# Nonconstrained Sleep Monitoring System and Algorithms Using Air-Mattress With Balancing Tube Method

Jae Hyuk Shin, Young Joon Chee, Do-Un Jeong, and Kwang Suk Park, Member, IEEE

Abstract—We evaluated the performance of a bed-type sensor system using the air-mattress with balancing tube (AMBT) method to noninvasively monitor the signals of heartbeat, respiration, and events of snoring, sleep apnea and body movement of subject on the system. The proposed system consists of multiple cylindrical air cells, two sensor cells and 18 support cells, and the small physiological signals were measured by the changes in pressure difference between the sensor cells, and the dc component was removed by balancing tube that is connecting the sensor cells. Using newly developed AMBT method, heartbeat, respiration, snoring, and body movement signals were clearly measured. For the concept of a home healthcare system, two automatic processing algorithms were developed: one is to estimate the mean heart and respiration rates for every 30 s, and another one is to detect the snoring, sleep apnea, and body movement events from the measured signals. In the beatto-beat heart rate and breath-by-breath respiration rate analyses, the correlation coefficients of the heart and respiration rates from the proposed AMBT method compared with reference methods, electrocardiogram, and respiration effort signal from piezoelectric belt, were 0.98 (p < 0.01) and 0.96 (p < 0.01), respectively. Sensitivity and positive predictive value (PPV) of the detection algorithm for snoring event were 93%, 96%, for sleep apnea event were 93%, 88%, and for body movement event were 86%, 100%, respectively. These findings support that ABMT method provides an accurate and reliable means to monitor heartbeat, respiration activities and the sleep events during sleep.

*Index Terms*—Air-mattress and balancing tube, heartbeat, non-invasive, respiration, sleep monitoring, snoring detection.

### I. INTRODUCTION

LEEP and sleep-related disorders are related with a large number of human disorders and affect many parts of our daily life. For example, obstructive sleep apnea has been proven to cause systemic hypertension [1], heart failure [2], and

Manuscript received February 8, 2009; revised July 24, 2009. First published October 20, 2009; current version published January 15, 2010. This work was supported by a grant from the Advanced Biometric Research Center, the Korea Science and Engineering Foundation, and the Ministry of Information and Communication under the Information Technology Research Center support program.

- J. H. Shin is with the Interdisciplinary Program on Biomedical Engineering, Seoul National University, Graduate School, Chongno-Ku, Seoul 110-799, Korea (e-mail: russell@bmsil.snu.ac.kr).
- Y. J. Chee is with the Department of Biomedical Engineering, Ulsan University, Ulsan 680-190, Korea (e-mail: yjchee@naver.com).
- D.-U. Jeong is with the Division of Sleep Studies, Department of Neuropsychiatry, Clinical Research Institute, Seoul National University College of Medicine and Hospital, Chongno-Ku, Seoul 110-799, Korea (e-mail: jeongdu@snu.ac.kr).
- K. S. Park is with the Department of Biomedical Engineering, College of Medicine, Seoul National University, Chongno-Ku, Seoul 110-799, Korea (e-mail: kspark@bmsil.snu.ac.kr).

Digital Object Identifier 10.1109/TITB.2009.2034011

myocardial infarction [3]. Deprivation of sleep can induce the impairment of carbohydrate metabolism and endocrine function such as glucose tolerance [4]. Also, quality of life can be influenced by sleep duration [5] or sleep apnea syndrome [6]. Daily monitoring of physiological signals during sleep would be an efficient tool for the prevention and early detection of sleep disorders like snoring, sleep apnea, and periodic limb movement (PLM). However, in a traditional sleep diagnostic method, polysomnography (PSG), usually several adhesive electrodes and sensors are needed to be attached to the subject to acquire physiological signals during sleep [7]. They obstruct the subject's comfortable sleep with wires that connect sensors to the acquisition device. From the practical home healthcare standpoint, a noninvasive or nonconstrained measurement is essential. Many attempts have been made to develop a noninvasive sleep monitoring system. The static-charge-sensitive bed was used to estimate the sleep stage and wakefulness in infants and young children [8], and to detect periodic leg movements during sleep [9]. An inflating mattress and pressure-sensitive sensor [the noninvasive respiratory monitoring system (NIRMS)] was designed to monitor respiratory movements of frail and cognitively impaired subjects during sleep [10]. Also, cardiac activity or pulse rate monitoring was studied using a pressure sensor placed in a pillow [11] and pressure pads on a bed [12]. In spite of these trials, no leading method exists for the nonconstrained measurement of entire sleep activities, respiration, heartbeat, body movement, snoring, and sleep apnea, which is considered to be stable, accurate, and economic.

In a previous study [13], we described an air-mattress with a balancing tube (AMBT) method designed to monitor respiratory and heart beat movements in a nonconstrained manner. Using the air-mattress, a bed-type sensor, signals can be measured over a wide sensor area even though the subject adjusted their body position during sleep. Watanabe et al. [14], [15] also used an air-mattress-type sensor for sleep monitoring. The difference between Watanabe's method and the proposed system is that Watanabe's method uses a one chamber system with an autogain controller (AGC) to remove the dc signal due to subject's weight and body movements. However, the proposed system used a two chamber system connected via a pneumatic resistor that reduces common mode problem in pressure measurements. In addition, the balancing tube is a robust and cost-effective method as it plays the role of a pneumatic high-pass filter to remove dc component of initial pressure from body weight. The tube can also compensate large pressure changes from body motion in a short time without any additional hardware,

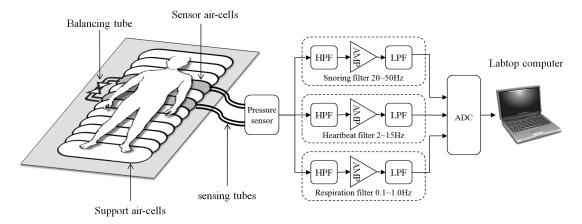


Fig. 1. Overall structure of the measurement system using AMBT method.

e.g., an AGC. Recently, we extended AMBT method to a nonconstrained sleep monitoring system (AMBT system) to monitor additional signals, snoring, sleep apnea, and body movement., and we developed two automatic algorithms to be useful as a practical home healthcare system, which were the estimation algorithm for calculating mean heart and respiration rates and the event detection algorithm for finding snoring, sleep apnea, and body movement.

