METHODS TO EXTRACT RESPIRATION INFORMATION FROM ECG SIGNALS

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ABSTRACT

The reliability of respiratory signal extraction methods from electrocardiogram (ECG) data is investigated. To provide a reference, a breathing sensor using a piezo-electric cable was designed and constructed. Two previously established methods [1], QRS amplitude modulation and respiratory sinus arrhythmia (RSA), are adapted to include the PQRST complex of the ECG. In addition, a third method, which we call the ECG mean, is proposed. The results show that interval methods perform better than envelope methods. However, the ECG mean method performs similarly to the interval methods.

Keywords: breathing rate, ECG, respiration

INTRODUCTION

In recent years, as sensors have become smaller, cheaper, and more flexible, we have witnessed radical growth in the field of mobile health monitoring. Interest comes from the health care providers for whom mobile monitoring may reveal health trends that are not always obvious in the ambulatory environment; patients who discover new confidence and freedom; healthy people who like new gadgets that help them objectively monitor their physical condition, or professionals who work in extreme environmental conditions, such as firefighters or soldiers. In any case, for either prolonged or on-demand health monitoring, the sensors should not be an encumbrance to the user.

A large variety of sensors, providing data on heart, movement, breathing, humidity, and more give researchers and medical professionals an abundance of information. However, a subject made uncomfortable by the numerous sensors placed on them is unlikely to act in a natural fashion, possibly compromising the results. In addition, the discomfort may cause the subject to decline participating in future studies or agreeing to be monitored to improve their health. Further, such burdensome equipment is unlikely to be adopted on a large scale study or for commercialization. A solution can be obtained by extracting as much information as possible from a single biological signal. Then the redundant sensors can be removed.

Respiration has long been shown to be correlated with certain aspects of the electrocardiogram [2]. Mason [1] examined several non-invasive methods of respiration monitoring including methods that use biological signals, involving respiratory sinus arrhythmia (RSA), the change in heart rate associated with breathing, and QRS amplitude modulation, the change in amplitude of the ECG associated with breathing. While no single method was determined to be ideal, Mason suggested the fusion of several methods to provide better results. However, employing several separate sensors is not acceptable in mobile health monitoring because such an approach leads to reduced mobility and increased encumbrance.

DATA COLLECTION

We employed an Alive Heart Monitor [3], which is a small convenient commercial product manufactured by Alive Technologies Pty. Ltd. of Arundel, Queensland, Australia; which records both ECG with a sampling rate of 300 Hz and acceleration with a sampling rate of 75 Hz. Designed for mobile health monitoring, it can run for several days on one battery charge. The ECG data is taken across the heart with one electrode placed on the top of the sternum, the hard area (bone) directly between the collarbones and below the throat. A second electrode is placed on the lower left rib area. This placement creates a line connecting the two electrodes that passes directly through the heart.

We designed and constructed a breath sensor to independently monitor breathing by measuring the expansion and contraction of the chest. The device wraps around a subject's chest and detects changes in tension as the chest expands and contracts.

A detailed diagram of the Breath Sensor circuit, with the signal flow, is shown below in Figure 1.

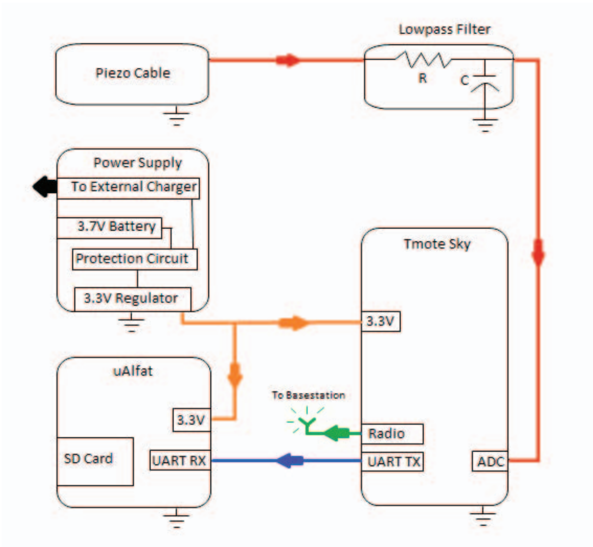

Figure 1. Breath Sensor Circuit Diagram. The plot shows sensor, signal conditioning, and storage of the breathing data. The raw signal is output from the piezo cable sensor [4] to a lowpass filter with cutoff frequency set to 25 Hz to prevent aliasing (red line). The signal is then oversampled at 100 Hz to account for non ideal characteristics of the filter by an ADC on the Tmote Sky [5]. From this point, there are two options. The data can be sent to the radio for broadcast to a base station, consisting of another Tmote Sky connected to a PC, allowing data to be viewed and recorded live (green line). With the second option, the data is transferred via UART to the µAlfat SD card interface which enables recording of data to an SD card (blue line). This option sacrifices live streaming for mobility. Both the Tmote Sky and the µAlfat are powered by a 3.3V regulated power supply (orange line).

