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Real Time Breathing Rate Estimation from a Non Contact Biosensor

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***Abstract*— An automated real time method for detecting human breathing rate from a non contact biosensor is considered in this paper. The method has low computational and RAM requirements making it well-suited to real-time, low power implementation on a microcontroller. Time and frequency domain methods are used to separate a 15s block of data into movement, breathing or absent states; a breathing rate estimate is then calculated. On a 1s basis, 96% of breaths were scored within 1 breath per minute of expert scored respiratory inductance plethysmography, while 99% of breaths were scored within 2 breaths per minute. When averaged over 30s, as is used in this respiration monitoring system, over 99% of breaths are within 1 breath per minute of the expert score.**

I. Introduction

BREATHING monitoring in a low cost, non-invasive fashion is an active area of research in engineering [1]. Continuous respiration monitoring can be considered in three main areas, namely devices which (i) measure motion, volume or tissue changes (e.g., impedance or inductance plethysmography), (ii) those that measure airflow (e.g., oro nasal thermistors), and (iii) those that measure blood gas changes (e.g., pulse oximeter or end tidal oxygen). Device complexity can range from those providing estimates of respiratory rate, to those providing quantitative data about tidal volume and blood gas exchange [2].

Typically, respiration is monitored in the intensive care unit setting using thorax impedance plethysmography (i.e., requiring at least two ECG electrodes), and in the sleep lab using respiration band inductance plethysmography [3].

In this paper we consider a low cost, non invasive estimator of breathing rate in real time. This non contact data acquisition device is the SleepMinder™ (BiancaMed, Dublin, Ireland) non contact sensor for home sleep monitoring, and is detailed in [4,5].

Droitcour et al. compared their Kai RSpot non-contact respiratory rate measurement device to thorax impedance (Welch Allyn Propaq), respiration band (Embla Embletta) and by counting chest excursions; they noted 95% limits of agreement between these of +/- 5 breaths per min [6].

The goal of this work is to produce an accurate (within 2 breaths per minute) respiration rate estimate every 30 seconds from a subject free of significant apnea, when compared with expert annotation by an experienced sleep technologist.

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II. Methods

A. Overview

The method discussed here is a real time block based system using temporal and frequency features of a two channel non contact I & Q (in phase and quadrature) biomotion sensor, logging to a Secure Digital memory card. The SleepMinder can be placed on a bedside table; it detects both gross body movement, and the movement of the chest with breathing of a subject within a range of 0.3-1.5m. It can detect movement when a subject is supine, prone or lying facing away from the sensor.

The SleepMinder sensor is connected to a logger board containing a Microchip (Chandler, AZ) PIC digital signal controller, Class 1 Bluetooth module operating as a master device, SD card interface, non volatile RAM for serial number and error tracking, and associated circuitry. The unit conforms to EN 60601-1:1990 and EN 60601-1-2, is FCC approved, and is a Class 1 CE Medical Device.

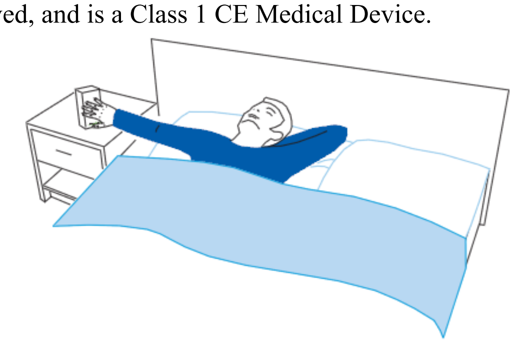

Fig 1. The SleepMinder unit is placed on your side of the bed, at about an arm's length – 3ft (90cm) – from your chest.

The code is written in C, and compiled with the Microchip C30 compiler for the PIC, and developed in Microsoft (Redmond, WA) C# using .Net Framework 3.5 and Franson (Stockholm, Sweden) Bluetools for the (optional) PC application. The SleepMinder unit can carry out processing on the PIC, and make these data available to a number of Bluetooth enabled devices, such as a PC, mobile phone or health hub. A PC application allows a real time view of the sampled data and estimated respiration rate; in addition, this application allows offline display and processing of data saved on the SD card.

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B. Data Acquisition and Processing

The two channel I&Q biomotion data are analog low-pass filtered on the sensor board using an active filter, 3dB point at 1.6 Hz, and then sampled at 64Hz, 12 bit resolution 0-3.2V, and saved to the SleepMinder's flash SD (secure digital) memory card in a proprietary binary format. Internally, these oversampled 64 Hz samples are averaged over 4 samples, producing two 16 Hz channels.

