Proceeding Paper

The Effect of Measurement Trends in Belt Breathing Sensors [†]

Erik Vanegas [ID], Raúl Igual *[ID] and Inmaculada Plaza [ID]

EduQTech, IIS, Electrical/Electronics Engineering and Communications Department, EUP Teruel, Universidad de Zaragoza, 44003 Teruel, Spain; 790974@unizar.es (E.V.); inmap@unizar.es (I.P.)

* Correspondence: rigual@unizar.es

† Presented at the 8th International Symposium on Sensor Science, 17–28 May 2021; Available online: https://i3s2021dresden.sciforum.net/.

Abstract: Sensors for respiratory monitoring can be classified into wearable and non-wearable systems. Wearable sensors can be worn in several positions, the chest being one of the most effective. In this paper, we have studied the performance of a new piezoresistive breathing sensing system to be worn on the chest with a belt. One of the main problems of belt-attached sensing systems is that they present trends in measurements due to subject movements or differences in subject constitution. These trends affect sensor performance. To mitigate them, it is possible to post-process the data to remove trends in measurements, but relevant data from the respiration signal may be lost. In this study, two different detrending methods are applied to respiration signals. After conducting an experimental study with 21 subjects who breathed in different positions with a chest piezoresistive sensor attached to a belt, detrending method 2 proved to be better at improving the quality of respiration signals.

Keywords: wearable sensors; breathing sensors; piezoresistive; measurements; trends; belt; respiration rate

1. Introduction

Continuous monitoring of physiological signals is frequently used by healthcare professionals, mostly with hospital patients. For instance, monitoring of respiration rate is commonly used to diagnose overall health of the patients [1], and several diseases can be detected through respiration rate, such as asthma or sleep apnea [2]. Other common applications for respiration rate monitoring are in sports to analyze the performance of athletes [3], the monitoring of the health state of drivers and commercial builders [4], and emotion recognition [5].

When designing a system for respiration rate monitoring, two different approaches are used by researchers: wearable and environmental systems, each of which has different techniques to achieve its purpose. For wearable systems, the most common technique is to measure chest diameter variations due to inhalation and exhalation of the user. This is commonly achieved by placing a flexible strap around the chest of the user. Through this strap, chest movements are transferred to the sensor of the system. Such a sensor could be a piezoresistive sensor [6], capacitive sensor [3], piezoelectric sensor [7], optical fiber sensors [8], or inertial measurement units [9], among others [10].

When measuring physiological signals through wearable devices for a relatively prolonged time, signals show a trend, which is a systematic increase or decrease in the obtained signal due to movements of the system or subject. However, linear fit can be applied offline to the registered respiration signals to mitigate this effect, as these trends may hinder data analysis [11]. A disadvantage of doing so is that relevant information from the original signal may be lost.

In this study, we show that the effectiveness of eliminating trends in signals depends on the length of the segmentation window of the measurements. To do so, different

segmentation windows (periods of time analyzed by the algorithms) are proposed, and two different algorithms are used to analyze the respiration signals from 21 volunteers. Respiration signals were obtained through a chest-strap sensing system from a previous work [12].

2. Results

To analyze the respiration signals from all 21 volunteers, two different algorithms are used, whose basic principle consists of detecting all zero-crossings from the obtained signals by determining the zero-axis of such signals. Algorithm 1 measures the time difference between consecutive zero-crossings (breath cycles), whilst Algorithm 2 counts the number of crosses by zero. In this way, both algorithms are capable of calculating the respiration rate from the signal in breaths per minute (bpm). Both algorithms perform a segmentation of the signal (from 6 to 30 s); from each segmented window, the respiration rate is calculated, and then the mean from all the segments is taken as the average respiration rate. From each volunteer, a total of 30 respiration signals are analyzed (six different respiration rates set by a metronome, and five different activities) for a total of 630 respiration signals analyzed. In a previous work [12], a complete description of the algorithms and the database is included.

