleep stages in young children when using SCSB. By using an air mattress as a non-intrusive measurement system, Watanabe and Watanabe (2004) estimated sleep stages in adult subjects using cardiopulmonary information. Several different devices have been suggested for the non-intrusive monitoring of heart rate and respiration, such as pillow-type sensors (Chen *et al* 2005), optical sensors (Brink *et al* 2006) and electromechanical films (EMFi) (Akhbardeh *et al* 2007). Respiration and heart rate are attractive parameters for estimating sleep stages without disturbing sleep.

Sympathetic and parasympathetic nervous system activities, which are largely reflected by variations in heart and respiratory rates, are highly correlated to sleep stages (Shinar *et al* 2006, Ako *et al* 2003, Versace *et al* 2003). In REM sleep, due to the sharp increase in sympathetic activation, irregular and rapid respiratory patterns are easily detected relative to non-REM sleep (Kantelhardt *et al* 2003, Orem 1994, Phillipson 1978). When the sleep stage shifts from non-REM to REM sleep, the tidal lung volume decreases and the respiratory frequency and variability increase. Moreover, apnea or hypopnea due to sleep-related breathing disorders is more frequent in REM sleep because of the irregularity in breathing (Findley *et al* 1985, Okabe *et al* 1994).

In addition to the difference of respiratory physiology between REM and non-REM sleep, the function of REM sleep has been considered as different from that of non-REM sleep. Karni *et al* (1994) showed that memory consolidation is strongly dependent on REM sleep and Marks *et al* (1995) showed that brain maturation is related to the amount of REM sleep. Moreover, some sleep-related disorders are associated with REM sleep. REM sleep-dependent OSA (Kass *et al* 1996), nightmare and REM sleep behavior disorder (Schenck and Mahowald 1996) occur predominantly in REM sleep. For these reasons, estimation for the onset and duration of REM sleep is important not only for the scientific investigation, but also for the clinical evaluation of sleep-related disorders.

Table 1. Sleep characteristics of subjects.

	Normal	OSA
Gender (male/female)	8/5	7/2
Age (mean ± SD)	26.7 ± 2.45	25.4 ± 2.51
Total sleep time (min)	421.9 ± 52.40	455.3 ± 38.57
Sleep efficiency (%)	91.2 ± 0.08	92.9 ± 0.07
Total REM sleep (%)	19.4 ± 4.04	18.4 ± 3.75
REM latency (min)	109.7 ± 73.97	100.9 ± 52.58
Wake after sleep onset (%)	10.0 ± 8.56	8.0 ± 6.55
AHI (events h^{-1})	0.5 ± 0.81	16.9 ± 16.75*

AHI, apnea hypopnea index.
* Significant difference between normal and OSA patient ($p < 0.05$).

In this study, based on respiratory dynamics, we aimed to discriminate between REM and non-REM sleep using only respiration signals. We assessed REM sleep by measuring the respiration rate and variability with thermocouples and a piezoelectric-type belt attached to the body of subjects. We performed this technique on healthy adults and patients with obstructive sleep apnea (OSA). The findings of this study have implications for understanding the potential of respiration-based REM sleep detection methods using non-intrusive sensors, such as air mattresses, load cells and EMFi.

2. Methods

2.1. Subjects

Thirteen healthy adults (eight males and five females; mean age: 26.7 ± 2.45) and nine OSA patients (seven males and two females; mean age: 25.4 ± 2.51) participated in this study (table 1). The healthy subjects had no clinical sleep disorders and were not taking any medication. Table 1 shows sleep parameters related to REM sleep and respiration. There were no significant differences between the groups in any of the parameters excluding the apnea–hypopnea index (AHI) ($p < 0.05$).

2.2. Polysomnographic recording

PSG over a whole night was conducted in each subject without first night adaptation for comparison. Fifteen channels of data were collected following the standard PSG routine: EEGs at the C3-A2 and O2-A1 positions, bilateral EOGs, three EMGs for the chin and anterior tibialis muscles, an electrocardiogram (ECG) at lead II, oro-nasal airflow with a thermocouple, abdominal and thoracic volume changes with piezoelectric-type belts, body position, snoring with a microphone and blood oxygen saturation (SpO_2). All channels were recorded with a Grass model 15LT amplifier (Grass Telefactor, USA) and collected using a digital computer system equipped with an analog-to-digital converter (NI PCI-6014, National Instruments, USA) and self-developed software (Xomnia 2005). PSG data were scored by experts at the Seoul National University Hospital according to the criteria developed by Rechtschaffen and Kales.

