A Comparison of Obstructive Sleep Apnoea Detection using Three Different ECG Derived Respiration Algorithms

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Abstract

In this paper, three different algorithms (QRS amplitude, PCA and kernel PCA) were applied to the ECG signal to extract information of the respiratory activity. Features were then extracted from the respiratory activity and used to classify sleep apnoea episodes using an Extreme Learning Machine classifier.

Data from the first 60 minutes of the 35 ECG signal recordings from the MIT PhysioNet Apnea-ECG database was used throughout the study. Performance was measured with leave-on-record-out cross validation. The fan-out number for the ELM classifier was varied between one and ten.

The results showed that the performance of the PCA algorithm was equal to or outscored the other two algorithms at all fan-out numbers we explored. Its highest performance was an accuracy of 79.4%, a sensitivity of 48.8%, and a specificity of 87.7% at a fan-out of ten.

1. Introduction

Obstructive Sleep apnoea (OSA) is a common sleep disorder, accompanied by episodes of upper airway obstruction and interruptions in breath [1]. It may lead to serious health issues such as cardiovascular disease [2]. Thus, apnoea diagnosis and treatment is important for both the patient and society.

Polysomnography (PSG) is the standard sleep test for apnoea diagnosis which records many signals during an overnight stay in a hospital. Sleep studies are expensive and patients may not sleep well due the attachment of wires and electrodes to the head, torso and limbs which can cause discomfort. Therefore, an ongoing research goal is to reduce the number of diagnostic signals and diminish the cost and invasiveness of sleep tests [3].

Amongst the PSG signals, the ECG signal is favoured to detect sleep apnoea, as it is recorded easily and causes minimal sleep disturbance. The ECG signal is modulated by the anatomical movements of the heart and lungs during breathing [4]. Signal processing can be used to isolate the respiratory signal [5,6] and it has been termed the ECG-derived respiratory signal (EDR) in the literature. Therefore, respiratory information is available in unison with cardiac monitoring through a minimally invasive system [4].

In this paper, three different methods were implemented for EDR extraction including QRS amplitude, PCA, and kernel PCA (kPCA).

2. Dataset

The learning set ECG recordings from the MIT PhysioNet Apnea-ECG database were utilized. The data was obtained for 35 overnight ECG recordings (modified lead V2) from normal and obstructive sleep apnoea patients. The sampling rate was 100 Hz, with the learning set randomly sampled from a larger database of 70 recordings from 32 subjects consisting 25 males and 7 females. The first 60 minutes of 35 ECG signal recordings were employed as the input dataset for this study. Each 60 seconds of the data has been labelled as "normal" or "apnoea" by an expert [7,8].

3. Preprocessing

The baseline wander of the ECG signal due to body position changes was removed before any further processing. This step was needed as sudden shifts in the signals baseline could have a large effect on the EDR. This was achieved by application of two median filters using windows of width 200ms and 600ms [9]. The QRS onset detection points provided with the database were used throughout the study.

4. EDR Signal

ECG Derived Respiratory (EDR) signal is a modulatory signal on the ECG which affects the amplitude of ECG by the frequency equivalent to the breathing cycle. When the airflow flows in and out of the lungs during breathing, ECG electrodes on the chest can detect electrode displacement and the resulting electrical impedance variation in thoracic cavity [10].

4.1. QRS amplitude

The first method to extract the EDR was to calculate the area under each QRS complex between the onset point and onset plus 100 milliseconds [11]. The EDR estimate at each QRS point was set equal to the area.

4.2. PCA

Principal component analysis (PCA) allows decreasing the dimensionality of a multivariate signal by an orthogonal transformation. It finds the direction in which the data are more likely to spread out and the new direction values for the data are called the principal components (PCs) [12]. The PCs capture majority of the variance of the data by computing eigenvectors of the features' variances. It has been shown that PCA can represent beat-to-beat variations in ECG features including R-peaks and QRS amplitude [13]. Thus, by detecting variation of the correlation between the signal features, the EDR signal is recognized as a modulatory signal changing the ECG beats [13]. This algorithm can be applied to any ECG feature. In this paper, QRS complex was chosen in order to be consistent with other EDR measurement methods to enable a reliable comparison. In brief, the PCA algorithm is as follows.