### II. MEASUREMENT SYSTEM

The proposed AMBT system is composed of an air-mattress and balancing tube, a differential pressure sensor, analog filters, an A/D converter, and a digital processor or a personal computer. Fig. 1 shows the overall structure and individual components of the measurement system.

The air-mattress contains 20 air cells, two of which are sensor air cells (shown gray in Fig. 1) and 18 support air cells (shown white in Fig. 1). Each cell is a cylinder 95 mm in diameter and 1.5 m in width made from polyurethane sheets. The cells were filled with air at 35 mmHg pressure at the beginning of the experiment. When a subject lies on the air mattress, the inflated air cells and compressible characteristics of the air can increase contact area between the body and sensor air cells, increasing the delivery efficiency of small vital signals from the body to the sensor air cells.

In order to increase the sensitivity of the sensor, the differential measurement technique was applied [13]. The pressure difference between two sensor air-cells was measured by the differential pressure sensor (NPC-1210D, GE), which is connecting the sensor cells through sensing tubes in Fig. 1. Very small physiological movements such as the heart beat or snoring vibrations were clearly measured by the differential measurement method. However, the high sensitivity of the sensor air-cells was weak in comparison to the initial pressure due to the body weight or the large pressure difference occurring with the body movements. Therefore, we coupled the two sensor air-cells by a balancing tube with high air resistance in order to make an air passageway between the two sensor air-cells, equalizing the pressure difference between them within a certain time constant when a large pressure difference occurs. Fig. 2(a) shows the

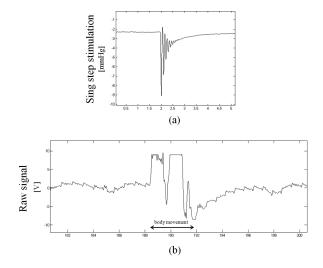


Fig. 2. Equalization of differential pressure by the balancing tube. (a) Step response by dropping 1 kg weight at t=2. (b) Time trace example of removal of the dc component occurred by changing the body position.

pressure response when a single step stimulation was applied to the sensor cells connected with the balancing tube. At  $t=2\,\mathrm{s}$ , 1 kg weight was dropped on one of the sensor cells. The differential pressure was nearly equalized by the balancing tube at t=5.

During the measurement of the differential signal, the balancing tube performs the role of a pneumatic high pass filter to remove the dc component caused by position change. Fig. 2(b) shows a time trace example of the high pass effect of the balancing tube, removing the dc component due to the occurrence of body movement. The role of the balancing tube is similar to an AGC, but the balancing tube guarantees the robustness with high sensitivity and is a low-cost method without the need of an additional hardware unit.

As shown in Fig. 3, the sensing air-cells are positioned under the backside of the thoracic and abdominal area. Even though the patterns of waveforms could be slightly changed according to the contacting position of the sensing air-cells, the heart beat signals and the respiration effort signals can be found from the wide region between the neck and the waist of the subject.

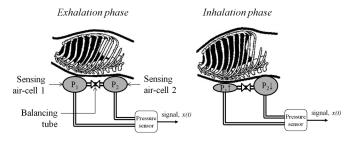


Fig. 3. Example of the located position of the sensor air-cells and an illustration of pressure changes during the inhale and exhale movements.

In a validation experiment, the sensor cells were located on the backside of the chest and abdominal region, where the heart beat signal, as compared with other locations, can be more easily obtained. The respiration signal can be measured by the pressure changes between two sensing cells caused by the inhalation and exhalation movements. Fig. 3 shows alterations of the sensing cells during the inspiration and expiration phases.

The heart beat signal from the AMBT system was a vital sign in the 2–15 Hz frequency range that was caused by the mechanical movement of the heart. This heart beat movement was related with a ballistocardiography (BCG), which is a technique for measuring the force generated from beating heart. The old BCG measurement technique was actively studied in the middle of the twentieth century using a swinging bed or weighted table with light beam slit [16]–[18]. Recently, there are several studies about the BCG measurement according to the longitudinal direction of body with a weighing scale [19]–[21] and with respect to horizontal body position and sleep which is similar to our method [12], [22], [23]. In this paper, we used the airmattress-type sensor system, which was designed to measure the BCG signal with respect to horizontal body position when the subject were lying on the system.

The respiration was measured as periodic signals, having a frequency range of 0.1–1 Hz. The snoring was measured as a vibration signal of the thorax, having a frequency range of 20–50 Hz caused by the subtle oscillation of larynx when a patient snores.

All of these physiological activities, heartbeat, respiration, and snoring, alter the internal pressures of the sensor cells and can be measured by the differential pressure sensor. After the pressure sensor translates the differential pressure into a voltage signal or raw signal, the signal passed through three different types of bandpass filters and amplifiers as illustrated in Fig. 1. Fig. 4(a) shows an example of raw signal, including a heartbeat component, low frequency fluctuations due to respiration, high frequency oscillation due to snoring, body movement, and sleep apnea events. In the filtering stage, the mixed signals were filtered by the fourth-order Butterworth bandpass filters. The cutoff frequencies from 20 to 50 Hz were selected to separate the snoring signal, and the output signal from the snoring filter was named snoring AMBT. The heart beat signal was separated by band pass filter with a frequency range 2-15 Hz, and the output signal from filter was named heartbeat<sub>AMBT</sub>. Finally, the frequency range of 0.1–1 Hz was selected to separate the respiration signal, and the output signal from the filter was

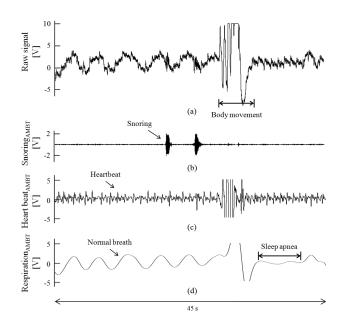


Fig. 4. Time trace example of the output signals from the proposed system. (a) Raw signal with several signal components, e.g., heartbeat, respiration, snoring, body movement, and sleep apnea. (b) Filtered snoring  $_{\rm AMBT}$  signal with two times of snoring events. (c) Filtered heartbeat  $_{\rm AMBT}$  signal with body movement event. (d) Filtered respiration  $_{\rm AMBT}$  signal with sleep apnea event.

named respiration $_{\rm AMBT}$ . Fig. 4(b)–(d) shows the time trace examples of the AMBT signals, snoring $_{\rm AMBT}$ , heartbeat $_{\rm AMBT}$ , and respiration $_{\rm AMBT}$ , respectively, which were filtered from raw signal in Fig. 4(a) with the described bandpass filters.

