Estimation of respiration rate and sleeping position using a wearable accelerometer

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***Abstract*—Wearable inertial sensors offer the possibility to monitor sleeping position and respiration rate during sleep, enabling a comfortable and low-cost method to remotely monitor patients. Novel methods to estimate respiration rate and position during sleep using accelerometer data are presented, with algorithm performance examined for two sensor locations, and accelerometer-derived respiration rate compared across sleeping positions. Eleven participants (9 male; aged: 47.82±14.14 years; BMI 30.9±5.27 kg/m^2; AHI 5.77±4.18) undergoing a scheduled clinical polysomnography (PSG) wore a tri-axial accelerometer on their chest and upper abdomen. PSG cannula flow and position data were used as benchmark data for respiration rate (breaths per minute, bpm) and position. Sleeping position was classified using logistic regression, with features derived from filtered acceleration and orientation. Accelerometer-derived respiration rate was estimated for 30 s epochs using an adaptive peak detection algorithm which combined filtered acceleration and orientation data to identify individual breaths. Sensor-derived and PSG respiration rates were then compared. Mean absolute error (MAE) in respiration rate did not vary between sensor locations (abdomen: 1.67±0.37 bpm; chest: 1.89±0.53 bpm; p=0.52), while reduced MAE was observed when participants lay on their side (1.58±0.54 bpm) compared to supine (2.43±0.95 bpm), p<0.01. MAE was less than 2 bpm for 83.6% of all 30 s windows across all subjects. The position classifier distinguished supine and left/right with a ROC AUC of 0.87, and between left and right with a ROC AUC of 0.94. The proposed methods may enable a low-cost solution for in-home, long term sleeping posture and respiration monitoring.**

I. Introduction

Respiration rate is an important vital sign, which has been shown to predict adverse cardiac events [1], and admission to an intense care unit. It is a useful indicator of disease progression to monitor patients with chronic respiratory or neuromuscular disease [2]. Respiration rate has also been reported to be better than pulse rate or blood pressure at discriminating between stable patients and patients at risk during acute medical admissions [3]. Low cost, unobtrusive monitoring of respiration rate and sleeping position using accelerometers could allow patients to be monitored in their own home, reducing hospital readmissions following surgery, or facilitating in-home monitoring of elderly or sick patients.

Research supported in part by Science Foundation Ireland under grant number SFI/RC/2289 and the European Research Council under the grant number ERC-2014-CoG-646923. *(Corresponding Author: E.P. Doheny)*

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Respiration differs during sleep compared with wakefulness [4], and may be used to detect and distinguish between different types of sleep disordered breathing. Respiration rate during sleep is typically monitored using nasal cannulas, which measure the flow of air at the nostrils.

Previous studies have used accelerometers to measure respiration rate while subjects are awake, and a more limited number have focused on sleep [5]–[10]. Previously reported accelerometer-based respiration rate algorithms have primarily used time domain methods, including peak detection [5], wavelet analysis [6] or state machine techniques [7]–[9]. Frequency domain methods to estimate respiration rate using accelerometers have also been reported [10], however the overlapping frequency bands of human respiration and movement cause issues for this method.

Movements during sleep, including changes in sleeping position or arousals due to flow limitation events, are problematic for accelerometer-based respiration rate algorithms, as the noise due to this movement occurs in the same low frequency band as human respiration rate. Hence, most accelerometer-based respiration rate algorithms do not return valid respiration rates during these periods [8,11,12].

Sleeping position is associated with sleep disordered breathing [13], [14] and development of pressure ulcers [15]. Sleeping position has previously been classified using under mattress sensors [16], and accelerometers [17], [18]. Recent studies have reported methods to estimate posture and respiration rate simultaneously using a single accelerometer [11], or using two accelerometers on the chest [6], but validation against overnight PSG is required.

In this study, a novel method to estimate respiration rate and classify position during sleep using a tri-axial accelerometer mounted on the torso is presented. The accuracy of the proposed methods is assessed by comparing results with position and respiration data determined using gold-standard clinical polysomnography (PSG). The effect of sleeping position and sensor location on the accuracy of the estimated respiration rate is presented.

II. Method

A. Participants

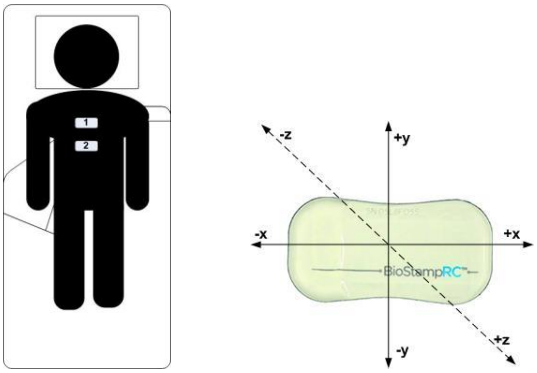
Eleven participants (9 male; aged: 47.82 ±14.14 years; BMI 30.9 ± 5.27 kg/m^2) gave their informed consent to participate in this study. Ethical approval was obtained from the human research ethics committee at St Vincent's University Hospital, Dublin, Ireland. All participants were undergoing a scheduled overnight clinical polysomnography (PSG) study (10 full PSG, 1 limited channel PSG).

