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Performance evaluation of three methods for respiratory signal estimation from the electrocardiogram

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Abstract— **A comparative study of three methods for estimating respiratory signal through electrocardiogram (ECG) was carried out. The three methods analyzed were based on R wave area, R peak amplitude and heart rate variability (HRV). For each method, cross-correlation coefficient and spectral coherence in a range of frequencies up to 0.5 Hz were computed between the ECG derived respiratory signals (EDR) and the three real respiratory signals: oronasal, and two inductance plethysmographies recordings (chest and abdominal). Results indicate that EDR methods based on R wave area and HRV are better correlated and show a wider spectral coherence with real respiratory signals than the other EDR method based on R peak amplitude.**

I. Introduction

NORMAL breathing alterations may cause serious metabolic, physic, organic and central nervous system disorders [1]. Therefore, breathing monitoring allows a continuous respiratory dynamic analysis and measurement which can be used to detect different respiratory and sleep diseases, like the Sleep Apnea Syndrome, a common sleep disorder characterized by repetitive cessation of breathing during sleep time.

The most appropriate method in order to diagnose this kind of alterations is overnight polysomnography, which consists in a multichannel signal study recorded during all patient sleep process. However, it is an expensive process that requires specialized staff and that the patient remains in the hospital for one or more nights.

In this way, different techniques have been proposed in order to derive the respiratory signal from the electrocardiogram (ECG), a simple and low-cost non invasive recording. There are several estimation methods to obtain the ECG Derived Respiratory Signal (EDR): based on R wave area [2], [3], Heart Rate Variability (HRV) [4], R amplitude [5], autoregressive modeling [6], etc.

In this work a comparative analysis of three different EDR estimation methods has been developed. Validation of these techniques has been carried out computing two parameters that measure the relation between the three EDR signals and three real respiratory signals (oronasal airflow, and chest and abdominal plethysmographic signals): the maximum of the cross correlation sequence and the maximum of the coherence function in frequencies up to 0.5 Hz.

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II. Materials and Methods

A. Signals

The free distribution Apnea-ECG Database, assembled for the PhysioNet/Computers in Cardiology Challenge 2000 [7] was utilized in this study. This signal database consists of 70 ECG recordings, each typically 8 hours long, with accompanying sleep apnea annotations obtained from a study of simultaneously recorded respiration signals, which are included in 8 of the recordings. To make the comparison between the different EDR methods and the respiratory signals these 8 records were used. All signals are sampled at 100 Hz.

The respiratory signals include chest and abdominal respiratory effort signals obtained using inductance plethysmography; oronasal airflow measured using nasal thermistors; and oxygen saturation (SpO2), but only plethysmographyc and oronasal signals were used in this study.

Figure 1 shows a schematic representation of the diverse stages followed in order to obtain the EDR signal and to compare with real respiratory signals.

B. Signal Preprocessing

During breath cycle the ECG signal is influenced by electrodes movements and changes in the thorax electrical impedance due to inhalation and exhalation actions. This effect is seen as an ECG modulation by the respiratory system. The signal preprocessing is based on [3].

1) Baseline correction: Two median filters were used to remove the baseline in ECG signal. Firstly, the ECG was filtered with a 200 ms median filter; this process removes the QRS complexes. Then, the resulting signal was passed through a 600 ms median filter, removing in this case the P and T waves. This final signal corresponds to the baseline wander, which was subtracted from the original ECG.

2) R peak detection and RR interval correction: Following the QRS complexes machine-generated annotations available from the database, the R peaks were detected finding the maximum ECG amplitude on a 300 ms window centered on each time annotation.