The snoring, sleep apnea, and body movement occurred occasionally and can be found in snoring  $_{\rm AMBT}$ , respiration  $_{\rm AMBT}$ , and heartbeat  $_{\rm AMBT}$  signals, respectively, therefore, these signals can be referred to as "events." Actually, the body movement causes relatively big pressure changes and has a wide frequency range. Therefore, when it occurs, the output signal of the pressure sensor is temporally saturated, and it can be found in every output terminals of the bandpass filters. In this paper, we used the heartbeat  $_{\rm AMBT}$  signal to detect the body movement events, because the frequency ranges of the heart beat and body movement were almost overlapped.

Finally, the filtered signals are stored in a laptop computer using A/D converters (16-bit digital values with 1 kHz sampling rate) for further analysis.

### III. EXPERIMENTAL VALIDATION

### A. Subjects and Signal Acquisition

A total of 13 healthy male subjects participated in the validation experiment. All subjects had no history of cardiopulmonary diseases, though four of them had suffered from sleep disorders, snoring, and sleep apnea. Mean age was 29 years (standard deviation 5 years, range 23–40 years), with a mean body mass index (BMI) was 22.7 kg·m<sup>-2</sup> (standard deviation 3.3, range 19.5–29.4). The signal validation experiments were performed during the day between 14:00 and 18:00 h, respectively, while the subjects were awake and without any sleep-deprivation.

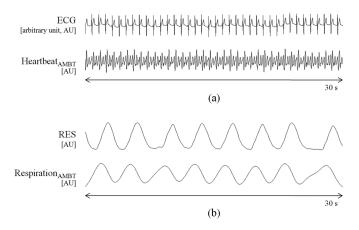


Fig. 5. Examples of the measured heart beat and respiration signals for the validation analysis. (a) ECG (upper) and heartbeat $_{\rm AMBT}$  (lower) signal. (b) Respiration from piezoelectric chest belt (upper) and respiration $_{\rm AMBT}$  (lower) signal.

For signal validation, electrocardiogram (ECG), respiration effort, oronasal airflow, and activity were continuously acquired as reference signals using the MP150 system (Biopac Inc.). Snoring  $_{\rm AMBT}$ , heartbeat  $_{\rm AMBT}$ , and respiration  $_{\rm AMBT}$  from the proposed system were also recorded simultaneously with the reference signals.

For the validation of the heartbeat  $_{\rm AMBT}$  and respiration  $_{\rm AMBT}$  signals, ECG was monitored in the Lead I configuration and the respiration effort signal (RES) was monitored using a chest belt (piezoelectric respiratory effort transducer, TSD201, Biopac Inc.) in the abdominal area for all subjects. Each subject was lying in a supine position on the air-mattress and was instructed to relax and avoid body movements for 5 min. Fig. 5 shows an example of the simultaneously measured ECG and the heartbeat  $_{\rm AMBT}$  signal in (a) and an example of reference chest belt signal and respiration  $_{\rm AMBT}$  signal in (b) for 30 s, respectively.

To validate the detection algorithm for the snoring, sleep apnea, and body movement events, the subjects were instructed to simulate each event on purpose. The reference snoring signals were recorded by an oronasal airflow (ONAF) transducer (SS11A, Biopac) and the simulation was performed five times in the inhalation phase. The snoring signals were collected from the six subjects who had suffered from snoring disorders. The sleep apnea simulation was performed by holding a breath for 10–15 s, with the signal recorded by the piezoelectric chest belt. After each sleep apnea simulation trial, the subject breathed normally for 30 s to make an epoch of normal breathing. Three subjects performed the sleep apnea simulation five times each and total 15 epoch of sleep apnea and 15 epochs of normal epoch were collected. The tri-axial accelerometer (TSD109, Biopac) was used to validate body movement events, and the experimental signal was collected from six subjects. The subjects performed three different body movements, shifting the body position, turning left/right and kicking out their leg according to the instructor's order.

In Fig. 6(a)–(c), the snoring, sleep apnea and body movement events are shown for 60 s, respectively. Five snoring events were

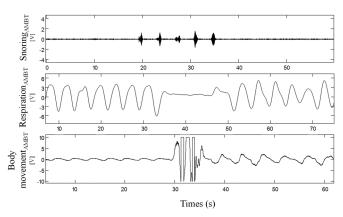


Fig. 6. Examples of the simulated event signals for the event detection algorithm. (a) Snoring event. (b) Sleep apnea event. (c) Body movement event by postural change.

clearly shown in the snoring $_{\rm AMBT}$  signal in Fig. 6(a). The sleep apnea event lasted for about 15 s in the middle segment in the respiration $_{\rm AMBT}$  in Fig. 6(b). In Fig. 6(c), the body movement event occurred by a change in posture of the subject. After the movement, the baseline fluctuation due to respiration was slightly increased, but the range of respiration signal is still within the operating range of the sensor. In this case, the body movement event in Fig. 6(c) was plotted from a raw signal of the AMBT system.

The proposed system was also tested at home for the concept of home healthcare. The AMBT signals were recorded during sleep and the data was processed by the laptop computer after a day of sleep. The test was performed for 7 days by one of the subjects who had a mild snoring disorder and had no cardiovascular disease. The home sleep experiment was performed during the night between 21:00 and 9:00 h, and during the experimental period, the subject was not allowed to drink caffeine or alcohol at night.

## B. Data Analysis and Automatic Algorithm

After the experiments were completed, the signals were manually annotated by human experts to provide a reproducible and comparable performance assessment of the measurement system. For each subject, about 350–450 beat pairs were measured from the ECG and heartbeat<sub>AMBT</sub> and a total of 4840 beat pairs were collected from all subjects. The beat-to-beat instantaneous heart rates and mean heart rates over 30 s were calculated from the R peaks of ECG and annotated fiducial beat points of heartbeat<sub>AMBT</sub> signals. About 65 min of the respirations recorded from the piezoelectric chest belt and AMBT system were analyzed, and exhalation points of each signal were manually annotated to calculate the breath-by-breath respiration rate and mean of respiration rate per 30 s. A total of 919 exhalation points were collected and the instantaneous respiration rates were calculated from both signals.

