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EXTRACTION OF RESPIRATION SIGNAL FROM ECG FOR RESPIRATORY RATE ESTIMATION

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Abstract

The necessity of respiratory monitoring is rapidly increasing in medical field to diagnose various cardio-pulmonary diseases. It is difficult to monitor respiration for ambulatory and ICU patients, as conventional methods are either obtrusive or suffer from low accuracy. The extraction of ECG derived respiration (EDR) signal using single-lead ECG has been proposed lately. This allows monitoring of ECG and respiration signal simultaneously from a recorded ECG signal. Recently few methods for EDR extraction from ECG are reported in literature. In this work, respiratory rates (RR) are derived from Heart Rate Variability (HRV) and Peak Amplitude Variation (PAV) method and a comparative study of these two methods is reported. Moreover, the validation of the proposed methods is made by comparing the obtained RR with that derived from original respiration signal. Subjects from Fantasia database and real-time data for both normal and with pulmonary diseases are considered for the work.

1. Introduction

The measurement and monitoring of respiration is a very important parameter in clinical and diagnostic field. Abnormal respiratory rates (RR) and changes in RR are broad indicators of major physiological instability. Sometimes abnormal respiratory rate is one of the best independent predictors of cardiac arrest. RR can be used for early detection of chronic illness like Chronic Obstructive Pulmonary Disease (COPD) and Congestive Heart Failure (CHF). Even respiratory disorder like sleep apnea is a big risk factor for various cardiac diseases which provides an early indication about cardiac failure.

In recent years, the necessity of using non-invasive and non-obtrusive respiratory monitoring has witnessed a rapid growth. For this purpose various methods like respiration inductive plethysmography, 3D-accelaration derived respiration rate, and ECG derived respiration are introduced. The ECG derived respiration (EDR) method is very useful because both respiration and ECG signal can be monitored simultaneously and respiration can be derived from an available ECG source, in the absence of any other signal [1]. The number of leads can be reduced by using single-lead ECG which is very beneficial for continuous monitoring of ambulatory and critical care patients.

It has been seen that ECG can be considered as a respiratory information-carrying signal due to predominant effect of respiration on cardiac cycle generally known as Respiratory Sinus Arrhythmia (RSA) [2]. Previous studies have shown that respiratory rate can be derived from ECG signal by analysing either the variability in R-R intervals (caused by RSA) during respiratory cycle or the change in QRS amplitude (caused by change in cardiac axis) during breathing. Previously, Moody et al. introduced a multi-lead ECG system to derive EDR using cardiac axis deviation method [3]. Later Khaled et al. used single-lead ECG to derive EDR from R-peak amplitude variation method [4]. Methods like Wavelet Transform and Empirical Mode Decomposition are also used to derive respiration rate in recent studies [5].

In this study, the EDRs are derived from the ECG of 30 subjects (20 from fantasia database and 10 real-time data) by using single-lead ECG system and the respiration rates are calculated from both the EDRs derived from Peak Amplitude Variation (PAV) and Heart Rate Variability (HRV) and the derived Respiratory rates are compared against the respiratory rates calculated from the original respiration signal.

2. Database

A data acquisition system MP45 by Biopac Systems, Inc. is used to collect the ECG and respiration signal simultaneously [6]. The single-lead ECG is digitalized using a sampling rate of 1000Hz, and the respiration signal is recorded by a chest belt respiration effort transducer (Biopac). The database used in this study is collected from a group of 10 subjects participated in the study. In addition to this, the widely known Fantasia database [7, 8], is also used. Details of the database are given below in Table I-

TABLE I
Subject Database used in this study

DATABASE		SUBJECT DETAILS
Fantasia database		20 subjects(young subjects with age between 21-34 years, old subjects with age between 68-85 years)
Real-time database	Normal subject	5 subjects (3 subjects with age between 20-25 years, 2 subjects with age above 50 years)
	Subject with pulmonary disease	5 subjects (age between 52-65 years)

