Comparing ECG Derived Respiratory Signals and Chest Respiratory Signal for the Detection of Obstructive Sleep Apnoea

Nadi Sadr[1], Philip de Chazal[1,2]

[1] School of Electrical and Information Engineering, University of Sydney, Sydney, Australia
[2] Charles Perkins Centre, University of Sydney, Sydney, Australia

Abstract

In this paper, three approaches for estimating ECG derived respiratory signal (EDR) were utilized for apnoea detection and the results were compared with apnoea detection by chest respiratory signals. Two methods are presented for computing the EDR signal by principal component analysis (PCA) applied to entire overnight ECG signals. The proposed approaches simplified the PCA computation and resulted in fast algorithms with low memory requirements. The third method used the QRS area method of EDR estimation. In the first phase, the 8 recordings available in the MIT PhysioNet Apnea-ECG database which contained simultaneously recorded respiratory signals were utilized and the chest respiratory signals were employed for OSA detection and the results were compared to OSA detection by EDR signals. In the second phase, the EDR signals of the 35 available ECG recordings from the same database were used for apnoea detection. The results of both phases for the EDR and respiratory signals were classified by three different machine learning techniques including the extreme learning machine, linear discriminant analysis and support vector machine. It was revealed that QRS area method with LDA classifier results in the highest performance. However, the respiratory signal leads to better apnoea detection compared to the EDR signals.

1. Introduction

Obstructive Sleep apnoea (OSA) is a sleep-related breathing disorder associated with consecutive blockage of upper airways and interruption in breathing [1]. Respiration can be monitored directly by nasal sensors which may interfere with breathing or indirectly by inductance plethysmography [2]. Recently, several studies have investigated deriving a surrogate respiratory signal of electrocardiogram (ECG) [2]. This signal, the ECG-derived respiratory signal (EDR), can be estimated using a number of methods including principal component analysis (PCA) [3] and QRS area [4].

A computation limit of the published studies [5][3] using PCA is the need of storing large covariance matrices where the size of each dimension of the covariance matrix is equal to the number of beats in the recording. The memory storage needed for an average ECG length of 8 hours with a double precision calculation is about 7 GB which exceeds the memory capabilities of a standard PC. We propose two novel approaches to apply the PCA method for derivation of EDR signals of overnight recordings. Both approaches solved the computational problem and memory storage issue while running on a standard PC. In the first approach, the overnight recordings were segmented into 30 minutes of signals and the EDR signals extracted by PCA method over the segments were aligned to form the EDR signal of the overnight recordings. The second novel approach employed an approximated PCA methodology which has been successfully applied to speaker recognition [6]. These two PCA methods were compared to the QRS area method for EDR estimation. Apnoea detection of these three EDR signals was compared with apnoea detection by chest respiratory signal.

2. Dataset

The MIT PhysioNet Apnea-ECG database proposed for Computing in Cardiology 2000 Challenge was used for this study [7][8]. The training data of 35 ECG signals, minute-by-minute apnoea annotations by respiratory experts, and QRS annotations produced by machine were utilized. The digitized single channel of modified lead V2 ECG signals were recorded from healthy subjects and OSA patients with sampling rate of 100 Hz and 16-bit resolution. Eight recordings of the training data contained chest and abdominal respiratory effort signals collected by inductance plethysmography. The signals were recorded from 32 subjects of 25 men and 7 females with average age 33 years (between 27 to 42 years). The length of each overnight recorded signal ranged between 7 to 10 hours [8]. The simultaneous recordings of respiration signals and ECG signals were exploited for apnoea detection evaluation in the first phase of the study. The

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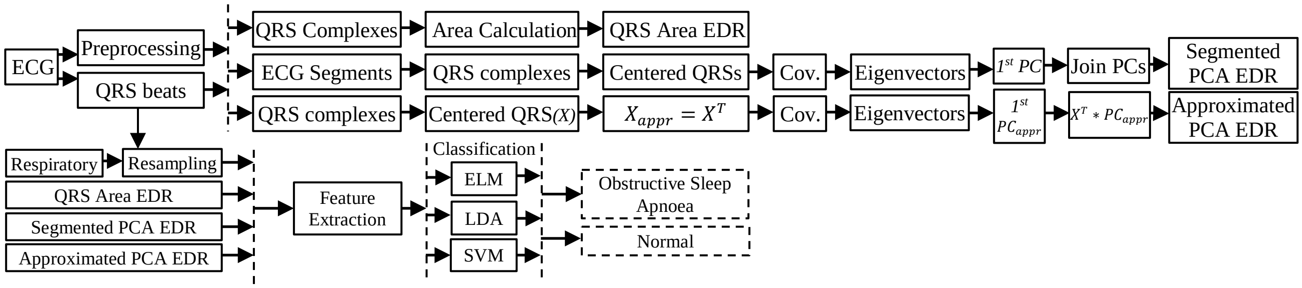

Figure 1. Block diagram of three methods of EDR measurement including two proposed algorithms for PCA estimation applied to overnight ECG signals and sleep apnoea detection by EDR signals and respiratory signal.

full overnight ECG signals were used for three EDR signal extraction in both phases and the simultaneously recorded chest respiratory signals were used for apnoea detection in the first phase of the study.