DATA PROCESSING

We assumed that a maximum breathing rate we can observe in breathing signals is one breath per second, and applied a low pass filter with cutoff frequency of 1 Hz to remove artifacts from rapid movements, in particular the impact of the foot on the floor while walking (see Figure 2). Although this response could enable the breathing sensor to be employed as activity monitor, it hinders the accurate monitoring of breathing. The filtered breathing signal is then compared with signals derived from the ECG signal.

In addition to the smoothed breathing signal, comparisons can be made using breathing rate. For ease of calculation, breaths are marked when inhale changes to exhale which occurs at the peaks of the signal. We detected peak times using a scaled moving mean with a window size of five seconds (for details see Figure 3), and then we calculated instantaneous breathing rates using Equation 1. ΔPeakTime is the interval between two successive peaks.

$$BR = (60/\Delta PeakTime)\ [breaths/minute] \qquad (1)$$

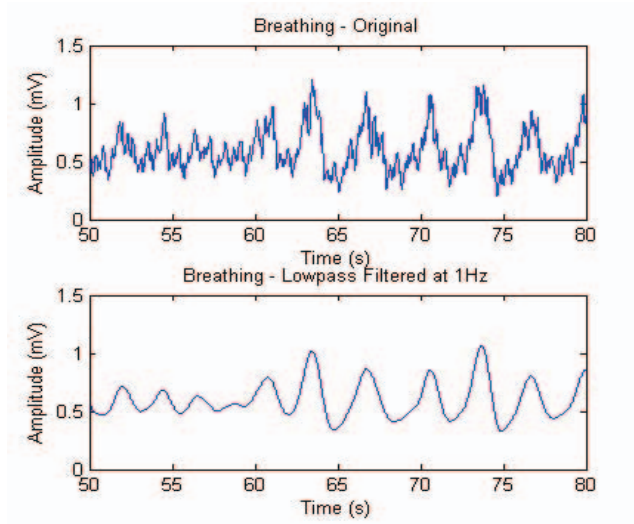

Figure 2. Filtering of Breathing Signal while Running. The top plot shows the raw breathing signal from the breath sensor during a run. Notice the noise caused by body movement making it difficult to discern low amplitude breathing signals. Lowpass filtering at 1Hz shown in the bottom plot effectively removes the unwanted signals.

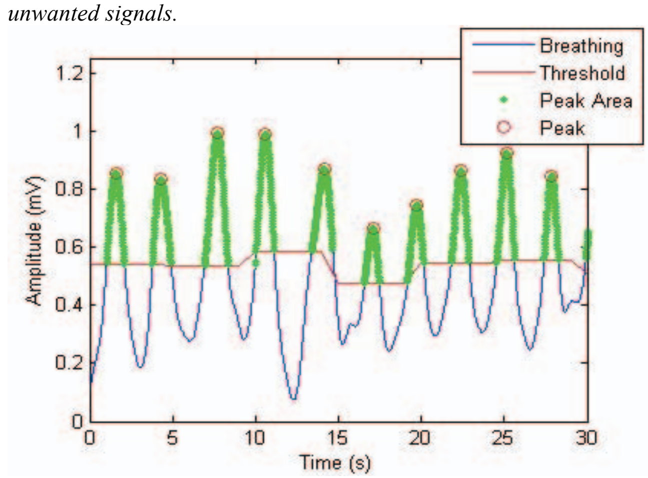

Figure 3. Breathing Peak Detection. The breathing signal (solid blue line) is filtered using the dynamic threshold (solid red line) to find the discontinued peak areas (green asterisks). The threshold is calculated by adding 10% to each mean value determined over 5sec non-overlapping sliding windows. Finding the time of the local maximum in each discontinuous peak area determines the peak times (red circle).

THE ECG

The electrocardiogram is a recording of the electrical activity of the heart. Typically, it will consist of a P Wave, QRS Complex, and a T Wave (Figure 4). Each of these waves corresponds to different actions occurring in the heart through out one heart beat [6]. The R-Peak is the most prominent point in an ECG signal and therefore the easiest to detect. Though simpler methods may work for a noise free ECG, to detect R-peaks we used a real-time algorithm given in [7]. This algorithm performs well on a noise corrupted signal. The remaining PQST points are calculated in reference to the R-Peak times. Details are given in Figure 4.