When detrending the respiration signals, two different methods were used. In the first method, the whole signal was detrended before calculating the respiration rate from each segment, whilst in the second method, each segmentation window was detrended individually. A depiction of both methods is shown in Figure 1. Relative error from each signal and each segmentation window was obtained from the original signals and each detrending method; then, a comparison in the increase or reduction in relative error was performed.
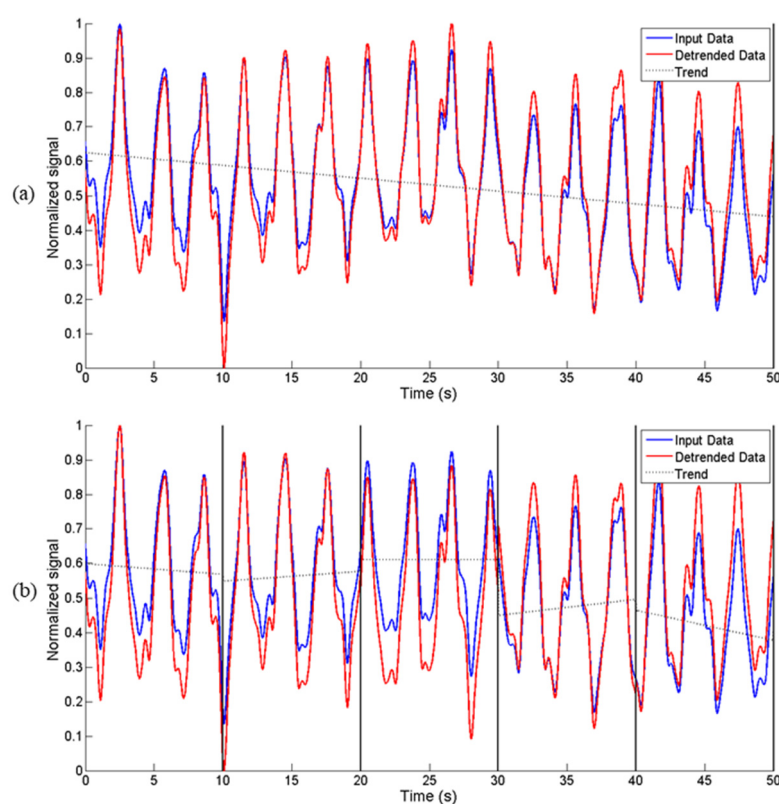

Figure 1. Signal detrend techniques used: (**a**) method 1, detrend is applied in the whole signal; (**b**) method 2, detrend is applied in each segmentation window.

For detrending method 1 and Algorithm 1, the 6 s segmentation window shows an increase in relative error by 5.46%, whilst for the rest of the windows, the relative error

decreases. By detrending the signals and calculating respiration rate with Algorithm 1, there is an average improvement (decrease in relative error) of 1.08%, with a maximum improvement of 2.52% (11 s window) and a maximum deterioration (increase in relative error) of 5.46% (6 s window). For Algorithm 2, only windows from 12 to 15 s show a deterioration of predicted respiration rate. There is an average improvement of 0.48%, with a maximum improvement of 1.78% (30 s window) and a maximum deterioration of 0.55% (13 s window).

