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Breathing Sensor Selection During Movement

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***Abstract*— A pressure sensor array placed below a mattress can be used to estimate the breathing effort signal unobtrusively. When multiple breathing effort sensor outputs are available, there is sometimes a need to choose the sensor with the best approximation of the actual breathing effort. Previous work with pressure sensor arrays placed on top of or under mattresses used for respiration rate and breathing signal estimation have used either the amplitude or the power spectrum to choose the most representative sensor. These methods are both useful when the subject is still; however, pressure sensor signals also contain movement. We propose and test a spectral ratio method for selection in the presence of movement. The spectral ratio method is good at finding strong breathing signals and at discriminating movement signals from strong breathing signals. This method provides a mean correlation to respiration bands that is 4% higher than the next best method during small movements and 14% higher during larger movements.**

I. INTRODUCTION

As infrastructure that allows for long term home monitoring of ageing adults becomes feasible and sensors become smaller and less expensive, the field of unobtrusive, non-contact monitoring of breathing signals has expanded. With such monitoring, detection of apneas could signal sleep disordered breathing; disturbed breathing patterns, such as Cheyne-Stokes breathing, could be identified; and respiratory rates could be measured to ensure that they are within an expected range. A long lack of breathing effort could be used to detect respiratory emergencies.

A number of sensor technologies have been exploited for non-contact monitoring of breathing effort signals from chest and abdominal motion, including pressure sensors [1], ultrasonic sensors [2], radio wave transducers [3], [4], and hydraulic sensors [5]. Multiple sensors, of the same or different type, may be used to increase signal reliability [1]. For instance, a pressure sensor array can provide a distribution of sensors across a mattress, allowing multiple sensors to pick up the bed occupant's breathing effort.

When multiple sensors carry breathing information, there is often a need to select the sensor whose output is most representative of the breathing effort signal. Perhaps a single sensor's output is desired in order to estimate the respiratory rate [6], [7], or perhaps the sensor selection is required as part of a larger algorithm [8].

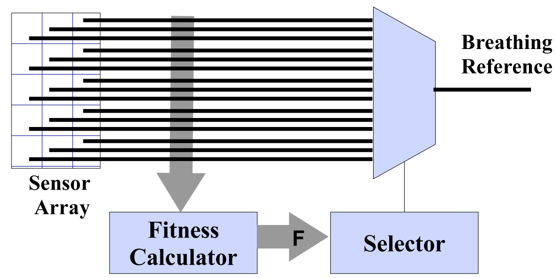

Fig. 1. Selection of representative sensor from a sensor array

A general selection system is shown in Fig. 1. A selector block chooses the best sensor based on a fitness score, usually by approximating the strength of the breathing effort signal at each sensor. A signal with a high amplitude or strong power is expected to have less interference from noise and other interfering signals.

Although the problem of sensor selection from pressure sensor arrays has not yet been examined in isolation, researchers have used sensor selection as part of wider projects. Townsend et al. selected a reference sensor by locating peaks and troughs to determine breathing amplitude [8]. This method requires only simple calculations, but is prone to errors due to small signal fluctuations. A more sophisticated method used by Niizeki et al. [6] and Nishida et al. [7] computed the power spectral density (PSD), and selected the sensor output with the highest power over the respiratory frequency range.

However, when bodily movements occur, such as during position changes, limb movements, or twitches, movement artifacts are introduced and interfere with the breathing signal. Part of the breathing spectrum will be affected by the movement and the sensors which are eventually selected may be the ones most affected by movement.

We consider the use of pressure sensor arrays for respiratory monitoring and the selection of the most representative sensor, paying particular attention to the fact that movement corrupts the breathing output. Through judicious sensor selection, we anticipate that movements can be better tolerated. This paper aims to make use of further information in the power spectrum to create a ratio-based fitness calculator that discerns the signal from interference. The proposed method is tested with data from participants, taking into account movement that is identifiable by a movement detection algorithm [9] and movement that is left undetected.