For the concept of a home healthcare system, the proposed system has to provide reliable cardiopulmonary information without manual annotation or expert's observation. A number of automatic algorithms were already studied to detect heart beat points in ECG signals [24]. However, the noninvasively measured signals, automatic heart beat detection algorithms are still in its early stage of development, therefore, a few studies are available presenting the status quo. The power spectrum analysis technique was used to estimate the SNR and mean heart rate in a noninvasively measured heart beat signal [15], and cross correlation with template method had shown a reliable performance in finding fiducial peak points and estimating the mean heart rates from a ballistocardiogram signal [22]. In this paper, we developed an automatic algorithm based on an auto-correlation function to estimate the mean heart rate and mean respiration rate from signals of the AMBT system. The estimation algorithm was applied to the heartbeat  $_{\rm AMBT}$  and respiration  $_{\rm AMBT}$  signals at every 30 s for all subjects.

Several event detection algorithms were studied in the field of signal processing. An apneic event detection algorithm from signal channel nasal airflow was developed using the mean magnitude of the second derivative [25], and automatic detection of snoring events from snoring sounds was studied using the power spectral features and feed-forward multilayer neural network [26]. In this paper, we used a simple detection algorithm based on a variance analysis with moving window technique. In Fig. 6, the three different types of signals have the events, which make the signals irregular. When the snoring occurs, it produces high frequency oscillations within the snoring period. In the respiration<sub>AMBT</sub> signal, sleep apnea flattens the signal, and in the case of body movement, high pressure changes due to the body movement saturate the signal. The variance operation can be used to isolate these abnormalities and the windowing method was used to localize the event period in the signal.

If a representative sequence of measured signal  $x_t$  is

$$\overbrace{\ldots, x_{t-5}, x_{t-4}, x_{t-3}, x_{t-2}, x_{t-1}, x_t, x_{t+1}, x_{t+2}, x_{t+3}, x_{t+4}, x_{t+5}, \ldots}^{n}$$

where n is a window length. Then, the windowed signal x(t-n/2,t+n/2) is selected with moving window operation. The variance of the windowed signal is defined as

$$P_{t,n} = \operatorname{Var}\left[x\left(t - \frac{n}{2}, t + \frac{n}{2}\right)\right]$$

$$= \sum_{k=-(n/2)}^{n/2} \frac{(x_k - \overline{x})^2}{n} \tag{1}$$

where  $\overline{x}$  is a mean of x(t-n/2, t+n/2) and  $P_{t,n}$  is the variance signal at t with window length n.

After signal  $P_{t,n}$  generation, it was compared with a detection level T to find corresponding events. If  $P_{t,n} > T$ , an event was claimed present for a snoring and body movement signal. If  $P_{t,n} < T$ , an event was claimed present for a sleep apnea signal. The window length n was selected differently for each event because the duration and frequency characteristics of the events were different. The window lengths of 0.5, 3, and 1 s, respectively, were experimentally determined for the snoring, sleep apnea, and body movement events, respectively. Table I summarizes the parameters for the detection algorithm and Fig. 7 shows an example of the snoring detection procedure by the described algorithm. Fig. 7(a) shows an ONAF signal, which is

TABLE I
WINDOW LENGTH AND DETECTION LEVEL OF DETECTION ALGORITHM FOR
THE SNORING, SLEEP APNEA, AND BODY MOVEMENT EVENTS

Event	Window length (sec)	T, threshold level > 0.1		
Snoring	0.5			
Sleep apnea	3	< 0.5		
Body movement	1	> 2		

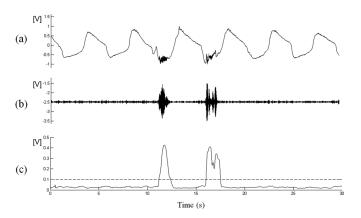


Fig. 7. Procedure of snoring detection algorithm. (a) ONAF signal as a reference signal. (b) Snoring $_{\rm AMBT}$  signal with snoring events. (c) Result of (1) with window length n=0.5 s and detection level T=0.1.

used as the reference signal and Fig. 7(b) shows snoring  $_{\rm AMBT}$  signal with snoring events. Fig. 7(c) shows the result of the variance signal of the snoring  $_{\rm AMBT}$  signal by (1) and detection level T in dashed line. After performing the thresholding operation, the start and end point of the events were found, and the duration of the event was calculated by subtracting time of start point from end point. In the case of sleep apnea, if the duration was less than 10 s, the detected region was neglected by the definition of sleep apnea.

### IV. STATISTICAL ANALYSIS

For the individual subject data, the beat-to-beat heart rate and breath-by-breath respiration rate were analyzed to calculate the mean difference and relative error percentage between the reference methods and the AMBT method. Pearson correlations and Student's t-tests were performed to the individual data to find the relationships between two methods. The same analysis was then repeated using all data from all subjects as a group. Linear regression analysis was used to detect relationships between the overall data, and Bland-Altman plot [27] was used to analyze the overall differences between the heart and respiration rates from the reference methods and proposed AMBT method. We used a p-value < 0.05 as a cutoff for statistical significance. To evaluate the performance of the mean heart and respiration rate estimation algorithm, relative error percentages were calculated from the reference methods with annotation and the AMBT methods with estimation algorithm.