B. Protocol

Low profile wearable inertial sensors (BiostampRC, MC10 Inc.) were programmed to record tri-axial acceleration data at 125 Hz (±4g), and were attached to the chest and upper abdomen of each participant during an overnight PSG test. Sensors were secured to the skin using double sided adhesive stickers. Additional taping was used to ensure the sensors stayed in place during the overnight test.

The flexible inertial sensors measured 6.6 cm in length, 3.4 cm in width and 0.45 cm in height. The x axis was aligned with the medial-lateral anatomical axis, the y axis was then perpendicular to the x axis, aligned with the distal-proximal anatomical axis, and the z axis was perpendicular to surface of the skin, approximately vertical when the participant was lying in supine position, Fig. 1.

PSG data were recorded using SomnoScreen (SomnoMedics GmbH, Germany). As part of the PSG protocol, air flow at the nostrils was measured using a nasal cannula, sampled at 32 Hz. Flow events (apneas, hypopneas) and arousals were reported by the PSG software, and were manually edited by an expert sleep physiologist. Posture (supine, prone, upright, left, right) was also reported every 30 s, automatically by the PSG software.



A B

Fig. 1.A Illustration of participant lying supine in bed with sensor locations (1: chest sensor, 2: abdomen sensor) indicated; B: Sensor axes.

C. Data analysis

During each test, accelerometer data were stored locally on the sensor. After each test they were downloaded and exported to MATLAB (The MathWorks, Inc, Natick, MA) for offline analysis using custom developed algorithms.

1) Pre-processing

Healthy human respiration rate is typically in the range 12-20 bpm, (0.05-0.5 Hz), with rates above 30 indicating respiratory distress. Tri-axial accelerometer data were therefore filtered using an eighth order low-pass filter with cutoff frequency 0.5 Hz, and notch filtered to remove frequency components below 0.05 Hz, allowing respiration rates between 3 and 30 bpm to be captured.

The movement of the chest wall due to breathing mainly occurs in the z axial direction for the sensor placement used in this study, Fig. 1, and the change in orientation of the sensor due to breathing will primarily be the rotation about the x axis, or the pitch. Sensor pitch, roll and yaw were calculated using the methods described in [5]. Baseline pitch was then subtracted from the signal, and resampled to 32 Hz (to match PSG flow signals).

Accelerometer data was segmented into nonoverlapping 30 s epochs, and respiration rate and sleeping position was estimated for each epoch as described in the following sections.

2) Respiration rate estimation

Respiration rate was derived using the z acceleration and pitch signals. For each nonoverlapping 30 s epoch, data were normalized with respect to the signal maximum within that epoch. A peak detection algorithm was then applied to the accelerometer and pitch signals for each epoch, with a fixed minimum time between peaks, and adaptive thresholds (based on signal amplitude, and sleeping position) applied to peak prominence, and peak height. During each epoch, peaks were compared for the pitch and z acceleration signals, with the signal resulting in the most regular peaks (defined as the lower standard deviation in time between peaks) selected. Respiration rate (breaths per minute) was calculated as twice the number of peaks detected during each 30 s epoch for the selected signal.

To reduce the influence of body movement on the acceleration-derived respiration signal, a binary movement vector was constructed using PSG-reported posture change, flow events and arousal data. Each 30 s nonoverlapping epoch was deemed to be during a period of movement if a posture change, a flow event, or arousal occurred during that window. Respiration rate was not calculated for windows during which movement occurred.

3) Position classification

Two classifiers were developed to distinguish between the three observed sleeping positions (supine, left and right). Firstly, epochs during which the patient was lying on their left or right were merged, and a logistic regression classifier was developed to distinguish these epochs from epochs where the patient was supine (Model 1). If an epoch was classified as left/right, a second classifier was then applied to distinguish left and right positions (Model 2).

Change in mean acceleration and orientation are expected as patients move between sleeping postures due to the changing influence of gravitational acceleration on each sensor axis. Hence, for each 30 s epoch, the mean acceleration along the x, y and z axes and the mean pitch, roll and yaw were used to create a feature matrix to develop a sleep position classifier. A training set was constructed using this feature matrix, including 20% of all epochs, pseudo-randomly selected to provide an even distribution across sleeping positions. The remaining 80% of data epochs were used to test the developed classifiers. Sequential forward feature selection was implemented to reduce the number of features included in the models, followed by logistic regression. PSG position data were used as the reference.