3. Methodology

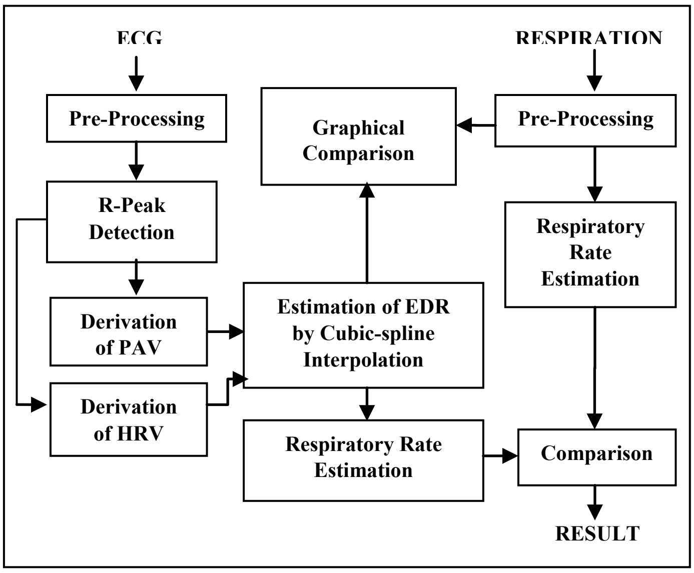

Figure 1. Block diagram of Respiratory Rate (RR) comparison between RR calculated from EDR & RR calculated from original respiration

The proposed method is presented in block diagram shown in Figure 1. Respiratory Sinus Arrhythmia (RSA) is basically a modulation of heart rate due to respiration which influences the sympathetic activity of autonomic nervous system (ANS) and, hence, affects heartbeat [9]. As a result, heart rate increases during inspiration (shorter R-R interval) and decreases during expiration (longer R-R interval). So the R-R interval can be used as an alternative of respiration signal. Based on this, the ECG Derived Respiration (EDR) is obtained using both Heart Rate Variability (HRV) method and Peak Amplitude Variation (PAV) method.

In this study, the ECG signal is filtered using a second order bandpass Butterworth filter within the band of 1-47 Hz for reducing the noise components present in the signal. Figure 2 shows both the original ECG and respiration signals and the signals after filtering.

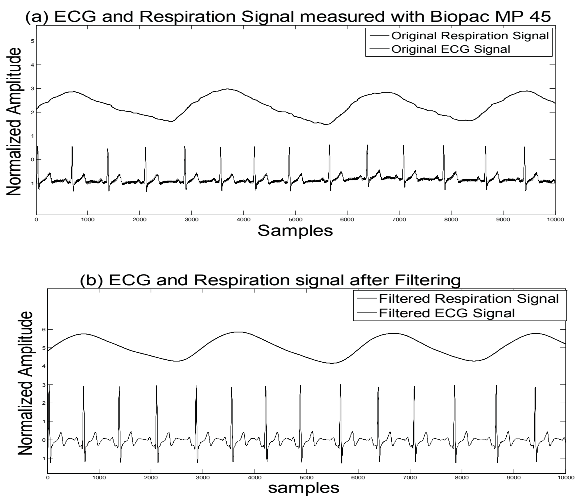

Figure 2. ECG and Respiration signal; (a) before filtering the ECG signal, (b) after filtering the ECG signal

R-peak is detected (as shown in Figure 3) using multi-resolution wavelet analysis as proposed in the work of S.Pal et al. [10]. A number of proper and optimum set of wavelet coefficients are used to reconstruct an ECG wave of interest.

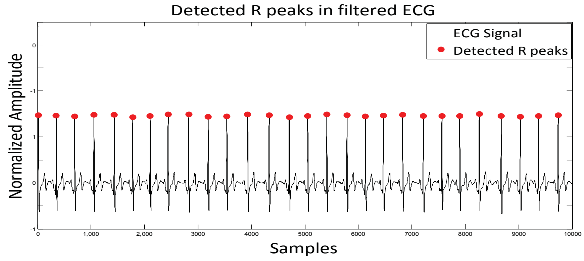

Figure 3. R-peak detection in filtered ECG signal

The frequency band of respiration signal is generally in the range of 0.1-0.7 Hz. As it is a very slow signal (one respiration cycle can be derived from ECG corresponds to 4-10 heartbeats) linear interpolation can be used for good signal reconstruction speed, but it cannot build waveform similar to original respiration signal. So, to get an original respiration-like waveform, cubic-spline interpolation is used here [11]. Suppose for a data set of original signals, $f_i=f(x_i)$ [where i=0,1,2,...n-1], the output of the cubic-spline interpolation at a given interval (x_i,x_{i+1}), f can be written in equation 1 as shown below,

$$f = pf_i + qf_{i+1} + rf_i^{//} + sf_{i+1}^{//} \tag{1}$$

Where,

$$p \equiv \frac{x_{i+1}-x}{x_{i+1}-x_i},\; q \equiv \frac{x-x_i}{x_{i+1}-x_i}$$

$$r \equiv \frac{1}{6}(p^3-p)(x_{i+1}-x_i)^2,\; s \equiv \frac{1}{6}(q^3-q)(x_{i+1}-x_i)^2$$

