

Monitoring of various breathing rate with an accelerometer

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Abstract - This study evaluates the respiratory rate from the signal of a single-axis accelerometer fixed at the top of the abdomen and for three types of breathing: slow, normal and fast. Different filters are applied and compared to determine the most accurate method to extract this information. The results showed that the use of a third-order low pass Butterworth filter following an initial estimate of the respiratory rate was the most accurate method. This study demonstrates the potential of the accelerometer as a low-cost, non-intrusive method of screening for sleep disorders and patients follow-up.

Keywords: single-axis accelerometer, respiratory rate, breathing monitoring, wearable biomedical sensors, biomedical signal processing

I. INTRODUCTION

Currently, the most common method of sensing the respiratory signal is to measure airflow through the nostrils with a pressure transducer in combination with a spirometer [1], while tracking chest wall movement with a piezoelectric belt. Exhaled carbon dioxide sensors are also used. Although the results are very complete and accurate, these methods are uncomfortable and intrusive. The complete examination to diagnose sleep disorders, called polysomnography, uses these different methods [2] and is usually performed in a hospital setting. It is a one-time examination lasting about 10 hours and is not continuous monitoring. Thus, monitoring the breathing of patients with respiratory disorders, chronic obstructive pulmonary disease or neuromuscular disorders could help to identify whether their condition is stable or not. This monitoring can also prevent sudden infant death syndrome [3]. A new area of interest is therefore the use of motion sensors such as accelerometers fixed on the chest or the abdomen as a discreet, comfortable and inexpensive method.

Morillo et al. [4] extracted the respiratory, cardiac and snoring signal in the supine position with a single-axis accelerometer. The respiratory rate was then estimated by identifying the peak of the power spectrum or by autocorrelation. Hung et al. [5] used a biaxial accelerometer to detect inspirations and expirations and to differentiate several breathing modes: normal breathing, apnea, and deep breathing. The signals from both axes are summed and a bandpass filter

with a variable bandwidth centred on the dominant breathing frequency was applied.

Thus, based on these methods which demonstrate their abilities to monitor low rate breathing mode we aim to study the feasibility of implementing an accelerometry-based portable device as a simple and cost-effective solution for contributing to the monitoring of slow, normal and even fast breathing modes from immobile subjects.

II. METHODS

A. Experimental protocol and participants

Six adult volunteers took part in the study: five women and one man, aged 19, 19, 22, 24, 55 and 56 years old, with no history of cardiopulmonary disease. Informed consent was obtained from each subject.

During the test, the subjects lay in the supine position with their arms at their sides. They were asked to breathe normally, then rapidly and slowly. Normal and slow breathing modes last for 1 minute, and fast breathing lasts for 30 seconds. A minimum of 30 seconds separates the recordings of each breathing mode.

B. Devices

To measure abdominal motion, a miniature inertial measurement system (Gait Up's Physiolog®) was attached to an elastic belt, worn around the subject's abdomen. The raw data recorded with the inertial measurement system was transferred via USB to a computer as a file with the extension ".BIN". The accelerometer signal was sampled at 256Hz. The data were acquired and processed on Matlab (Mathworks, Massachusetts, USA).

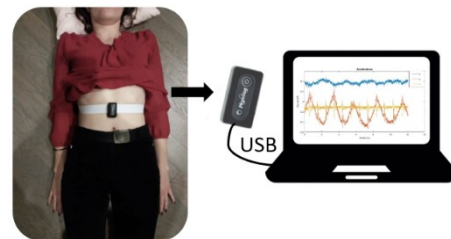


Figure 1. illustration of the measurement protocol

C. Data processing

The filters described below are used and compared to extract the respiratory peaks.

The moving average filter (MA) consists of taking the unweighted average of all 128 consecutive samples of the signal.

Resampling (R) reduces the sampling frequency from 256Hz to 5Hz. For each sub-vector of 51 points, only the average of these 51 values is kept which allows to greatly reduce the size of the acceleration vector, and at the same time to smooth the signal.

A 3rd order Butterworth low-pass filter is implemented. This requires the definition of the cutoff frequency with good accuracy for all breathing modes. A first estimation of the breathing rate must therefore be found. Two solutions have been used for this. The first solution consists of applying successively the moving average filter and the resampling. The respiratory peaks are extracted from this already smoothed signal, which provides a first approximation of the respiratory frequency f_{MM_R} . The cutoff frequency f_c is obtained using the following formula :

$$f_c = f_{MM_R} + 0.01 \quad (1)$$

A second solution consists of estimating the spectral density of the raw acceleration. Since the majority of the respiratory frequency is located in the interval [0.1; 1] Hz, the frequency on the spectrum corresponding to the largest amplitude on this interval is the approximation of the respiratory frequency [4]. The cutoff frequency is obtained with :

$$f_c = f_s + 0.1 \quad (2)$$

The margin to the estimated frequency is very small with the first method because additional peaks tend to be counted but almost no breaths are ever missed.

After the application of these methods: *Moving Average filter (MA)*, *Resampling (R)*, *MA and R*, *Spectral density (Spd)*, *Butterworth with Spd*, *Butterworth with MA and R*, the respiratory frequency is calculated via the peaks extracted from the obtained waveform signal.