a) A sliding window was applied to the ECG signals in order to partition the signal into consecutive QRS complexes [13]. The length of the window is selected in a way to cover the whole QRS complex. In this study, a window of 250ms was chosen, as it completely extracted the QRS complexes through the signals. The window ran from the QRS onset -75ms to QRS onset +175ms. Therefore, if there are *n* QRS complexes, *n* windows covering each QRS complex will be available.

b) Next, n QRS complexes were centered in a matrix of $\times n$ of which columns are the values of ECG signal in *m* sample points of each QRS complex [13],[14] and the rows are the number of QRS complexes:

$$X(t) = [QRS_1(t), QRS_2(t), \dots, QRS_n(t)]_{m\times n} \quad (1)$$

c) Then, the covariance of *X(t)* was measured resulting in a $n \times n$ matrix:

$$C = \frac{1}{}\sum_{i=1}^{m} x_i x_i^T \quad where\ x_i = \ QRS_i(t) \quad (2)$$

d) Finally, the eigenvectors, α_j, and eigenvalues, λ_j, were computed of *C* and principal components (PC) were obtained:

$$C\alpha_j = \lambda_j \alpha_j \ , \quad j = 1,2,\dots,n \quad (3)$$

$$PC_j = \alpha_j x \quad , \quad j = 1,2,\dots,n \quad (4)$$

The principal components are linearly transformed from the signal beats by transformation coefficients of eigenvectors which represent the EDR signal [13]. Due to the fact that there is a significant correlation between ECG signal beats and a large variation in EDR signal, the first principal components are the most sensitive ones to respiration [13]. Thus, the first principal component was chosen as the EDR signal.

4.3. Kernel PCA

In case of nonlinear patterns existing in the dataset, linear PCA may not recognize them and nonlinear kernel PCA can provide more information [15]. In kernel PCA, a nonlinear function, $\Phi(x_j)$, is applied to the dataset and PCA is applied to the mapped space, $\Phi(x_j)$. The covariance matrix becomes [12],

$$\bar{C} = \frac{1}{n}\sum_{j=1}^{n} \Phi(x_j)\Phi(x_j)^T \quad (5)$$

Then, the eigenvectors and eigenvalues are computed,

$$\lambda V = \bar{C}V \ , \qquad V = \sum_{i=1}^{n} \alpha_i \, \Phi(x_i) \quad (6)$$

In order to prevent mapping difficulties in high dimensional datasets and measuring the dot products of $\Phi(x_j)$, the nonlinear function is replaced by a Mercer kernel such as Gaussian kernels and polynomial kernels [15]. The Gaussian kernel was used in this paper, which is a symmetric $n \times n$ kernel matrix of *K*,

$$K_{ij} = \left(\Phi(x_i).\Phi(x_j)\right) \quad (7)$$

$$K(x_i, x_j) = exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right) \quad (8)$$

Summarizing the steps of applying kernel PCA [16];

First, the K_{ij} matrix was computed. The variance of the Gaussian kernel in equation (8), σ^2, was chosen as $\sigma^2 = \ .mean(var(X))$ [14]. Next, the eigenvalue problem was solved by diagonalizing *K* [14],[16],

$$\lambda K\alpha = K^2\alpha \ , \quad \lambda\alpha = K\alpha \quad (9)$$

Then, the eigenvalues of *K*, λ_i, were ordered in terms of the magnitude and the eigenvectors, α^i, were normalized which was satisfied by centering the QRS complexes. The first principal component was chosen as the EDR signal.

5. Classification

The EDR signals were partitioned into one minute segments. A matrix of 34 features for each segment was extracted from the EDR signals derived from each algorithm. The features used in this study were mean value, standard deviation, and 32 power spectral density (PSD) of EDR signals [17].

The feature matrix was applied to an Extreme Learning Machine (ELM) classifier. The ELM is a feed-forward network with one hidden layer with a large number of non-linear hidden neurons. It gives the advantage of randomly initialized connection weights of the input layer providing a flexible and fast to train classifier. The first layer weights were randomly set between -1.5 to 1.5 and *Tanh* was appointed as the activation function. The "fan-

