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Sleep Apnea Detection based on Spectral Analysis of Three ECG - Derived Respiratory Signals

Lorena S. Correa, Eric Laciar, *Member IEEE*, Vicente Mut,
Abel Torres, *Member IEEE*, and Raimon Jané, *Member IEEE*

Abstract— **An apnea detection method based on spectral analysis was used to assess the performance of three ECG derived respiratory (EDR) signals. They were obtained on R wave area (EDR1), heart rate variability (EDR2) and R peak amplitude (EDR3) of ECG record in 8 patients with sleep apnea syndrome. The mean, central, peak and first quartile frequencies were computed from the spectrum every 1 min for each EDR. For each frequency parameter a threshold-based decision was carried out on every 1 min segment of the three EDR, classifying it as 'apnea' when its frequency value was below a determined threshold or as 'not apnea' in other cases. Results indicated that EDR1, based on R wave area has better performance in detecting apnea episodes with values of specificity (Sp) and sensitivity (Se) near 90%; EDR2 showed similar Sp but lower Se (78%); whereas EDR3 based on R peak amplitude did not detect appropriately the apneas episodes reaching Sp and Se values near 60%.**

I. Introduction

OBSTRUCTIVE Sleep Apnea Syndrome (OSAS) is a common sleep disorder characterized by recurring cessation of breathing for at least 10 seconds during sleep time. It results from the upper airway obstruction and affects more than 15 million americans [1]. OSAS patients have an excessive daytime sleepiness, an increased probability to suffer job or traffic accidents and a higher prevalence of cardiovascular diseases, like hypertension, myocardial infarction and stroke [2].

Polysomnography is the most suitable and reliable study used to diagnose OSAS. However, it consists of a multi-channel signal recording (ECG, EEG, EOG, EMG, SaO2, nasal and abdominal pletismography signals, blood pressure and heart volume) during all sleep process and the patient has to spend one or more nights in hospital with specialized staff in attendance overnight, which makes it an expensive unaccesible process.

The electrocardiogram (ECG) is a simple and low-cost non-invasive recording that can be used to get respiratory information. In consequence, different techniques have been proposed to derive the respiratory signal from the electrocardiogram [3]-[7].

In a previous work of our group, a comparative study of three methods for estimating ECG derived respiratory (EDR) signal was carried out. The three methods analyzed were based on R wave area (EDR1), heart rate variability (EDR2) and R peak amplitude (EDR3). They were validated by computing cross correlation and spectral coherence between the three EDR signals and three real respiratory signals [8].

There are several apnea detection methods available in bibliography based on: per-epoch classification algorithm [4], autoregressive model [7] and artificial neural networks [9], [10].

In this work, we implemented an apnea detection method based on spectral analysis to assess the performance of the three EDR estimation methods computed.

II. Materials

In this study, the free distribution Apnea-ECG Database was used, assembled for the PhysioNet/Computers in Cardiology Challenge 2000 [9]. It consists of 70 ECG recordings sampled at 100 Hz, aproximately 8 hours long each, with accompanying sleep apnea annotations obtained from a study of simultaneously recorded respiration signals, which are included in only 8 of the recordings. These recordings (age: 43.3 ± 8.3 years, 7 M and 1F) were used to establish an apnea detection comparison by using the different EDR signals.

The apnea scoring in the recordings was done by experts according to standard criteria based on the respiration signals analysis (oronasal airflow, measured by using nasal thermistors, abdominal respiratory effort signals obtained by using inductance plethysmography, and oxygen saturation measured with pulsioximetry). Each minute of the recording was labeled with 'A' or 'N', indicating the presence or absence of apnea respectively during that min.

Patients were classified as 'Class C - Normal', 'Class B - Borderline' and 'Class A - OSAS' when they showed fewer than 5 min, between 5 and 99 min and at least 100 min of disordered breathing respectively. The recordings used in this study include 3 Class C patients (pc1, pc2 and pc3), 1 Class B (pb1) and 4 Class A (pa1, pa2, pa3 and pa4).

