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Application of EDR in Pulmonary Studies

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Abstract

Respiration monitoring plays a very important role in patient diagnosis. Regular monitoring of respiration is necessary for detecting the presence any kind of physiological instability and chronic illness. Several techniques are used for respiration monitoring and pulmonary disease detection. But these methods often show some difficulties in application. In this background, ECG derived respiration (EDR) can be an alternative tool for respiration measurement, as the effect of respiration on electrocardiogram (ECG) is already established by researchers. In this study, twenty normal subjects were taken and divided into two subgroups- subjects without any kind of symptoms and subjects with symptoms like cold, cough, allergy etc. Three features were extracted based on the respiration pattern difference from both original respiration and EDR signal and a comparative analysis was done in between them.

Key words

ECG, Respiration, ECG derived respiration, R peak amplitude variation, p value

1. Introduction

The measurement of respiration is very crucial for patient monitoring as it is a major and earliest indicator of physiological instability [1]. Sudden and abnormal changes in respiration rate often indicates serious adverse events [2,3]. Therefore, respiration should be monitored routinely in case of both healthy and sick people to prevent further deterioration and sudden ICU admission [4,5]. In addition to this, the number of patients affected in various lung diseases are alarmingly increasing [6] The morbidity and mortality rate due to lung diseases become alarmingly increasing [7, 8]. However, most of the time respiration signal is neglected compared with the other vital signs in routine check-up [2]. Some of the main reasons include lack of awareness about importance of respiration measurement and unavailability of accurate and unobtrusive respiratory monitor [9]. Available methods like spirometry, body plethysmography, pneumography, chest belts, nasal probe and various lung imaging techniques (X-ray, CT scan etc.) are often used in respiration monitoring and abnormality detection [10-13]. But these methods sometimes exhibit error in measurement due to some reasons like lack of trained technician, high patient effort dependency, presence of noise etc. [3]. Apart from all these conventional methods some new technologies are also developed [9, 15, 16]. ECG derived respiration is another well accepted method for respiration monitor after researchers found the effect of respiration on cardiac activity [17-19]. Electrical axis of heart changes due to cardiac movements during inspiration and expiration [20]. Another effect of respiration on heart is called Respiratory Sinus Arrhythmia (RSA) due to which R-R interval decreases during inspiration and increases during expiration [21]. Based on these effects of respiration on heart, several algorithms are developed to produce EDR signal [22-24].

In this study, two different subject groups were included in study population. Subjects from one group were completely healthy without any symptoms present, whereas, subjects from another group had symptoms like cold, cough, etc. Both ECG and respiration signals were collected simultaneously and EDR signal was extracted from the ECG. Three different features were extracted from both the original respiration signal and from the extracted EDR signal. Feature values extracted from both the signals were compared and the statistical significance was analysed.

2. Method

The study was done based on data collection of subjects followed by pre-processing of original signals, extraction of EDR signal and feature extraction as described next.

2.1.Data collection of subject

ECG and respiration signal were recorded simultaneously from real-time subjects using a data acquisition device called MP-45, by Biopac Systems Inc. [25]. ECG and respiration signals were collected using a lead II single-channel ECG and a respiratory effort transducer tied across the chest of the subject while the subject was resting at supine position. Both ECG and respiration signals were recorded at a sampling frequency of 1000 Hz for the duration of 300 seconds. The respiration signal acquired from the chest belt was used as the original respiration signal in the study. All real-time data were collected as per the study protocol approved by Institutional Ethics Committee of the Institute of Pulmocare and Research and further study work was carried out in the Biomedical Data Acquisition and Processing Laboratory of Department of Applied Physics, University of Calcutta. Only the subject giving written consent was sent for medical history check-up. Each subject was evaluated by spirometry testing as per the ATS guideline [26] and a physical examination was taken place by the chest specialists prior to the enrolment. The subjects were included only if their spirometric values were normal. A total of twenty subjects were included in the study population. Ten of them are completely healthy without any symptom present, whereas, another ten subjects presented mild symptoms like sneeze, cold, cough, etc. during the time of data collection. The subjects having any kind of cardio-pulmonary diseases and the subjects taking steroids were excluded from this study. The details of the two subject groups are shown below in table 1.

