Development of an apnea detection algorithm based on temporal analysis of thoracic respiratory effort signal

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Abstract. This work describes the design of an algorithm for detecting apnea episodes, based on analysis of thorax respiratory effort signal. Inspiration and expiration time, and range amplitude of respiratory cycle were evaluated. For range analysis the standard deviation statistical tool was used over respiratory signal temporal windows. The validity of its performance was carried out in 8 records of Apnea-ECG database that has annotations of apnea episodes. The results are: sensitivity (Se) 73%, specificity (Sp) 83%. These values can be improving eliminating artifact of signal records.

1. Introduction

Breathing can be defined as the function which aims is to provide necessary amount of oxygen (O_2) to the body's cells and remove carbon dioxide (CO_2) resulting from the cell's combustion [1]. Pathologies as the asthma, chronic obstructive pulmonary disease (COPD) and sleep apnea/hypopnea syndrome (SAHS) are examples of deficiencies in breathing process. In particular, SAHS consists in cessation of the respiratory activity by ten seconds (10s) or more which is produced five times or more by hour during the sleep [2]. The apneas can be the results of an obstruction in airways (Obstructive Apnea), absence of airflow and inspiration effort caused by failure in central nervous conduction (Central Apnea) and a combination of both (Complex Apnea).

The prevalence of this pathology in general population is 3.1 to 7.5% in men and 1.2 a 4.5% premenopausal women, while in children is 1 to 3% [2]. This statistics only shows SAHS in patients diagnosed but it is estimated that there is a lot of children and adults with this disease, and are not diagnosed.

SAHS patients have an excessive daytime sleepiness, and an increased probability to suffer job or traffic accidents and a higher prevalence of cardiovascular diseases, like hypertension, myocardial infarction and stroke [3].

Polysomnography (PSG) is considered to be the "Gold standard" study for diagnose SAHS. It consists in acquired biomedical signals during one or more nights. Usually a PSG study include signals registers of EEG, EOG, ECG, EMG, oronasal airflow, oxygen saturation (SaO_2) and abdominal and thoracic respiratory effort signal [4]. In particular, the last is an indirect technique for continuous and dynamic measurement of respiratory volume and it is based on inductive plethysmography method [5].

Even though PSG is an effective method and allows diagnose others pathologies too, it is an expensive study. In addition, It is uncomfortable for the patient due to lot of signals that can be acquired and it can´t get a normal sleep, which decreases the diagnostic effectiveness of this technique. Because of these drawbacks arises the need to reduce the number of signals and for it we must develop algorithms to detect apnea events from them.

In this work the development of an apnea detection algorithm based on temporal analysis of thoracic respiratory effort signal is proposed. The algorithm must have a low computational load to enable its use in very low power consumption microcontrollers and allow, in the future, their use in portable medical equipment. In these, the processing speed and memory resource are limited as well as the energy consumption because these devices are powered with batteries.

Even though there are others works about apnea detection, they use other methods with high computational load and require more type of signals. Zamarrón et al. developed an algorithm for detect apneas using spectral analysis of heart frequency obtained from pulse oximetry signal (PPG) [6]. Ravelo et al. proposed two algorithms based on support vector machine (SVM) and mixed Gaussian models for detect apneas from RR intervals from ECG signal [7]. In addition, there are works which use only the PPG signal to detect apneas, that use different types of thresholds for detection [8] and logistic regression classifier [9].

2. Materials

2.1. Database
For the validation of the designed algorithm were used eight records of the Apnea-ECG Database which is available free in Physionet's web site [10]. This database consists of 70 records of patients (age: 45 ±18 years, 57M and 13F) with breathing diseases including SAHS. The duration of each record is among 401 and 578 minutes and have annotations done by experts showing the QRS complex of ECG and apnea episodes. In this last case, there are marks that indicate if there are current apnea (A) or normal breathing (N).

The eight records used for the validation (a01 to a04, b01, and c01 to c03) are the only ones that have electrocardiography signal, thoracic and abdominal respiratory effort signal (SR and Resp A) obtained by inductive plethysmography method, oxygen saturation (SpO2) and oronasal airflow measured by nasal thermistor. The other records weren't used, because they only have ECG signals [11].