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L. Correa and E. Laciar are with Gabinete de Tecnología Médica, Universidad Nacional de San Juan, San Juan, Argentina (e-mail: lcorrea@gateme.unsj.edu.ar, laciar@gateme.unsj.edu.ar)

V. Mut is with Instituto de Automática (INAUT) Universidad Nacional de San Juan, San Juan, Argentina (e-mail: vmut@inaut.unsj.edu.ar)

A. Torres and R. Jané are with Dept. ESAII, Universitat Politècnica de Catalunya, Institut de Bioenginyeria de Catalunya (IBEC) and CIBER de Bioingeniería, Biomateriales y Nanomedicina (CIBER-BBN), Barcelona, Spain (e-mail: abel.torres@upc.edu, raimon.jane@upc.edu)

III. METHODS

A. Signal Preprocessing

The signal preprocessing is based on [4]. First, two median filters of 200 ms and 600 ms width respectively were used to remove the baseline in ECG signal.

Following the QRS complexes machine-generated annotations available from the database, the R peaks were detected by finding the maximum ECG amplitude on a 300 ms window centered on each time annotation.

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

An algorithm based on the beat time location differences was used for the correction of false QRS detections and missing beats [4], [8]. 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 width. Both intervals were merged into one when their sum was less than 1.2 times the robust estimate. When one interval was greater than 1.8 times the robust estimate the interval was subdivided into as many intervals as the robust estimate matched into the actual interval. The R peak time series was obtained 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.

B. EDR computation

Three EDR signals related with the respiratory activity were determined from features computed in the detected QRS complexes: a) *R wave area* (EDR1) was calculated as the absolute sum of R wave values inside the region enclosed into a fixed 100 ms window centered in each R peak position [3], [4], [7] and was selected because the R wave is affected by the breathing modulation b) *Heart Rate Variability* (EDR2) was computed as the RR-interval time series and was chosen since in OSAS patients it is strongly influenced by the respiratory system in a process named Respiratory Sinoatrial Arrhythmia (RSA), resulting in a sequence of bradycardia and tachycardia synchronized with the respiratory cycle [5], [12], [13], and c) *R peak amplitude* (EDR3), similarly to EDR1, is modulated by respiration [7]. Figure 1 illustrates the ECG features used in the computation of the EDR signals.

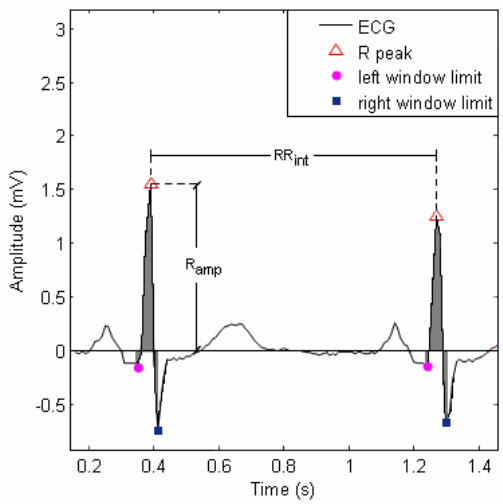
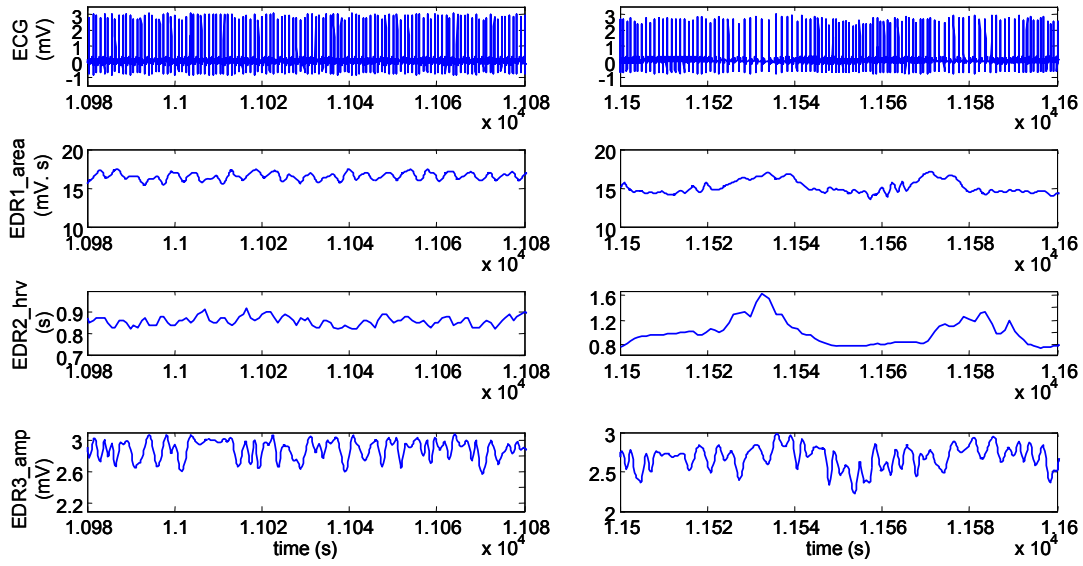


