ESTIMATION OF RESPIRATORY WAVEFORM USING AN ACCELEROMETER

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ABSTRACT

The cardio-respiratory signal is a fundamental vital sign to assess a person's health. Additionally, the cardio-respiratory signal gives a great deal of information to healthcare providers wishing to monitor healthy individuals. This paper proposes a method to detect the respiratory waveform from an accelerometer strapped onto the chest. A system was designed and several experiments were conducted on volunteers. The acquisition is performed in different status: normal, apnea, deep breathing and also in different postures: vertical (sitting, standing) or horizontal (lying down). This method could therefore be suitable for automatic identification of some respiratory malfunction, for example during the obstructive apnea.

Index Terms— Respiratory system, Accelerators

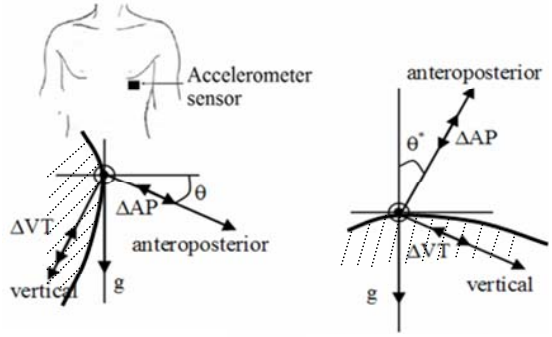
1. INTRODUCTION

The measurement and the monitoring of the respiratory waveform are important in many circumstances [1]. In general, continuous respiratory monitoring techniques can be classified as follows: (a) devices which measure motion, volume, or tissue changes (e.g., trans-thoracic impedance techniques, rib inductance plethysmography), (b) devices which measure airflow (e.g., thermistors for measurement of oro-nasal airflow), and (c) devices which assess blood gas changes (e.g., pulse oximetry, or end-tidal O_2 measurement). These devices can also be considered in terms of the level of information about respiration which they provide to the clinician. The simplest devices give only estimates of respiratory rate; more sophisticated ones will also provide quantitative information about tidal volume, and gas exchange parameters. The appropriate choice of technology for respiratory monitoring will therefore largely depend on the clinical application under consideration [2].

Our study investigates the derivation of the respiratory waveform from an accelerometer. This signal will be compared to a reference one obtained from the inductive band. The system prototype is simple, and a computer program permits us to collect, to analyze the signals and to validate the algorithms.

2. MATERIAL AND METHODOLOGY

The proposed system consists of an accelerometer strapped onto a flexible belt, its power supply, and a data acquisition board connected to a computer. The ADXL204 is a biaxial accelerometer, ± 1.7g type (g: acceleration of gravity 9.8m/s^2). Its sensitivity is 620mV/g. Accelerometer is located in the sagittal plane (Figure 1).



vertical condition horizontal condition

Figure 1. Sensor module location
(AP: anteroposterior, VT: vertical)

The breathing causes a periodical movement of the thorax and thus it changes the inclination of accelerometer placed on the chest, $\Delta\theta$. In the rest state, the accelerometer measures the acceleration of gravity and reflects this periodical change as the respiration [3].

In the vertical condition, $\theta \approx 0$ (Figure 1):

$g_{AP} = g \,.\, \sin\theta \approx g \,.\, \theta \Rightarrow \Delta AP \sim g \,.\, \Delta\theta$,

$g_{VT} = g \,.\, \cos\theta \approx g \,.\, [(1 - \theta^2)]^{1/2} \Rightarrow \Delta VT << \Delta AP$.

In the lying condition, $\theta^* \approx 0$:

$g_{VT} = g \,.\, \sin\theta^* \approx g \,.\, \theta^* \Rightarrow \Delta VT \sim g \,.\, \Delta\theta^*$,

$g_{AP} = g \,.\, \cos\theta \approx g \,.\, [(1 - \theta^{*2})]^{1/2} \Rightarrow \Delta AP << \Delta VT$.

These arguments prove that the direction perpendicular to gravity is the most sensitive for measuring the thorax movement. Thus we decided to process the signal in the sagittal plane so that the accelerometer signal is independent of either the vertical or the horizontal postures.

The breathing signal is visible along the anteroposterior axis in the upright position and along the vertical axis in horizontal position (Figure 2), so we use a signal, which is the sum of vertical signal and anteroposterior signal to present the accelerometer signal.

The respiration signal collected from the change of the inclined angle is a slow variation (< 1 Hz) with weak amplitude, which is easily mixed with the body movement. Both signals are in the same frequency band [0÷1] Hz, so it is necessary that the person stays still while taking measurements.