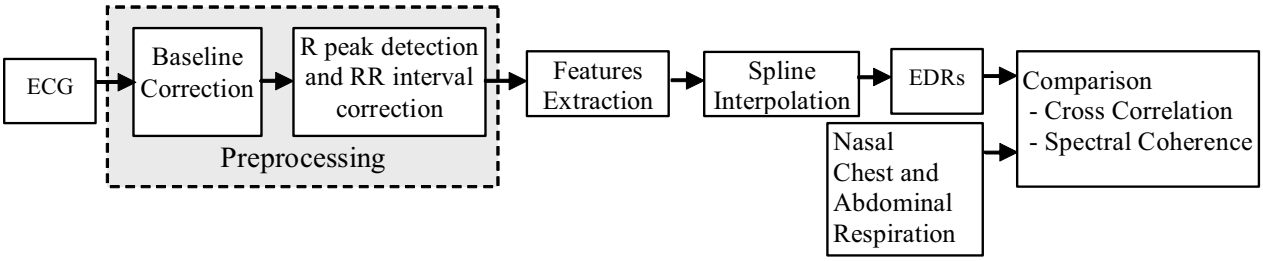

Fig. 1. Block diagram used for estimating the EDR signal from ECG and for comparison with actual respiratory signals.

The resulting time series was used to obtain the RR intervals as the difference between two consecutive R peaks occurrence times.

However, some QRS annotations contained anomalies due to detector errors or to ectopic beats. The detector errors can be false positive, when a false beat is detected due to noise or a high amplitude T wave, or false negative, when a real beat is missed due to low amplitude QRS or noise masking [8]. An algorithm based on the beat time location differences was used for the correction of these anomalies.

Starting from the RR interval time series a robust estimate of the expected RR interval value was created by applying a moving median filter of five intervals. Spurious detections were found by comparing the sum of consecutive RR-intervals with the corresponding estimation in the robust series. Both intervals were merged into one when their sum was less than 1.2 times the robust estimate. On the other hand, the existence of missing beats was supposed when one interval was greater than 1.8 times the robust estimate. In this case, the interval was subdivided into as many intervals as the robust estimate matched into the actual interval. The R peak time series was actualized from the modified RR interval series and R peaks corresponding to new detections were corrected finding the maximal amplitudes on a 100 ms window centered on the predicted time occurrence. Finally, the RR interval time series was recalculated taking into account these last modifications. Figure 2 illustrates different kinds of anomalies correction.

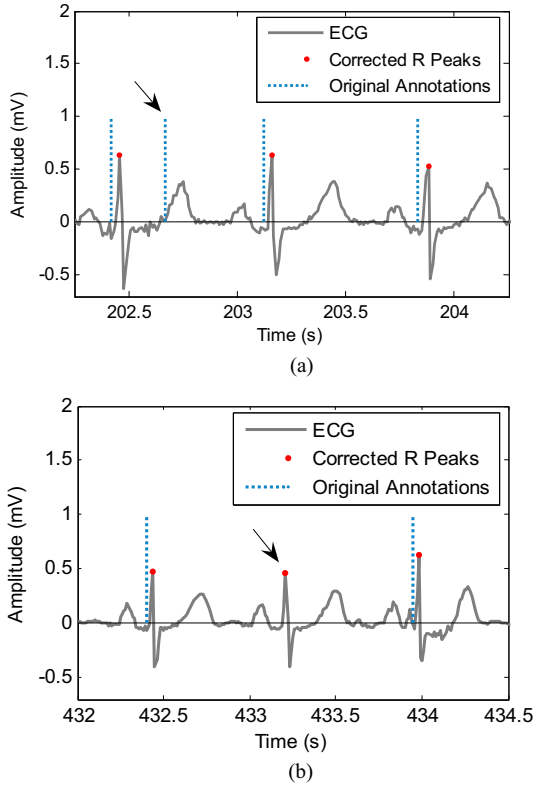

Fig 2: Examples of R peak correction algorithm. (a) Correction of false positive: the arrow indicates a T wave detected as a QRS complex. (b) Correction of false negatives: the arrow indicates a not detected QRS complex.

C. *Features extraction*

Once the preprocessing stage has been finished three features related with the respiratory activity were computed: a) R peak amplitude, b) Heart Rate Variability and c) R wave areas. The first feature was selected because the R peak amplitude time series are affected by the breathing modulation [6].

The Heart Rate Variability (HRV), computed as the RR-interval time series, is influenced by the respiratory system in a process named Respiratory Sinoatrial Arrhythmia (RSA), resulting in an almost imperceptible sequence of bradycardia and tachycardia synchronized with the respiratory cycle [4], [9], [10].