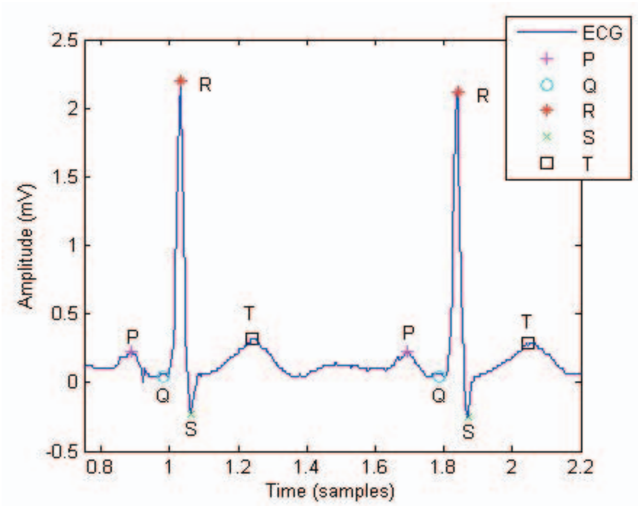

Figure 4: PQST Peak Detection is performed after initial R-Peak detection. With known R-Peaks, we find the preceding and following local minima to obtain Q and S, respectively. P can then be found by finding the local maximum preceding Q. T is found by finding the local maximum following S. Time windows are used to determine the local max/min. The size of the time windows is dependent on the period between R-Peaks.

We created time windows preceding and following the R-Peak to detect Q and S peaks. Windows are then created preceding Q and following S to detect P and T, respectively. The maximum/minimum value is found within each window. The size of these windows is calculated as a percentage, 15%, 5%, 7%, and 25%, of the R-R interval respectively for PQST features. Note that the P and T waves are now referred to by the points that represent the peak of the respective waves.

With the determination of PQRST points complete, various measures can be computed. We will examine breathing extraction using two groups of techniques involving amplitudes and intervals. In the first group we look at the envelope of the chosen peaks to derive respiration, and therefore we call them envelope methods. As well as examining the envelopes, we looked at the average local amplitude of the ECG to determine the ECG Mean method. In the second method we look at the time intervals of the chosen features of the ECG signal, and thus we employ the term interval methods.

RR-Envelope is a curve connecting all R-Peaks. We found the curve by interpolating the R-Peaks using a cubic spline. Similar curves are found for the PQST points.

The RR-Interval is defined as the time period between subsequent R-Peaks. The variation in RR-Interval has been shown to be influenced by breathing. Instead of examining only RR-Intervals, all intervals for the PQRST complex were examined respectively. Values for the intervals were calculated by finding the time difference between each neighboring pair of points.

The ECG Mean captures the oscillation of the baseline due to breathing. It attempts to capture the same phenomenon as the envelope method, while averaging adds increased robustness to noise as an additional benefit. The method involves finding the mean value of the ECG signal over the course of one heartbeat. The RR-Interval does not suffice since it actually extends over two successive heartbeats. Rather, we employed a window that starts before a given R-Peak by a time offset that is 40% of the current RR-Interval, i.e., slightly before the P-Peak of the cycle, and ends just before the P-wave of the next beat. Slight increases and decreases in the mean value of this chosen interval represent the breathing signal. We performed a cubic spline interpolation on this data to create a curve representative of the breathing signal.

RESULTS

Subjects performed a controlled set of activities, consisting of standing, which was also used for calibration, walking at two different paces, running and jogging. We used the correlation coefficients and the root mean square error (RMSE) as measures to compare the ECG breathing extraction methods to the breathing sensor signal.

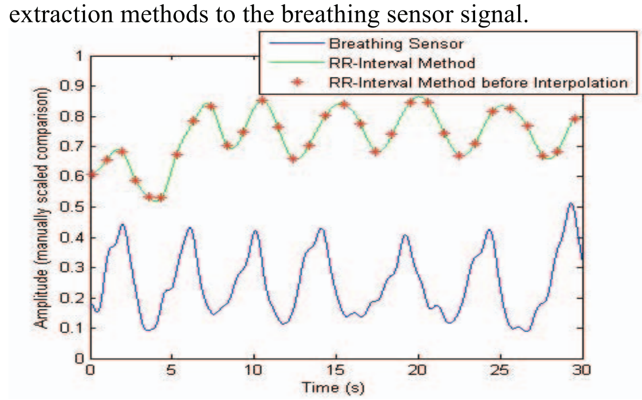

Figure 5: A Visual Comparison of RR-Interval and Breathing. This shows a clear similarity between the two signals. Each peak of the breathing signal occurs during the same time frame as the peak of RR-Interval. Note that although they are close, the maxima of the peaks do not match exactly.

