On the Development of an Algorithm for Automatic Estimation of the Respiratory Rate using Wearable Electrocardiography

C. Veiga[1], L. Coelho[1,2], D. Dias[3], J.P.S. Cunha[3,4]

[1] Department of Physics, Instituto Superior de Engenharia do Porto, Portugal, {1160286,lfc}@isep.ipp.pt

[2] INEGI – Laboratory of Optics and Experimental Mechanics, Portugal

[3] INESC TEC – Instituto de Engenharia de Sistemas e Computadores, Tecnologia e Ciência

{duarte.f.dias,jpcunha}@inesctec.pt

[4] Faculdade de Engenharia da Universidade do Porto, Portugal

Abstract

Technology is currently present in several areas of healthcare. The respiration rate (RR) along with the electrocardiogram (ECG) are important vital indicators whose values are often obtained by specific sensors. However, there is the possibility of effectively estimating RR from the electrocardiogram's signal analysis, allowing a reduction of equipment costs, as well as an increase in user's comfort. In this paper we propose an algorithm capable of detecting and evaluating respiratory cycles from an acquired ECG signals from a wearable device according to physiologically limits. For this purpose, two methods of self-evaluation were developed: the first using the duration and amplitude proper to the respiratory signals with 81.48% of precision and the second through the respiratory wave's characteristics with 100% of precision. The performance of both methods was validated in order to analyse, selecting one for the final calculations of the main characteristics of the respiratory signal. The obtained results show that the proposed algorithm can perform very well with propensity for future improvement, given the importance of the theme and the study developed.

1. Introduction

The observation of electrocardiogram (ECG) and the respiratory rate (RR), both static and dynamic values, are essential indicators for health condition evaluation [1]. To acquire the ECG signal, due to its electrical nature, it is always required to place electrodes in contact with the wearer's skin. For monitoring the respiratory rate, when highly accurate measures are needed, we can find inductive, resistive or pressure based plethysmographs as common instruments. However these can be unpractical and uncomfortable while in a wearable technology context. Other options can be, for example, a wearable thorax band with accelerometers [2] or a finger or pulse based oximetry observations [3], but these still pose many technical issues to allow accurate results.

For our purposes the estimation of RR based on the ECG signal [4] is the best option to effectively monitor the vital signs of individuals in challenging environments or activities (e.g. athletes, firefighters, army soldiers) or to conduct sleep studies comfortably, for example.

Within this framework, there are several respiratory signal extraction from the ECG processes such as Respiratory Sinus Arrhythmia (RSA), using the instantaneous heart rate variability [5,6], the RS segment's interval or slope [5], the QRS complex [5,6], the R peak amplitude [5] and the Principal Component Analysis [7–9].

In this paper we propose a method for automatic estimation of the RR using a wearable ECG. The algorithm is to be implemented on an electronic processing device that should: a) provide real time accurate RR information; b) have a minimal power consumption; c) have a minimal cost. With these constraints in mind an approach based on the detection and evaluation of the ECG's R peaks algorithm was developed.

In the next section the materials and development methodologies that were used will be described. After, the algorithm performance is evaluated followed by a thoroughly discussion of the results. Finally, the main conclusions and foreseen improvements are shown.

2. Methods

2.1. ECG Signal Acquisition

To acquire the ECG signal there are several devices, such as VitalJacket® [10], Vital Patch® [11], SensiumVitals® [12,13], and Lifeguard [14,15], medical and wearable devices and Zephyr BioHarness [14,16], a sports equipment. In our case we have used the first option that was already available and fulfilled our signal acquisition requirements. This device is a wearable vital signs monitoring system designed and developed to be a practical approach for different clinical scenarios, in hospitals, home or on the move, that need continuous or frequent high quality vital signs monitoring from its wearer [10]. One of the objectives is to incorporate the final optimized algorithm into the device's microcontroller.