Another recent feature used to derive the respiratory signal from the ECG is the R wave area [2], [3], [6]. The area was calculated as the absolute sum on R wave values inside the region enclosed into a fixed 100 ms window centered in each R peak position [3].

D. *Spline Interpolation and EDR estimation*

Cubic spline interpolation was used to make the time series signals obtained with these three features (R peak amplitude, HRV and R wave area) similar to the real respiratory signals. Consequently, time series are resampled to 100 Hz, the same respiratory signal sample frequency [10].

Next, interpolated signals were low pass filtered with a 1500 coefficients FIR filter with a 5 Hz cut-off frequency. The outputs of this low pass filter were the three EDR estimations: one based in the R wave area (EDR1), other

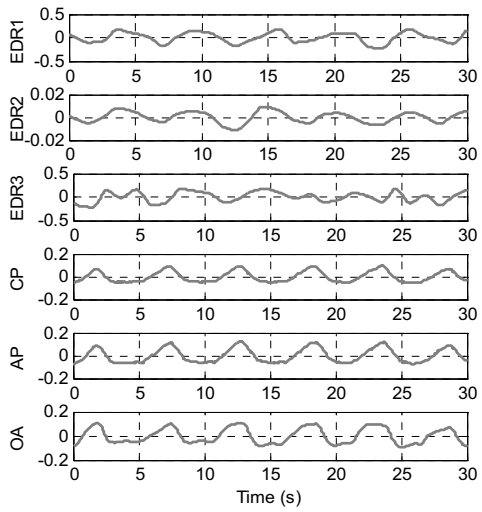

Fig. 3: Different EDR estimations compared with actual respiratory signals. In descendent order: EDR signal obtained from: R wave area (EDR1), HRV (EDR2) and R peak amplitude (EDR3), Chest Plethysmography (CP), Abdominal Plethysmography (AP) and Oronasal Airflow (OA).

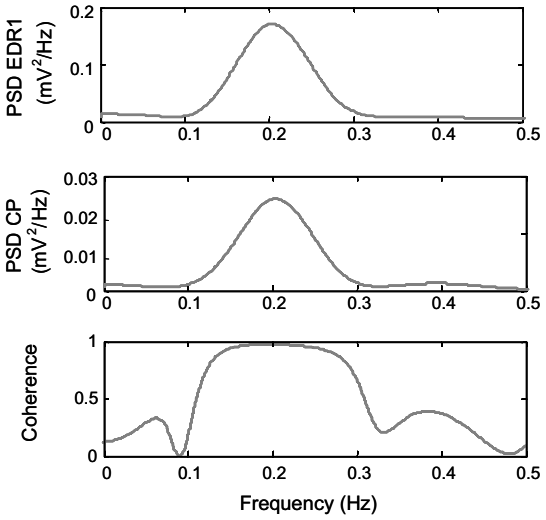

Fig. 4: Power Spectral Density (PSD) Comparison and Coherence result between chest plethysmography (CP) and EDR estimated with R wave area method (EDR1).

based in HRV (EDR2) and the last based in R peak amplitude (EDR3). Figure 3 shows an example of 6 respiratory cycles of the three EDR signals and the three real respiratory signals.

E. Comparison Parameters

A comparison between each estimated EDR signal and the real respiratory signals was carried out by means of computing two parameters, that were estimated for every 1-minute detrended intervals of the signals:

1) Cross-Correlation Coefficient: This parameter assesses the temporal similitude between two signals compared. It was computed at each interval and the maximum absolute value was annotated. After comparing the complete signals, mean and standard deviation of these intervals annotations were computed. Values near to 0 indicate low temporal relationship, and values near to 1 denote high temporal matching [2], [5].

2) Spectral Coherence: This parameter compares the spectral content between two signals with values between 0 and 1, that indicates how well one signal corresponds to the other at each frequency [11].