Table 2. Parameters and thresholds to estimate REM sleep.

Parameters	Description
(1) Mean respiration rate	Mean respiration rate in an epoch (30 s) obtained by the autocorrelation method
(2) Smoothed rate	Smoothed value of (1) with 30 spans (900 s)
(3) Absolute variance of rate	Absolute value of ((1)–(2))
(4) Smoothed absolute variance	Smoothed value of (3) with 30 spans (900 s)
	Thresholds
(5) Linear threshold	Mean value of (4) for all normal subjects during Non-REM sleep (0.4)
(6) Adaptive threshold 1	Smoothed value of (1) with 300 spans (9000 s) + (5)
(7) Adaptive threshold 2	Smoothed value of (3) with 300 spans (9000 s)

2.3. Analysis of respiration rate

Of the 15 channels of recordings obtained via PSG, we used the two channels representing respiration. The first channel involved placing a thermocouple near the nose or mouth, while the other channel was related to changes in volume of the abdomen or thorax. A thermocouple in the nose is the most reliable sensor for obtaining a clear respiration rate. However, during OSA events, the belt sensor and thermocouple have different waveform shapes because the thorax and abdomen still have respiratory efforts. To validate the robustness of the proposed algorithm, we used both thermocouple and belt-type sensors. Changes in volume were more apparent for the thorax than the abdomen in most participants, with the exception of two subjects. For these two subjects, we used abdominal respiratory effort data.

Table 2 shows an explanation of the parameters and thresholds used to estimate REM sleep in the proposed algorithm. The proposed algorithm determined REM sleep to occur when the following three conditions were satisfied simultaneously:

- *Condition 1:* Smoothed rate > Adaptive threshold 1
- *Condition 2:* Smoothed absolute variance > Linear threshold
- *Condition 3:* Smoothed absolute variance > Adaptive threshold 2.

2.3.1. Estimation of respiration rate. Since the respiration signal is highly susceptible to external noise interference, determining the breath-by-breath rate can be very problematic. Thus, we determined the average rate of an epoch (30 s) by using an autocorrelation method (Jones *et al* 2006):

$$R_{xx}(\tau) = \frac{1}{N}\sum_{m=0}^{N-\tau-1} s[m]s[m+\tau], \tag{1}$$

where s, τ and N denote the breathing signal, time delay and total number of samples in an epoch, respectively. Autocorrelation, calculated from the raw respiration signal, fluctuates periodically with an average respiration interval. Following the detection of the first peak, the average respiratory rate was determined using the following formula:

$$f_{\text{rate}} = \frac{f_s}{\tau_{\text{peak}}}, \tag{2}$$

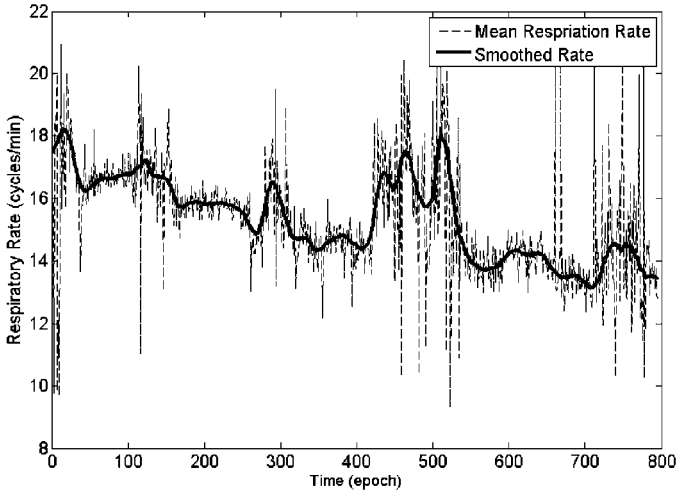

Figure 1. Mean respiration rate and smoothed rate during a whole night sleep. Mean respiration rate in each epoch was obtained using the autocorrelation method, and smoothed rate was estimated using weighted linear regression.

where τ_{peak} represents the delay of the first peak, and f_s and f_{rate} denote the sampling and estimated respiratory rates, respectively.

