Estimating respiration rate using an accelerometer sensor

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ABSTRACT

Breathing activity can be independently measured electronically, e.g., using a thoracic belt or a nasal thermistor or be reconstructed from noninvasive measurements such as an ECG. In this paper, the use of an accelerometer sensor to measure respiratory activity is presented. Movement of the chest was recorded by an accelerometer sensor attached to a belt around the chest. The acquisition is realized in different status: normal, apnea, deep breathing or after exhaustion and also in different postures: vertical (sitting, standing) or horizontal (lying down). The results of the experimental evaluation indicate that using a chest-accelerometer can correctly detect the waveform and the respiration rate. This method could, therefore, be suitable for automatic identification of some respiratory malfunction, for example during the obstructive apnea.

CCS CONCEPTS

• **Applied computing → Bioinformatics**

KEYWORDS

Respiration signal; respiration rate; chest – accelerometer

ACM Reference format:

Phan Duy Hung. 2017. Estimating respiration rate using an accelerometer sensor. In *CSBio '17: Eighth International Conference on Computational Systems-Biology and Bioinformatics, December 7–8, 2017, Nha Trang City, Viet Nam.* ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/3156346.3156349

1 INTRODUCTION

It is well known that the cardio-respiratory signal is a fundamental vital sign to assess a person's health [1,2] [1].

Continuous respiratory monitoring techniques can be broadly classified into three categories: (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) and (d) signal be reconstructed from noninvasive measurements such as an ECG. The simplest devices give only rough estimates of respiratory rate while more sophisticated ones will also provide quantitative information about the tidal volume, and the gas exchange parameters. The appropriate choice of technology for respiratory monitoring will therefore largely depend on the clinical application under consideration [3,4].

The respiratory signal is normally buried in the noise of the friction between vest and skin, and the small movement of the body. The doctors and researchers will use only the respiratory segments, which present well the respiration, for analyzing pathologies.

In this article, we propose a threshold algorithm to derive the respiration rate based on a chest-accelerometer and the estimated respiratory waveform in [5,6]. This will allow monitoring vital signs in a simple manner with a non-obtrusive, highly integrated device. We will demonstrate that our accelerometer-based estimates of vital signs compete well with reference methods in static conditions. The system prototype is simple, and we have also developed a computer software to permits us to collect, to analyze the signals and to validate the algorithms. We will present our results in five sections:

1: Introduce origin and object of the article.
2: Describe the ambulatory system and collect the database.
3: Detect automatically and validate the respiration signal from accelerometer sensor.
4: Propose the method to calculate the respiratory rate.
5: Conclusions and perspectives.

2 SYSTEM DESCRIPTION

The system consists of an accelerometer sensor strapped to 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). Its sensibility is 620mV/g. Two axes of the accelerometer are located in the sagittal plane (Figure 1).

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

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

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

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

CSBio '17, December 7–8, 2017, Nha Trang City, Viet Nam

ACM ISBN 978-1-4503-5350-2/17/12…$15.00
https://doi.org/10.1145/3156346.3156349

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

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

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

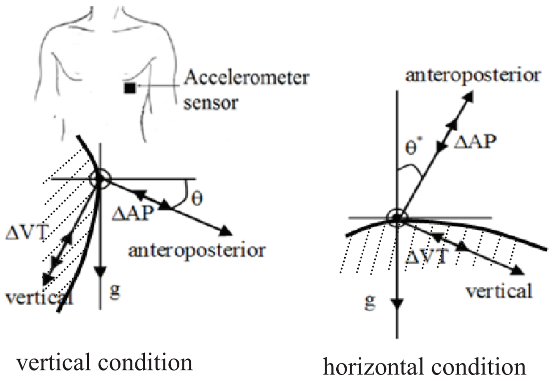

Figure 1: Sensor module location.

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

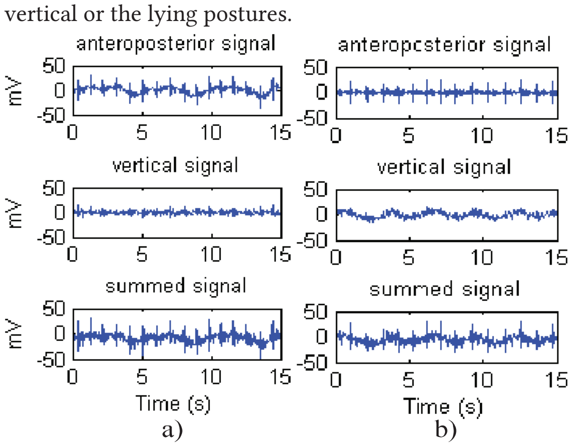

Figure 2: The measured signals in two postures: vertical (a), horizontal (b).

Figure 2 illustrates the measurements from accelerometer sensor. The heart vibration is visible along the anteroposterior axis in the lying position and along the vertical axis in the upright position, so we use a signal, which is the sum of vertical signal and anteroposterior signal to present the accelerometer signal.

The breathing 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.