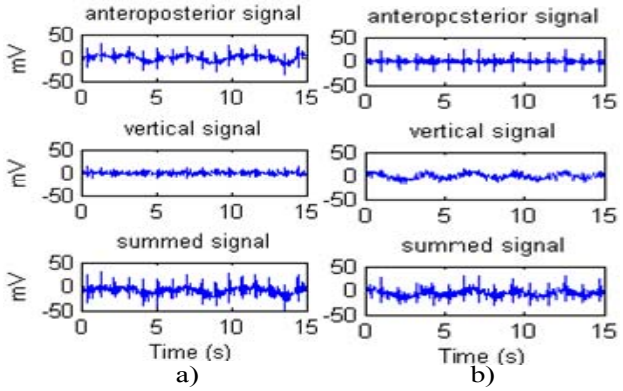


Figure 2. The measured signals in two postures: vertical (a), horizontal (b)

The data is collected (1 KHz per each channel) by a DAQ-6024E card which has a 14-bit analog-to-digital converter, and Labview 7.0 software of National Instruments Inc. This sampling frequency is necessary for the fusion of the ECG signal with the accelerometer-based respiratory waveform in our relative researches. A recorded signal is normalised in "g" unit in Figure 3.

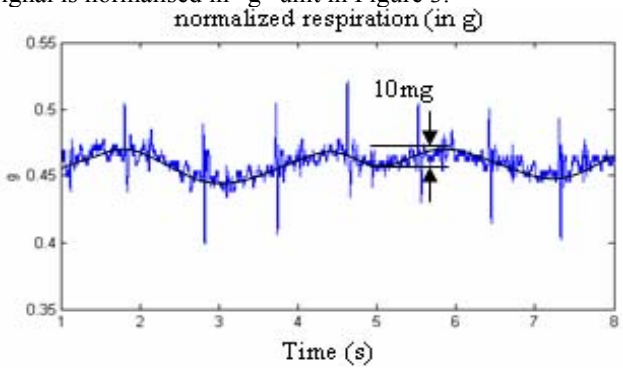


Figure 3. Three periods of thorax movement

The dynamic range of the accelerometer is ± 1.7g, to detect the breathing of 10mg with the resolution 0.5 mg (20 steps), the analog-to-digital converter needs have:

the number of bits = $\log_2(3400 / 0.5) \approx 13$ bits.

If the dynamic range of the accelerometer increases, the number of bits in the converter must correlatively increase. The DAQ-6024E permits us to measure respiratory variation data with a very good resolution.

3. AUTOMATIC DETECTION OF THE RESPIRATORY WAVEFORM

In conventional methods, the respiratory waveform is detected using a constant band-pass filter to denoise the measured signal. The frequency band is usually within the range [0÷1] Hz [4,5].

With the signal measured from the accelerometer in case of deep breathing, we observed that there is too much noise after filtering the signal by a constant band-pass filter. For example, the "dash signal" in Figure 4 which has many peaks, so it can give some errors for calculating of the respiratory rate.

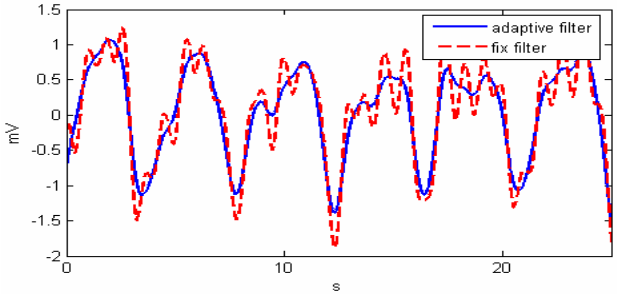


Figure 4. Comparison the respiratory waveforms in case deep breathing

Our strategy is to estimate the dominant respiratory frequency, which has the maximal energy, and after that we will supplement the neighbor frequency components. The algorithm detects the respiratory waveform as follows:

- Divide the signal into 1-minute segments with 10-s overlapping.
- Calculate the spectrum and detect the maximum (f_0) of the accelerometer signal in the range [0.1÷1] Hz. This selection is based on an observation that the number of the respiration peaks by minute is observably between 6 and 60 beats.
- Filter the accelerometer signal around f_0 with a band-pass Butterworth filter [f_1, f_2], 4th order. The choice of the bandwidth is conditioned by the following rules:

f_1= max(0.1,fo-0.4) Hz; f_2= fo+0.4 Hz

An "adaptive method" example is the "solid signal" in Figure 4. We use the 1-minute segments because this duration is enough to detect f_0 in the domain [0.1 ÷ 1 Hz] and these segments will also be applied for calculating of respiratory rate.

4. VALIDATION OF THE RESPIRATORY WAVEFORM

In this section, we will give a quantitative assessment of the accuracy of the respiratory waveform measured by the accelerometer (ACC) as compared to a traditional technique for respiratory monitoring such as the respiratory inductive plethysmography band (RIP) which is taken as the gold standard.