2.3.2. Analysis of respiration variance. Using rates obtained by the autocorrelation method, we extracted the variance in respiration rates. To extract the parameter representing variance in respiration, we first estimated the smoothed respiration rate over a wide range of epochs. Of the smoothing methods available in MATLAB (Mathworks, version 7.6), we used *rlowess* to adequately represent the changing pattern in respiration rate; *rlowess* stands for 'robust locally weighted scatterplot smoothing', which is a method for smoothing a scatterplot (Cleveland 1979). This method is a type of weighted linear least-squares regression:

$$S = \sum_{i=1}^{M} W_{ii} r_i^2, \tag{3}$$

where W is a weight matrix and r is the average respiratory rate (figure 1).

Second, the variance in respiration was determined by subtracting the smoothed respiration rate from the mean respiration rate; the absolute value was then taken. Finally, to estimate the overall pattern in the respiration variance, further smoothing was performed (figure 2). With regard to the window size for smoothing, 30 spans of epochs were chosen as optimal durations for both applications.

2.3.3. Threshold level. To detect abrupt changes in respiration dynamics during REM sleep, setting up an adaptive threshold is necessary. To determine the adaptive threshold, we smoothed the data with spans ten times larger than the optimal duration—i.e. 300 epochs—selected for representing the rate and variance of respiration (smoothed rate and smoothed absolute variance). To detect abrupt increases in respiration rate during REM sleep, the adaptive threshold line (adaptive threshold 1) was used as shown in figure 3. To detect increases in irregular patterns in respiration rate during REM sleep, two threshold lines were

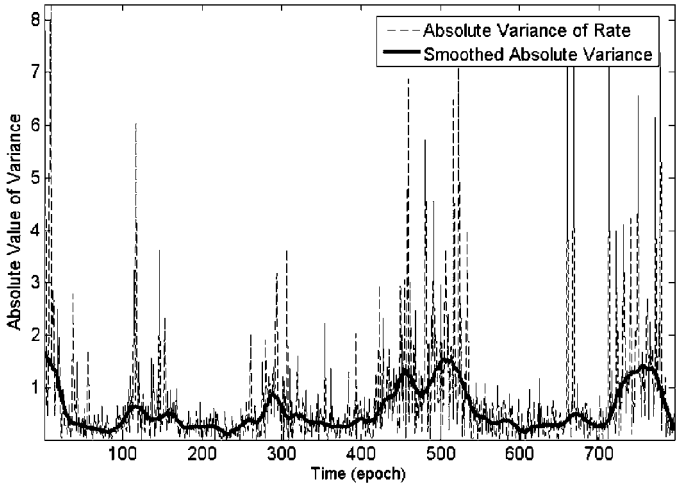

Figure 2. Absolute variance of rate and smoothed absolute variance. Absolute variance of rate refers to the absolute value obtained following subtraction of the smoothed rate from mean respiration rate. Smoothed absolute variance was also obtained using weighted linear regression.

employed. The first threshold line was the adaptive threshold line (adaptive threshold 2) shown in figure 2, which was applied in the same manner as adaptive threshold 1. The second threshold line was the constant threshold level determined by averaging the smoothed absolute variance during non-REM sleep for normal subjects. The value of the constant threshold level was 0.4 cycles min^{-1}; this value was used as the offset level and added to adaptive threshold 1 to determine the increased respiration rate, as shown in figure 3. The linear threshold was introduced to reduce the incidence of false positive epochs since estimation using only adaptive lines resulted in the detection of REM sleep even when no REM sleep periods occurred during the whole night. The threshold lines are shown in figures 3 and 4. The transparent gray regions indicate REM sleep periods scored by a sleep expert.

2.3.4. Determination of REM sleep. By subtracting the three threshold levels from each trend pattern, we defined the following function:

$$\hat{y}(i) = \begin{cases} 1, & y(i) > 0 \\ 0, & \text{otherwise,} \end{cases} \tag{4}$$

where $\widehat{y}(i) = y_{\text{parameter}}(i) - y_{\text{threshold}}(i)$, i.e. subtraction of the threshold level from the average respiration rate trend or the trend for disturbance of respiration at the ith epoch. By applying three threshold levels, three $y(i)$ functions can be obtained. Finally, we determined REM sleep periods when all three functions simultaneously had a value of 1 after examination of multiplied results for each epoch:

$$\dot{y}(i) = y_1(i) \cdot y_2(i) \cdot y_3(i), \tag{5}$$

where $y_1(i)$, $y_2(i)$and $y_3(i)$ represent the subtraction of adaptive threshold 1 from the smoothed rate, subtraction of adaptive threshold 2 from the smoothed absolute variance and subtraction of the linear threshold from the smoothed absolute variance, respectively. If $\dot{y}(i) = 1$ for each epoch, these epochs represent REM sleep due to increased respiration rate and disturbance.