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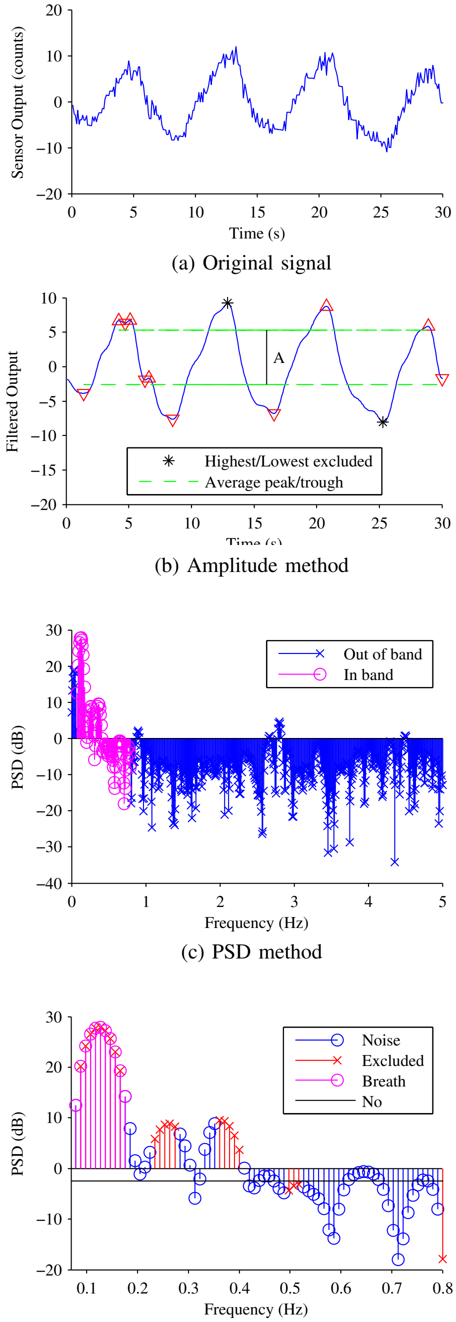

(a) Original signal

(b) Amplitude method

(c) PSD method

(d) Spectral ratio method

Fig. 2. Selection methods

II. METHOD

After being sampled at 10 Hz, the outputs of all of the sensors are segmented into epochs of 30 seconds, overlapping by 15 seconds. The 50% overlap ensures that any interesting change occurring right at an epoch border is captured by the next epoch. The mean over each epoch is subtracted to remove the average loading on the sensor. The resultant signals are then fed to the fitness calculator and the sensor with the highest fitness is selected for each epoch.

Fig. 2 displays each of the methods of fitness calculation examined in this paper. Fig. 2a shows a typical breathing signal. In Fig. 2b, the amplitude method is performed on a low-pass filtered breathing signal. It detected some erroneous peaks and troughs, which led to a smaller average amplitude than was warranted. Fig. 2c shows the power spectrum of the breathing signal and highlights the respiratory frequency band that is accumulated for the spectral power (PSD) method.

A. Spectral Ratio Method

The proposed spectral ratio method (Fig. 2d) takes advantage of the periodicity of the breathing signal to discern the breathing signal from movement. First, we calculate the PSD for the epoch data from each sensor using a windowed periodogram. We then examine the power densities over the frequency range of respiration, defined here from 0.07 Hz to 0.8 Hz to correspond to respiratory rates from 4 to 48 breaths per minute (bpm). As in the spectral power method, the total power in the band is accumulated to form the total spectral power P_{tot}.

An estimate of the breathing rate is obtained by finding the lobe with the highest peak in the frequency range of interest. Excluding this main lobe and its harmonics, the PSD at all other in-band frequencies is considered to be noise or interference. Noise spectral density, N_0, is estimated as the median value of this noise. Total noise power, N, is computed from this constant N_0

$$N = \int_{f_1}^{f_2} N_0 = N_0(f_2 - f_1) = N_0 B \qquad (1)$$

where B is the bandwidth from f_1 to $f2$. Here, $f_1 = 0.07$ Hz, $f_2 = 0.8$ Hz, and $B = 0.8 - 0.07 = 0.73$ Hz. An estimate of the breathing power P_b is obtained by subtracting N_0 from PSD and accumulating over the main lobe. The main lobe of the breathing signal is highlighted in Fig. 2d. The bins for noise estimation are indicated and the resultant N_0 is shown.

