AUTOMATIC HRV ESTIMATION METHOD FOR RESPIRATORY EVENTS DISCRIMINATION

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ABSTRACT

The present contribution presents results of wavelet based methods for computing short-term Heart Rate Variability (HRV) in order to better identify respiratory events by means of analyzing only one lead electrocardiographic (ECG) recordings. Besides RR time interval variability, the performance of other approaches was investigated for the assessment of HRV, such as the intervals between the onsets of successive P waves (PP time series), PR intervals, or ST intervals time series. We analyzed their detection capabilities on respiration events, such as apneas, hypopneas, arterial blood O_2 desaturation or arousals, which are used in the diagnoses and characterization of obstructive sleep apnea syndrome (OSAS). The proposed approach gives good results without prior baseline wandering elimination.

Index Terms— heart rate variability (HRV), obstructive sleep apnea (OSA), discrete wavelet transform (DWT)

1. INTRODUCTION

Detection of respiratory events by means of single ECG lead automatically analysis has been stated as an issue in 2000 being related to a joint initiative of *Physionet* and the organizers of the *2000 Computers in Cardiology Conference* [1] and it is not yet fully satisfactory solved, from the point of view of specificity and sensitivity.

Obstructive sleep apnea syndrome (OSAS) is the most common sleep-disordered breathing, with a high prevalence in the general population, with levels varying around 10% of the people around the world, men, women and children, of different ages [2]. It is characterized by the repetitive total or partial collapse of the pharyngeal airway during sleep, with the need to arouse and resume ventilation. OSAS is defined as the intermittent cessation of breathing during sleep for at least 10 sec, accompanied by more than 4% blood oxygen desaturation, with a frequency of over 5 respiratory episodes per hour, apnea eventually alternated with hypopnea episodes [3], the intensification of thoracic and abdominal respiratory effort, and also by arousals, usually at the end of the respiratory episodes, when the hypercapnia level becomes dangerous.

Many algorithms have been developed to automatically detect, classify and analyze the electrical cardiac signal [4–6]. The more recent and performing of them include wavelet decomposition [7, 8], as a preprocessing method, and radial basis function (RBF) [9], and derived methods such support vector machines or learning vector quantization [10, 11], for classification and labeling characteristic segments of the excerpts. Some of the methods, concerning patterns extraction and recognition are based on principal component analysis (PCA, kernel PCA) [13]. Hidden Markov Models [12] and other neural network based methods [14] are among the classification methods approached for the difficult task of automatically recognizing electrical cardiac waveforms related with certain pathologies.

In the present paper we present some results of our work concerning the evaluation of a HRV (heart rate variability) that may allow better automatic discrimination criteria for different overnight respiratory dysfunctional events. The effect of respiration on atrioventricular conduction delay (and hence PR interval length), for instance, has not yet received much attention, especially related to nocturnal respiratory diseases, such as obstructive sleep apnea syndrome (OSAS). A discrete wavelet transform coefficients method was used in order to extract features that are very relevant for quantitative electrocardiology, such as P, Q, R, S, T peaks, and onsets/offsets. Those detected positions permitted us to determine the corresponding segments and intervals, PR interval, PR segment, QRS, QT interval, ST interval, ST segment, RR interval and PP interval. We investigated the capacity such measurements to characterize and discriminate the respiratory events during sleep, reflected in single lead ECG recordings, even without filtering out baseline wandering.

2. AUTOMATIC DETECTION OF ECG CHARACTERISTIC POINTS USING DISCRETE WAVELET TRANSFORM

2.1. The ECG data sets

The ECG recordings used in this study were extracted from the PSG recordings from 15 human subjects, men and women, diagnosed with obstructive sleep apnea by clinical expert at the Sleep Unit of the Clinical Hospital of Pneumology of Iaşi. Age of investigated persons ranged around 58.62±5.37 years. EEG with electrode positions C3, C4, O1, and O2, chin electromyogram, airflow, and chest and abdominal respiratory efforts allowed the labeling of the respiratory event during sleep on the one lead ECG, simultaneously recorded, by means of cross signal identification [13]. Signals were stored with a sample rate of 200 Hz. OSAS evaluation was made from PSG data, using the analysis tool of the Somnologica Studio software and the supplementary scoring of the clinical expert by using the standard procedures and criteria. EEG with electrodes positions C3-A2, C4-A1, O1-A2, and O2-A1, and eye movements provides the annotations for the sleep stages and arousals. Airflow assesses for the blood O2 desaturations, while chest and abdominal effort emphasize eventual central or mixed apnea events. The overnight recordings of single continuous ECG signals were of 8 hours time length, with 16 bit resolution, one sample bit representing 5μV.