The ECG signals was acquired with a sampling frequency of 500 Hz using three electrodes configuration. The adopted acquisition strategy consisted in the elaboration of a protocol with four different typical breathing scenarios: a) Normal Breathing (NB), where the person is asked to breathe normally; b) Apnoea (AP), where the person is asked to hold his breath for 30 seconds; c) Slow Deep Breathing (SDB), where the person makes long duration respiration cycles and d) Fast Deep Breathing (FDB), where the person is hyperventilating. Using a predeveloped script, the R peaks location and amplitude are automatically extracted from the raw ECG signal.

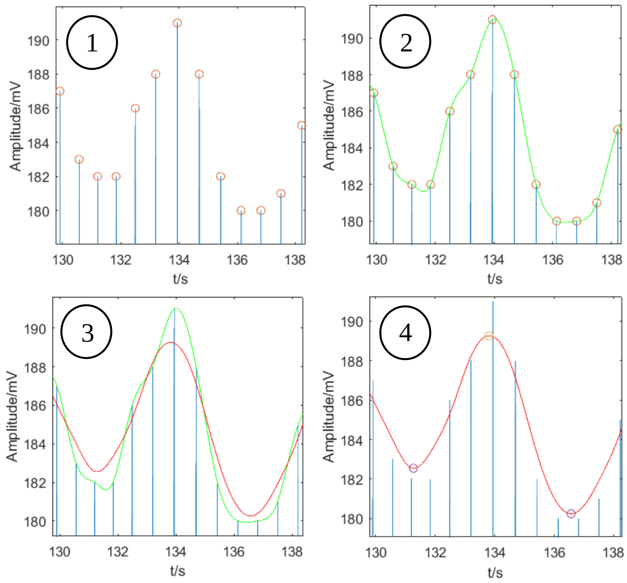

Figure 1. *Schematization of the process: (1) Original Signal, (2) Signal after Cubic Spline Interpolation, (3) Signal after Filtering, (4) Detected Cycles.*

2.2. Respiration Rate Estimation Algorithm

In figure 1 we can observe the signal after each step of the processing pipeline. On the upper left the initial data is depicted. Starting with this signal a filter will be applied since the ECG signal is likely to have noise due to muscle contraction for example. Before applying the filter and in order to have a better control of the process, once this respiratory signal has a very low sampling frequency, it was necessary to first increase it. Using the available points, a cubic spline interpolation was applied, which allowed to obtain a continuous form of the breathing wave. The sampling parameter used in this spline was 10 so the period of the respiratory signal was transformed to 10ms, resulting in the new sampling frequency of 100Hz. This value's choice was due to the counterbalance between having sufficient data for the following transformations and a calculation effort for the microcontroller. The obtained result can be seen on figure 1, upper right.

After increasing the sampling frequency the filter is applied. During development three filtering strategies were evaluated: a) a moving average filter; b) a 2nd order Butterworth filter; c) a 6th order Butterworth filter. These filters were first selected due to their low computational requirements. For the first filter, after testing with other values, a sliding window with covering 100 samples gave the best results, allowing a good representation of the wave without too much attenuation. For the 2nd and 6th order Butterworth Filters, a cut-off frequency of 1Hz [17] and pre-calculated parameters were used. In this stage the obtained results were very similar and since the first method is computationally simpler, it was selected for the final process. The obtained results after filtering are represented on figure 1, bottom left.

Finally, in order to define complete respirations cycles the derivative is calculated using the spline based estimated signal. Every cycle has a peak between two valleys and it is possible to identify them when the derivative changes signal. The final signal is showed on figure 1, bottom right.

2.3. Self-Evaluation Algorithm for Error Detection

Since not all oscillations detected are truly respiratory cycles and to ensure accurate results, the obtained signal is still checked according to physiological limits. Two different methods have been tested, the first regarding the time and amplitude of the respiratory wave and the second through its characteristics.

This first evaluation (Evaluation I) consists in the acceptance of cycles with duration between 0.9-12.5 sec [18,19] and inspiratory or expiratory amplitudes of each cycle greater than about 1.3% of the average amplitude peak-valley [19].