Position results were only reported for sections of data where the same position persisted for at least 30 s.

4) Statistical analysis

The mean absolute error (MAE), root mean squared error (RMSE) and the mean average error (MAvE) in respiration rate were calculated across all 30 s epochs by comparing accelerometer-derived respiration rates with cannula flow (PSG) respiration rates, and results are reported as an average across all subjects. Each error measure was compared across sleeping postures (with left and right postures merged), and between sensor locations (chest or abdomen), and the effect of posture and sensor location on the resulting error metrics were examined using Friedman's test. The total usable data (hours) in each position were compared using rank sum tests. P values less than 0.05 were considered statistically significant.

The performances of the position classifiers, Model 1 and Model 2, were assessed using sensitivity, specificity and the area under the curve of the receiver operator characteristic (ROC AUC). The correlation between the number of position changes scored by the accelerometer method and PSG was also examined.

III. Results

The mean recording length across all subjects was 7.16 ± 1.5 hrs for the chest sensor, and 7.12 ± 1.63 hrs for the abdomen sensor. After movement data was removed, an average of 4.78 ± 1.53 hrs and 4.84 ± 1.63 hrs of data remained per subject for the chest and abdomen sensor respectively.

The mean apnea hypopnea indices (AHIs) for the cohort was 5.77 ± 4.18 events per hour, with a maximum AHI of 12.95 in this cohort. An AHI less than 5 is considered normal, 5-15 mild, 15-30 moderate, and greater than 30 is considered severe.

Participants spent a mean time of 2.85 hrs supine, and 3.11 hrs lying on their left or right side. There was no significant difference between time supine and time on left/right (p = 0.07). Participants also spent an average of 0.19 hrs upright, and 0.17 hrs prone, but these data were excluded due to excessive movement.

1) Respiration rate estimation

Error in respiration rate estimation did not vary between sensor location, Table 1. When results were compared for each sleeping position, reduced error in respiration rate estimation was observed when participants lay on their side compared to supine, Table 1.

The accelerometer-derived respiration rate was within 2 bpm of PSG for 83.6 % (chest sensor) and 80.9 % (abdomen sensor) of all 30 s epochs across all subjects.

TABLE I. ERROR IN RESPIRATION RATE ESTIMATION

Sensor location	Abdomen	Chest	p
MAE (bpm)	1.67 ± 0.37	1.89 ± 0.53	0.09
RMSE (bpm)	2.56 ± 0.5	2.88 ± 0.72	0.05
MAvE (bpm)	0.4 ± 0.43	0.07 ± 0.6	0.33
Position	**Side**	**Supine**	**p**
MAE (bpm)	1.58 ± 0.54	2.43 ± 0.95	<0.05
RMSE (bpm)	2.45 ± 0.78	3.25 ± 0.97	<0.05
MAvE (bpm)	0.3 ± 2.18	0.69 ± 0.59	<0.05

2) Position classifier

Performance metrics for Model 1 (supine vs left/right) and Model 2 (left vs right) are presented in Table 2.

The correlations between the total number of position changes reported by PSG and the number detected by the abdomen and chest sensors were 0.76 and 0.83 respectively ($p<0.05$).

TABLE II. RESULTS FOR POSITION CLASSIFIERS

	Model 1: Supine vs Left/Right	Model 2: Left vs. Right
Sensitivity	81.05	84.37
Specificity	81.32	90.79
ROC AUC	0.87	0.95

IV Discussion

A method to monitor position and respiration rate during sleep using wearable accelerometers is presented in this paper. The cohort examined were referred for an overnight