Labeled segments duration may vary from about 2 seconds (arousal) to over 20 seconds (desaturation). Normal segments were considered to be those without labeling. Only excerpts of at most 10 seconds were used from them.

2.2. The processing method

The recorded ECG time series, as described in [15], were segmented and grouped according to PSG labeling, before being input to the automatic identification algorithm.

The automatic identification of ECG QRS complex and P, T waves was performed by wavelet transform delineation, as detailed in [16]. We performed both denoising and extreme (maxima and minima) points estimation based on discrete Daubechies dyadic wavelet functions, up to level four. Noise removal was performed by wavelet decomposition using the approximation filters and reconstruction by neglecting the detail filters. The largest maxima, corresponding to R points and lowest minima, representing the S ones, were detected using the delineation algorithm in [16], based on Malat theoretical results in [17, 18]. Due to the fact that we used the decimated reconstruction process in the delineation algorithm, small corrections were performed after redundant reconstruction, by maxima and minima search on short time intervals, of length equal to the double of the decimation ratio.

P, Q and T wave maxima were detected by search on the smoothed signal, according to estimated positions with respect to R and S waves.

The onset and offset points are then determined based on signal and derivative (approximated as discrete difference) level thresholding.

The positions of the characteristic points of the ECG signals were then used to calculate distances, such as:

PR = Rpeak(i+1) - Ponset(i)
PRinterval = Qonset (i) - Ponset(i)
PRsegment = Qonset (i) - Poffset(i)
PPonset = Ponset (i+1) - Ponset(i)
PPpeaks = Ppeak (i+1) - Ppeak (i)
RRpeaks = Rpeak (i+1) - Rpeak (i)
QTinterval = Toffset (i) - Qonset(i)
STinterval = Toffset (i) - Jpoint(i)
STsegment = Tonset (i) - Jpoint(i)
QRS = Jpoint(i) - Qonset(i)

3. RESULTS AND DISCUSSION

One of the crucial steps in the morphological ECG analysis is to accurately detect the different waveforms compounding a normal cardiac cycle, in order to perform HRV analysis.

We studied 15 ECG recordings of different patients, diagnosed with OSA at Clinical Hospital of Pneumology of Iasi. Our goal was to detect differences in HRV characteristics that allow a good discrimination between respiratory events, such as obstructive apnea, arousals, central apnea, O_2 desaturation and normal segments. We investigated around 20 segments/subject, each having an average of 15 normal waves, resulting in about 4500 normal waves to be detected.

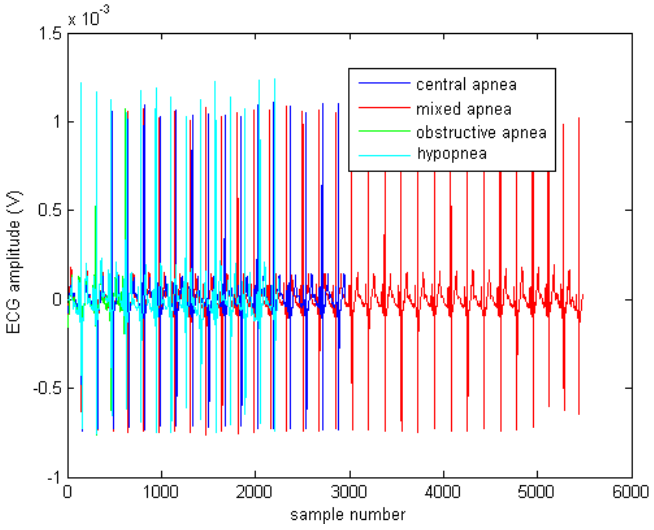


Fig. 1. Superposed ECG segments of different apnea episodes of the same subject, reflecting differences in waves amplitudes and durations.