Fig 1: ECG features used in the computation of EDR signals: R peak amplitude (Ramp), RR interval (RRint) and R wave area - shaded area.

Figure 2 shows the ECG signal and the three EDR estimated for patient pa3 (Class A). It can be seen that the amplitude and frequency of all EDR signals change in the presence of apnea events. However, the alterations observed in EDR1 and EDR2 are significantly more notable compared with EDR3.



(a) (b)

Fig 2: ECG signal and the three EDR signals estimated for patient pa3 (Class A), during: (a) normal breathing, and (b) an apnea episode.

The three EDR signals were interpolated to 5 Hz by using cubic spline interpolation. This reduced the computation time required to estimate the spectrum over the frequency range of interest without affecting significantly the energy of frequency components of the EDR signals.

C. Spectral Analysis

The power spectral density (PSD) was computed for every 1 minute signal for each detrended EDR estimation. Due to the short length of the signal segments (300 samples), the PSD was computed with the autorregresive Burg parametric method, in which the signal is assumed to be the output of a linear system driven by white noise. This method is based on minimizing the forward and backward prediction errors while satisfying the Levinson-Durbin recursion and does not apply window to data [14]. Before PSD estimation, each EDR signal was detrended in order to remove its mean value.

Once computed the PSD, the following frequency parameters were obtained: central frequency (f_c), mean frequency (f_m), peak frequency (f_p) and first quartile frequency (f_{q1}) defined as follows:

Central Frequency:

$$f_c \text{ such that } \sum_{i=1}^{f_c} PSD_i = \sum_{i=f_c}^{N} PSD_i \tag{1}$$

Mean frequency:

$$f_m = \frac{\sum_{i=1}^{N} f_i \cdot PSD_i}{\sum_{i=1}^{N} PSD_i} \tag{2}$$

Peak Frequency:

$$f_p \text{ such that } PSD(f_p) \geq PSD(f_i) \qquad \forall f_i \neq f_p \tag{3}$$

First Quartile Frequency:

$$f_{q1} \text{ such that } \sum_{i=1}^{f_{q1}} PSD_i = \frac{1}{4} \cdot \sum_{i=1}^{N} PSD_i \tag{4}$$

The parameters series were then filtered with a median filter of length 6 so that each decision was made by taking into account several minutes before and after the actual minute, since apnea events usually form a pattern that takes a period of time of several minutes [2].

IV. Results

A threshold (*Thr*) for each frequency parameter (fm, fc, fp or fq1) was computed considering all of the 8 analyzed patients as follows:

$$Thr = \frac{\left(MV_{ap} + MV_{not\_ap}\right)}{2} \tag{5}$$

where MV_{ap} is the median value of the considered parameter for all 1 min segments with apnea (following experts' annotations) and MV_{not_ap} is the corresponding one for all segments without apnea. The thresholds obtained for each frequency and for all of the EDR methods are shown in Table I.

For each EDR, segments were classified as 'apnea' when the frequency parameter was lower than its threshold, and as 'normal' when its value was higher.