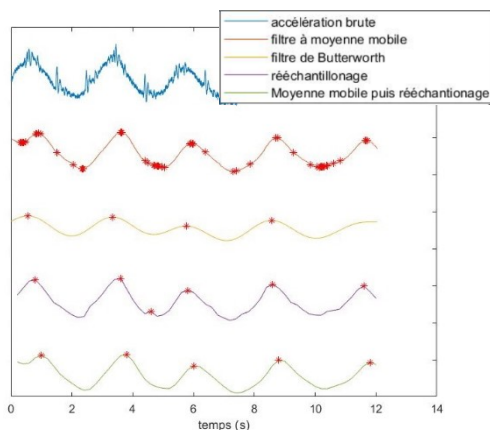


Figure 2. example of raw signal and after denoising with different filters

III. RESULTS

TABLE I. MEAN FREQUENCY AN STANDARD DEVIATION

Breathing frequency	Slow	Normal	Fast
Mean (Hz)	0,12	0,31	0,92
Standard deviation (%)	41,00	15,38	38,77

The error on the respiratory rate after the execution of each filter (Table I) is positive if on average the rate is overestimated (peaks are added) and negative if it is underestimated. The assumed true respiration rate is counted by observation. This solution is certainly not optimal but the detection is generally not ambiguous, so this simple method is quite effective in this case.

TABLE II. AVERAGE ERROR ON RESPIRATION RATE ASSESSMENT

Average error on respiration rate (%)	Breathing mode		
	Slow	Normal	Fast
Moving average filter	112.12	26.05	4.43
Resampling	4.89	0.57	0.00
Moving average filter and Resampling	0.97	0.06	-0.03
Spectral density	0.39	0.14	-0.24
Butterworth with spectral density	0.10	0.00	-0.26
Butterworth with M.A. and R.	0.12	0.00	-0.03

The errors on normal, fast and slow respiratory rate obtained with the moving average filter are much larger than the other methods. The second least accurate method is resampling. However, for fast breathing, this filter is very accurate since no error was made on the 6 values obtained. The 4 other methods allow the assessment of the breathing rate with errors lower et than 1%. The application of the Butterworth filters leads to minimal errors, especially when the cutoff frequency is defined after resampling and moving the average filter.

IV. DISCUSSION

With the moving average filter, the error is important because the irregularities, the peaks due to the background noise, have a smaller amplitude, but they are still present. The calculated frequencies are therefore very high. Resampling is already much more efficient and by combining these two filters (Moving average filter and Resampling), a good approximation of the breathing rate is obtained. The approximation with the amplitude spectrum is never exact (unlike resampling and moving average) because the frequency axis is also sampled. The difficulty with this filter lies in the decision of the frequency interval to study. Indeed, some subjects breathed

slower than 0.1Hz or faster than 1Hz. The approximation of the frequency on the interval [0.1; 1] Hz is then totally skewed. A solution could be to widen the interval, but the risk is then to obtain a maximum amplitude at the heart rate and not at the respiration rate. Finally, Butterworth filters are the most accurate in determining the respiratory rate. However, when the cut-off frequency is deduced from the spectrum approximation, it is not always correct, which in this case leads to a large error in the respiratory rate with the Butterworth filter.

For fast breathing, the error is negative whatever the filter, which means that some respiratory peaks are not detected, whereas, for normal and slow breathing, the error is positive: some signal are detected as respiratory peaks. We also observe that for the slow mode, on average whatever the filter, the error in absolute value is much higher than for the two other modes. The main reason for this is that the background noise is more important in the low frequencies, which leads more easily to errors with non-breathing peaks taken into account. A second reason is that breathing is less fluid when it is slow, it can be composed of small jolts which add extra peaks.

This study is a case study, and the sample size and the age of the subjects (on average 32.5) is not representative of the population concerned by sleep disorders. Indeed, this concerns more the elderly who tend to have a slower breathing and a lower amplitude. The protocol should therefore be tested with elderly people. To deepen the study it will be necessary to increase the sample size, to integrate older subjects and to realize a repeatability study (each subject performs each condition several times).

V. CONCLUSION AND PERSPECTIVES

In this paper, we present six methods to extract the respiratory signal through the movement of the abdomen captured by a single accelerometer axis. Three breathing modes were tested: normal, slow and fast. In all cases, the obtained signal allowed to find the breathing frequency with a good accuracy, when a third-order low-pass Butterworth filter was applied (errors <0.3%). When the filter cutoff frequency was determined with a moving average filter followed by resampling of the signal, the error on the breathing frequency was very small in all cases (errors <1%). However, more work is needed to obtain an adequate cutoff frequency by using the signal amplitude spectrum. Indeed, to take into account the subjects breathing very quickly, or very slowly, the frequency interval analyzed on the spectrum could be widened, provided that the main peak remains at the level of the respiratory signal: the cardiac signal should not distort the measurement. Thus, since the cardiac signal remains visible on the spectrum as on the raw waveform, it could be interesting to try to extract it with the same protocol as the one performed in this study.

The respiratory and cardiac signals could then be extracted with a single measurement performed at the abdomen.

Finally, to further investigate the study, the measurement and processing of the signal could be performed in real-time, by realizing an adaptive low-pass filter whose cut-off frequency would depend on the instantaneous breathing rate. It would also be interesting to refine the parameters of some filters to adapt them to the studied subject by performing an auto-calibration. One could thus vary the number of samples chosen for the moving average, the order of the Butterworth filter or the calculation of the cutoff frequency (more or less important margin compared to the first estimate of the frequency). To perform these more in-depth studies, it would then become necessary to employ another means of measuring breathing, such as a spirometer, to serve as a reference and validate the method. Finally, this case study simply seeks to optimize the signal processing to obtain the breathing rate with a single axis accelerometer. Here, no autonomous system is really proposed to monitor people with sleep disorders. On the other hand, following the protocol obtained here, it would be possible to consider monitoring the breathing of an immobile person (e.g. during a short nap on the back) thanks to a smartphone (they have a triad of accelerometer).

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