It is important to mention that the plethysmography signals are not calibrated and therefore the algorithm designed uses only relatives values, no absolute.

3. Methods

3.1. Signal pre-processing
A digital filter is applied to SR signal first, to obtain the spectral range that defines the respiratory process, which comes up to 0.5Hz [12]. The 4to order Butterwoth low-pass filter has been selected with cut-off frequency in 0.5 Hz. The figure 1 shows the effect of the filter on the signal.

Then 80 seconds windows has been analysed to obtain locals maximum and minimum of the filtered signals and calculate the inspiration and expiration time.

First derivative method is used in order to determine local extrema, i.e. finding the zero crossings of the derivative signal and according to the crossing, it is made from positive to negative if it is a maximum and if it goes from negative to positive, it is a minimum.

Although this is a robust method for detect local maximums and minimums, it can detect local extremes produced by noise or interferences in the signal as be show in figure 2. To solve this problem the instant range of the signal is calculated. It consists in getting the difference of amplitude between a consecutives minimum and maximum and then it is applied a median filter (MF) of 250ms to the resulting temporal series. Finally the filter output is compared with each range and if it is less than

30% of the filter output then associated extremes are considered incorrect. The figure 3 shows the effect of this stage.
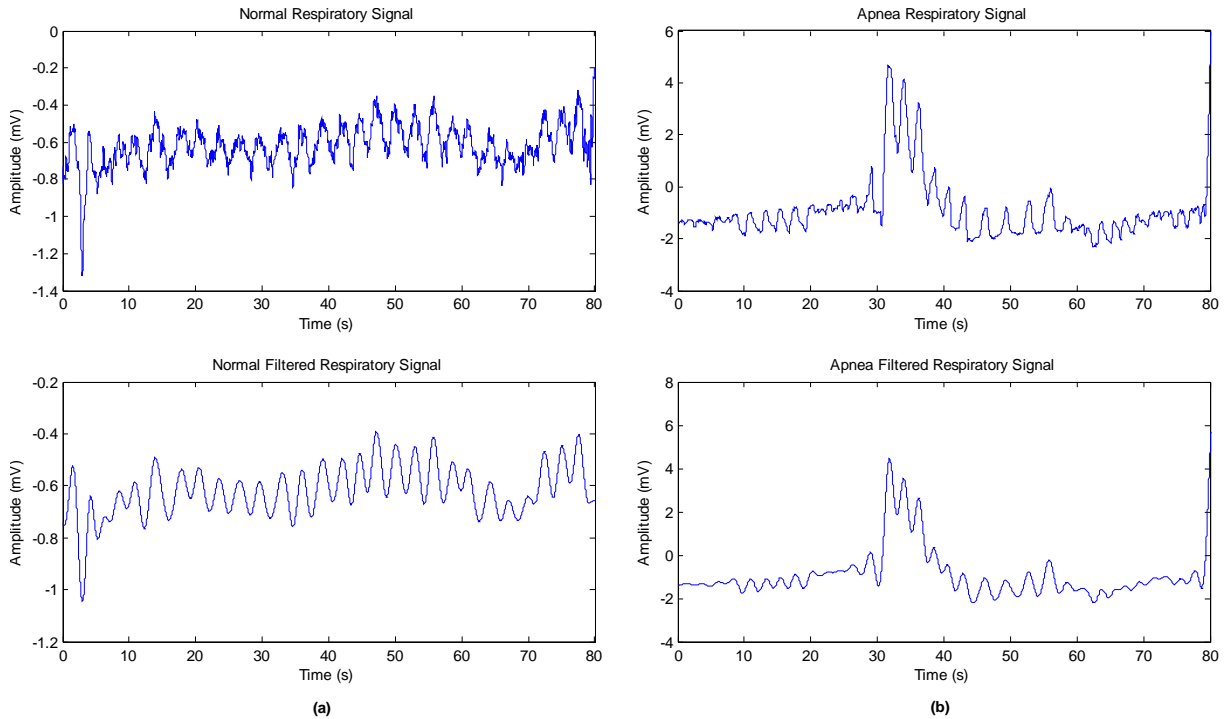