To provide such an estimate, we used two subjects in two postures (sitting and lying). Subjects were asked to be immobile with each posture. After the accelerometer and the band inductive were set up, the subjects were given a few minutes to relax and to familiarize themselves with the experimental conditions. During this time, the positions of the accelerometer and the band were modified around the

thorax to maximize the signal amplitude during quiet breathing. The optimal accelerometer placement was typically found to be around the heart on the thorax.

To incorporate a wide variety of different breathing situations, the experimental protocol consists in normal breathing, apnea and deep breathing.

An example of experimental results is shown in Figures 5 and 6. It illustrates that the normalized ACC signal provides a respiratory one which is qualitatively similar to the reference signal obtained from the RIP band for different situations (A: apnea, N: normal).

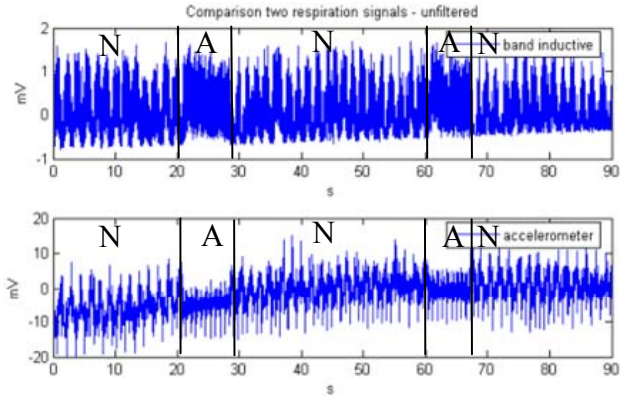


Figure 5. Example of raw signal from RIB band (top) and accelerometer sensor (bottom)

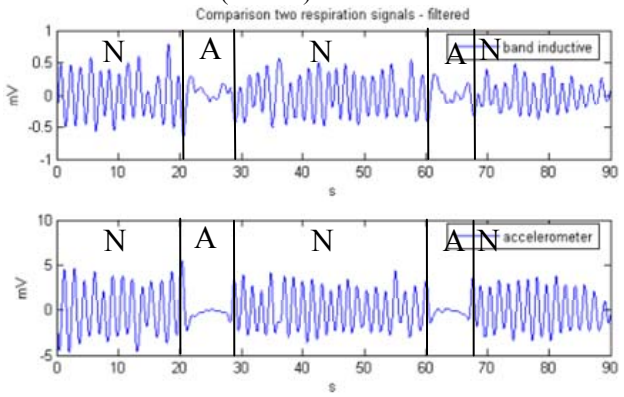


Figure 6. Example of filtered signals: Normalized respiratory waveforms of ACC and RIP for different situations. (band pass filter [0 ÷ 1] Hz for RIP signal; "adaptive in the frequency domain" filter for ACC signal).

For a more detailed analysis, we have compared both respiratory waveforms in the following way:

- the phase shift determined for the different situations;
- the normalized magnitude and the dominant respiratory frequency;
- the correlation coefficients between the two signals.

During apnea, the amplitude of two signals is close to zero. The small variation of the signal in these regions is really the noise but it is smaller than the normal regions. This is right in all postures. So our analysis will compare in two situations: normal breathing and deep breathing.

4.1. Phase shift between two signals

In order to determine the accuracy of the detection of the expiration and of the inspiration, the relative differences (phase shift), ΔT_{insp} ΔT_{exp} between these events in two signals were determined as:

$$\Delta T_{insp}(i) = T_{insp}^{ACC}(i) - T_{insp}^{RIP}(i)$$

$$\Delta T_{\exp}(i) = T_{\exp}^{ACC}(i) - T_{\exp}^{RIP}(i)$$

where i is the index number of the breath (Figure 7). A positive value of ΔT indicates that the RIP signal precedes the ACC signal while ΔT < 0 means that the event was detected earlier in the ACC signal. The phase shifts were calculated separately for the different breathing situations: normal and deep breathing.

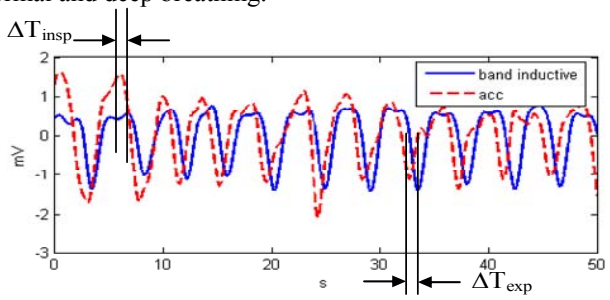


Figure 7. Illustration of the ΔT calculation

Figure 8 shows a boxplot representation of phase shift data for all subjects, indicating the median, upper and lower quartile, and the spread of the data.