In order to compare the performance of the proposed apnea 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 [15]:

$$Sp = 100 \cdot \frac{TN}{(TN + FP)} \tag{6}$$

$$Se = 100 \cdot \frac{TP}{(TP + FN)} \tag{7}$$

$$PPV = 100 \cdot \frac{TP}{(TP + FP)} \tag{8}$$

$$NPV = 100 \cdot \frac{TN}{(TN + FN)} \tag{9}$$

where *TP* and *TN* are the number of True Positive and Negative decisions respectively, whereas *FP* and *FN* are the quantity of False Positive and Negative decisions. Those values were computed comparing the "Apnea" or "Not Apnea" decision of the detection method with the annotations 'A' or 'N' available in the database.

Table II summarises the statistics results of apnea detection method for each frequency parameter and for each EDR signal considering the 8 patients of the database, where shaded cells indicate the best frequency results obtained for each EDR.

V. Discussion and Conclusions

This paper introduces a preliminary comparative study of the capability of different ECG-derived respiratory estimation methods to detect breathing disorders like apneas in OSAS patients. These methods were based on R wave area (EDR1), heart rate variability (EDR2) and R peak amplitude (EDR3).

The apnea detection method was based in the spectral analysis of each EDR. Four parameters were computed from the PSD: central frequency (f_c), mean frequency (f_m), peak frequency (f_p) and fist quartile frequency (f_{q1}).

TABLE I
FREQUENCIES THRESHOLDS FOR EACH EDR

Parameter	Thr EDR1 (Hz)	Thr EDR2 (Hz)	Thr EDR3 (Hz)
fc	0,0787	0,0516	0,2246
fm	0,0935	0,0780	0,2361
fp	0,0522	0,0352	0,1770
fq1	0,0366	0,0264	0,1135

fc: central frequency, fm: mean frequency, fp: peak frequency, fq1, first quartile frequency.

TABLE II
PERFORMANCE COMPARISON OF EDR APNEA DETECTION METHODS

	EDR1 (Area)				EDR2 (Hrv)				EDR3 (Amp)			
	Sp	Se	PPV	NPV	Sp	Se	PPV	NPV	Sp	Se	PPV	NPV
fc	80,99	97,63	78,04	98,02	82,07	84,24	76,47	88,27	47,89	51,78	40,74	58,94
fm	88,28	88,66	83,95	91,84	89,53	77,76	83,7	85,33	50,86	51,09	41,84	60,05
fp	67,03	99,19	67,54	99,17	70,13	63,18	59,4	73,35	61,47	55,14	49,75	66,45
fq1	79,22	98,38	76,61	98,61	80,3	68,72	70,71	78,77	61,21	60,06	51,72	68,9

Sp = Specificity, Se = Sensibility, PPV = Positive Predictive Value, NPV = Negative Predictive Value. Values were obtained for the group of the 8 analyzed patients. The best result for each EDR is shaded.

From Table I, frequency thresholds are higher for EDR3 than for EDR1 and EDR2, which is meaningful since EDR3 showed more variability than EDR1 and EDR2. These have a kind of modulation correlated with apnea episodes, as it could be observed in Fig. 2.

Comparing the three estimation methods in Table II, it was found that EDR1 and EDR2 showed similar performances, EDR1 having the highest sensibility (Se) and EDR2 the highest specificity (Sp) for all frequencies. In both methods f_m showed better performance. EDR1 and EDR2 worked better in apnea detection than EDR3. On the other hand, apnea events could not be discerned by EDR3 based on R peak amplitude method.

The results obtained in this work are consistent with the ones found in the previous work [8], in which the three EDR methods were compared with three real respiratory signals: Oronasal Airflow (OA), Chest and Abdominal Plethysmographies (CP and AP, respectively) by means of cross correlation and spectral coherence. In that work it was concluded that EDR1 had better temporal and spectral results than the other two EDR. However, EDR2 method had similar spectral coherence values to EDR1.

It is concluded that EDR1 and EDR2 could be used to detect apneas with a Holter study, with the benefits of low cost and simplicity that characterize this study. The information contributed by EDR3 may be used to improve the performance of the other apnea detection methods, taking into account the changes observed in Fig. 2.

In future works the proposed apnea detection method will be tested with the rest of the ECG recordings available in the database.

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