Figure 1. 4th order low-pass filter output. a) Normal Respiration. b) Respiration with apnea
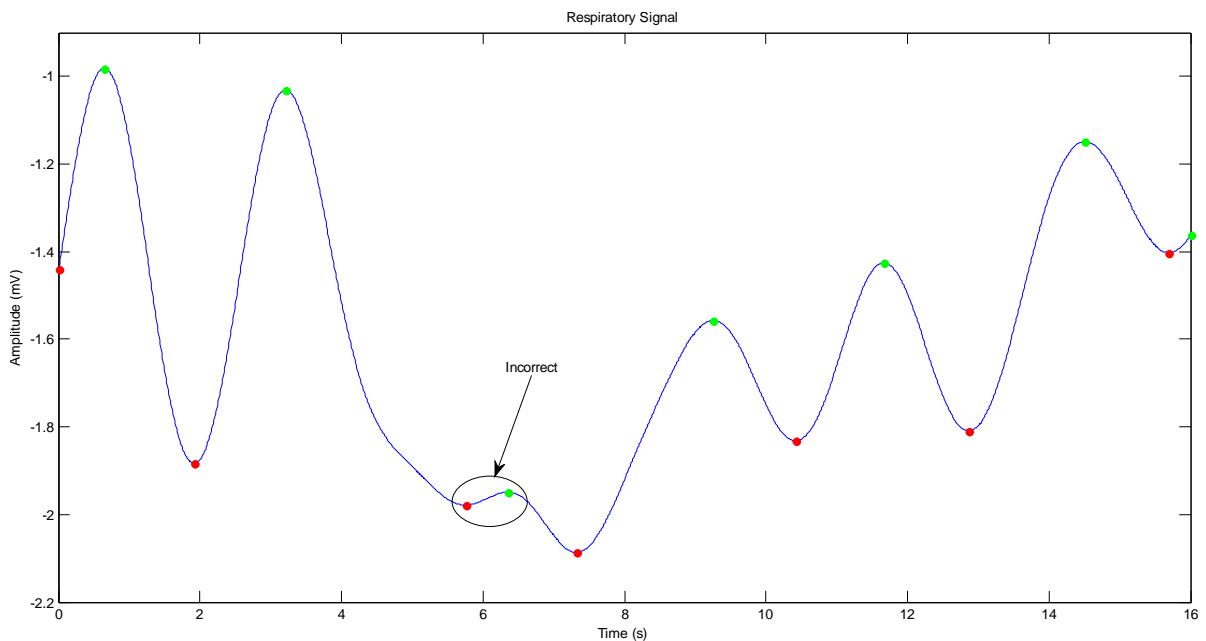