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 software of National Instrument Inc. This sampling frequency is necessary for the fusion of the signal electrocardiogram with the respiration signal in our relative researches. A recorded signal is normalized in unit "g" in Figure 3. The dynamic band 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 is calculated thus:

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

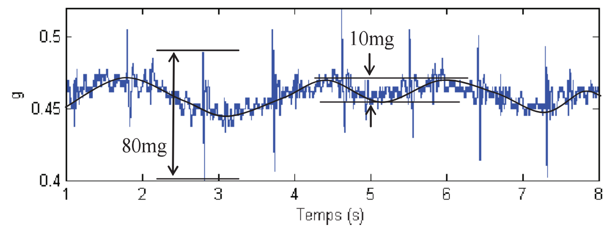

Figure 3: Three periods of thorax movement.

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 RESPIRATION SIGNAL

3.1 Realization

In conventional methods, the respiratory waveform is detected using a fixed-frequency band-pass filter to enhance the measured signal. The frequency band is usually within the range [0, 1]Hz [7,8]. In the 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 the respiratory rate.

In contrast to previous approaches, we have derived an algorithm that adaptively changes the filter frequency band to optimize the SNR.

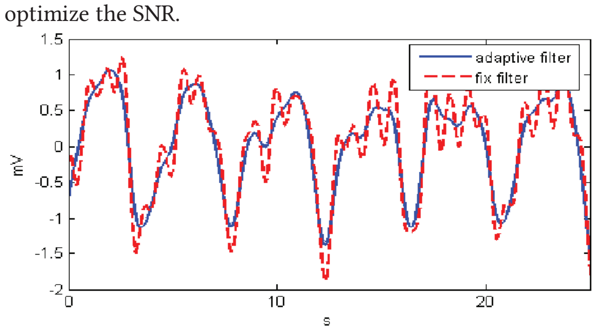

Figure 4: Comparison of respiratory waveform in case of deep breathing.

The algorithm computes the respiratory waveform as follows:

- Divide the signal into 1-minute segments with 10s overlap;

- Compute the accelerometer spectrum and detect the dominant frequency (f_0) in the range [0.1, 1]Hz. This selection is based on the observation that the number of respiration cycles per minute is between 6 and 60;
- Band-pass filter the accelerometer signal around f_0 with a Butterworth filter [f_1, f_2], 4th order. The choice of the bandwidth is conditioned by the following rules: f_1=max(0.1,f_0-0.4) Hz; f_2= f_0+0.4 Hz.

3.2 Comparison with RIP

In ISBI 2008 [5], we compared the accuracy of the respiratory waveform between this approach and the respiratory inductive plethysmography band (RIP) taken as the gold standard. 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).

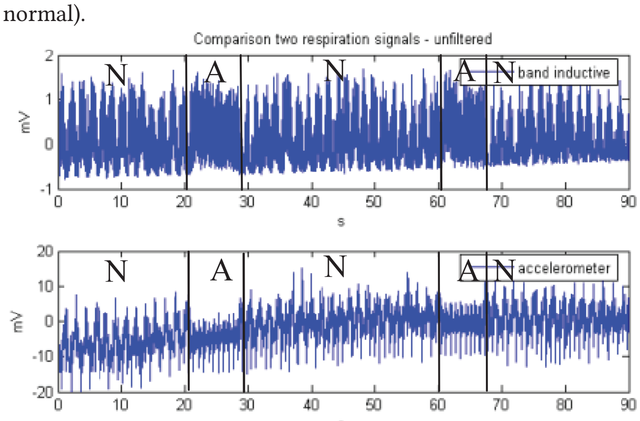

Figure 5: Example of raw signal from RIB band (top) and accelerometer sensor (bottom).

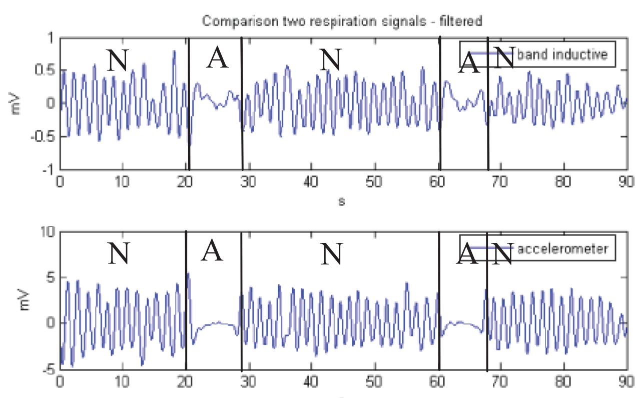

Figure 6: Example of filtered signals: Normalized respiratory waveforms of ACC and RIP for different situations (band pass filter [0÷1] Hz for RIP signal; "adaptive in the frequency domain" filter for ACC signal).

To provide a comparative assessment, we used 5 subjects in two postures (horizontal and vertical). Subjects were asked to be immobile with each posture. After the accelerometer and the RIP band 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 accelerometer and RIP band were modified around the chest to maximize the signal amplitude during quiet breathing. The optimal accelerometer placement was typically found to be around the heart on the chest.

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

- the phase shift between the onsets of expiration and inspiration;
- the normalized magnitude and the dominant respiratory frequency;
- the correlation coefficients between the two signals.