TABLE 1 – Detection results

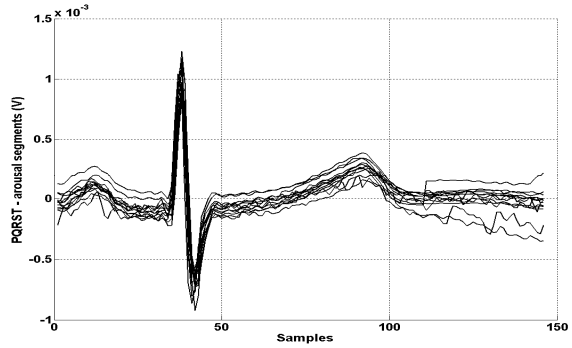
Segment	Total number of beats	FD (FP)	ND (FN)	PPA	Detection error rate	SE
arousal	315	4	2	98.72%	1.90%	99.36%
OA	702	0	8	100.00%	1.14%	98.86%
MA	161	1	3	99.37%	2.48%	98.13%
CA	132	0	0	100.00%	0.00%	100.00%
O2 desaturation	1873	6	32	99.67%	2.03%	98.29%
normal	432	0	7	100.00%	1.62%	98.38%
MEAN	**603**	**2**	**9**	**99.63%**	**1.53%**	**98.83%**

Table 1 shows the detection result over the entire dataset that was analyzed, evaluated by means of sensitivity (TP/(TP+FN)), positive prediction error (PPE = TP/(TP+FP)) and detection error rate. (FP+FN)/Total_beats).

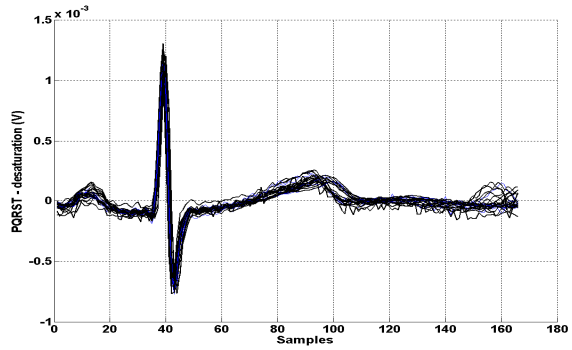
For each segment type, the detection of characteristic points on each ECG beat in the segment may encounter errors: the characteristic was not detected on the waveform (FN), or the detected characteristic was bedly labeled (FP).

In Figure 1 superposed segments of different types of apnea, from the same subject are depicted in order to emphasize differences between wave intervals and amplitudes.

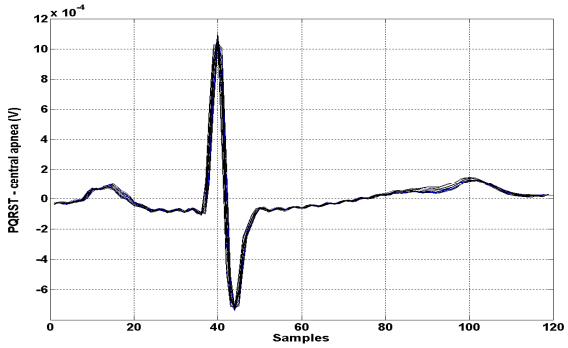
Figures 2 (a) – (f) show superposed P, Q, R, S, T complexes of the same subject, and the same event type, which reflect variances of the measured parameters.