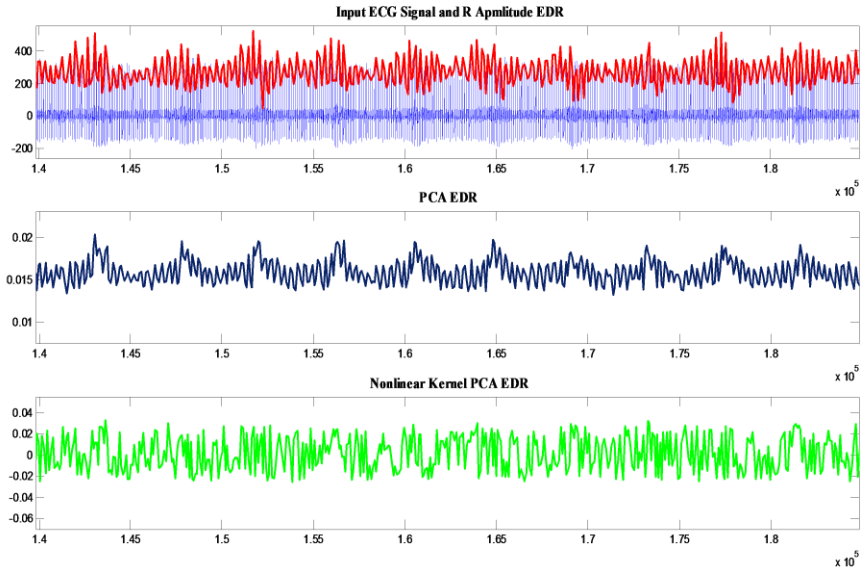

Figure 1. Input ECG signal and the QRS amplitude EDR, linear PCA, and Nonlinear EDR.

Table 1. Classification results from training set.

	Fan-out	Accuracy	Sensitivity	Specificity
QRS amp	1	66.71	73.81	68.59
	2	70.58	67.72	71.36
	5	79.87	68.85	82.88
	10	84.95	76.29	87.31
PCA	1	75.80	52.60	82.10
	2	82.55	58.69	89.03
	5	85.92	61.40	92.58
	10	84.95	76.30	87.32
KPCA	1	71.88	29.80	83.29
	2	73.90	33.63	84.82
	5	77.71	39.95	87.94
	10	80.36	44.70	90.02

Table 2. Classification results from cross validation (test-set).

	Fan-out	Accuracy	Sensitivity	Specificity
QRS amp	1	71.49	53.72	76.31
	2	74.91	56.20	79.98
	5	75.30	48.75	82.49
	10	75.73	44.69	84.15
PCA	1	71.12	43.34	78.66
	2	77.24	48.98	84.92
	5	77.39	45.15	86.14
	10	79.36	48.76	87.68
KPCA	1	68.08	26.18	79.44
	2	67.31	25.51	78.64
	5	66.68	23.48	78.39
	10	65.82	24.61	76.99

out" number defines the proportion of hidden layer neurons to input layer neurons [18][19]. Through a single training run, the hidden layer weights were obtained by the product of the pseudoinverse of hidden layer activation output and the labeled outputs from the learning set [18].

6. Results and Discussion

The ELM classifier was trained by 35 training records of the dataset for the three different EDR algorithms separately. The performance results, shown in Table 1, were obtained using the 35 test records and it was evaluated by leave-one-out cross validation as indicated in Table 2. The EDR signals from three different algorithms are illustrated in Fig.1. Classification results were achieved by fan-outs of 1 to 10. The highest accuracy for training set was 85.92% achieved by PCA EDR features at a fan-out of 5 with sensitivity of 61.4% and specificity of 92.58%. Also, the highest performance during cross validation was obtained by PCA EDR features at a fan-out of 10 with an accuracy of 79.36%, sensitivity of 48.76%, and a specificity of 87.68% [20].

From these results, it is evident that the linear PCA algorithm improved OSA detection by EDR features compared to the other two algorithms. The results are consistent with the results of other studies indicating the better performance of linear PCA algorithm in EDR estimation [14] compared to QRS amplitude. What we have not been able to confirm is the benefits of the kernel PCA method shown by [16]. We note that in [16], they manually selected clean sections of data and removed ectopic beats. We presented all beats to the EDR estimation algorithm and the non-linear transformation may have been adversely affected by the presence of ectopic beats and movement artefact corrupting QRS complexes.

7. Conclusion

The test-set results indicate that higher performance was obtained from EDR features computed from the PCA algorithm compared to the classic QRS amplitude measurement and kernel PCA performed the worst.

For future development, we will focus on excluding ectopic beats in order to improve the kernel PCA algorithm. Moreover, these EDR features could be combined with other ECG features such as RR variability to further enhance the classifier performance.

Relation to Prior Work

In my work presented at Computing in cardiology 2014 [21], EDR was computed through the QRS amplitude method. The performance results have been reported by applying both EDR and RR interval features.

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