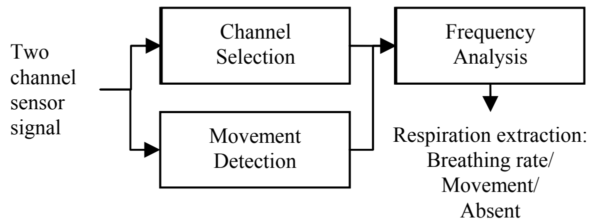

Fig 2: Main processing steps

These data are then (a) sent to the signal analysis block, and (b) optionally available in a buffer for real time streaming over a Bluetooth serial port profile (SPP) connection via a protocol encapsulating timestamp, data payload, breathing rate, motion and sleep estimates. Because a typical client device has a shorter range Bluetooth Class 2 (10m range) radio, the SleepMinder Bluetooth radio is set to 2dBm.

The data are also made available on an internal serial RS232 header, if a cabled connection is required. The SleepMinder can stream data, even if an SD card is not present in the unit.

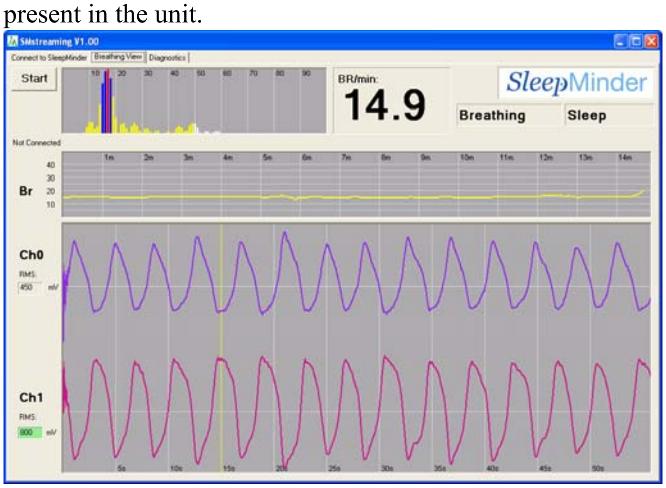

Fig. 3: SleepMinder PC C# GDI+ application – breathing rate tab selected. Top panel shows frequency bins, with peak selection, breathing rate estimate, and current state ("Breathing" in this case). Middle panel shows a 15 min plot of breathing rate. Lower panel shows real time streaming I and Q data (with auto-scaling), new data on the left.

C. Signal Analysis – Channel Selection

The system buffers 15s of data internally (FIFO) to form a 240 sample block, and then processes a block every 1s. In order to reduce the RAM overhead (particularly for the FFT), it is desirable to carry out a channel selection.

Channel combination methods such as Principal Component Analysis (PCA) require covariance and Eigenvalue estimation (effectively pulling out a signal with greatest variance), which may be difficult to implement on the PIC. Since the two sensor channels are not exactly out of phase, combination methods such as arcsine are not appropriate.

Thus, a simpler way of carrying out channel selection is used; the root mean square (RMS) value of each channel is calculated every 1s, with the maximum RMS value deciding the channel to use. The lower RMS value is also used as a feature in the absent/presence detection stage.

D. Time Domain Processing – Movement Detection

In order to distinguish sinusoidal-like high amplitude breathing from movement, edge detection is performed on the signal. A "movement" estimate is produced every 1s in file following manner:

- Scan both channels, and note the maximum peak-peak amplitude V_{p-p}.
- If V_{p-p} is less than a threshold value then a decision is made that no gross movement is occurring (i.e., not "movement", but block could still be either of "breathing" or "absent").
- Otherwise, an edge count is performed by stepping through the samples, and counting the number of samples varying by greater than one fifth of V_{p-p}. If this edge count is greater than a movement threshold, then a "moving" timer is started to mask (hide) breathing rate estimate values, and data from the current 1s chunk are not sent to the FFT module.

E. Frequency Domain Processing

For the 15s block under consideration, the 240 samples are zero padded to 512 (i.e., interpolation in the frequency domain), the mean removed, and an FFT is carried out using Danielson-Lanczos lemma (power of 2) based on the method described in [7], resulting in a buffer containing the complex amplitudes.

The bins relating to a breathing range of 5-47 breaths per minute are selected. A peak search is performed, followed by an interpolation performed around the peak value $A[n]$ with frequency $f[n]$:

$$f\_interp[n]=(f[n-1]*A[n-1]+f[n]*A[n]+f[n+1]*A[n+1])/(A[n-1]+A[n]+A[n+1])$$

F. Respiration Extraction

In order to allow the FIO buffer to fill, no output is produced for the first 15s of data. Thereafter, a classification into "Movement", "Absent" or "Breathing" categories is performed.

A "Movement" state is chosen if the 'edge count' value exceeds a threshold value (i.e., lots of fast high amplitude content).