Table 1: Details of two subject groups

Subject	Number of subjects	Age (Mean±SD)	Male:Female ratio	BMI (Mean±SD)
Normal subject without any symptom (N)	10	44.5±4.02	1:1	22.88±1.9
Normal subject with symptoms like cold, cough, etc. (NS)	10	46.9±7.47	1:1	22.17±4.22

2.2. Pre-processing of original signals

Both ECG and respiration data were taken for eighty seconds time duration for further processing of signals. A second order bandpass Butterworth filter was used to remove noises from the ECG signal. After denoising the ECG signal was normalized to unity and a sliding window with window length of 2 sec. was used on that normalized signal. A threshold was applied on the signal before passing another sliding window with window length of 500 msec. Finally R peaks were identified from the selected peaks with maximum amplitude within the selected window. The amplitude of the selected R-peaks were calculated and plotted against the baseline. Corresponding respiration signal was also filtered using a 2nd order Butterworth filter to remove the external noises without hampering the respiration information present in the signal.

2.3. Extraction of EDR signal

The influence of respiration that modulates the heart rate (RSA) has been established for many years. The electrical axis of heart changes due to the expansion and contraction of lungs during breathing in and out respectively. As a result the lung impedance changes with the change in lung volume [27]. The change in thoracic impedance also affects the RS amplitude of ECG signal where the amplitude increases during expiration and vice versa.

Various algorithms were developed so far for extraction of EDR signals based on the effects of respiration on cardiac activity [20,23]. For this study, we have used R peak amplitude variation method for EDR extraction.

Previously detected R-peaks were interpolated for constructing EDR signal. Cubic spline interpolation was used here to create EDR waveform similar to the original respiration signal [28]. If the original data set, $h_k = f(x_k), where\ k = 0,1,2,3,...,n-1,$ then the cubic-spline interpolation output within a specific interval of $[y_k, y_{k+1}],$ can be written as,

$$h = Ah_k + Bh_k + 1 + Ch_k^{''} + Dh_k^{''} + 1 \quad (1)$$

The coefficients are shown as below.

$$A = \frac{y_{k+1} - y}{y_{k+1} - y_k},\ B = 1 - A,\ C = \frac{1}{6}(A^3 - A)(y_{k+1} - y_k)^2,\ D = \frac{1}{6}(B^3 - B)(y_{k+1} - y_k)^2$$

2.4. Feature extraction

Respiration is one of the most important vital sign. Sometimes respiration plays a major role in early detection of physical instability [29]. Respiration pattern of normal healthy people varies from those with any type of lung disease or having any chronic disorder. During data collection, we have noticed that the respiration pattern also differs in case of normal subjects having cough, cold, allergy etc. from those subjects without having any kind of symptoms present. Based on this three different features were extracted from both original respiration signal and extracted EDR.

2.4.1 Area ratio

Peak detection algorithm was used to detect the corresponding locations of the starting point, peak and ending point (as shown in figure 1) within a cycle. A reference point, opposite to the peak, was taken against the baseline. Using the locations of start point, peak and reference point inspiration area was calculated, whereas, expiration area was calculated using the locations of peak, reference point and end point. Area ratio (A_r) was calculated using equation 2 for each cycle (both respiration and EDR) and the final area ratio was calculated by taking the average from five randomly chosen cycles (both EDR and respiration).

$$A_r = \frac{Expiration\ area}{Inspiration\ area} \quad (2)$$

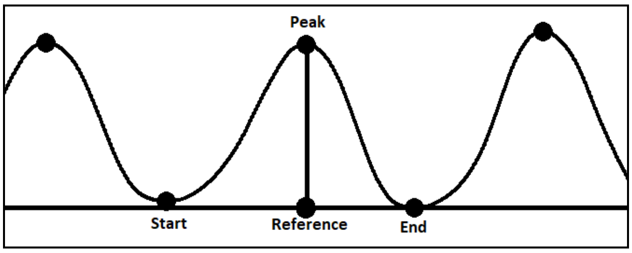

Figure 1: The starting point, peak and ending point of a respiration cycle are shown in this figure

2.4.2 Time ratio

Before calculating time ratio, inspiration time and expiration time were computed and time ratio (T_r) was calculated using the following formula,

$$T_r = \frac{Expiration\ time}{Inspiration\ time} \quad (3)$$

The whole procedure was done for five consecutive times and the average time ratio was taken finally.