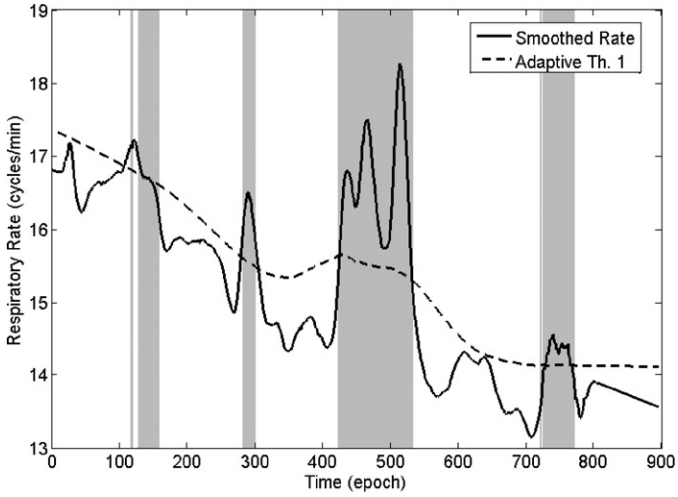

Figure 3. Smoothed rate and adaptive threshold 1. Gray regions indicate REM sleep epochs scored by a sleep expert. The adaptive threshold 1 was obtained using a smoothing function over 300 epochs, with the offset value (= linear threshold).

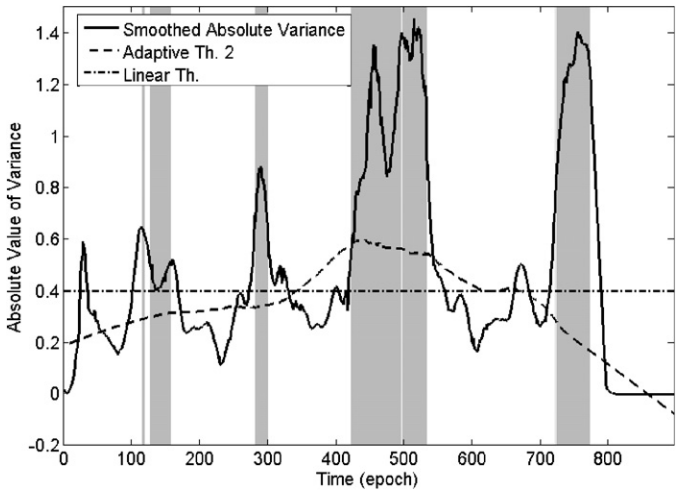

Figure 4. Smoothed absolute variance with two different threshold levels. Gray rectangles indicate REM sleep epochs scored by a sleep expert. Adaptive threshold 2 was obtained using a smoothing function over 300 epochs. A linear threshold level was determined by averaging absolute variance of rate for normal subjects during non-REM sleep periods.

2.4. Statistical analysis

To assess the agreement rate for the sleep stages between standard PSG and outcomes obtained using the proposed algorithm, we used six parameters: positive predictive value [TP/(TP+FP)], negative predictive value [TN/(TN+FN)], sensitivity [TP/(TP+FN)], specificity [TN/(FP+TN)], accuracy [(TP+TN)/Total], F-measure and kappa (κ) statistics. TP and TN denote the number of true positive and true negative epochs, and FP and FN