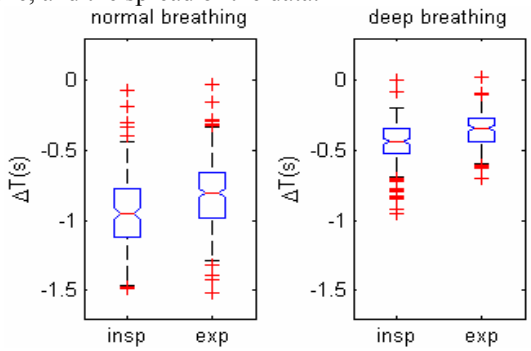


Figure 8. Boxplot of the phase shifts in different breathing patterns.

This result indicates that the difference between two signals, ΔT, is generally constant. The value ΔT is small during deep breathing. The spread of phase shifts in case of normal breathing is larger than in case of deep one. This is reasonable because we examined the thoracic respiration, and the thoracic movement in case of normal breathing is faster than in case of deep one.

The results shown in figures 6 indicate that the signal obtained with the accelerometer is qualitatively similar to the reference breathing signal measured with the inductive band, further analysis in figure 8 confirms that the number

of onsets of expiration and inspiration can be correctly determined based on the accelerometer.

4.2. Normalized magnitude of signal and dominant respiratory frequency

We do not compare directly the amplitude of the two signals but we compare the normalized magnitude of the signals in the range [0 ÷ 1] Hz. Figure 9 shows the magnitudes of two respiratory waveforms over a time period of 60s. The magnitude is normalized to the maximum amplitude.

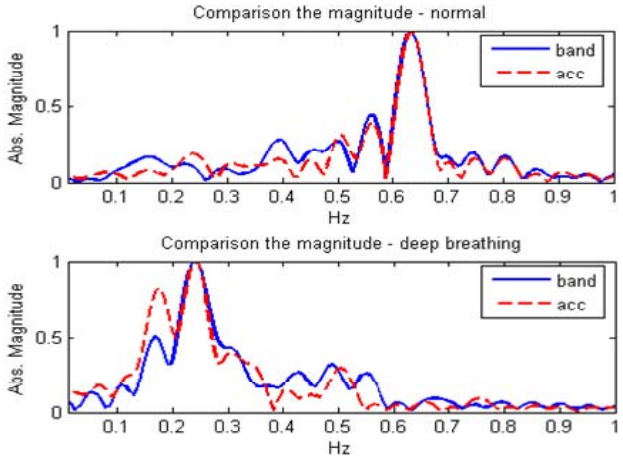


Figure 9. The magnitude estimates of two respiratory waveforms in cases: normal (top), deep breathing (bottom).

The magnitude can be used to identify the dominant respiratory frequency during that time period by identifying the frequency at which maximum power is displayed. For example, with the signal of figure 9, the dominant respiratory frequency is 0.24 Hz in case of deep breathing, and is 0.63 Hz in case of normal breathing. Moreover, the magnitudes are reasonably close in overall shape and distribution.

4.2. Correlation coefficients between two signals

We calculate correlation coefficients between ACC and RIP signals. The correlation is taken in the following way. Denoting the sampled ACC signal as x[k] and the band inductive signal as y[k], the correlation coefficient ρ is calculated as:

$$\rho = \frac{1/(N-1)\sum_{k=1}^{N-n}\left(x(k)-\overline{x(k)}\right)\left(y(k+n)-\overline{y(k+n)}\right)}{\sqrt{1/(N-1)\sum_{k=1}^{N}\left(x(k)-\overline{x(k)}\right)^2 1/(N-1)\sum_{k=1}^{N}\left(y(k)-\overline{y(k)}\right)^2}}$$

In all cases, we maximized the correlation coefficients by finding the optimum phase between the ACC and RIP signals. To avoid end effects, for each postural position, we select the clear segments from the middle of the recording. Results are represented in table 1 as the mean values in the different situations.

Table 1. Results of the correlation coefficients

	Vertical	Horizontal
Normal breathing	0.60	0.89
Deep breathing	0.45	0.70

These values indicate that the correlation in the horizontal case is higher than in the vertical case, and the correlation in case of normal breathing is higher than in case of deep one. It is reasonable when we consider that the noise is emitted from the friction of (under)vest and skin, from the small movement of the body.

5. CONCLUSIONS AND PERSPECTIVES

The signal from an accelerometer attached on the thorax can be used to differentiate between different breathing situations. Unfortunately, the accelerometer is sensitive to body movements. In the current study only one accelerometer was used and the subject was instructed to sit or lie steadily. An additional accelerometer could be applied to the abdomen and both signals combined to provide a more reliable and more accurate respiratory waveform. The combination of the accelerometers waveforms could also be used to detect body movements and to differentiate these from the movements caused by respiratory activity [6]. This could lead to an extended system which would work in the presence of movements associated with activities of daily living and would be suitable for applications outside a controlled experimental setting.

6. REFERENCES

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