The results are given in Tables 1 through 5. The interval methods perform better than envelope methods, with the exception of the ECG mean method. The slight phase shifts, which can be visually observed in Figure 5, decreases performance of the envelope methods. However, detection of "ghost" peaks shortens the true interval between peaks, and thus decreases performance of both methods. The accuracy of the methods is determined by the accuracy of the peak detection algorithms. The performance of all methods degrade with increased activity level, because increased movement of the ECG wires directly impacts the noise level. We compared the instantaneous breathing rates, calculated using Equation 1, as well as the average rate over one minute.

Methods	PP	QQ	RR	SS	TT	ECG_Mean
Envelopes	0.258	0.048	0.274	0.145	0.030	0.430
Intervals	0.504	0.513	0.504	0.505	0.488	N/A

Table 1: Cross-Correlation Coefficients of Breathing Signal and ECG Derived Signals. The interval methods create a better representation of the breathing signal than the envelope methods with the exception of ECG Mean which performs much better than its counterparts.

Breathing Rate/Methods	P	Q	R	S	T	ECG_Mean
Inst/Envelope	0.008	0.109	0.241	0.156	0.012	0.117
Inst/Interval	0.315	0.223	0.117	0.287	0.240	N/A
Avg/Envelope	0.112	0.409	0.892	0.236	0.612	0.829
Avg/Interval	0.785	0.825	0.829	0.843	0.757	N/A

Table 2: Cross-Correlation Coefficients of Breathing Rates. Grey highlights show the optimal method for each row. Several methods may be highlighted if the results are comparable. In this case, several of the Average Breathing Rate/Interval Methods perform comparably along with Average Breathing Rate/R-Envelope and Average Breathing Rate/ECG Mean Methods.

Breathing Rate/Methods	P	Q	R	S	T	ECG_Mean
Inst/Envelope	6.68	5.43	3.3	6.09	7.43	3.87
Inst/Interval	2.77	3.15	3.87	2.67	2.60	N/A
Avg/Envelope	3.95	4.64	2.34	5.03	6.62	1.41
Avg/Interval	1.21	1.51	1.41	1.14	1.30	N/A

Table 3: Root Mean Squared Error of Breathing Rates. All the values in the table are given in breaths per minute (bpm). Grey highlights show the optimal method for each row. Several methods may be highlighted if the results are comparable. In this case, all of the Average Breathing Rate/Interval Methods perform similarly along with Average Breathing Rate/ECG Mean Method.

Activity	PP	QQ	RR	SS	TT	ECG_ Mean
Lying Down	0.785	0.825	0.829	0.843	0.757	0.829
Walking	0.700	0.581	0.831	0.846	0.643	0.831

Table 4: Stationary vs. Moving Correlation. This table shows a comparison of the correlation between the interval and ECG Mean breathing rate extraction methods with the measured respiration rate from the breath sensor during lying down and walking activities. It is not clear from the correlations if movement causes an effect on the performance of the breath detection method.

Activity	PP	QQ	RR	SS	TT	ECG_Mean
Lying Down	1.21	1.51	1.41	1.14	1.30	1.41
Walking	2.09	2.38	2.23	2.19	3.06	2.23

Table 5: Stationary vs. Moving RMSE. All the values in the table are given in bpm. This table shows a comparison of the RMSE of interval and ECG Mean breathing rate extraction methods from the measured breathing rate from the breath sensor during lying down and walking activities. It is clear that movement reduces the respiration rate accuracy, as the RMSE for walking is greater than it is for lying down in all cases.

In addition, we compared the performance of the methods in the presence of motion (see Tables 4 and 5). The results show degradation of the performance of all methods, however, the interval based methods and the ECG mean method perform similarly and both are superior to the envelope methods.

CONCLUSION

This study has explored methods to derive respiration rate from ECG data thereby eliminating the need for a separate respiration sensor. We classified the methods into two groups: amplitude and interval methods. We have found that the interval methods are more accurate than the envelope methods. Comparing to the respiration rate as directly measured by the piezo-cable sensor, the interval methods have higher average correlation coefficients than the envelope methods, with 0.808 versus 0.515 for breathing rates, and a RMSE of 1.31 breaths per minute (bpm) versus 4.00 bpm. Not surprisingly, the performance of the ECG Mean method exhibited robustness to noise and was similar to the performance of the interval methods with a 0.830 correlation coefficient to the measured breathing rate and a RMSE of 1.41bpm. High amplitude of the R-peaks proved to be advantageous for the RR-Envelope method, which also showed good performance and low sensitivity to noise.

Future studies will focus on fusing the optimal methods to improve overall performance and an examination of longer data sets with unknown activities for a more complete assessment of these methods for mobile health monitoring. An alternative approach may even involve elimination of the ECG sensor altogether and the use of a device similar to the breath sensor described in this paper calibrated to provide information on heart rate, breathing rate, and motion.

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