3. Signal processing

The overnight ECG recordings and respiration signals were used for signal processing and OSA detection. For ECG signals, preprocessing was utilized to reduce the artefact. Then, ECG derived respiratory (EDR) signals were measured through three different methods evaluated at the QRS detection beats. Then, the OSA detection was evaluated using three classifiers. Finally, respiratory signals were used for apnoea detection and the performance was estimated by the same classifiers. The block diagram of the proposed system is shown in Fig 1.

4. ECG signals

First, preprocessing was applied to the ECG signals to remove the high frequency noise and baseline wander noise. Two median filters with 200-ms and 600-ms width were applied to extract the QRST complexes and the filtered components were subtracted from the raw ECG signals to remove the noisy part of the signals [4]. Then, the clean and preprocessed ECG signals were used for EDR measurement. The QRS onset beats provided by the database were used for the following ECG signal processing as well as resampling the respiratory signals for apnoea detection.

5. EDR signals

The surrogate respiratory signal can be detected as the modulatory signal on the ECG signals with a variation tracking the breathing cycles [2]. There are a number of mechanisms which modulate the ECG recording by respiration. The movements of the ECG electrodes placed on the chest corresponding to the heart, rotation of cardiac vector, and electrical impedance changes of thorax due to ventilation and air volume changes in the lungs are some of the factors leading to capturing the respiratory information by ECG electrodes [9]. In this study, three methods were used to estimate the EDR signal. First, the QRS complex area method was exploited as the standard method which has been evaluated in several studies [4]. Then, to estimate EDR signals by PCA technique over the entire overnight ECG signal, two methods were applied including segmented PCA and approximated PCA. The methods are illustrated in Fig 1 and are explained the following sections.

5.1. QRS complex area

The preprocessed ECG signal was used to determine EDR signal. In this method, area under QRS complexes were measured between onset beat of QRS complexes and 100 milliseconds after the onset beat [4]. Therefore, the area under each QRS complex is designated to each QRS beat as the EDR measure for that beat.

5.2. Segmented PCA

The principal component analysis is usually used to decrease the dimensions of the multivariate signals. It determines the principal components by calculating eigenvalues of the variations in the signal features [10]. The QRS complex was chosen as the feature for PCA calculation to extract the temporal variation caused by respiration on ECG signal.

The segmented PCA algorithm is outlined as follows. The inputs to the PCA algorithms are the entire overnight ECG signals which have been preprocessed. The other input to the algorithms are the QRS onset detection beats provided with the database. Our method is adapted from the method described in [3].

1. The input signals were partitioned into 30 minutes segments.
2. A sliding window with 250ms *(m)* width was applied to the QRS onset beats to extract QRS complexes in each segment. It extracts QRS complexes between 75ms before each QRS onset beats and 75ms after the onsets.
3. A feature matrix $(m \times n)$ of n centered QRS complexes $[X_{QRS}(t)]_{m\times n}$ was constructed.
4. The covariance of $[X_{QRS}(t)]$ was measured and resulted in a $(n \times n)$ matrix.

5. The eigenvalue, eigenvectors and principal components (PC) were extracted.
6. The first PC was set to the EDR signal.

The algorithm was repeated for each 30 minute segment of ECG signals and the first PCs were aligned to form the EDR signal over the full recording.

5.3. Approximated PCA

An approximation method which has previously been implemented in a speaker recognition study was applied to PCA EDR estimation [6]. As is demonstrated in Fig 1, many of the steps of the approximated PCA algorithm are similar to the segmented PCA algorithm. The differences in the algorithms are summarized below.

1. The feature matrix of *n* centered QRS complexes for the whole recording $[X_{QRS}(t)]_{m\times n}$ was transposed and the PCA method was applied to $X_{appr} = X^T$.
2. The covariance matrix was measured over X^T resulting in $m \times m$ matrix, where m is the number of samples in the QRS window (in our case 25).

$$Cov_{appr} = \frac{1}{m}\sum_{i=1}^{m} X_i^T X_i \qquad (1)$$

3. Then, the first principal component of approximated PCA (PC_{appr}) was measured by eigenvectors of the Cov_{appr} matrix.
4. Finally, the product of the generated principal component and X_{appr} results in the EDR signal.

$$PC_{EDR}^1 = X^T * PC_{appr}^1 \qquad (2)$$

By processing the X^T matrix rather than the X matrix, the computational complexity, memory requirement and long processing time were resolved.