The spectral ratio fitness F is then calculated as

$$F = \frac{P_b}{N} P_{tot}. \qquad (2)$$

The $\frac{P_b}{N}$ component allows strongly rhythmic signals to stand out compared to signals with movement. When the actual breathing is not rhythmic, the P_{tot} component allows the method to fall back to the spectral power method.

III. EXPERIMENT

Three adult participants wore chest and abdominal respiratory inductance plethysmography bands (respibands) while lying on a hospital mattress, beneath which lay a pressure sensor array with 48 sensors. The respibands were used as a gold standard reference for breathing effort, to compare against the sensor outputs from the pressure sensor array.

The participants each performed a protocol of breathing and movement and lay on the mattress for a total of two hours. Movements, including moving the head, moving an arm, moving a leg, changing position, and twitching, were requested of the participants every few minutes.

The pressure sensor array was formed by two Bed Occupancy Sensor (BOS) mats from S4 Sensors, each containing

TABLE I

SUMMARY OF RESULTS

	Percent Correct (%)	Mean Correlation Coefficient	Median Correlation Coefficient
Amplitude	11.92	0.77	0.87
PSD	25.45	0.81	0.92
Spec. Ratio	28.85	0.82	0.92

TABLE II

EFFECT OF SELECTION ON RESPIRATORY RATE ERRORS

	Percent within 1 bpm (%)	Mean Rate Error	Mean Rate Bias
Amplitude	85.01	2.23	1.12
PSD	89.63	1.91	0.82
Spec. Ratio	90.78	1.75	0.59

24 pressure sensors. The outputs from the two mats were logged at 10 Hz to a nearby laptop. The two respiband outputs were also connected to the laptop and their data logged at 20 Hz, and downsampled to 10 Hz after alignment with the pressure sensors.

The respibands were found to be sensitive to movement during position changes, which occasionally produced signals unmodulated by breathing during a number of the epochs. These epochs were manually marked as invalid to prevent corrupted comparisons.

An ideal sensor choice was calculated for every valid epoch by comparing each sensor output to the respiband output. Periods of movement, flagged from manual annotations, were eliminated for this process. Comparisons of sensor outputs to respiband outputs were made using Pearson's correlation coefficient. This coefficient produces a value between -1 and 1, where -1 denotes perfect linear correlation with a negative slope, 0 denotes no correlation, and 1 denotes perfect positive linear correlation. The sensor whose absolute value of correlation was the highest, closest to perfect linear correlation, was marked as the ideal choice.

In practice, a priori knowledge of respiband outputs and movement periods is not possible, and sensors must be chosen based on the merit of their outputs alone. The epoch data were fed to each method and the choice of sensor was compared to the ideal sensor choice. Although the percentage of correct sensor choices indicates broadly how well the method works, when multiple sensor outputs are strongly correlated to the respibands, a choice other than the ideal sensor may still be effective. This was verified by calculating the correlation coefficients between the respiband outputs and the outputs of the sensors selected by each algorithm.

IV. RESULTS

A total of 1560 epochs were processed. Of these, 172 (over 10%) were declared invalid due to corruption in respiband output. Such a high number may not occur in regular sleep, but the participants in this study changed position every twenty minutes. A further 334 of the remaining 1388 epochs (24%) contained some type of movement that did not affect the respiration bands, but could affect the pressure sensor array. Again, this may be higher than in regular use, since participants were asked to move every two minutes.

Table I shows a summary of results. The percentage of selections which matched the ideal sensor is shown in the first column. The spectral ratio method was almost three times more likely to choose the ideal sensors than the amplitude method. Although correct selections arose in less than 30% of epochs for all methods, the correlation coefficients show good matching between the selected sensor outputs and the respibands nonetheless. All methods but the amplitude method provide mean correlation coefficients above 0.8, with median values above 0.9.