The second method (Evaluation II) appears from the insufficiency of the previous one and since no other was found in the scientific articles consulted with greater capacity to respond to the problem, nor using the characteristics of the respiratory wave. The conditions analysed in this Evaluation II are that the ratio between the inspiratory and expiratory duration and amplitude should not exceed 1.5 and also that this inspiratory and expiratory ratio should have values lower than 290 (figure 2), in order to discard low amplitude oscillations. Finally, the length of the slope between each peak and its respective valleys must never exceed 1.7, as shown in figure 3.

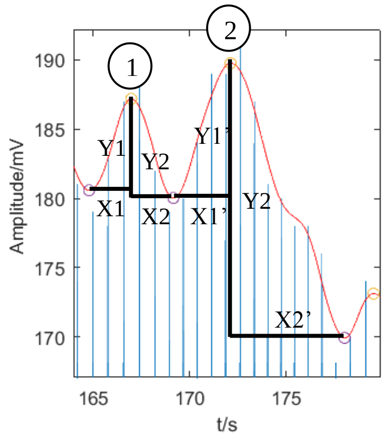

Figure 2. *Ratio between inspiratory and expiratory duration and amplitude: (1) true cycle; (2) cycle to discard.*

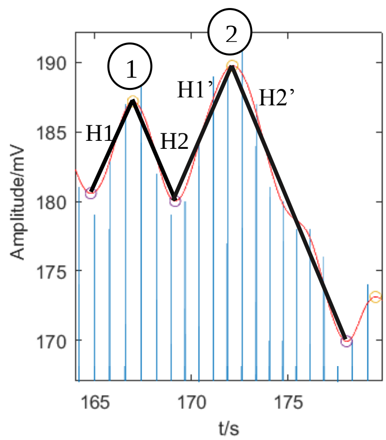

Figure 3. *Ratio between the slope's length between a peak and its respective valleys: (1) true cycle; (2) cycle to discard.*

3. Validation

At this stage, the methods applied are validated by comparison with the cycles that were marked at the time of acquisition in order to assess the best one, which would present better validations results. This phase began with the elaboration of a confusion matrix with the calculation of the True Positives and Negatives and False Positives and Negatives as shown in figure 2.

This was followed by the calculation of the Recall/Sensitivity, Specificity, Precision, Accuracy and Prevalence metrics. Finally, the relative error of each validation and the ratio between validated and true cycles for each method were also calculated. The validation results presented in Table 1 point to the second approach as the best evaluation.

Calculations	**Results**	
	Evaluation I (Time and Amplitude)	**Evaluation II (Characteristics)**
Recall/Sensitivity	91,67%	79,17%
Specificity	64,29%	100,00%
Precision	81,48%	100,00%
Accuracy	81,58%	86,84%
Prevalence	63,16%	63,16%
Relative Error	12,51%	-20,82%
Ratio Validated/True Cycles	1,13	0,79

Table 1. *Performance evaluation results for the proposed algorithms.*

As an additional way of validation, the main respiratory characteristics have been calculated as shown on Table 2. On each column, we can observe the mean values for each respiratory signal characteristic.

Characteristic	**NB**	**SDB**	**FDB**
Duration of Inspiration	1659	4640	1124
Duration of Expiration	1523	3780	1162
Duration of Breathing	3182	8420	2286
Respiratory Rate	9.85	3.56	13.46
Inspiration Volume	1.3×10^7	3.8×10^7	8.3×10^6
Stretch	11.33	25.26	20.42
Ratio	1.09	1.22	0.98
RSA	57.20	134.00	38.72

Table 2. *Mean values of the characteristics by respiratory cadence.*

The correlation between all these values in the table is as expected, since for instance the duration of breathing is minimum at the fast deep breaths and maximum at the slow deep breaths. There were different times with the same breathing type and the results also suggest that the cadences have a region within the values of a certain characteristic are determined.