An "Absent" state (nobody present in field of sensor) is flagged if either of the following conditions (empirically chosen thresholds based on sensor characteristics) applies:

(i) The sum of the magnitude values in the breathing range falls below an absent threshold or (ii) the ratio of the breathing range to higher frequency components indicates that higher frequency noise is dominating.

If neither "Absent" nor "Movement" is classified, then the third possible state "Breathing" is automatically selected. The associated respiration rate figure *br_est* (as displayed by the system to one decimal place) is calculated as follows:

br_est[n] = *br_est*[n-1] - (*br_est*[n-1] /10) + (*br*[n]/10)

where *br*[n]=60**f_interp*[n]. Each new frequency peak is assigned one tenth weighting in this methodology.

G. *Testing with Expert Scored Breathing Rate Data*

A validation of the real time respiration rate estimate from the SleepMinder non contact signal was performed on 2180 manually scored breaths from 10 adult subjects free of significant apnea. These datasets were randomly selected over an eight-month period from patients referred to the St. Vincent's University Hospital Sleep Disorders Clinic, Dublin, because of a clinical suspicion of sleep apnea syndrome. Inclusion criteria were that subjects must be over 18 years of age, have no known cardiac disease; no known autonomic dysfunction; and not be on medications such as beta-blockers, digoxin, or calcium receptor antagonists known to interfere with heart rate. The protocol was approved by the Hospital Research Ethics board and all subjects provided written informed consent.

Full polysomnography was performed using the Jaeger-Toennies 1000E system. Measurements were made of EEG (C3-A2 and C4-A1), right and left EOG and submental EMG. Subjects also had anterior tibialis EMG measured. Respiration was monitored using oro-nasal airflow (thermistor) and movements of the ribcage and abdomen were monitored using uncalibrated pressure sensors around these regions. The presence of snoring was detected using a tracheal microphone. Oxygen saturation was measured using finger pulse oximetry and a modified lead V2 ECG signal was recorded. Body position was also monitored. A SleepMinder sensor was installed in the Sleep Laboratory and its biomotion signal was recorded simultaneously with the PSG signals. Following completion of the study, sleep staging was performed using the full polysomnogram by a single experienced sleep technologist. The scorer also produced an annotated respiratory event list which provides onset times, and durations of all sleep-disordered breathing events including obstructive, mixed, and central apneas and hypopneas, and periodic breathing episodes.

A 15 minute breathing section was selected from the chest and abdomen-band respiratory inductance plethysmography signal of the PSG for each subject, based on the requirements that it be free of significant body-movement and disordered breathing events. Gold-standard breath endpoints were manually scored by an experienced respiratory scientist for each recording (for both the chest and abdomen channels). The expert scorer was blinded both to the objectives of the study, and also to the non contact SleepMinder signal.

TABLE 1: SUBJECT DEMOGRAPHICS, WHERE BMI IS BODY MASS INDEX AND AHI IS APNOEA HYPOPNOEA INDEX.

Gender (M:F)	Age [years]	BMI [kg/m2]	AHI [events/hour]
7:3	41.1±12.0	28.8±4.2	4.8±2.4

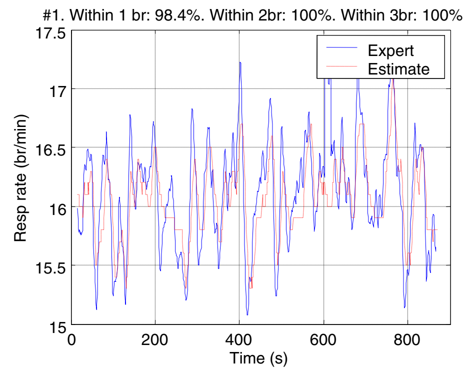

Fig 4. Subject 1 – expert vs. estimated breathing rate.

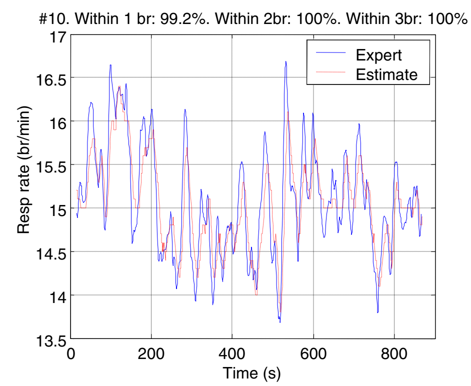

Fig 5. Subject 10 – expert vs. estimated breathing rate.

An expert derived respiration rate is generated on a 1s basis in the following manner:

- A 15s block is shifted by 1s over the 15 minute breathing section, and a search for expert marked chest peaks and troughs (chst pk-pk, chst tr-tr), and abdomen peaks and troughs (abd pk-pk, abd tr-tr) is performed.
- The number of pk-pk/tr-tr annotations within the block is counted for chest and abdomen. Fractional breaths (i.e., a pk-pk or tr-tr straddling the block boundary) are calculated. E.g., 3 complete breaths might fall within a block, with 0.25 of a breath at the start, and say 0.6s of a breath at the end, giving a total of 3.85 breaths, or a rate of 15.4 br/min.
- The expert derived rate is the mean of the 4 rate estimates, updated every 1s.