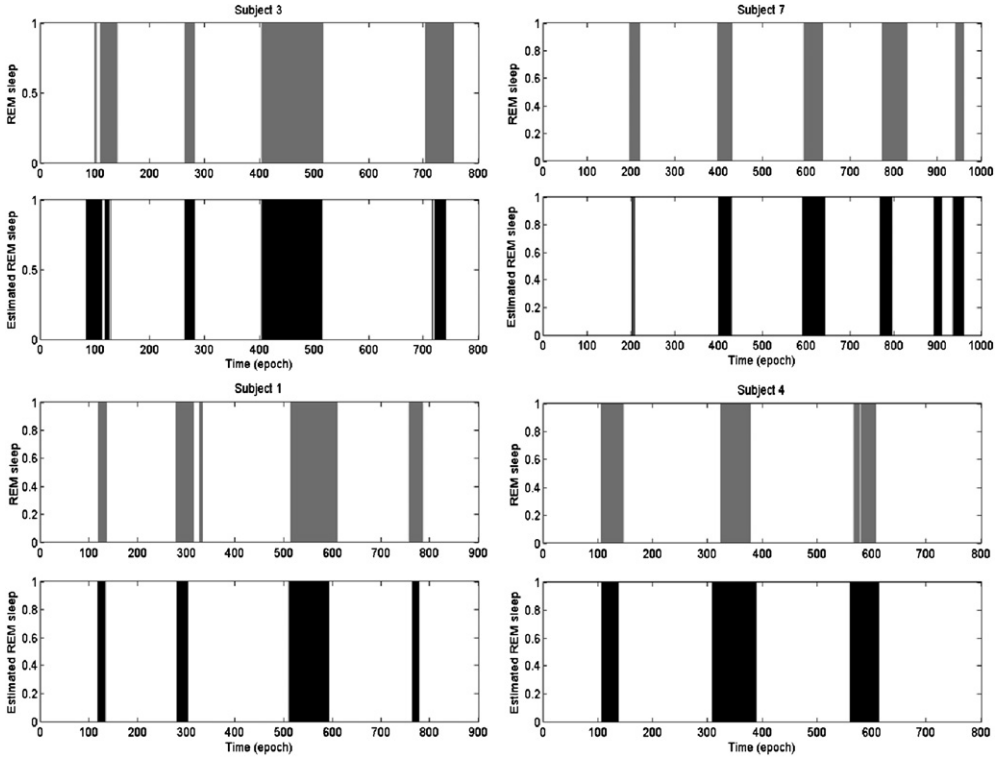

Figure 5. Comparison of visually scored REM sleep with results obtained from estimation using our proposed algorithm. Solid bars indicate REM sleep epochs (subject 3: $\kappa = 0.80$; subject 7: $\kappa = 0.65$; subject 1: $\kappa = 0.78$; subject 4: $\kappa = 0.78$).

correspond to the number of false positive and false negative epochs. The F-measure is the harmonic mean of sensitivity and specificity and ranges from 0 to 1. As the agreement rate between the two systems increases, the F-measure approaches 1. Kappa (κ) statistics are generally used to reveal the goodness-of-fit between the conclusions of two separate raters. According to Viera and Garrett (2005), the proposed method has moderate agreement with the PSG results if κ ranges from 0.41 to 0.60 and substantial agreement if exceeds 0.60. Statistical analyses were performed for a whole night of sleep for each subject. In addition, one-way analysis of variance (ANOVA) was used to assess differences between the modalities (sensors and methods) for total REM sleep.

3. Results

For each subject, we applied our algorithms from the sleep onset to the end of sleep. The total number of sleep epochs processed by our proposed method was 696.9 $\pm$ 111.3 (497–1140) in normal subjects and 908.7 $\pm$ 99.94 (660–970) in OSA patients. Figure 5 shows the scoring results from an expert and the results estimated by our algorithm using thermocouple respiration data. The solid vertical bars indicate REM sleep epochs. The sleep cycles were correctly recognized.

Table 3. Statistical results for normal subjects using respiration measured by a thermocouple.

Subject	SENS	SPEC	PPV	NPV	ACCU	KAPPA	F-measure
S1	0.72	0.99	0.95	0.93	0.93	0.78	0.83
S2	0.83	0.84	0.63	0.94	0.84	0.60	0.84
S3	0.83	0.96	0.88	0.94	0.92	0.80	0.89
S4	0.92	0.93	0.75	0.98	0.93	0.78	0.92
S5	0.63	0.98	0.80	0.95	0.93	0.67	0.77
S6	0.69	0.97	0.89	0.91	0.91	0.72	0.81
S7	0.67	0.95	0.76	0.93	0.90	0.65	0.79
S8	0.60	0.93	0.67	0.91	0.87	0.55	0.73
S9	0.83	0.80	0.53	0.95	0.80	0.52	0.81
S10	0.42	0.96	0.72	0.87	0.85	0.45	0.58
S11	0.89	0.87	0.63	0.97	0.87	0.66	0.88
S12	0.66	0.85	0.51	0.91	0.81	0.46	0.74
S13	0.99	0.91	0.71	0.99	0.92	0.78	0.95
Total	0.74 ± 0.16	0.92 ± 0.06	0.73 ± 0.13	0.94 ± 0.03	0.89 ± 0.05	0.65 ± 0.12	0.81 ± 0.10

SENS (sensitivity), SPEC (specificity), PPV (positive predictive value), NPV (negative predictive value), ACCU (accuracy), Kappa (κ statistic), Total (mean ± SD).

