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# Reliable Respiratory Rate Estimation from a Bed Pressure Array

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*Abstract*— **Unobtrusive sleep monitoring allows older adults to have continuous monitoring during the night in their own homes. We propose a method to reliably estimate respiratory rate using a bed-based pressure sensor array. Movements are detected prior to respiratory rate estimation and suppressed. The amount of movement during an estimate and a weighting for the estimate are used to create a reliability metric. The reliability metric is scored out of 100 for each sensor where high scores denote more reliable data. Once respiratory rates were calculated, the mean reliability metric determined the estimate reliability. Nocturnal data from a male and female participant was analyzed. Results show better accuracy and validity than both analysis without movement suppression and analysis with movement suppression but without post-processing data fusion. While more than 50% of estimates include movement corruption, only 15% are unreliable and, moreover, removal of unreliable estimates significantly reduces estimate variance and provides validity estimation.**

## I. INTRODUCTION

Unobtrusive monitoring of people in their own homes allows for a comfortable monitoring environment and an increased quality of life. The TAFETA (Technology Assisted Friendly Environment for the Third Age) project is working towards facilitating aging in place by applying technology to aid in everyday life. The goal of the project is to help reduce the impact of the following effects of aging: declining cognition, declining mobility, and increasing medical complexity.

Sleep is essential to daily life. In fact, low sleep quality or efficiency is a predictor of mortality in older adults [1]. A bed-based pressure sensor is an unobtrusive instrument for nocturnal monitoring of people at home. The sensor is placed on top or below a mattress in order to detect movements in the bed [2]. No devices need to be worn by the individual, allowing for an easy, comfortable sleep.

A number of researchers have successfully monitored respiration using bed-based sensors. Some researchers have used a single sensor [3],[4] while others have used sensor arrays to obtain spatial resolution of the signals [5]. Movement in bed has been reported to affect the reliability of estimated respiratory rates [6],[3].

We are interested in the processing required to reliably establish respiratory rate from such an array of pressure sensors located in a bed. We propose a reliability metric methodology similar to one that has been proposed for audio-video localization in video conferencing [7]. The reliability metric will be used both for data fusion and for a final decision of respiratory rate validity.

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## II. MATERIALS AND METHODS

### A. Pressure Sensor Array

Pressure sensors emit a signal that is correlated to the weight applied to the sensor. The output from a single sensor includes applied weight, gross movements such as limb movements, and slight movements from respiration and pulse [8]. We use a Tactex Controls Inc. Bed Occupancy Sensor, which contains 24 pressure sensors in a 3x8 grid configuration and samples at a rate of 10 Hz. The pad dimensions are 24 cm by 90 cm, with sensor elements spaced 10 cm apart.

### B. Data Analysis

A block diagram of the proposed system is shown in Fig. 1. The algorithm proposed here was implemented with MATLAB$^{TM}$ (Mathworks, version 6.5). Sensor data from N sensors are input the system.

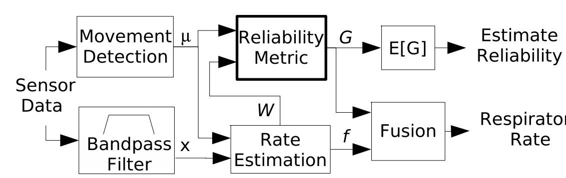


Fig. 1. Block diagram of rate estimation and reliability metric

Movements were detected using a previously proposed method of control limit thresholding [2]. Movement detection output, denoted $\mu$, is one at locations of movement and zero elsewhere. The bandpass filter had cutoff frequencies of 0.02Hz and 0.8Hz.

### C. Respiratory Rate Estimation

Fig. 2 presents the proposed respiratory rate estimation algorithm.

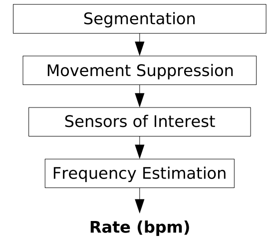


Fig. 2. Respiratory rate estimation algorithm

*1) Segmentation:* Respiratory rates were calculated every five seconds. The length of each data segment is dependent on the lowest expected respiratory rate. Measurement of respiratory rates between two breaths per minute (bpm) and 50 bpm are usually supported by clinical equipment [9].

Data segments of 30 seconds allow rates down to four bpm to be estimated while minimizing interference in each segment due to aperiodic movement. Since this segment size is larger than the update interval, segments will overlap and short movements can corrupt at least six consecutive respiratory rate estimations.