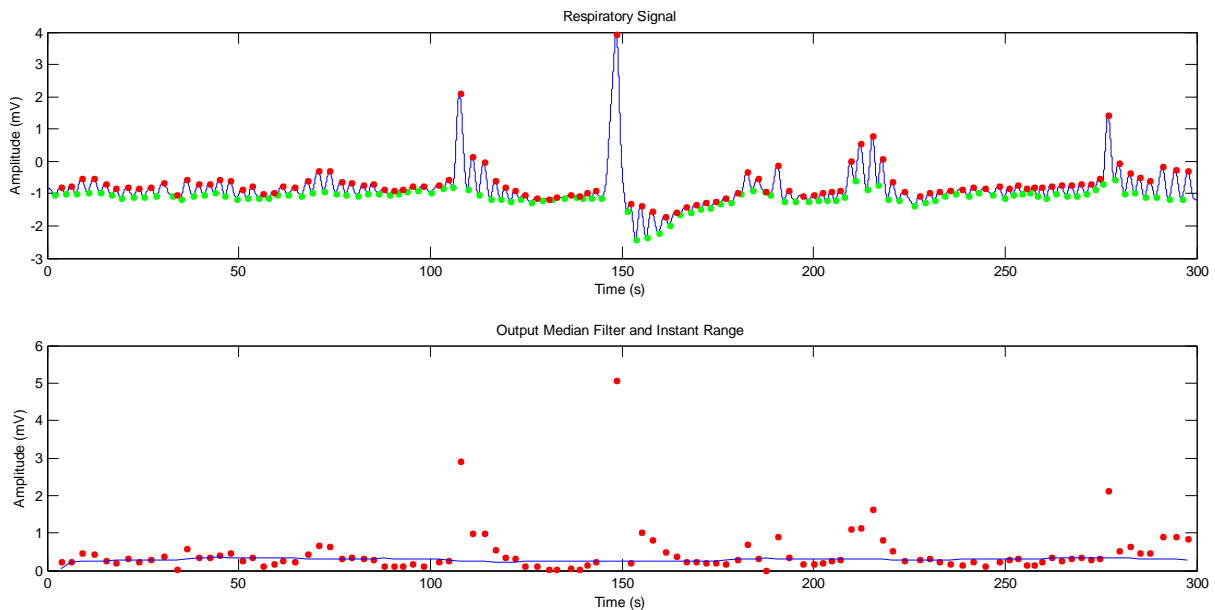**Figure 2.** Incorrect detection of maximum and minimum

Figure 3. Median filter output

3.2. Respiratory Period

The respiratory cycle is formed by inspiration time (IT) and expiration time (ET). The IT can be estimated as the time between a minimum and the maximum. ET is estimated as the time between this maximum and the next minimum. The figure 4 shows a complete respiratory cycle.

Respiratory rate in adults varies between 12-20 respirations per minute [1]. The minimum period resulting is 3 seconds but it is no equally distributed between IT an ET, the ratio in normal respiration is 2:1 respective. Therefore, the minimum time between a maximum and minimum is one second (1s). The algorithm eliminates all pair of maximum and minimum with difference less than one second.
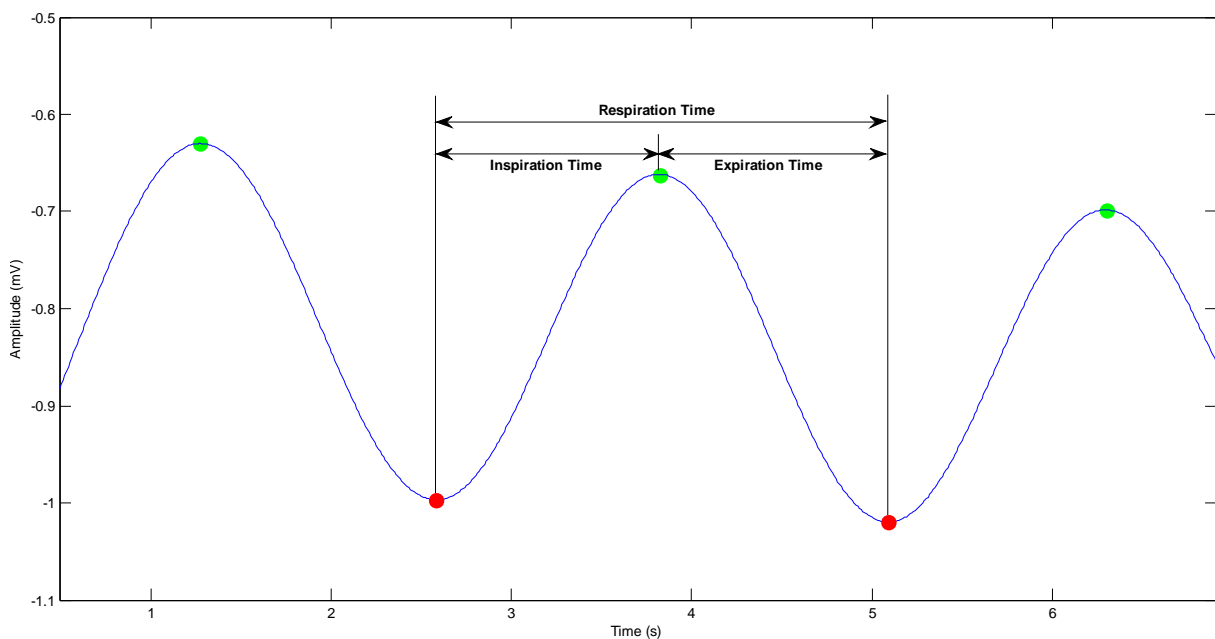

Figure 4. Inspiration and Expiration time.