This expert derived rate is used for comparison with the real time estimate from the SleepMinder non contact sensor. In addition, a 30s non-overlapping expert derived rate is also formed by averaging every 30s.

III. Results

The outlined real time breathing rate estimation method was tested on the expert data on a 1s and also on 30s averaged basis, using the C# PC application (implementing the microcontroller algorithm), for each of the ten 15 minute selected periods. Two exemplar plots of expert and estimated rates are presented in Figs. 4 and 5. The filtering performed in producing the real time estimate produces a more low pass filtered looking signal (i.e., it does not capture quite as much breath-breath variation as the expert scored signal).

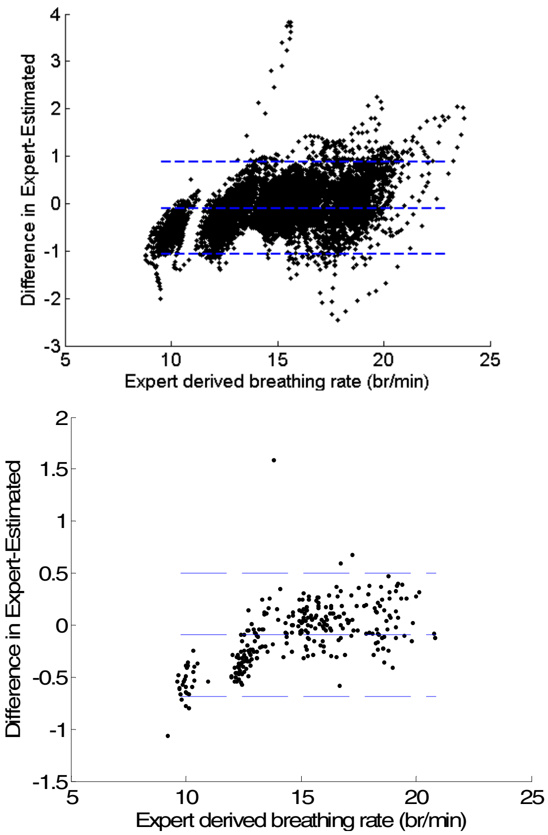

Fig. 6: Bland-Altman plot of 1s (upper) and averaged 30s (lower) comparison between expert and estimated br/min.

The mean absolute error (MAE) values are presented on a per subject basis, along with the percentage of breaths with 1 and 2 breaths per minute of the expert scoring (see Table 2). The average MAE across the ten subjects is 0.5 and 0.3 breaths per minute, for the 1s and 30s comparisons respectively. On a 1s basis, 96% of breaths are scored within 1 breath per minute of the expert derived measure, and 99% within 2 breaths per minute. When averaged over 30s, over 99% of breaths are within 1 breath per minute of the expert score.

Bland-Altman plots (including mean and +/-2*SD lines) are presented for the 1s and 30s comparisons (see Fig 6).

Table 2: Mean absolute error (MAE) between expert derived breathing rate and estimated breathing rate, and percentage of estimated rate values with 1 and 2 br/min, on a 1s and 30s basis.

Rec	MAE br/min (1s)	MAE br/min (30s)	% within 1br/min (1s)	% within 1br/min (30s)	% within 2br/min (1s)	% within 2br/min (30s)
1	0.2	0.1	98.4	100.0	100.0	100.0
2	0.4	0.2	97.0	100.0	100.0	100.0
3	0.4	0.2	92.2	100.0	99.6	100.0
4	0.4	0.4	100.0	100.0	100.0	100.0
5	0.6	0.6	93.9	96.4	100.0	100.0
6	0.5	0.2	90.1	100.0	99.1	100.0
7	0.5	0.3	94.5	96.4	98.5	100.0
8	0.2	0.1	99.8	100.0	100.0	100.0
9	0.4	0.2	98.8	100.0	100.0	100.0
10	0.3	0.1	99.2	100.0	100.0	100.0
Avg	0.4	0.2	96.4	99.3	99.7	100.0

IV. Discussion and Conclusion

The results indicate that a real time respiratory estimate from a non contact signal can closely track an expert scored contact based chest and abdomen impedance band signal during normal breathing, with over 99% of values within 1 breath per minute on a 30s basis. This suggests that a low cost, non invasive, non contact sensor can have utility in breathing rate estimation. These results compare favorably with the 5 breaths per min limits of agreement at 95% between non contact and reference measurement detailed in [6]. Further work will focus on estimating the reliability of the system during movement such as periodic leg movement, or apnea events.

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