Here, p and q are linearly dependent on x and r and s have cubic-x dependence.
So for first derivative,

$$\frac{df}{dx} = \frac{f_{i+1}-f_i}{x_{i+1}-x_i} - \frac{3p^2-1}{6}(x_{i+1}-x_i)f_i^{//} + \frac{3q^2-1}{6}(x_{i+1}-x_i)f_{i+1}^{//} \tag{2}$$

And for second derivative,

$$\frac{d^2 f}{dx^2} = pf_i^{//} + qf_{i+1}^{//} \tag{3}$$

The estimation of EDR from Heart Rate Variability is performed using the following steps.

First The R peaks are detected and the value of R-R interval is calculated for each of the two consecutive cycles. Next the Heart Rate (HR) for each R-R interval is calculated using the formula as shown in equation 4,

$$Heart\ Rate = \frac{60}{R-RInterval} \tag{4}$$

The values of each Heart Rate thus obtained are interpolated using cubic spline interpolation to obtain the EDR waveform from HRV. Following the same procedure, the EDR from PAV is reconstructed from the amplitudes of the detected R peaks using the cubic spline interpolation.

The Respiratory Rate (RR) from both the EDRs and the original respiration signal are calculated individually using equation 5 as shown below,

$$RR = \frac{t_{(n+1)} - t_n}{60} \qquad (5)$$

Where, RR= Respiratory Rate
$t_{(n+1)}$= time period for occurrence of $(n+1)^{th}$ R-peak
t_n= time period for occurrence of n^{th} R-peak

The individual respiratory rates thus obtained for each consecutive cycle for a specified time window length of 60 seconds are averaged to find the Breathing Rate per min (BrPM). An error analysis between the BrPM obtained from original respiration signal and the BrPM derived from each of the EDRs is performed which is further described in the results section.

4. Results

Data from the database of 30 subjects are used to analyse the EDR. Among the 30 subjects, 20 subject-data has been taken from Fantasia database and another 10 subject-data is collected from real-time subject. Both ECG and respiratory signal is recorded for a time-duration of 5 minutes by the data acquisition device (Biopac). The ECG signal is pre-processed and the EDR is evaluated by both PAV and HRV method. After the R-peaks are detected, there amplitudes are interpolated using cubic-spline interpolation (shown in Figure 4) to get a waveform like original respiration signal.

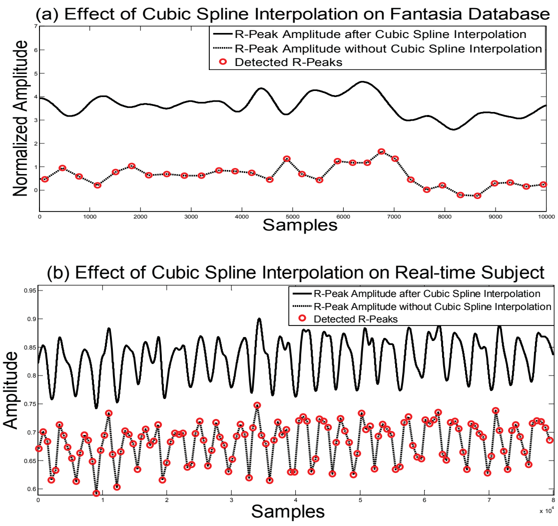

Figure 4. Interpolation of detected R-peaks; (a) for fantasia database, (b) for real-time subject

A comparative study has been done between the EDRs evaluated from PAV and HRV method (shown in Figure 5) and the absolute error and mean absolute error (MAE) is computed. A partial list of results is shown in Table II. From the result it can be noticed that the MAE of HRV method (±0.57) is much less than MAE of PAV (±0.7).