3.3. Decision Rule

Two rules were used to classify normal respiration and apneas episodes. The first is based on analysing the IT and ET values. In normal respiration, ET shouldn't be greater than 3.4 seconds and IT to 1.67 seconds. The algorithm analyses a portion of record (40 seconds, by example) and considers all normal respiration cycles if the periods are not greater than 4 seconds. This rule arise from the analysis of normal respiration records in which those periods of time times are between 3 and 4 seconds, as shows in figure 5.
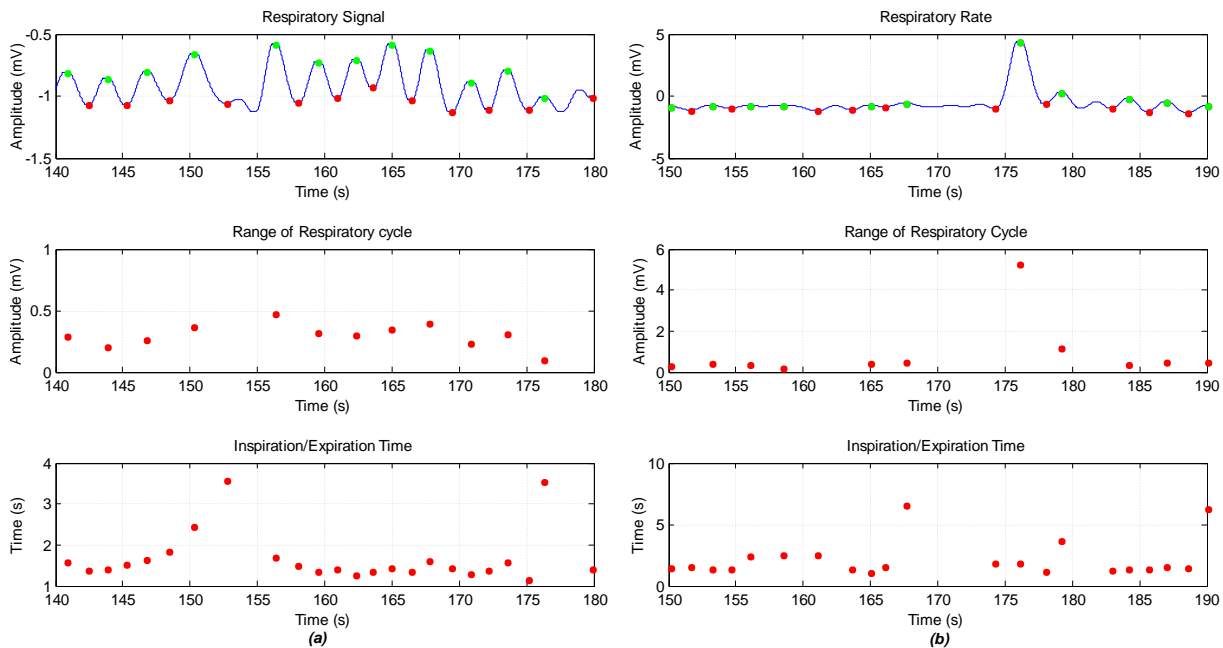

Figure 5. Ranges and times of inspiration. a) Normal Respiration. b) Respiration with apnea.

For second rule the variation of ranges were analysed and Standard Deviation (S) statistical tool was used, defined equation (1). Then based in normal and abnormal records a threshold was set.

$$S = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left|x_i - \bar{x}\right|^2} \qquad (1)$$

Where x_i is each range obtained by algorithm, $\bar{x}$ is the average of ranges and N is the number of these. In this work S is computed over 40 second's windows. The figure 5(a) shows a normal respiration with $S_a = 97\,\mu V$ and figure 5(b) shows an apnea episode with $S_b = 1.95\,mV$. A threshold value is established from the average of those values, that is $S_{th} = 792\,\mu V$.