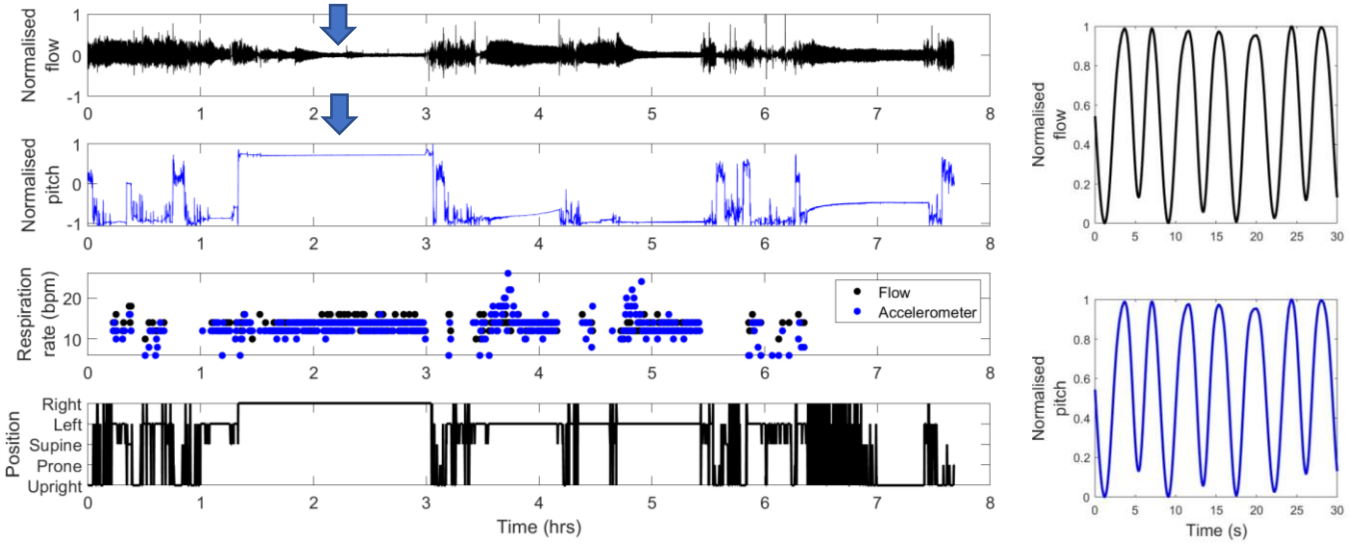


Fig. 2 Example chest sensor and PSG data from an overnight recording from a 54-year-old male participant (BMI = 33 kg/m^2; AHI = 7.42). For this recording, MAE in respiration rate was 1.27 bpm. A: Flow, sensor-derived pitch, PSG (flow) and accelerometer-derived respiration rates, and PSG position data are presented for the overnight recording. B: A 30 s section of normalized flow and pitch data for this participant, indicated using blue arrows in A.

clinical sleep study to investigate a potential sleep disorder, providing a challenging dataset with a wide range of sleep disordered breathing and restlessness severities. Nevertheless, the respiration rate method presented performed well, with estimated respiration rates within 2 bpm of PSG values for 83.6% of all data examined. Respiration rate results were consistent across the two examined sensor locations.

The sleeping posture classifiers presented had ROC AUCs of 0.87 for distinguishing supine from side positions, and 0.95 for distinguishing left from right, with better results for the sensor placed on the chest. By automatically identifying sleeping position, and changes in sleeping position, in accelerometer signals, such a method could be used to monitor bed posture to avoid pressure ulcers, or to investigate position dependent sleep apnea.

In this study, the maximum mean absolute error in respiration rate estimation across all subjects were 2.25 bpm and 2.67 bpm for the abdomen and chest sensors respectively. Jarchi *et al.* [10] reported similar results with a maximum mean absolute error of 2.56 bpm between their accelerometer-derived respiration rate method and photoplethysmography, based on data collected from ten patients on discharge from the ICU. Drummond et al. [8] examined a post-surgery cohort and reported that their accelerometer-derived instantaneous respiratory rates results were within 2 bpm of nasal cannula results for 86% of their data. In the current study, which examined pathological sleepers, 83.6% of respiration rates estimated using the abdomen sensor were within 2 bpm of cannula results. Another study reported a MAvE in respiration rate of 0.26 bpm [9], similar to the results of this study (0.4 and 0.07 bpm for the abdomen and chest sensors respectively).

Previous studies have classified sleeping posture using clustering methods, reporting a mean error of less than 3 seconds in detecting a posture change in a healthy young cohort [18]. Decision rule techniques have also been reported to estimate body posture in healthy subjects [6], [17]. In the current study, supine, left and right positions were classified in a group of pathological sleepers, using a method trained on 20% of the dataset, and tested on the remainder, with all reported results based on the test data only. The sleeping position classifiers presented in this study performed well with a ROC AUC of 0.87 to discriminate supine from left/right, and 0.95 to discriminate left from right. Previous studies using accelerometers to classify sleeping position in healthy cohorts have reported accurate results [17], [18]. However, based on a thorough literature review, no previous studies have reported results for sleep position classification using accelerometers on a cohort of pathological sleepers.

A limitation of the present study is the lack of prone position data in the collected dataset collected. This is a common issue for PSG studies [17], where the number of wires and sensors attached to the subject makes sleeping prone uncomfortable. Human factors may also influence data quality, including variations in sensor placement as examined in this study. The methods presented successfully estimate respiration rate and classify position during sleep. In future work, additional subjects will be included, and flow events and arousals will be reintroduced to the analysis.

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