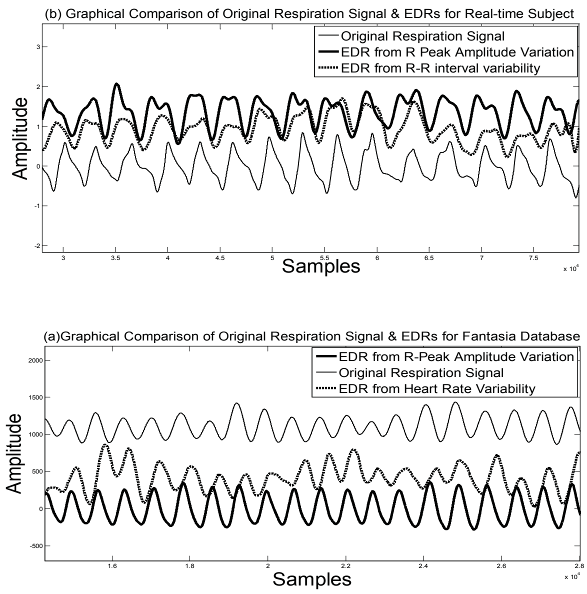

Figure 5. Visual comparison between the original respiration signal and EDRs obtained from PAV & HRV method; (a) for fantasia database, (b) for real-time subject

TABLE II

Comparison of RR obtained from different EDRs (partial list)

Sl.	Subject	RR from Original Signal (BrPM)	RR from HRV Signal (BrPM)	RR from PAV signal (BrPM)	Absolute Error for EDR from HRV signal	Absolute Error for EDR from PAV signal
1	Subject 1	18	18	18	0	0
2	Subject 2	23	23	24	0	1
3	Subject 3	15	15	15	0	0
4	Subject 4	21	23	24	2	3
5	Subject 5	17	17	17	0	0
6	Subject 6	19	19	20	0	1
7	Subject 7	18	18	19	0	1
8	Subject 8	19	17	20	2	1
9	Subject 9	14	14	16	0	2
10	Subject 10	17	17	17	0	0

MAE for EDR signal obtained from HRV signal : ±0.57 BrPM
MAE for EDR signal obtained from Peak Amplitude Variation signal : ±0.7 BrPM

A comparison between few previously reported results and the proposed one is given below in the Table III.

TABLE III

Quantitative comparison of present method with few earlier results

Sl.	Method	Feature Used	No. of Subjects	Performance Parameter in RR estimation
1	A.M.Chan et. al. [12]	HRV(RSA), QRS Amplitude Modulation	15	MAE 1.02 BrPM during metronome breathing, 1.67 BrPM during spontaneous breathing, 2.03 BrPM during ADLs.
2	L.Guan-zheng et. al. [13]	Beat Morphology, Heart Rate, and a combination of both	12	Mean Absolute Percentage Error 4.37%
3	J.Lázaro et. al. [14]	QRS Slope	29	RR Estimation Error - 1.07±8.86%
4	S.B.Park et. al. [15]	QRS Area	15	Correlation Coefficient 0.8
5	C.Orphanidou et. al. [16]	RSA, RPA	40	MAE 0.81 BrPM for the young subjects and 0.84 BrPM for the elderly
6	J.Boyle et. al. [17]	Wavelet Decomposition	16	MAE ±4 breaths per minute (bpm) for all activities, ±2 bpm for lying and sitting, and ±1 bpm for overnight studies
7	Proposed	HRV, PAV	30	MAE ±0.57 BrPM for HRV and ±0.7 BrPM for PAV

5. Conclusions

ECG is the most important parameter to be monitored for cardiac patients. Respiratory rate is another important parameter required for overall monitoring of the patients, which needs more instrumentation for continuous observation. In this study, the effort to derive respiration signal from ECG leads to fewer requirements of device. Two different methods like PAV and HRV are used here as proposed by different researchers. But earlier studies are based on the stored database or subjects in laboratory condition. In this work pulmonary abnormality conditions like COPD, asthma are also studied and derived respiratory signals show significant resemblance with original one.

The comparative study also shows that HRV based method performs better with respect to PAV based technique as shown in the result section. So for continuous monitoring purpose HRV method can be used for better accuracy than PAV method. In addition, these methods are very easy to implement because it is completely non-invasive and non-intrusive method and only ECG signal is needed for this.

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