Table II underlines the clinical effect of improvements in sensor selection offered by the spectral ratio method. Comparisons were made between the respiratory rates calculated from the respiband outputs to the respiratory rates calculated from the sensor outputs chosen by each method. All methods have median absolute rate errors of 0 bpm, so that over 50% of the rates exactly match the rates that were measured from the respibands; however, the spectral ratio method resulted in smaller mean rate errors. The improvement in the percentage of epochs with rate errors less than 1 bpm is almost 1% over the spectral power method and more than 5% over the amplitude method. The mean rate errors were all less than 2.5 bpm and all methods had a slight positive bias: the sensors were more likely to overestimate the respiration rate.

To examine the effect of movement, a ratio of the movement energy present in each epoch to the total energy was calculated, using manual movement annotations to determine when movement occurred. The movement energy ratio, MER, combines movement length and power into a single number to quantify the amount of movement present in each epoch:

$$\text{MER} = \frac{E_m}{E_{tot}} = \frac{P(X_m)M}{P(X_{all})N} \tag{3}$$

where M is the number of samples of movement in the epoch of length N, X_m represents the samples that occurred during the movement period, X_{all} represents all of the samples in the epoch, and $P(X)$ is power, calculated as the variance of X. Epochs were classified according to amount of movement: none (MER = 0), small (MER < 0.25), medium ($0.25 \leq$ MER < 0.75), and large (MER ≥ 0.75).

Fig. 3 shows the difference in performance for each of the methods with respect to amount of movement. When no movement occurs, the spectral ratio method barely exceeds the spectral power method. Once even a small amount of movement occurs, the spectral ratio method widens the performance gap with a correlation 4.1% higher than the spectral power method. For large amounts of movement the

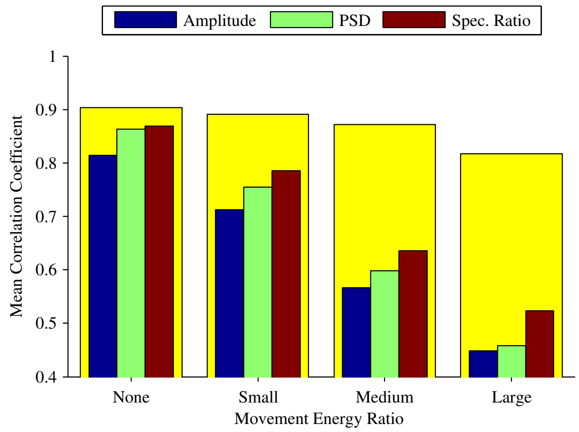

Fig. 3. Correlation of respibands to selected sensor, with respect to the movement energy ratio of each epoch. The bars behind represent the maximum possible correlation if all epochs were ideally chosen with a priori knowledge of the respiband output and where movement artifact occurred

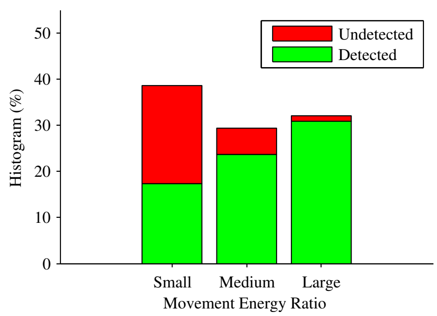

Fig. 4. Histogram of movement energy ratios for detected and undetected movement

gap becomes 14%. However, movement is detrimental to all methods, and the difference between these methods and the ideal sensor selection also widens with higher movement ratios.

By using a movement detection algorithm prior to sensor selection, the effect of movement can be moderated [9]. However, not all movement artifacts are detected by this algorithm. To better understand the distribution of movement energy in the data set and how much of the movement energy can be negated by movement detection, Fig. 4 displays the distribution of the movement ratio over the epochs that included movement. Additionally, each histogram bar is broken into the ratio of epochs where movement was detected versus undetected. The majority of epochs with movement contained only small movements. For these epochs, the proportion of epochs where movement was detected was only 45%, while for medium and large movements, the proportion of detections were 81% and 96% respectively. As the movement energy ratio increases, and movements become stronger, the proportion of movements that are easily detected increases.