Four describing values were used in the comparison of snoring, sleep apnea, and body movement events between manual

Subject ID	Data length [sec]	Beat-to-beat heart rate			Breath-by-breath respiration rate				
		# of heart beats	difference [mean (SD), beat/min]	error [mean, %]	correlation,	# of breaths	difference [mean (SD), breath/min]	error [mean, %]	correlation,
1	301.21	340	0.54 (0.43)	0.80	0.98	70	0.18 (0.24)	1.3	0.91
2	301.5	296	0.45 (0.36)	0.76	0.99	77	0.37 (0.77)	1.96	0.97
3	301.36	400	0.63 (0.43)	0.79	0.95	104	0.62 (0.53)	2.96	0.93
4	306.86	354	1.43 (1.76)	2.06	0.86	81	0.47 (0.50)	2.83	0.95
5	297.82	381	0.73 (1.28)	0.95	0.95	77	0.90 (1.59)	4.57	0.84
6	301.56	293	0.27 (0.21)	0.45	0.99	89	0.31 (0.36)	1.69	0.96
7	302.66	338	0.68 (0.59)	1.01	0.97	97	0.85 (0.82)	4.15	0.82
8	301.06	314	0.58 (0.53)	0.92	0.98	61	0.48 (0.70)	2.98	0.97
9	301.91	447	0.45 (0.37)	0.71	0.99	83	0.23 (0.34)	1.28	0.99
10	300.90	375	0.38 (0.31)	0.5	0.98	69	0.45 (0.35)	3.21	0.97
11	302.85	352	1.30 (1.54)	1.82	0.94	72	0.30 (0.26)	1.99	0.95
12	300.73	307	1.01 (1.91)	1.38	0.9	50	0.41 (0.37)	4.42	0.85
13	301.61	281	0.34 (0.29)	0.59	0.99	110	0.90 (1.40)	3.74	0.9
Avg.	301.69	344.46	0.68 (0.77)	0.98	0.96	84.92	0.5 (0.63)	2.85	0.92
Std.	1.97	47.81	-	-	-	16.88	-	-	-
Total	3922.03	4478	-	-	-	1104	-	-	-

TABLE II
DIFFERENCE AND CORRELATION OF INSTANTANEOUS HEART RATE AND RESPIRATION RATE

annotation and the detection algorithm as follows:

Sensitivity = true positive/(true positive + false negative)  $\times$  100

Specificity = true negative/(true negative + false positive) × 100

Positive predictive value (PPV) = true positive/(true positive + false positive)  $\times$  100

Negative predictive value (NPV) = true negative/(true negative + false negative)  $\times$  100.

The agreement between the two methods were calculated and quantified by Cohen's kappa [28].

### V. RESULTS

# A. Results of Beat-to-Beat Heart Rate and Breath-by-Breath Respiration Rate

The analysis results for each subject of the beat-to-beat heart rate and breath-by-breath respiration rate are summarized in Table II. The analyzed data were collected from 13 subjects, the total time was approximately 65 min, and the total number of heart beat pairs from both ECG and proposed system was 4478. Total average of mean difference of beat-to-beat heart rate was 0.68beat/min for all subjects, and average of mean error was less than 1%. The average correlation between the ECG and heartbeat<sub>AMBT</sub> signal was 0.96 for the beat-to-beat heart rate.

The overall relationship of the beat-to-beat heart rate in relation to all the heart heartbeat data is presented in the scatter plot of Fig. 8(a). The coefficient of the slopes of the regression line of the overall heart rate from the ECG and heartbeat\_{AMBT} signal was 0.98 with a p-value < 0.01, meaning the heart rate from the proposed system was strongly correlated with the reference method. The Bland–Altman plot in Fig. 8(b) indicates the

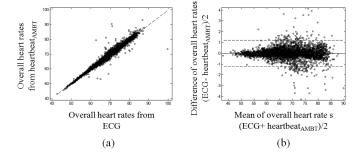


Fig. 8. Results of overall heart rate analysis. (a) Scatter plot by ECG and heartbeat  $_{\rm A\,M\,B\,T}$  signal ( $r=0.98,\,p<0.01$ ). (b) Bland–Altman plot by ECG and heartbeat  $_{\rm A\,M\,B\,T}$  signal.

difference in the instantaneous heart rate obtained by ECG and heartbeat $_{\rm AMBT}$  signal. Most are plotted along a horizontal line, but some are scattered vertically. The mean difference of heart rates was almost zero and the 95% of the heart rate differences were between -1.22 and 1.22beat/min, the confidential interval (CI) of mean difference.

The time length of analyzed respiration data was the same as the heart beat data, but the total number of breaths from RES and respiration  $_{\rm AMBT}$  signal was 1104. The total average of mean difference of breath-by-breath respiration rate was 0.5 breath/min with a relative error of 2.85% and an average correlation of 0.92 between the chest belt and the respiration  $_{\rm AMBT}$  (see Table II).

Fig. 9 shows the relationship of the overall respiration rate between RES and respiration<sub>AMBT</sub> signal. The coefficient of the slopes of the regression line of the scatter plot of Fig. 9(a) was 0.96 with a p-value < 0.01, indicating a significant relationship between the two methods. The 95% of the respiration rate differences were between -0.96 and 0.96 breath/min, the CI of mean difference.

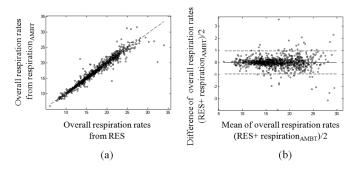


Fig. 9. Results of overall respiration rate analysis. (a) Scatter plot by RES and respiration  $_{\rm A\,M\,B\,T}$  signal ( $r=0.96,\,p<0.01$ ). (b) Bland–Altman plot by RES and respiration  $_{\rm A\,M\,B\,T}$  signal.

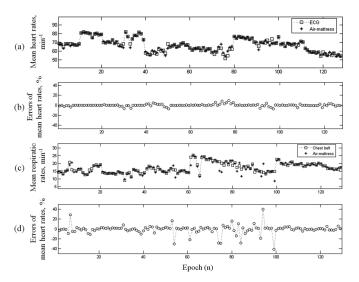


Fig. 10. Estimated results and relative errors of algorithm. (a) Mean of heart rate from the ECG ( $\square$ ) and heartbeat<sub>AMBT</sub> (\*). (b) Relative errors between ECG and heartbeat<sub>AMBT</sub> (c) Mean of respiration rate from RES ( $\square$ ) and respiration<sub>AMBT</sub> (\*). (d) Relative error between RES and respiration<sub>AMBT</sub>.

# B. Heart and Respiration Rates Estimation Algorithm Results

Fig. 10 shows a 65 min profile of estimated mean heart and respiration rate results and relative errors between the auto-correlation of heartbeat\_{AMBT} and respiration\_{AMBT} signals without manual annotation data. The real heart rate ( $\Box$ ) from ECG and estimated heart rate from heartbeat\_{AMBT} (\*) were shown in Fig. 8(a). The relative error percentages of estimated heart rate were shown in Fig. 8(b). It was shown that almost all of the errors for estimated heart rate were within a range of +5%. The real respiration rate ( $\Box$ ) from RES and estimated respiration rate from respiration\_{AMBT} (\*) were shown in Fig. 8(c). The relative error percentages of estimated respiration rate were shown in Fig. 8(d). It is shown that the most of the errors for estimated heart rate were within a range of +10%, but a few were around +30%.