6. Respiratory signal

The respiratory signals of the database comprise of chest and abdominal respiratory signals. The chest respiratory signals were utilized in this study as they are most closely related to the modulated EDR signals recorded by ECG electrodes. To achieve a like-for-like comparison, we applied the same feature extraction methods to the chest respiratory signals and the EDR signals. Hence, our first processing step was to resample the chest respiratory signal at the instants of the QRS onset beats. The resampled respiratory signals were then exploited for feature extraction.

7. Feature extraction

The resampled respiratory signals and the three EDR signals were processed by the same feature extraction algorithm. There were 34 features extracted from each one-minute segment of the signal including the average, standard deviation and 32 power spectral density (PSD) features. For measuring PSD features, the signals were zero padded to 256 points and discrete Fourier transform (DFT) was applied after the mean value was removed. Then, the square amplitude of the DFT coefficients was calculated and average of every four frequency bins was measured and the first half of the symmetrical values were adopted as 32 PSD features.

8. Classifiers

The matrices of 34 features for each one-minute epoch of the signals were used as the input to three different classifiers. The performance of each signal was evaluated by applying each feature matrix individually.

Extreme learning machine (ELM) is a fast feed-forward network and one hidden layer with a large number of non-linear neurons. It is trained through a single iteration learning procedure by using random values as input layer weights and the pseudo inverse to calculate the output weights [11]. In this study, the number of hidden layer neurons per input (fan-out) was set to 10. It was chosen according to the results from our earlier publication [12].

Among pattern recognition techniques, linear discriminant analysis (LDA) is a simple classifier which categorizes the classes with linear boundaries in a low dimensional space and through a simple probabilistic decision making [13].

The third utilized classifier was support vector machine (SVM) which is a supervised learning technique and differentiates the scattered data without over fitting. Linear kernel SVM was employed as the third classifier using LibSVM [14].

9. Results

Each signal was evaluated individually through leave-one-record-out cross validation for each classifier. Their performances were assessed by three measures comprised of accuracy, sensitivity and specificity. In the first phase of the study, the EDR signals were measured for 8 ECG recordings accompanied by the respiratory signals. The performance results are shown in Table1. In the second phase, the EDR signals were extracted from 35 ECG recordings and the extracted features from each EDR signal were applied to three classifiers and the performance results are illustrated in Table 2.

The results of the first phase show that respiratory signal achieved the highest performance for apnoea detection by SVM classifier with an accuracy of 87%, sensitivity of 86% and specificity of 88%. The performance results of the second phase indicated the highest performance of apnoea detection was obtained by QRS area EDR signal with accuracy of 80%, sensitivity of 83% and specificity of 74%. The performance results of SVM classifier are close to the performance results obtained by LDA classifier in both phases.

Table 1. The cross validation results from 8 recordings containing the respiratory signals.

Signals	**Accuracy(%)**	**Sensitivity(%)**	**Specificity(%)**
	ELM classifier *(Fan-out=10)*		
Respiratory	78	92	71
QRS Area	80	88	74
Approximated PCA	74	84	67
Segmented PCA	63	51	71
	LDA classifier		
Respiratory	87	83	92
QRS Area	81	84	77
Approximated PCA	64	61	67
Segmented PCA	67	79	50
	SVM classifier		
Respiratory	87	86	88
QRS Area	81	71	88
Approximated PCA	69	64	73
Segmented PCA	66	49	78

Table 2. The cross validation results of EDR signals extracted from 35 ECG recordings.

EDR signals	**Accuracy(%)**	**Sensitivity(%)**	**Specificity(%)**
	ELM classifier *(Fan-out=10)*		
QRS Area	77	84	73
Approximated PCA	77	80	75
Segmented PCA	75	74	76
	LDA classifier		
QRS Area	80	83	74
Approximated PCA	79	84	70
Segmented PCA	77	84	66
	SVM classifier		
QRS Area	79	70	85
Approximated PCA	79	70	84
Segmented PCA	79	67	86

10. Discussion and conclusion

The results of first phase of the study indicate that respiratory signal leads to better apnoea detection compared with EDR signals. This result probably reflects the intuition that the direct measurement of respiration is better than indirect measurement. On the other hand, the EDR signals are captured from ECG recordings without the need of an extra sensor. Thus, there is a trade-off between some information loss of the EDR based system and increased convenience to the patient by reducing the sensors. The comparison of EDR measurement approaches in cross validation of 35 recordings revealed that QRS area method with LDA classifier results in the highest performance while they are both the simplest methods with the lowest computational complexity and processing time.

Further work could be comparing the QRS sampled respiratory signals with the original signals containing full samples to check the impact of the information loss.

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Nadi Sadr
University of Sydney
NSW 2006, Sydney, Australia
nadi.sadr@sydney.edu.au