The ability of a selection method to withstand weaker or shorter movements is more critical than for larger ones. Most importantly, smaller movements are less likely to be detected, and breathing effort signals may be unknowingly corrupted. Secondly, smaller movements are more likely to occur. Almost 40% of the movements performed here were classified as small movements, and in clinical practice, where movements like leg twitches occur during sleep, tolerance to such movements is key.

V. CONCLUSION

We set out to reduce the error in sensor selection when movement artifacts intruded on pressure sensor signals. By taking advantage of the periodicity of the breathing signal to find the sensor output that is at the same time strongly rhythmic and powerful, the proposed spectral ratio method offered better performance than the next best method, the spectral power method, during both still and movement-corrupted epochs. For epochs containing small movements, which are the least likely to be detected, this method shows a convincing advantage, with a 4% improvement in correlation to respiband outputs.

Across all methods, the drop in performance due to movement was substantial when compared to the best possible outcome. Further investigation is warranted to increase movement corruption resilience.

Although the methods outlined here were tested with pressure sensors, they may be applicable to any respiratory sensor technology that is beset by movement artifacts.

REFERENCES

[1] M. H. Jones, R. Goubran, and F. Knoefel, "Reliable respiratory rate estimation from a bed pressure array," in *Proc. 2006 Ann. Int. Conf. IEEE Engineering in Medicine and Biology Society (EMBC 2006)*, Aug. 2006, pp. 6410–6413.

[2] K. Mukai, Y. Yonezawa, H. Ogawa, H. Maki, and W. M. Caldwell, "A remote monitor of bed patient cardiac vibration, respiration and movement," in *Proc. 2009 Ann. Int. Conf. IEEE Engineering in Medicine and Biology Society (EMBC 2009)*, 2009, pp. 5191 –5194.

[3] V. Vasu, N. Fox, C. Heneghan, and S. Sezer, "Using the lomb periodogram for non-contact estimation of respiration rates," in *Proc. 2010 Ann. Int. Conf. IEEE Engineering in Medicine and Biology Society (EMBC 2010)*, 2010, pp. 2407–2410.

[4] A. Zaffaroni, P. de Chazal, C. Heneghan, P. Boyle, P. R. Mppm, and W. T. McNicholas, "SleepMinder: an innovative contact-free device for the estimation of the apnoea-hypopnoea index," in *Proc. 2009 Ann. Int. Conf. IEEE Engineering in Medicine and Biology Society (EMBC 2009)*, 2009, pp. 7091 –9094.

[5] D. Heise and M. Skubic, "Monitoring pulse and respiration with a non-invasive hydraulic bed sensor," in *Proc. 2010 Ann. Int. Conf. IEEE Engineering in Medicine and Biology Society (EMBC 2010)*, 2010, pp. 2119–2123.

[6] K. Niizeki, I. Nishidate, K. Uchida, and M. Kuwahara, "Unconstrained cardiorespiratory and body movement monitoring system for home care," *Medical and Biological Engineering and Computing*, vol. 43, no. 6, pp. 716–724, 2005.

[7] Y. Nishida, M. Takeda, T. Mori, H. Mizoguchi, and T. Sato, "Monitoring patient respiration and posture using human symbiosis system," in *Proc. 1997 IEEE/RSJ Int. Conf. on Intelligent Robots and Systems (IROS '97)*, vol. 2, 1997, pp. 632–639.

[8] D. I. Townsend, M. Holtzman, R. Goubran, M. Frize, and F. Knoefel, "Measurement of torso movement with delay mapping using an unobtrusive Pressure-Sensor array," *IEEE Trans. Instrumentation and Measurement*, vol. 60, no. 5, pp. 1751–1760, May 2011.

[9] M. H. Jones, R. Goubran, and F. Knoefel, "Identifying movement onset times for a Bed-Based pressure sensor array," in *Medical Measurement and Applications, 2006. MeMea 2006. IEEE International Workshop on*, 2006, pp. 111–114.