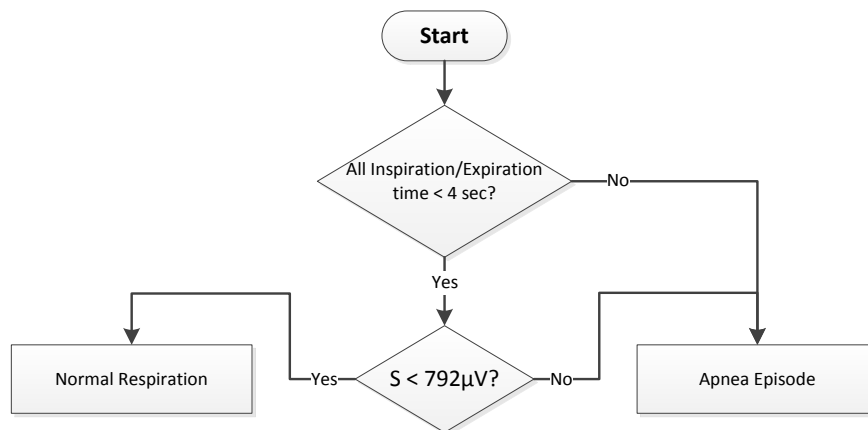The complete decision rule is showed in figure 6, as a flow diagram.

Figure 6. Flowchart of Decision Rule

4. Results

The algorithm was tested with the thresholds set in previous section in 8 records of Apnea-ECG Database and the windows analysis were centred in the episodes marks available in the records. The windows analysis is 40 seconds.

In order to compare the performance of the propose detection method, the following statistical parameters were calculated: Specificity (Sp), Sensitivity (Se), Positive Predictive Value (Vpp) and Negative Predictive Value (Npp) which were computed as follows [14]:

$$Sp\% = 100 \cdot \frac{TN}{(TN + FP)} \qquad (2)$$

$$Se\% = 100 \cdot \frac{TP}{(TP + FP)} \qquad (3)$$

$$PPV\% = 100 \cdot \frac{TP}{(TP + FP)} \qquad (4)$$

$$NPV\% = 100 \cdot \frac{TN}{(TN + FN)} \qquad (5)$$

Where True Positives (TP) is the number of apnea episodes detected correctly and True Negatives (TN) is the number of normal respirations detected correctly. Then the False Positives (FP) is the number of normal respiration detected as apnea episodes and False Negatives (FN) the episodes no detected. Table 1 summarises the statistics results of apnea detection method.

Table 1. Performance of the Proposed Algorithm

Sp%	Sen%	VPP%	VPN%
84	73	80	78

5. Discussion and Conclusion

In this preliminary work we have designed an algorithm capable to detect apnea episodes through a simple method and non-invasive as inductive plethysmography. In addition the algorithm doesn't need a calibrated instrument. The detection is performed in the time domain, finding the period of respiratory signal and the standard deviation of the respiratory cycle's instant range over 40 seconds temporal window.

The performance of algorithm has been evaluated with 8 real records of Apnea-ECG database which has been validated by experts. The results are summarized in Table 1 and reach a Specificity of 84% and Sensitivity of 73%, those are coherent with the simplicity of the algorithm and they only use a signal. It is noteworthy that other works use more signals with similar results. In [8] the Sp is 75% and Se is 73% but the computational load is high because uses neural networks.

It is important to mention that pulse oximetry signals has variations that are not exclusive of the apnea episodes, therefore it causes an increment of FP number [9].

One of the problems detected is the large amount of noise artifacts in the records analysed. Although in this paper we have tried to eliminate or mitigate its effects, the algorithm has some sensitivity to these perturbations.

In a future work, we will improve the signal pre-processing using thoracic and abdominal respiratory effort signal in order to achieve a more robust algorithm.

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