*2) Movement Suppression:* To minimize the effect of movement on each segment, movement was suppressed. The mean of the samples that did not coincide with detected movement was subtracted and samples that coincided with movements were zeroed.

$$s_{(i,n)} = \begin{cases} x_{(i,n)_{\mu=0}} - E[x_{(i,n)_{\mu=0}}] & \text{for } \mu\text{=0} \\ 0 & \text{for } \mu\text{=1} \end{cases} \quad (1)$$

*3) Extraction of Signals of Interest:* For sensor arrays, a single signal can be extracted from the sensors and processing applied to the single signal, or signals from multiple sensors can be extracted and the results fused after processing. Previous research has used the sum of all sensor activity as a single extracted signal [8], or has picked a reference sensor with the highest frequency score [10],[11]. That is, the sensor that exhibits the the maximum ratio of in-band spectral energy to out-of-band energy.

We investigate a method that selects signals from sensors that demonstrate a variance above the instrument's noise threshold. This does not require the calculation of the Fourier transform for each sensor and will allow for post-processing data fusion. This is expected to be more robust in the presence of localized movements.

*4) Rate Estimation:* A person's breathing pattern can change from breath to breath and pressure sensors may not have linear outputs. Wavelet methods of rate estimation have been used for pressure sensor respiratory rate estimation [11], but they are computationally intensive. Power spectrum peak detection from the Fourier transform may be used when stationarity and linearity can be estimated during short data segments. However, to obtain adequate frequency resolution, segments cannot be short: A resolution of 0.5 bpm requires 120 seconds of data. Alternatively, zero-padding provides interpolation of the spectrum from a shorter segment.

Autocorrelation was employed as it can be computed relatively quickly and provides good frequency resolution at the frequencies of interest with the shorter 30-second data segments. For instance, frequency resolution is between 0.3 bpm and 0.5 bpm at respiratory rates between 12 bpm and 20 bpm respectively when the sampling rate is 10 Hz.

For each specified sensor, the autocorrelation is found for delays $\tau$ from 1.25 seconds to a maximum of 30 seconds (0.8Hz - 0.02 Hz). The variable $i$ denotes the $i$th data segment and $n$ denotes the $n$th sensor in the array of N sensors.

$$R_{xx(i,n)}(\tau) = \frac{1}{N} \sum_{m=0}^{N-\tau-1} s_{(i,n)}[m] s_{(i,n)}[m+\tau] \quad (2)$$

The value of the delay at the first peak is chosen as the respiratory rate in Hz.

$$f_{(i,n)} = \frac{f_s}{\tau_{\text{peak}}} \quad (3)$$

## D. Reliability Metric

The autocorrelation function can be used to obtain a weighting measure for the given respiratory rate estimation. This weighting is calculated by taking the ratio of the peak value to the value of the autocorrelation at $\tau$ = 0. To ensure that peaks located on the main lobe of the autocorrelation function do not get artificially heavy weightings, we take the difference between the peak and the previous valley. The weighting of the $i$th estimate becomes:

$$W_{(i,n)} = \frac{(R_{xx(i,n)}(\tau_{peak}) - R_{xx(i,n)}(\tau_{valley})}{2 * R_{xx(i,n)}(0)}, \quad (4)$$

and produces an output between 0 and 1.

We propose a reliability metric that is defined as this weighting multiplied by the percentage of samples that do not contain movement. This gives a reliability between 0 and 100 for each sensor.

$$G_{(i,n)} = W_{(i,n)} * M_{(i,n)} \quad (5)$$

$M_{(i,n)}$ is the percentage of samples in the segment that do not contain movement.

## E. Data Fusion

To fuse the estimated respiratory rates given by each sensor, we make use of the reliability metric and the probability that the given sensor contains respiratory rate information. This probability is calculated similarly to the probability estimate given in [7].

$$P_{(i,n)} = \frac{\sum_{k=i-K-1}^{i-1} D_n[k]}{N} \quad (6)$$

Here, we define $D_n[k]$ as one if sensor $n$ was chosen during the $k$th of last $K$ rate estimates and zero otherwise. A value of K = 24 includes all rate estimates from the last two minutes.

A cluster-based voting method is used to decide the final estimated respiratory rate. Candidate rates are grouped and the cluster with the highest weighting is chosen. The equation for the weighting of each cluster is shown in Fig. 7.

$$Wc_i = \sum_{n_c=0}^{N_c} G_{i,n_c} * P_{i,n_c} \quad (7)$$

with $n_c$ is the $n_c$th sensor in the cluster of size $N_c$. Clustering eliminates noisy sensors from affecting the final output respiratory rate estimation. The final estimation is the weighted mean of the rates given by the sensors in the chosen cluster.