4. Discussion

The first topic that required more deliberation was choosing the most appropriate filter, with a better counterbalance between filtering what was essential and without significant information losses. The diversity of frequencies due to the several breathing moments caused some difficulty. In the slow deep breaths there are some oscillations that aren’t respiratory cycles, which would be ideally softened by the filter so as to be possible to identify the true cycles in this cadence. However, this wasn’t possible with any of the filters tried since by soothing the slow deep breaths, the cut-off frequency chosen on the Butterworth filters would severely compromise the fast deep breaths. Thus, the moving average filter was chosen as it is computationally simpler, easing the future algorithm implementation in the device.

Another phase of great relevance was the validation. The second method does not have cycles considered False Positives, that is, all validated cycles are in fact respiratory cycles. On the one hand, the True Positives number is higher in the first validation. On the other hand and as expected, there is a greater number of False Negatives in the second, which are the true cycles that were not validated and therefore, that were not part of the True Positives.

Regarding the validation metrics, the obtained values show that both the proposed algorithm combined with both self-evaluation methods was able to perform very well on the subject’s used data. The results of specificity and precision for the second method are 100%, thanks to the explained lack of False Positives, which means a good disposal of oscillations not respiratory cycles. The sensitivity numbers are predictably higher in the first one since there are fewer cycles selected. The prevalence values are the lowest but these and accuracy’s are not of such importance for this study since they consider the number of cycles in the test sample, which is more relevant data in a study of apnoea moments during sleep, for example.-In the final statistics, the relative error was higher when considering the second self-evaluation mechanism, since it is a calculation with the number of cycles and the first method may admit cycles that are not actually true, which increases the final results. In the healthcare context each decision must be taken into deep thought, so it becomes more useful an algorithm that does not validate all correct cycles but discards very well what is not of interest, to the detriment of another that admits as breathing cycles some that are not. Hence in this context, the second self-evaluation method gives a greater confidence and represents an advantage.

A direct comparison of the results with other studies is not direct since it depends on the size of the analysis window [5]. In [6], an EDR analysis algorithm had a reported accuracy of 79% using polysomnogram data. Also, a study during Cardiac MRI using an automated breath detection algorithm yielded sensitivity of 99% for EDR and 79% using RSA [6].

5. Conclusion

In this paper an algorithm for the accurate estimation of the respiratory rate using wearable electrocardiography is proposed. It represents an improvement in the monitoring of two of the most important vital signs, the cardiac activity by the ECG and breathing, since, to obtain both information, only the ECG signal is necessary. Traditional approaches require specific sensors for both measurements, increasing the user's discomfort and the overall also the cost of the equipment.

In the text, the proposed algorithm has been clearly described as well as the several validation tests that were performed. The obtained results show that this algorithm can perform very well and is a valid option when comparing with other high complexity algorithms proposed by other authors. Our project constraints imposed that the developed code could be embedded in a low power, low cost microcontroller.

As foreseen developments we envision the enhancement of the slow deep breaths cycles' interpretation. This improvement would allow the algorithm to identify this type of oscillations and hence providing more accurate breath cycles. Also, as a future improvement, we envision the use of a larger dataset in the evaluation of respiratory cycles. This would allow to elaborate an intra-variability and inter-variability analysis, to apply the proposed algorithm in a larger population and with different devices, increasing the confidence and the reliability of the results.

Since the ECG signal can be corrupted with noise due to muscle contractions of the thoracic cavity, there may be an opportunity to use this algorithm in respiratory tests during sleep to diagnose pathologies such as sleep apnoea.

As mentioned before there are several methods to obtain respiratory cycles from an ECG signal and the amplitude of the R peaks come as a first approach. It has the advantage of being computationally inexpensive and easily ported to embedded system. The obtained results show that this is a reliable technique, bringing feasibility and propensity for future improvement, given the extremely importance of the thematic and the study developed.

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