# C. Event Detection Algorithm Results

Table III shows the results of the event detection algorithm for the snoring, sleep apnea, and body movement events. Six subjects with a snoring problem participated in the snoring simulation, and the sensitivity and PPV of the results were 0.93 and

0.96, respectively. Nearly all of the snoring events were detected, but two were missed because the vibrations of the snoring were very weak. Also, one false positive finding occurred due to the noise signal from rough exhalation. The sleep apnea simulation was performed by three subjects and the sensitivity was 0.88 and the PPV was 0.93. The result of the sleep apnea detection has two false negatives, which were neglected as the calculated duration was less than 10 s. The simulated duration of sleep apnea was 10 s, and the variance signal from the detection algorithm was a little less than 10 due to the moving window operation. The body movement simulation was performed by six subjects with a sensitivity of 0.85 and a PPV of 1.00. All of the normal epochs and simulated body movements by shifting or turning the body were correctly classified. However, four kicking leg simulations were not detected due to the weak signal variance. All of the k-values of the detection algorithms were higher than 0.8, which support the usefulness of the method in comparison to the manual annotating for the detection of events.

### D. Home Sleep Monitoring Results

Fig. 11 shows one day results of home sleep monitoring using the AMBT system. The mean heart rate and respiration rate were estimated using the described auto-correlation method, and the snoring, apnea, and body movement were detected by the event detection algorithm. Data of seven and half hours were analyzed, and the results show several body movements, snoring, and sleep apnea events during sleep.

In Fig. 11, the heart rates shows four to five times of very low frequency cycles during the entire sleep, and each cycle has a period about one and half hours. Several times of snoring, sleep apnea, and body movement events were also detected. When body movements occurred, the AMBT signals were saturated and could not be processed to detect the heart rate or event information. The percentage of undetectable epochs due to the body movement was defined as

Undetectable epoch percentage (UEP)

$$= \frac{\text{a number of body movement occurred epochs}}{\text{a total number of epochs}} \times 100(\%).$$
(2)

UEP scores were calculated by (2) for 7 days in Fig. 12. The average UEP score was 7.33% with a standard deviation +1.62%.

### VI. DISCUSSION

In this paper, the potential of the AMBT method as a nonconstrained sleep monitoring system was investigated in conjunction with two automatic algorithms. The balancing tube carried out a role of pneumatic high pass filter to remove the dc component from the body movement and return the changed pressure to the equilibrium state. The performance of the balancing tube was evaluated in the preliminary experiment in Fig. 2, and also tested in the real sleep monitoring experiment in Fig. 11. Although the subject had several body movements, the balancing tube quickly equalized the inner pressures of the sensor air-cells, and prevented signal loss during sleep.

Event	Subject ID	# of epochs	sensitivity	specificity	PPV	NPV	kappa
Snoring	1, 2, 5, 6,7, 8	60	0.93	0.97	0.96	0.94	0.93
Sleep apnea	1, 4, 5	30	0.88	0.93	0.93	0.87	0.85
Body movement	1, 2, 5, 6, 7, 8	60	0.85	1.00	1.00	0.90	0.92

TABLE III
RESULTS OF DETECTION ALGORITHM

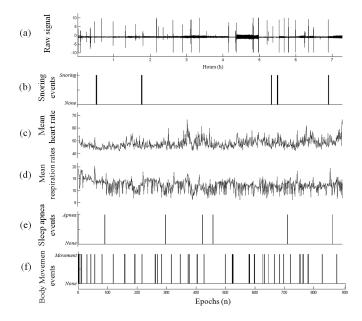


Fig. 11. Result of home sleep analysis using the AMBT system. (a) Raw signal. (b) Detected snoring events. (c) Estimated mean heart rates. (d) Estimated mean respiration rates. (e) Detected sleep apnea events. (f) Detected body movement events.

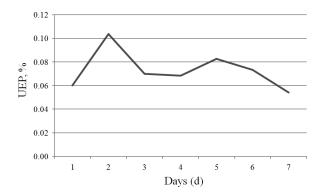


Fig. 12. UEP scores for 7 days.

The measured heartbeat<sub>AMBT</sub> and respiration<sub>AMBT</sub> signals have shown a significantly high correlation with the reference signals (see Table II). Although the beat-to-beat or breath-by-breath analysis showed relatively low correlation coefficients and high errors as in subjects 4, 11, and 12 for instantaneous heart rate, and in subjects 5, 7, and 12, for respiration rate (see Figs. 8 and 9), the overall result shows a significantly high correlation with the reference method (for heart rate r=0.96 with p<0.01, for respiration rate r=0.92 with p<0.01) in average. The relatively low correlation results from some specific subjects were due to the different tendency of the signals among

individuals. Each individual subject has a different height and body weight, and it affected the waveform characteristics of the measured physiological signals. To improve the proposed system with this problem, further study about intersubject analysis with a calibration of the sensor air-cells' position, size, and inner pressure will be needed.

The relative errors between the manually calculated heart rates from the ECG and the estimated heart rates from the proposed algorithm using heartbeat\_{ABMT} were within a range of +5%, meaning that the auto-correlation algorithm was reliable for calculating the mean heart rate in the proposed system. The errors from the respiration rates were higher than those from heart rates with the same methods, but the correlation coefficient between the reference method and proposed method was 0.89 with a p-value < 0.01, meaning the estimated respiration rates using the proposed algorithm has a strong relationship with manually calculated ones.

The event detection algorithm showed reliable results with k-values for snoring (0.93), sleep apnea (0.86), and body movement (0.92) in Table III. The body movement detection showed good results for both PPV and k-value, because when body movement occurs, the signal amplitude increased to the saturation level, therefore, it was easy to find the proper detection level T. However, for snoring and sleep apnea detection, there were a few of false positives due to weak signal level or short event duration for some specific subjects. Although the event detection algorithm showed sufficiently reliable results with PPV and k-value for the snoring and sleep apnea in Table III, the individual calibration of the detection level T and window size n of the detection algorithm is also needed to improve the performance.