When detrending original signals with method 2 for Algorithm 1, an average improvement of 1.54% is achieved, with a maximum improvement of 3.19% (11 s window) and a maximum deterioration of 3.58% (6 s window). For Algorithm 2, only windows of 6–8 s show a deterioration in the predicted respiration rate. There is an average improvement of 1.28%, a maximum improvement of 2.88% (30 s window), and a maximum deterioration of 2.35% (6 s window). A summary of these results is shown in Table 1. The improvement and deterioration obtained from each segmentation window are show in Figures 2 and 3 for detrending method 1 and detrending method 2, respectively.
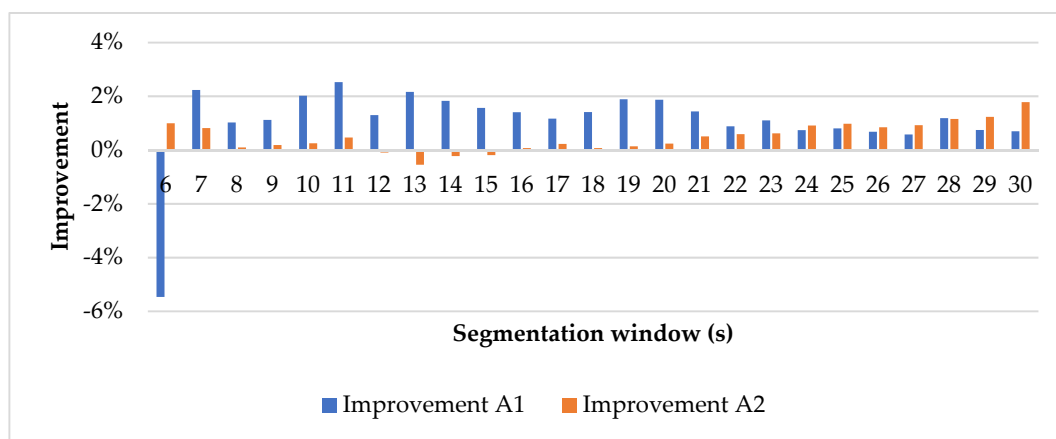
Figure 2. Improvement and deterioration obtained when calculating respiration rate after detrending the original signal with method 1.
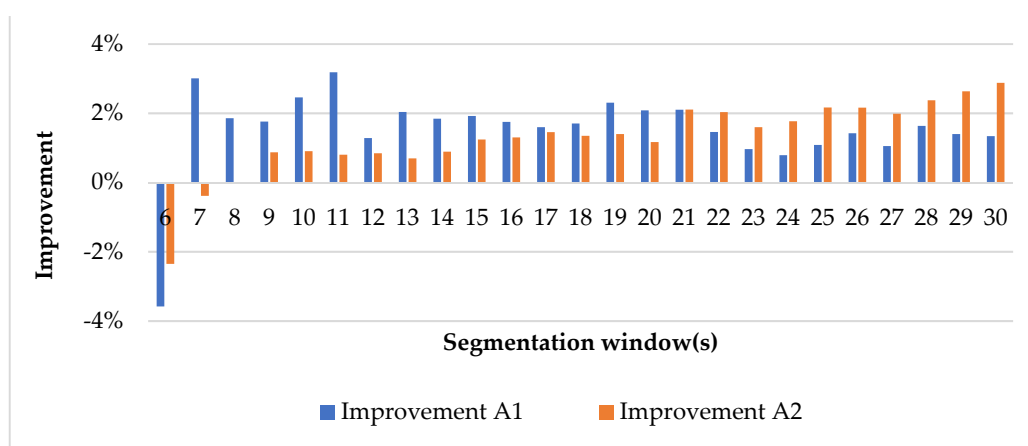
Figure 3. Improvement and deterioration obtained when calculating respiration rate after detrending the original signal with method 2.

Table 1. Improvement in respiration signal after detrending the original signal with both methods, for each algorithm.

	Algorithm 1			Algorithm 2		
	Average	MI [1]	MD [2]	Average	MI [1]	MD [2]
Method 1	1.08	2.52	5.46	0.48	1.78	0.55
Method 2	1.54	3.19	3.58	1.28	2.88	2.35

[1] Maximum improvement. [2] Maximum deterioration.

3. Conclusions

Both detrending methods show an improvement when calculating respiration rate; however, detrending method 2 shows a better performance, as the average improvement is higher for both algorithms. From detrending method 2 and Algorithm 1, only the 6 s window shows deterioration, and all other windows show improvement when calculating respiration rate. However, this improvement is not consistent when moving along the different windows. On the other hand, for Algorithm 2 it is noticed that, as the segmentation window increases, the improvement increases accordingly. Therefore, even though improvement in respiration rate prediction is moderate when detrending the signals, both detrending methods shows improvement when compared with the original signals with trends. For this specific application, detrending method 2 proves to be better.