3.1. Thermocouple data

Tables 3 and 4 show statistical results for REM sleep estimation using a thermocouple that measures nasal airflow in normal subjects and OSA patients. The severity is indicated by the degree of AHI (1: < 5; 2: 5–15; 3: 15–30; 4: > 30 (events h^{-1})). The mean values for the kappa statistics showed substantial agreement for normal subjects ($\kappa = 0.65$) and OSA patients ($\kappa = 0.60$). Eight normal subjects and five OSA patients exhibited greater agreement rates ($\kappa > 0.60$). Some study subjects showed an almost perfect agreement rate ($\kappa > 0.80$) between the two methods. In normal subjects, the mean values for sensitivity, specificity, accuracy and the F-measure were 74%, 92%, 89% and 81%, respectively. In OSA patients, the corresponding values were 73%, 91%, 87% and 79%, respectively.

3.2. Belt-type sensor data

Tables 5 and 6 show the results for both study groups obtained by measuring respiration using belt-type sensors at the thorax and abdomen. The results show a slightly lower agreement rate than those obtained using thermocouples. Nevertheless, there was substantial agreement for both normal subjects ($\kappa = 0.62$) and OSA patients ($\kappa = 0.62$). Eight normal subjects and five OSA patients showed greater agreement rates ($\kappa > 0.60$). In normal subjects, the mean values for sensitivity, specificity, accuracy and the F-measure were 72%, 91%, 88% and 79%, respectively. In OSA patients, the corresponding values were 71%, 93%, 89% and 79%, respectively.

3.3. Comparisons of total REM sleep

Figures 6 and 7 show comparisons between the two methods for total REM sleep and REM sleep percentage (total REM sleep/total sleep $\times$ 100). The mean values for total REM sleep scored by an expert were 88.8 and 89.6 min for normal subjects and OSA patients, respectively.

Table 4. Statistical results for OSA subjects using respiration measured by a thermocouple.

Subject (Severity)	SENS	SPEC	PPV	NPV	ACCU	KAPPA	F-measure
S1 (2)	0.43	0.95	0.64	0.88	0.85	0.43	0.59
S2 (2)	0.91	0.96	0.84	0.98	0.95	0.84	0.93
S3 (3)	0.60	0.95	0.82	0.87	0.86	0.61	0.74
S4 (4)	0.64	0.83	0.46	0.92	0.80	0.41	0.73
S5 (4)	0.90	0.78	0.38	0.98	0.80	0.44	0.84
S6 (4)	0.85	0.95	0.76	0.97	0.93	0.76	0.90
S7 (1)	0.83	0.87	0.59	0.96	0.86	0.61	0.85
S8 (1)	0.50	0.98	0.92	0.84	0.85	0.56	0.66
S9 (1)	0.90	0.91	0.73	0.97	0.91	0.75	0.91
Total	0.73 ± 0.19	0.91 ± 0.07	0.68 ± 0.18	0.93 ± 0.05	0.87 ± 0.05	0.60 ± 0.16	0.79 ± 0.12

Severity (degree of AHI, OSA is severest in '4'), SENS (sensitivity), SPEC (specificity), PPV (positive predictive value), NPV (negative predictive value), ACCU (accuracy), Kappa (κ statistic), Total (mean ± SD).

Table 5. Statistical results for normal subjects using respiration measured by a belt-type sensor.

Subject	SENS	SPEC	PPV	NPV	ACCU	KAPPA	F-measure
S1	0.71	0.99	0.94	0.93	0.93	0.77	0.83
S2	0.84	0.84	0.64	0.94	0.84	0.62	0.84
S3	0.67	0.95	0.87	0.88	0.87	0.66	0.79
S4	0.92	0.94	0.78	0.98	0.94	0.80	0.93
S5	0.55	0.95	0.61	0.94	0.90	0.52	0.70
S6	0.66	0.97	0.86	0.90	0.89	0.68	0.78
S7	0.68	0.98	0.88	0.93	0.93	0.73	0.81
S8	0.52	0.91	0.58	0.89	0.84	0.45	0.66
S9	0.83	0.74	0.47	0.94	0.76	0.44	0.78
S10	0.40	0.96	0.72	0.87	0.85	0.43	0.57
S11	0.89	0.87	0.62	0.97	0.87	0.65	0.88
S12	0.67	0.88	0.56	0.92	0.84	0.51	0.76
S13	0.99	0.91	0.72	0.99	0.93	0.79	0.95
Total	0.72 ± 0.17	0.91 ± 0.07	0.71 ± 0.15	0.93 ± 0.04	0.88 ± 0.05	0.62 ± 0.14	0.79 ± 0.10

SENS (sensitivity), SPEC (specificity), PPV (positive predictive value), NPV (negative predictive value), ACCU (accuracy), Kappa (κ statistic), Total (mean ± SD).