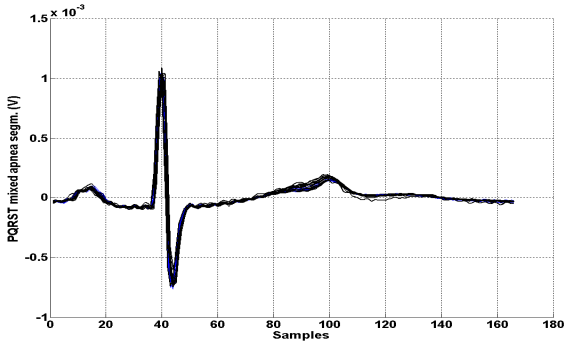
(a) arousal



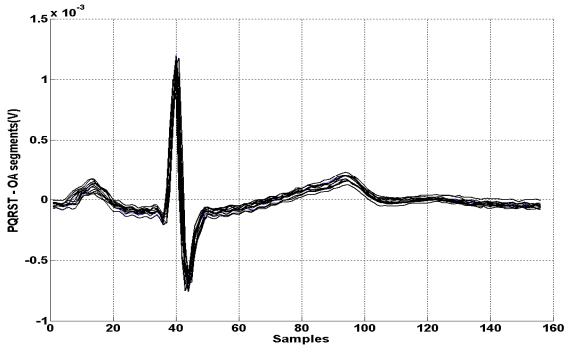
(b) arterial blood O_2 desaturation



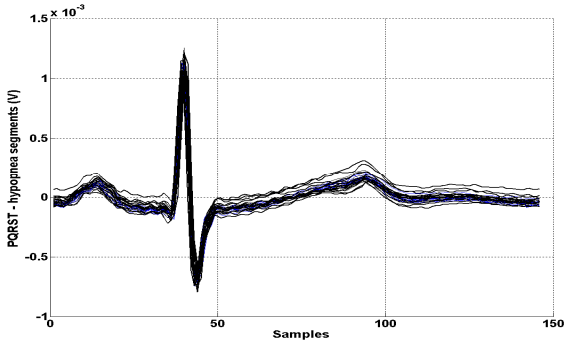
(c) central apnea



(d) mixed apnea



(e) obstructive apnea



(f) hypopnea

Fig. 2. Superposed PQRST samples of the same subject for specified respiratory segment type

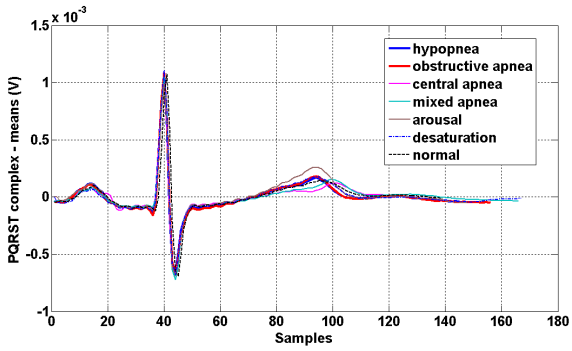


Fig. 3. PQRST complexes means reflect differences in waves amplitude and duration depending on the respiratory episode to which they correspond

In Figure 3 one can see the superposed PQRST means, centered on the R wave, for stressing the significant differences of the classes, reflected in wave amplitudes and widths. Table 2 summarizes the mean values and standard deviations of the relative distances between the detected points.

Figure 4 shows the detection performed on the characteristic wave for a central apnea segment. It emphasizes the fact that the characteristic points of the normal ECG wave are detected without the necessity of baseline elimination.

Figure 5 shows the mean characteristic interval variations for all the detected normal beats. One can see that PR segment has a very slight variation, which seems to be a characteristic for mixed apnea segments of all investigated patients, as can also be seen in table 2A. This table, and table 2B, show normal ECG wave characteristic intervals mean values, together with their standard deviations, for all the patients we've studied.

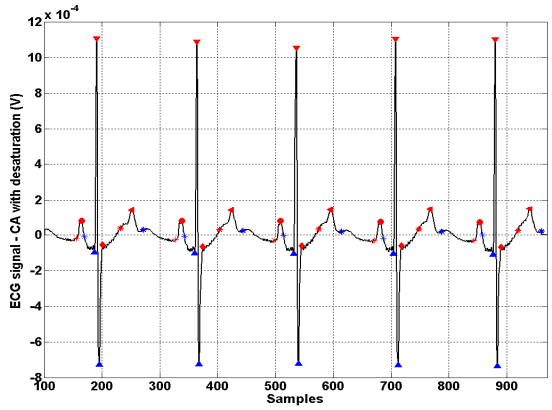


Fig. 4. P (red circle), Q (blue up pointing triangle), R (red down pointing triangle), S (green up pointing triangle) and T (red left pointing triangle) peaks and P and T onsets (red star) and offsets (blue star), for a central apnea with desaturation segment