Supplementary Materials: The poster presentation is available online at https://www.mdpi.com/article/10.3390/I3S2021Dresden-10118/s1.

Institutional Review Board Statement: The study was conducted according to the guidelines of the Declaration of Helsinki, and approved by the Institutional Review Board (or Ethics Committee) of CEICA (protocol title "Evaluación de la estabilidad y ritmo cardiaco en la práctica de mindfulness mediante sensores vestibles (wearables)", protocol code 12/2017 and date of approval 21/06/2017; derived experiment from that protocol).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The database used for this study can be found at IEEE DataPort by the name "Breathing data from a piezoresistive breathing sensor" [13].

References

1. Milenkovic, A.; Otto, C.; Jovanov, E. Wireless sensor networks for personal health monitoring: Issues and an implementation. *Comput. Commun.* **2006**, *29*, 13–14. [CrossRef]
2. Cao, Z.; Zhu, R.; Que, R.-Y. A wireless portable system with microsensors for monitoring respiratory diseases. *IEEE Trans. Biomed. Eng.* **2012**, *59*, 3110–3116. [PubMed]
3. Hoffmann, T.; Eilebrecht, B.; Leonhardt, S. Respiratory monitoring system on the basis of capacitive textile force sensors. *IEEE Sens. J.* **2010**, *11*, 1112–1119. [CrossRef]
4. Gatti, U.C.; Schneider, S.; Migliaccio, G.C. Physiological condition monitoring of construction workers. *Autom. Constr.* **2014**, *44*, 227–233. [CrossRef]
5. Ćosic, D. Neuromarketing in market research. *Interdiscip. Descr. Complex Syst.* **2016**, *14*, 139–147. [CrossRef]
6. Hesse, M.; Christ, P.; Hörmann, T.; Rückert, U. A respiration sensor for a chest-strap based wireless body sensor. In Proceedings of the 2014 IEEE Sensors, Valencia, Spain, 2–5 November 2014; pp. 490–493.
7. Mahbub, I.; Wang, H.; Islam, S.K.; Pullano, S.A.; Fiorillo, A.S. A low power wireless breathing monitoring system using piezoelectric transducer. In Proceedings of the 2016 IEEE International Symposium on Medical Measurements and Applications (MeMeA), Benevento, Italy, 15–18 May 2016; pp. 1–5.
8. Witt, J.; Narbonneau, F.; Schukar, M.; Krebber, K.; De Jonckheere, J.; Jeanne, M.; Kinet, D.; Paquet, B.; Depre, A. Medical textiles with embedded fiber optic sensors for monitoring of respiratory movement. *IEEE Sens. J.* **2011**, *12*, 246–254. [CrossRef]
9. Dan, G.; Zhao, J.; Chen, Z.; Yang, H.; Zhu, Z. A novel signal acquisition system for wearable respiratory monitoring. *IEEE Access* **2018**, *6*, 34365–34371. [CrossRef]
10. Vanegas, E.; Igual, R.; Plaza, I. Sensing systems for respiration monitoring: A technical systematic review. *Sensors* **2020**, *20*, 34365–34371. [CrossRef] [PubMed]
11. MathWorks. Remove Trends from Data. Available online: https://www.mathworks.com/help/signal/ug/remove-trends-from-data.html#:~{}:text=To%20eliminate%20the%20linear%20trend,the%20signal%20and%20subtract%20it (accessed on 7 April 2021).

12. Vanegas, E.; Igual, R.; Plaza, I. Piezoresistive Breathing Sensing System with 3D Printed Wearable Casing. *J. Sens.* **2019**, *2019*. [CrossRef]
13. Vanegas, E.; Igual, R.; Plaza, I. Breathing data from a piezoresistive breathing sensor. *IEEE Dataport* **2019**. [CrossRef]