TABLE I

MOVEMENT CORRUPTED ESTIMATES

| | Number of Segments | Segments with Movement | Percent with Movement |
|---|---|---|---|
| Female | 5358 | 3041 | 56.8% |
| Male | 3831 | 2208 | 57.7% |

TABLE II

THRESHOLDED RELIABILITY METRIC RESULTS

| | Mean Reliability Metric | Estimate Reliability $> 50$ | Estimate Reliability $< 50$ | Percent Reliable |
|---|---|---|---|---|
| Female | 73/100 | 4982 | 376 | 93.0% |
| Male | 66/100 | 3181 | 650 | 83.0% |

Finally, the mean of the reliability metrics from the cluster sensors determines the reliability of each estimate. We call this the 'estimate reliability'.

## III. EXPERIMENT AND RESULTS

Two healthy adults, one male and one female, each passed a night with the Bed Occupancy Sensor between their bottom sheets and mattresses. The male spent 5.5 hours in bed and the female spent 7.5 hours in bed. Samples were taken from all 24 sensors at a rate of 10 Hz. The female participant is 167cm tall, weighs 63 kg and sleeps on a futon mattress. The male participant is 165cm tall, weighs 77 kg and sleeps on a coil spring mattress with a pillow top.

Table I summarizes the movement corruption during the nocturnal monitoring. The 'estimates with movement' denotes how many estimates were based on data that included at least five samples of movement.

Respiratory rates were calculated with the method described herein and compared to results calculated without movement suppression and also to results calculated with movement suppression but estimated from a single reference signal selected for each segment according to a frequency score. The respiratory rates estimated for the female and male participants are shown in Fig. 3 and Fig. 4 respectively.

Fig. 5 plots the reliability metrics. A reliability less than 50 was chosen by observation as the threshold with which to eliminate bad results. Table II lists the number of reliable results chosen by a reliability metric $> 50$ and the mean reliability metric. Fig. 6 shows the estimated respiratory rates when unreliable results are removed.

A healthy adult's respiratory rate is expected to vary, but incorrect estimates lead to an even higher variance in the results. Table III compares the mean and variances of the estimated respiratory rates.

## IV. DISCUSSION

Without movement suppression, many rate estimations were inaccurate. Estimates with movement suppression, based on a reference sensor selected according to frequency content, produced more accurate estimates, but were still negatively affected by movement, especially near the end

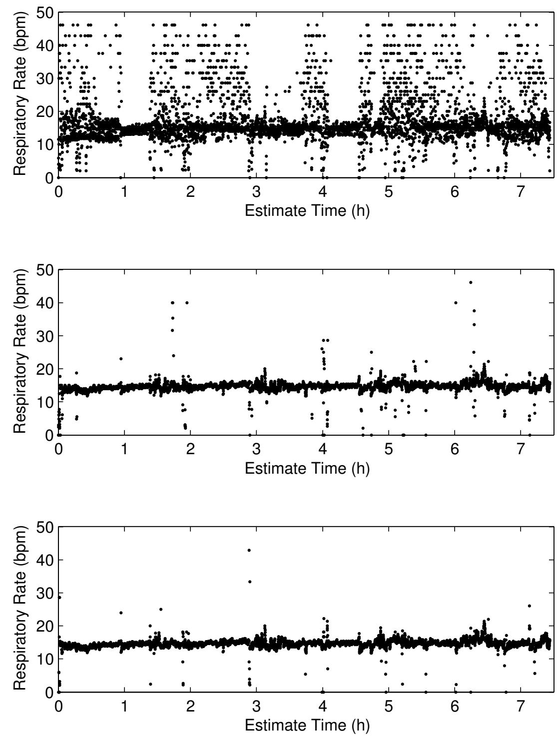


Fig. 3. Respiratory rate results of the female participant: top plot without movement suppression, middle plot with frequency scoring, and bottom plot with proposed method