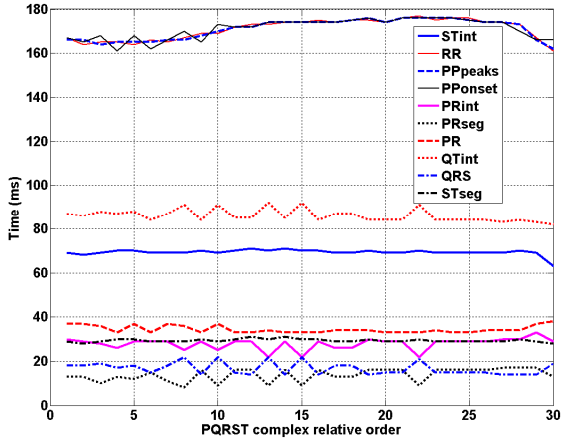


Fig. 5. Specific intervals variation in one patient's mixed apnea segments.

TABLE 2A – HRV characteristics mean values for respiratory events – corresponding ECG segments

HRV parameter:	PRinterval	PRsement	QRS	QTinterval	STinterval	STsegment
arousal	31.18±4.72	13.27±3.05	19.63±2.53	88.91±5.19	69.58±3.59	35.83±4.31
central apnea	30.76±1.98	16.64±2.03	14.35±1.54	70.58±3.85	30.58±2.86	84.94±2.72
mixed apnea	27.56±1.63	13.47±1.42	17.12±2.44	67.87±3.81	29.03±1.67	85.0±2.87
obstructive apnea	33.76±1.45	15.76±2.18	20.47±3.07	66.23±8.14	33.34±6.2	70.17±4.58
O2 desaturation	31.51±3.01	14.51±4.1	24.15±4.64	86.16±13.12	50.72±8.99	32.12±6.72
normal	34.33±4.06	15.58±2.53	21.73±8.26	88.56±12.56	66.78±7.82	26.88±8.45
hypopnea	33.44±5.05	15.88±3.13	17.89±4.81	87.51±12.28	70.39±7.04	24.28±7.93

TABLE 2B – HRV mean values - RR, PP, PR

HRV parameter:	RR	PPonset	PPpeaks	PR
arousal	186.9±48.25	186.52±47.17	186.69±47.01	226.29±51.12
central apnea	170.41±42.93	170.29±41.28	170.17±42.53	208.59±42.01
mixed apnea	170.64±45.18	170.64±45.63	170.77±45.12	205.09±45.16
obstructive apnea	202.48±41.8	202.97±41.23	202.61±41.02	294.17±41.2
O2 desaturation	193.08±48.22	192.67±48.66	192.55±48.83	273.3±48.21
normal	201.16±56.02	213.61±56.12	212.98±56.89	257.24±56.4
hypopnea	152.33±52.66	152.12±52.35	151.5±52.21	202.18±52.20

One can see from table 2A that the value of PR segment for mixed apnea is very close to that corresponding to arousal type segments, so that it can't be considered as a discriminating factor by itself. Also one can see that any characteristic interval of table 2A is a better choice for discrimination, based on their smaller variability, than any of those included in table 2B, which are usually selected for the HRV analysis.

5. CONCLUSIONS

This paper summarizes the actual stage of the research concerning the use of different HRV measures as a potential detection instrument for some sleep respiratory event reflected in cardiac functioning, related with the autonomic nervous system activity. PQ segment values, correlated with

ST interval values, for instance, may discriminate arousals from other cardiac behavior. The lead on which the observations were made didn't matter too much. Two ECG recording in our study were made on lead V5, while all others were made on lead V1. The subject had other associated pathologies, but the relative relation between characteristic time intervals was conserved by the respiratory event. Unlike other studies, our work aims at automatically identifying respiratory events from a single ECG lead, without prior filtering out baseline wandering.

Further work is necessary for accomplishing the initiated study and developing a fully functional automatic classification method based on HRV using wavelet preprocessing.

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