It is known that human has sleep cycle that lasts on average 90-110 min in normal adult [29]. During the sleep cycles, the cardiovascular activity changes, and it has a relationship with the sleep stage, the heart rate, and mean blood pressure decrease during the non-REM sleep and increase during the REM sleep or awake [30]. It is also known that sleep onset [31], arousal, and sleep apnea [32] affect the autonomic nervous system, inducing a change in the heart rate and respiration rate. In the home sleep monitoring result, the estimated mean heart rate shows a very long range of fluctuations during the entire sleep period, which is presumed a non-REM and REM sleep cycle. The increased heart rates after snoring or body movement events also indicate cardiovascular activity changes from the sleep disturbance. When body movement occurs, the corrupted signals make it difficult to estimate the mean heart and respiration rates, but the duration of body movements is relatively short to the entire sleep signal (6.02%). In addition, the body movement itself provides important information about the sleep stage,

arousal or awake [33]. As shown in the Fig. 11, the results of home sleep monitoring data shows overall sleep tendency for one night. To be a practical home sleep monitoring system, further study about summarizing the data of weekly or monthly long-term monitoring of sleep, and based on this, algorithm to extract the sleep parameters, time in bed, total sleep time, sleep stages, sleep efficiency and so on, is necessary. Fig. 12 shows a UEP for 7 days. At second night, the subject showed relatively large number of body movements and high UEP score. However, after the subject was getting used on the proposed system, the UEP scores were decreased.

The AMBT method provides an accurate and a reliable means to monitor the cardiopulmonary activity and sleep event during sleep. The proposed system can be valuable to be a home sleep monitoring system and after clinical evaluation and practical feasibility studies, this method is expected to be applicable in the automatic estimation of sleep stages and sleep diseases.

### REFERENCES

- P. Lavie, D. Silverberg, A. Oksenberg, and V. Hoffstein, "Obstructive sleep apnea and hypertension: From correlative to causative relationship," J. Clin. Hypertens. (Greenwich), vol. 3, no. 5, pp. 296–301, Sep.-Oct. 2001
- [2] E. Shahar, C. W. Whitney, S.Redline, E. T. Lee, A. B. Newman, F. Javier Nieto, G. T. O'Connor, L. L. Boland, J. E. Schwartz, and J. M. Samet, "Sleep-disordered breathing and cardiovascular disease: Cross-sectional results of the sleep heart health study," *Amer. J. Respir. Crit. Care Med.*, vol. 163, no. 1, pp. 19–25, Jan. 2001.
- [3] J. Hung, E. G. Whitford, R. W. Parsons, and D. R. Hillman, "Association of sleep apnoea with myocardial infarction in men," *Lancet*, vol. 336, no. 8710, pp. 261–264, Aug. 4, 1990.
- [4] K. Spiegel, R. Leproult, and E. Van Cauter, "Impact of sleep debt on metabolic and endocrine function," *Lancet*, vol. 354, no. 9188, pp. 1435– 1439, Oct. 23, 1999.
- [5] J. A. Groeger, F. R. H. Zijlstra, and D. J. Dijk, "Sleep quantity, sleep difficulties and their perceived consequences in a representative sample of some 2000 British adults," *J. Sleep Res.*, vol. 13, no. 4, pp. 359–371, Dec. 2004.
- [6] P. Moore, W. A. Bardwell, S. Ancoli-Israel, and J. E. Dimsdale, "Association between polysomnographic sleep measures and health-related quality of life in obstructive sleep apnea," *J. Sleep Res.*, vol. 10, no. 4, pp. 303–308, Dec. 2001.
- [7] A. Rechtschaffen and A. Kales, A Manual of Standardized Terminology, Techniques and Scoring System for Sleep Stages of Human Subjects. Los Angeles, CA: Brain Information Service/Brain Research Institute UCLA, 1977
- [8] T. Kirjavainen, D. Cooper, O. Polo, and C. E. Sullivan, "Respiratory and body movements as indicators of sleep stage and wakefulness in infants and young children," *J. Sleep Res.*, vol. 5, no. 3, pp. 186–194, Sep. 1996.
- [9] E. Rauhala, M. Erkinjuntti, and O. Polo, "Detection of periodic leg movements with a static-charge-sensitive bed," *J. Sleep Res.*, vol. 5, no. 4, pp. 246–250, Dec. 1996.
- [10] L. Hernandez, B. Waag, H. Hsiao, and V. Neelon, "A new non-invasive approach for monitoring respiratory movements of sleeping subjects," *Physiol. Meas.*, vol. 16, no. 3, pp. 161–167, Aug. 1995.
- [11] X. Zhu, W. Chen, T. Nemoto, Y. Kanemitsu, K. Kitamura, K. Yamakoshi, and D. Wei, "Real-time monitoring of respiration rhythm and pulse rate during sleep," *IEEE Trans. Biomed. Eng.*, vol. 53, no. 12 pt 1, pp. 2553–2563, Dec. 2006.
- [12] D. C. Mack, J. T. Patrie, P. M. Suratt, R. A. Felder, and M. A. Alwan, "Development and preliminary validation of heart rate and breathing rate detection using a passive, ballistocardiography-based sleep monitoring system," *IEEE Trans. Inf. Technol. Biomed.*, vol. 13, no. 1, pp. 111–120, Jan. 2009.
- [13] Y. Chee, J. Han, J. Youn, and K. Park, "Air mattress sensor system with balancing tube for unconstrained measurement of respiration and heart beat movements," *Physiol. Meas.*, vol. 26, no. 4, pp. 413–422, Aug. 2005.