Signals were first resampled to 10 Hz to decrease calculation time. In this application spectral coherence was computed using the Welch method with Hamming window of length to obtain eight equal sections for both signals and a 50 % of overlap between segments. Since more than 95% energy of the respiratory signals correspond to frequencies lower than 0.5Hz, spectral coherence was evaluated only in this range of frequencies and the maximum value was annotated for each minute interval [5], [10], [5]. Again, mean and standard deviation of these annotations was computed. Individual power spectral densities and the resulting coherence are shown in Fig. 4.

III. Results

Table I resumes the mean and standard deviation values of the two comparison parameters (cross-correlation coefficient and spectral coherence) for the group of 8 patients of the database. Each EDR was compared with each respiratory signal (chest and abdominal plethysmographies and oronasal signal), and the respiratory signals were also compared between each other to give some reference patron of the EDR performance.

Comparing the three estimations methods it can be observed that cross correlation values are in general higher for EDR1 than the other two methods, however coherence values are very similar between EDR1 and EDR2. On the other hand, the cross correlation and spectral coherence values for EDR3 method are the lowest of the table.

As regards real respiratory signals, it can be seen that the comparison parameters for inductive plethysmografies signals (CP and AP), considered the *gold standard* in respiration measurement, are in general higher than the obtained values for the other real signal obtained from the oronasal airflow (OA).

Also, it can be observed that both EDR1 and EDR2 perform better than EDR3 method. However, both EDR1 and EDR2 show good temporal and spectral correspondence with the real ones, with a certain temporal delay as it can be seen in the example of Fig. 3.

IV. Conclusions

This paper introduced a comparative study of the performance of different estimation methods for deriving the respiratory waveform from the ECG (EDR). These methods were based on R wave area (EDR1), HRV signal (EDR2) and R peak amplitude (EDR3). They were compared with

TABLE I
PERFORMANCE COMPARISON OF EDR METHODS

		EDR1 R wave area	EDR2 HR	EDR3 R amplitude	CP	AP	OA
CP	Correlation	0.55 ± 0.13	0.50 ± 0.05	0.38 ± 0.07	1.00 ± 0.00	0.84 ± 0.11	0.78 ± 0.14
	Coherence	0.71 ± 0.12	0.71 ± 0.10	0.53 ± 0.10	1.00 ± 0.00	0.94 ± 0.05	0.93 ± 0.06
AP	Correlation	0.56 ± 0.15	0.49 ± 0.06	0.36 ± 0.05	0.84 ± 0.11	1.00 ± 0.00	0.82 ± 0.07
	Coherence	0.72 ± 0.13	0.72 ± 0.10	0.53 ± 0.09	0.94 ± 0.05	1.00 ± 0.00	0.95 ± 0.02
OA	Correlation	0.53 ± 0.13	0.44 ± 0.08	0.36 ± 0.06	0.78 ± 0.14	0.82 ± 0.07	1.00 ± 0.00
	Coherence	0.71 ± 0.12	0.70 ± 0.10	0.53 ± 0.10	0.93 ± 0.06	0.95 ± 0.02	1.00 ± 0.00

Mean and standard deviation values of correlation and coherence parameters are shown. Values were obtained for the group of 8 analyzed patients. Respiratory signals: CP = Chest Plethysmography, AP = Abdominal Plethysmographyc, OA = Oronasal Airflow.

three real respiratory signals: Oronasal Airflow (OA), Chest and Abdominal Plethysmographies (CP and AP, respectively).

The EDR1 method computed based on R wave area has better temporal and spectral results since cross-correlation and coherence parameters are higher than EDR2 and EDR3. However, EDR2 method computed based on RR intervals (or Heart Rate Variability) has similar spectral coherence values to EDR1.

Both, EDR1 and EDR2 perform better than EDR3 calculated with R peak amplitudes, probably due to the fact that the last method is more sensitive to the noise present in ECG signal.

It is demonstrated that EDR1 and EDR2 estimations are good approximations of real respiratory signals, although their correlation and coherence parameters are lower than the obtained values between respiratory signals themselves. This is somehow expected since EDR signals are derived from ECG signal which mainly provides information about heart electrical activity and only gives secondary knowledge about respiratory activity.

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