One-way ANOVA tests showed no significant differences in measurements or methods within each group.

4. Discussion

Overall, the respiration method proposed in this study for REM sleep measurement showed substantial agreement ($\kappa > 0.60$) with the visually scored standard method in both normal

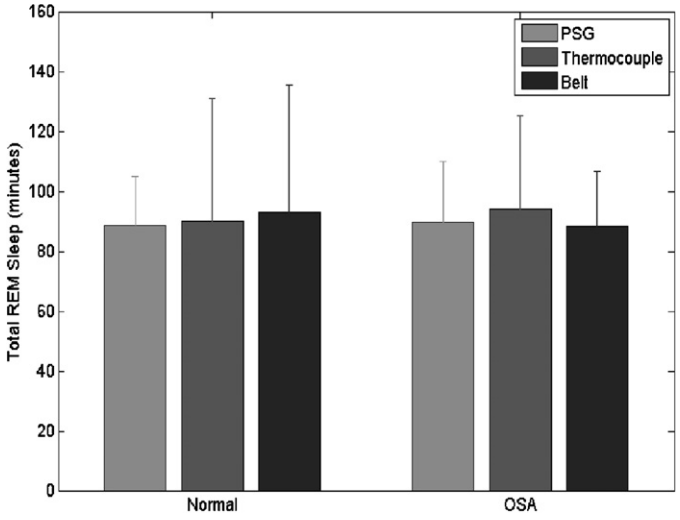

Figure 6. Comparisons for total REM sleep using different measurement acquisition methods. One-way ANOVA did not reveal significant differences within each group.

Table 6. Statistical results for OSA subjects using respiration measured by a belt-type sensor.

Subject (severity)	SENS	SPEC	PPV	NPV	ACCU	KAPPA	F-measure
S1 (2)	0.44	0.97	0.78	0.89	0.87	0.49	0.60
S2 (2)	0.92	0.96	0.84	0.98	0.95	0.84	0.94
S3 (3)	0.62	0.92	0.72	0.87	0.84	0.57	0.74
S4 (4)	0.53	0.88	0.48	0.90	0.82	0.39	0.66
S5 (4)	0.80	0.91	0.58	0.97	0.90	0.61	0.85
S6 (4)	0.83	0.93	0.71	0.96	0.91	0.71	0.88
S7 (1)	0.81	0.91	0.68	0.96	0.89	0.67	0.86
S8 (1)	0.54	0.97	0.85	0.85	0.85	0.57	0.70
S9 (1)	0.88	0.91	0.73	0.97	0.97	0.74	0.90
Total	0.71 ± 0.18	0.93 ± 0.03	0.71 ± 0.12	0.93 ± 0.05	0.89 ± 0.05	0.62 ± 0.14	0.79 ± 0.12

Severity (degree of AHI, OSA is severest in '4'), SENS (sensitivity), SPEC (specificity), PPV (positive predictive value), NPV (negative predictive value), ACCU (accuracy), Kappa (κ statistic), Total (mean $\pm$ SD).

subjects and OSA patients. In normal subjects, using the thermocouple signal for estimating REM sleep periods showed a greater agreement rate than using the belt-type sensor. This may be due to prominent waveform peaks during inspiratory and expiratory phases, which help to accurately establish the frequency of respiration. However, no significant differences were found between the results obtained using the two types of respiration recordings. In contrast, in OSA patients, the mean agreement rate with PSG data using belt-type sensor data was greater than that for thermocouple data. Generally, disruptions in breathing related to sleep disorders are more frequent during non-REM phases. During sleep apnea or hypopnea intervals, nasal