- [14] T. Watanabe and K. Watanabe, "Noncontact method for sleep stage estimation," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 10, pp. 1735–1748, Oct. 2004.
- [15] K. Watanabe, T. Watanabe, H. Watanabe, H. Ando, T. Ishikawa, and K. Kobayashi, "Noninvasive measurement of heartbeat, respiration, snoring and body movements of a subject in bed via a pneumatic method," *IEEE Trans. Biomed. Eng.*, vol. 52, no. 12, pp. 2100–2107, Dec. 2005.
- [16] I. Starr, O. Horwitz, R. L. Mayock, and E. B. Krumbhaar, "Standardization of the ballistocardiogram by simulation of the heart's function at necropsy; with a clinical method for the estimation of cardiac strength and normal standards for it," *Circulation*, vol. 1, no. 5, pp. 1073–1096, May 1950.
- [17] P. Pollock, "Ballistocardiography: A clinical review," *Can. Med. Assoc. J.*, vol. 76, no. 9, pp. 778–83, May 1, 1957.
- [18] D. C. Deuchar, "Ballistocardiography," Brit Heart J., vol. 29, no. 3, pp. 285–288, May 1967.
- [19] O. T. Inan, M. Etemadi, R. M. Wiard, L. Giovangrandi, and G. T. Kovacs, "Robust ballistocardiogram acquisition for home monitoring," *Physiol. Meas.*, vol. 30, no. 2, pp. 169–185, Feb. 2009.
- [20] R. Gonzalez-Landaeta, O. Casas, and R. Pallas-Areny, "Heart rate detection from an electronic weighing scale," *Physiol. Meas.*, vol. 29, no. 8, pp. 979–988, Aug. 2008.
- [21] J. H. Shin, K. M. Lee, and K. S. Park, "Non-constrained monitoring of systolic blood pressure on a weighing scale," *Physiol. Meas.*, vol. 30, no. 7, pp. 679–693, Jul. 2009.
- [22] B. H. Jansen, B. H. Larson, and K. Shankar, "Monitoring of the ballisto-cardiogram with the static charge sensitive bed," *IEEE Trans. Biomed. Eng.*, vol. 38, no. 8, pp. 748–751, Aug. 1991.
- [23] D. C. Mack, M. Alwan, B. Turner, P. Suratt, and R. A. Felder, "A passive and portable system for monitoring heart rate and detecting sleep apnea and arousals: Preliminary validation," in *Proc. 1st Transdisciplinary Conf. Distrib. Diagn. Home Healthcare (D2H2 2006)*, pp. 51–54.
- [24] B. U. Kohler, C. Hennig, and R. Orglmeister, "The principles of software QRS detection," *IEEE Eng. Med. Biol. Mag.*, vol. 21, no. 1, pp. 42–57, Jan.–Feb. 2002.
- [25] J. Han, H. B. Shin, D. U. Jeong, and K. S. Park, "Detection of apneic events from single channel nasal airflow using 2nd derivative method," *Comput. Methods Programs Biomed.*, vol. 91, no. 3, pp. 199–207, Sep. 2008.
- [26] R. Jane, J. A. Fiza, J. Sola-Soler, S. Blanch, P. Artis, and J. Morera, "Automatic snoring signal analysis in sleep studies," in *Proc. 25th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, 2003, pp. 366–369.
- [27] J. M. Bland and D. G. Altman, "Statistical methods for assessing agreement between two methods of clinical measurement," *Lancet*, vol. 1, no. 8476, pp. 307–310, Feb. 8, 1986.
- [28] H. L. Kundel and M. Polansky, "Measurement of observer agreement," *Radiology*, vol. 228, no. 2, pp. 303–308, Aug. 2003.
- [29] M. A. Carskadon and W. C. Dement, "Distribution of REM sleep on a 90 minute sleep-wake schedule," *Sleep*, vol. 2, no. 3, pp. 309–317, 1980.
- [30] V. K. Somers, M. E. Dyken, A. L. Mark, and F. M. Abboud, "Sympathetic-nerve activity during sleep in normal subjects," *N. Engl. J. Med.*, vol. 328, no. 5, pp. 303–307, Feb. 4, 1993.
- [31] M. J. Carrington, R. Barbieri, I. M. Colrain, K. E. Crowley, Y. Kim, and J. Trinder, "Changes in cardiovascular function during the sleep onset period in young adults," *J. Appl. Physiol.*, vol. 98, no. 2, pp. 468–476, Feb. 2005.
- [32] R. S. Leung and T. D. Bradley, "Sleep apnea and cardiovascular disease," Amer. J Respir. Crit. Care Med., vol. 164, no. 12, pp. 2147–2165, Dec. 15, 2001.
- [33] B. H. Choi, J. W. Seo, J. M. Choi, H. B. Shin, J. Y. Lee, D. U. Jeong, and K. S. Park, "Non-constraining sleep/wake monitoring system using bed actigraphy," *Med. Biol. Eng. Comput.*, vol. 45, no. 1, pp. 107–114, Jan. 2007.



Jae Hyuk Shin was born in Seoul, Korea. He received the B.S. degree in the electrical engineering from the Korea University, Seoul, in 2004. He is currently working toward the Ph.D. degree in Interdisciplinary Program on Biomedical Engineering, Seoul National University, Graduate School, Chongno-Ku, Seoul.

His research interests include biomedical engineering, especially for ubiquitous healthcare devices and noninvasive measurement techniques, e.g., ballistocardiography, noninvasive blood pressure mea-

surement, and nonconstrained sleep monitoring.



Young Joon Chee received the B.S. degree in control and instrumentation, in 1991, and the M.S. and Ph.D. degrees in interdisciplinary program of biomedical engineering from Seoul National University, Seoul, Korea, in 1993 and 2005, respectively.

He is currently a Professor and Head of the Department of Biomedical Engineering, University of Ulsan, Ulsan, Korea.



**Kwang Suk Park** (M'78) was born in Seoul, Korea, in 1957. He received the Ph.D. degree from the Department of Electrical Engineering, Seoul National University, Seoul, in 1985.

He is currently a Professor in the Department of Biomedical Engineering, College of Medicine, Seoul National University. He is also the Director of Advanced Biometric Research Center, Seoul National University. He was engaged in the field of biomedical engineering, especially for biological signal measurements and processing. His current research inter-

est includes ubiquitous healthcare mainly focusing on nonintrusive monitoring of biological signals.



**Do-Un Jeong** received the M.D. and Ph.D. degrees from the Seoul National University, Seoul, Korea, in 1976 and 1988, respectively.

He is currently a Professor of psychiatry in the Division of Sleep Studies, Department of Neuropsychiatry, Clinical Research Institute and a Director of the Center for Sleep and Chronobiology, College of Medicine and Hospital, Seoul National University.

Dr. Jeong is the President-Elect of the Korean Society of Medical and Biological Engineering as well as President of Korean Academy of Sleep Medicine

formerly and presently Vice President of the Asian Sleep Research Society.