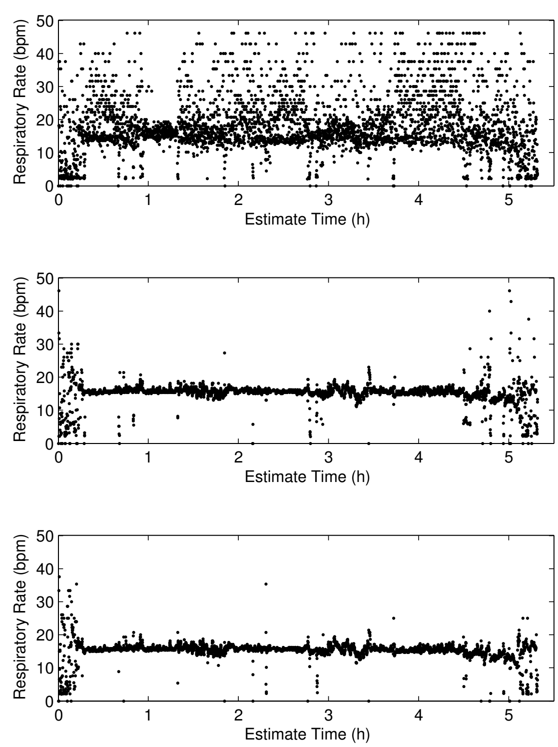


Fig. 4. Respiratory rate results of the male participant: top plot without movement suppression, middle plot with frequency scoring, and bottom plot with proposed method

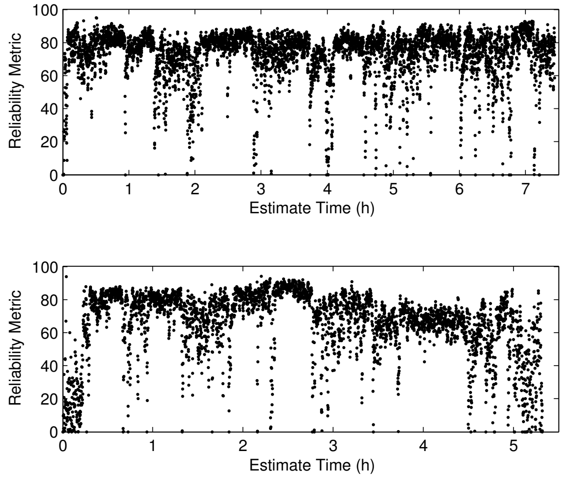


Fig. 5. Reliability metrics: female above, male below

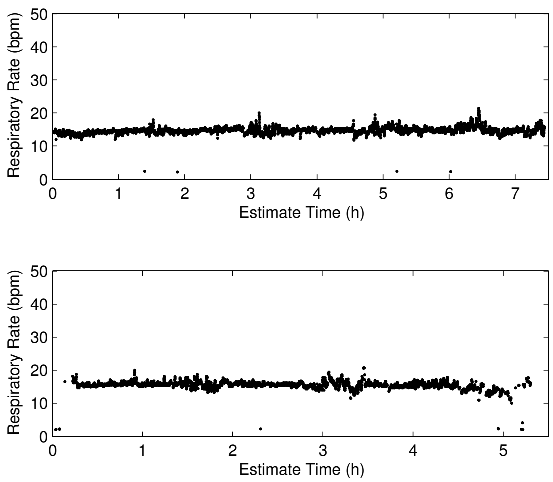


Fig. 6. “Reliable” respiratory rates: female participant on top, male below

of the male participant’s night. Inaccurate estimates at the beginning of that night were expected as he moved around in bed before settling down for the night.

The use of post-processing data fusion was more robust to movement corruption, but during times of high movement, respiration signals are not available and these results should be invalidated. Invalidating results with estimate reliabilities lower than a threshold of 50 improved the signal variability and removed many false estimates. Although most false estimates were found at this threshold, some were not detected. It may be possible to increase the required reliability metric threshold in order to eliminate all corrupt movements, but this may also result in invalidating a number of estimates that are in fact correct, albeit at a lower reliability metric.

Since the reliability metric is related to the amount of movement during the night, it may also be used as a restlessness index, with lower metric values related to higher restlessness.

TABLE III
RESPIRATORY RATE ESTIMATES

| | Female | | Male | |
|---|---|---|---|---|
| | Mean Rate (bpm) | Variance | Mean Rate (bpm) | Variance |
| No Movement Suppression | 17.4 | 62.7 | 18.6 | 82.0 |
| Frequency-based Sensor Selection | 14.6 | 5.2 | 15.2 | 11.6 |
| Data Fusion | 14.6 | 2.4 | 15.2 | 8.7 |
| Data Fusion with Estimate Reliability $> 50$ | 14.7 | 0.95 | 15.5 | 1.64 |

## V. CONCLUSIONS AND FUTURE WORK

The proposed method of respiratory rate estimation improves the accuracy and validity of respiratory estimates. Although movement was present during more than 50% of data segments, a reliable estimate was found for the majority of the time even during movement-corrupted data.

The TAFETA project has set up a ‘smart’ apartment in the Elisabeth-Bruyère Hospital which is used by outgoing patients on a short term, voluntary basis. This same algorithm should ultimately be tested with data from residents of the TAFETA apartment.

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