The results indicate: 1) the number of onsets of expiration and inspiration can be correctly determined based on the accelerometer; 2) the magnitude can be used to identify the dominant respiratory frequency; and 3) the values of correlation coefficients vary from 0.45 to 0.89 in the different situations, 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.

4 AUTOMATIC CALCULATION OF THE RESPIRATION RATE

The respiration rate is the number of breaths per minute. Many heart and lung diseases, particularly pneumonia, affect respiratory rate [9,10]. Therefore, monitoring of the respiratory rate is an important diagnostic method in medical care planning.

It seems that the respiration rate can be easily calculated by inverting the dominant respiratory frequency in the band [0÷1]Hz. However, this calculation gives an error in case of apnea. We can see this error in the Figure 8, the dominant respiratory frequency in case of apnea is equal with one in case of normal, but the respiration rate is less than. Therefore, we propose an algorithm to calculate the respiration rate (Figure 7):

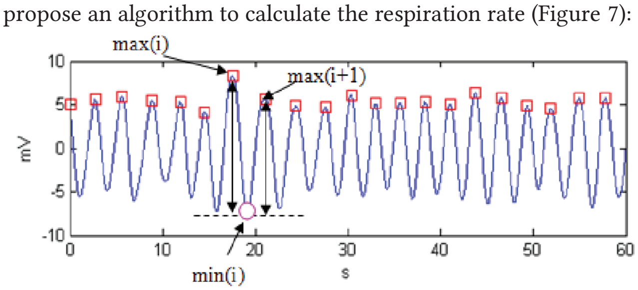

Figure 7: Illustration of the algorithm.

- Find the maximum max(i) in a 2-second window, which is shifted (no overlap) on the entire signal;
- Find one minimum min(i) between two maxima max(i) and max(i+1);

- Calculate the mean distance of |max(i)-min(i)|;
- Select threshold value T= 1/2*mean. This threshold should not be too large to miscalculate the actual variations due to the breathing action, nor too small to account for all the disturbance variations. Therefore, in this study, we selected the above threshold as an acceptable value to reconcile these two goals;
- Mark the maximum max(i) if |max(i+1)-min(i) | > T && |max(i)-min(i) | > T;
- Correct the beginning and the end. At beginning, we calculate {first maximum - (1/2 * medium interval)}, if result is negative then we add to 1/2 to respiration rate. At the end, the correction is similar.

The number of marked maxima is the respiration rate. An illustrated example is in Figure 8.

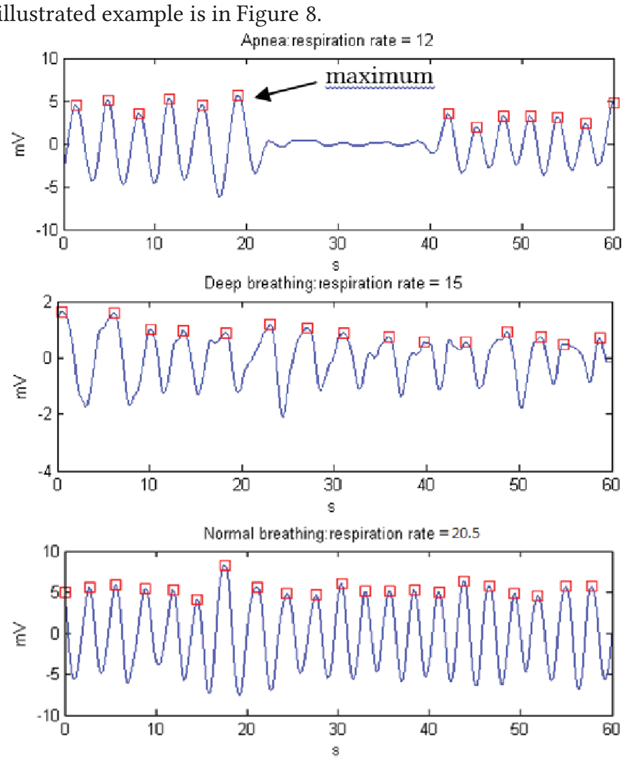

Figure 8: Result of the respiration rate.

We examined the result of the respiration rate on the data that was collected and labeled manually (200 segments, 1 minute/1 segment). The algorithm above gives the maximum error of one beat. Combine with the results in section 3.2, that the number of onsets of expiration and of inspiration can be correctly determined based on the accelerometer sensor; we can say that the accelerometer sensor is a trusted sensor for estimating the respiration rate.

5 CONCLUSIONS AND PERSPECTIVES

The signal from an accelerometer sensor attached to the thorax can be used to differentiate between different breathing situations. It can be used to determine both the respiration rate and the respiratory waveform. The accelerometer sensor is sensitive to body movements. In the current study, only one accelerometer sensor was used and the subject was instructed to sit or lie steadily.

An additional sensor could be applied to the abdomen and both signals combined to provide a more reliable and more accurate respiratory signal. The combination of the accelerometers signals could also be used to detect body movements and to differentiate these from the movements caused by respiratory activity [11]. 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.

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