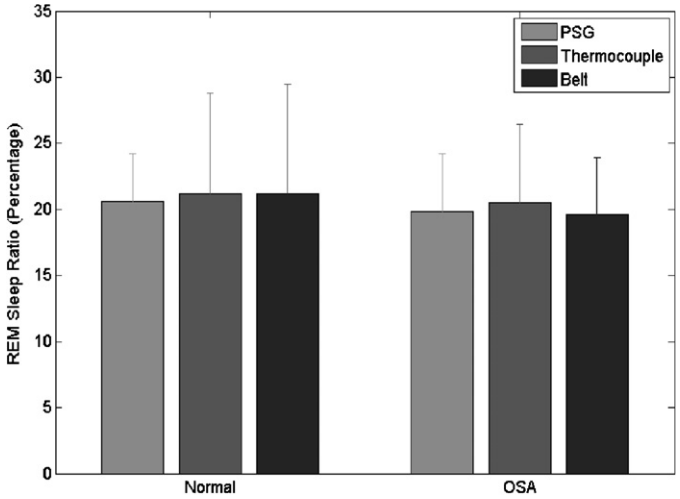

Figure 7. Comparisons for REM sleep. One-way ANOVA did not reveal significant differences within each group.

airflow waveforms are flat; however, thoracic and abdominal respiratory efforts can still be detected by the sensor, and waveforms continue to fluctuate according to respiratory effort. Thus, disturbances in respiration rate measured using the belt-type sensor in REM sleep are detected with greater sensitivity in OSA patients, and there is a closer rate of agreement to measurements obtained by PSG. No statistically significant differences were detected, however, between the measurements obtained using the belt-type sensor and nasal airflow signals.

When comparing the results for normal subjects and OSA patients, the average agreement rate was found to be greater for the normal subjects. This may be due to the unstable nature of the respiratory signals in OSA patients, making it more difficult to robustly extract the respiratory rate. However, the proposed method still showed substantial agreement with PSG-based methods in OSA patients. In the κ statistic test, no significant differences were found between normal subjects and OSA patients. This demonstrates that the method is applicable to OSA patients. Originally, the method was assumed to be inadequate for individuals suffering from sleep-related breathing disorders since it is a respiratory-based scoring method. From this point of view, our results are extremely meaningful, as they show that the accuracy of the scoring method is not affected by the severity of AHI. Some research on sleep stage estimation with cardiorespiratory signals was mainly based on subject-dependent training methods and used more than two signals: ECG, respiration and ECG-derived respiration (EDR) (Redmond *et al* 2007, Redmond and Heneghan 2006, Karlen *et al* 2009). However, the proposed algorithm uses only respiratory physiology during REM sleep, which has higher irregularity and frequency in respiration. With no training classifier except for a simple threshold method, the results show that the proposed method is enough to estimate REM sleep, especially for normal subjects. Since respiration signals are easily obtained without attaching electrodes, the results suggest the method's applicability to non-invasive measurement systems.

Although the proposed methodology exhibits high concordance with PSG, further improvements are needed. The smoothing methods described here to determine the threshold level can potentially increase the error rate, especially during short-term REM periods. Although it is useful to establish changes for respiration rates, if REM sleep is maintained only momentarily (for example, less than five epochs), then these periods are likely to be missed. In

other words, this algorithm is more suitable for detecting REM sleep maintained over a longer term. By using other types of information that can also be measured non-intrusively—such as movement activity and heart rate—we expect to be able to substantially reduce such estimation errors. Further validations are still required for patients with other sleep disorders.

In future work, our final goal is to discriminate sleep stages as wakefulness, light, deep and REM sleep without attaching any sensors. Data which can be measured with non-intrusive methods, such as heartbeats, activity and respiration, are good candidates for providing information to enable such discrimination. Although the respiration data used in this study were obtained by attaching sensors, this study shows the possibility of discriminating sleep stages using these signals.

5. Conclusion

In this study, we used just one signal, the respiration rate, to estimate REM sleep. It is simple and automatic to deal with only one channel of data. No preliminary training process is required for implementing the algorithm. Our proposed algorithm involves simple computational processes to enable rapid acquisition of results. It is also applicable to non-intrusive sleep monitoring systems by being able to add heart rate and respiration measurements. We expect that if our method is combined with a non-intrusive respiration monitoring system, sleep stage scoring would be possible at home, minimizing sleep disturbances associated with sensors that must be physically attached to the body. By combining additional and supplemental information with the proposed method, we expect more specific sleep stage scoring to be possible. In addition, our method would provide meaningful information to enhance automatic assessment of sleep stages in sleep laboratories.

Acknowledgments

This study was supported by a grant from the Advanced Biometric Research Center (ABRC) and the Korea Science and Engineering Foundation (KOSEF) and MKE (Ministry of Knowledge Economy), Korea, under the ITRC (Information Technology Research Center) support program supervised by the IITA (Institute of Information Technology Advancement) (IITA-2006-(C1090-0620-0002)).

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