2.4.3 Respiration rate

Respiration rate (RR) is actually the total number of respiration cycles present within one minute. In this study respiration rate was calculated in case of original respiration signal as well as from the extracted respiration signal from ECG. The time duration between two consecutive peaks was computed and RR was estimated using equation 4.

$$RR = \frac{60}{Time\ duration\ between\ two\ consecutive\ peaks} \quad (4)$$

After extracting the features from both the signals, the statistical significance of the feature sets were analysed using the student t-test.

3. Result

Twenty subjects, divided into two groups, were included in the study population. None of them were smoker or under any medication or having any kind of chronic disease. The extracted EDR waveform was compared graphically with the original respiration waveform for each subject as shown in figure 2.

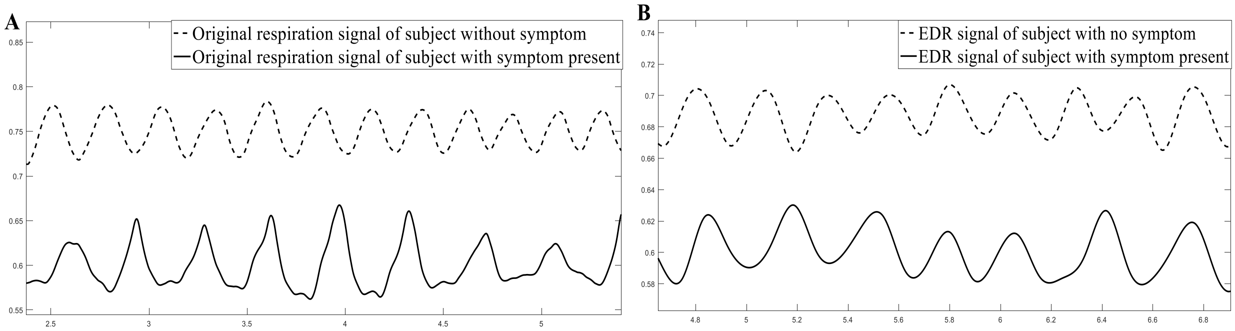

Figure 2: A) Original respiration signal and B) EDR signal of subject from both N and NS group

It can be clearly seen that the respiration pattern varies between two subject groups (figure 2A), whereas, the EDR signal pattern does not differ much from one group to another (figure 2B). The calculated feature values for both EDR and respiration signals are shown in table 2 and the p-values calculated for each feature are shown in table 3.

Table 2: Features extracted from EDR and original respiration signal

Subject group		EDR area ratio	Respiration area ratio	EDR time ratio	Respiration time ratio	*RR extracted from EDR	RR extracted from original respiration signal
N	Average	0.93	0.94	0.84	0.91	18.6	18.58
	Standard deviation	0.13	0.09	0.12	0.14	2.69	2.71
NS	Average	0.85	1.27	0.83	1.41	18.88	18.84
	Standard deviation	0.07	0.17	0.11	0.28	4.92	5.18

*RR denotes Respiratory Rate

Table 2 shows that in case two features, area ratio and time ratio, the value calculated for N group differs from that of NS group. But in case of respiration rate extracted from both the signals, the value for NS group does not vary significantly from that of N group.

Table 3: Calculated p-values against each feature

Subject group	p value calculated between EDR area ratio and respiration area ratio	p value calculated between EDR time ratio and respiration time ratio	p value calculated between EDR RR and respiration RR
N	>0.1	>0.1	>0.1
NS	<0.05	<0.05	>0.1

Table 3 shows the corresponding p-values calculated between the same feature set extracted from two different signals. From the table it can be seen that, only p-value estimated for area and time ratio for NS group show statistical significance ($p<0.05$), whereas, the other p-values remain statistically insignificant ($p>0.1$).

4. Discussion

Monitoring vital signs like ECG and respiration regularly is undoubtedly very important in clinical field. Regular monitoring may help in early detection of cardio-pulmonary abnormalities. Though it is very unfortunate that respiration remains neglected most of the time, compare to ECG, as regular check-up. In this situation, EDR may be very helpful tool as it can monitor both the signals at the same time. During the study, we observed that all the subjects showed normal spirometry, but the respiration pattern of subjects with symptoms present varies from the respiration pattern of those without any symptom present. The result also shows that the feature values extracted from the original respiration for NS group varies from that of N group.

Conclusion

From the study it can be concluded that, EDR can be a better alternative for respiration monitoring compare to conventional chest belt method. Further analysis can be done on bigger dataset for clinical applicability.

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