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Sleep apnoea detection from ECG using features extracted from reconstructed phase space and frequency domain

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ABSTRACT

Sleep apnoea is a very common sleep disorder which is able to cause symptoms such as daytime sleepiness, irritability and poor concentration. This paper presents a combinational feature extraction approach based on some nonlinear features extracted from Electro Cardio Graph (ECG) Reconstructed Phase Space (RPS) and usually used frequency domain features for detection of sleep apnoea. Here 6 nonlinear features extracted from ECG RPS are combined with 3 frequency based features to reconstruct final feature set. The nonlinear features consist of Detrended Fluctuation Analysis (DFA), Correlation Dimensions (CD), 3 Large Lyapunov Exponents (LLEs) and Spectral Entropy (SE). The final proposed feature set show about 94.8% accuracy over the Physionet sleep apnoea dataset using a kernel based SVM classifier. This research also proves that using non-linear analysis to detect sleep apnoea can potentially improve the classification accuracy of apnoea detection system.

1. Introduction

Sleep apnoea is defined as the momentary cessation or absence of breathing when one is sleeping [1]. Apnoeas are def ined as distinct pauses in human breathing where each breathing pause exceeds from 10 s [2]. Sleep apnoea can be determined by using a sleep study or in clinical terms, polysomnography (PSG). The true cause of sleep apnoea is still unknown simply can be occurred if the airway of patient is too narrow then there will be a likelihood of obstruction. There are three types for Sleep apnoea consists of obstructive sleep apnoea (OSA), central sleep apnoea and mixed sleep apnoea. OSA is the most common. Central sleep Apnoea (CSA) is a neurological condition, which causes the loss of all respiratory effort during sleep and is also usually marked by decreases in blood oxygen saturation. With CSA the airway is not necessarily obstructed. Mixed sleep apnoea combines components of both CSA and OSA, where an initial failure in breathing efforts allows the upper airway to collapse.

Heart rate variability (HRV) varies from wakefulness to sleep due to normal changes in the autonomic system activities. Sympathetic tone drops from wakefulness over Non Rapid Eye Movement (NREM) sleep stages, while it shows an increase in Rapid Eye Movement (REM) sleep [3]. Based on literature, it was recognized that the events of sleep apnoea are accompanied by concomitant cyclic variations in heart beat intervals of ECG signals [4], which consists of bradycardia during apnoea followed by tachycardia upon its cessation [5]. This pattern had been successfully used to detect sleep apnoea in patients with clinical symptoms for sleep apnoea. Several studies confirmed the finding that several new methods could recognize sleep apnoea from heart rate variability (HRV) changes [6–9]. As the dynamic pattern of HRV with OSA is by no means stationary, HRV analysis with wavelet decomposition was reported to be an efficient tool for screening OSA [7]. Apart from HRV analysis, complementary information can be obtained from the measure of variations in the QRS amplitude of ECG signals. As we breathe, positions of the ECG electrodes relative to heart change, thus modulating the amplitude of ECG signals. From this fact, surrogate respiration signal can be extracted, which is referred to as ECG derived respiration (EDR) [10]. Analysis of such signal was found to be useful in apnoea monitoring because absence or attenuation of respiratory effort is caused by obstruction of upper airway OSA [11,12]. A comparative study [11] on different algorithms for apnoea detection based on ECG signals reported that the concatenation of parameters of HRV and the EDR signal gave the best classification results. Several machine learning techniques, i.e., Linear and Quadratic Discrimant model [12], CART method [7], Bayesian hierarchical model [13] have been used for automatic recognition of OSA subjects based on the selected subset of parameters derived from HRV and EDR signals. However, one limitation of those studies is that these models did not allow for estimating relative severity of OSA.

Recent researches [14] suggest that signal fluctuations could have non-random specifications and could play an important role in the determination of generating complex system dynamic. Cardiovascular system is a very complex system that generates ECG signal. Poor prognosis for cardiological patients with diminished

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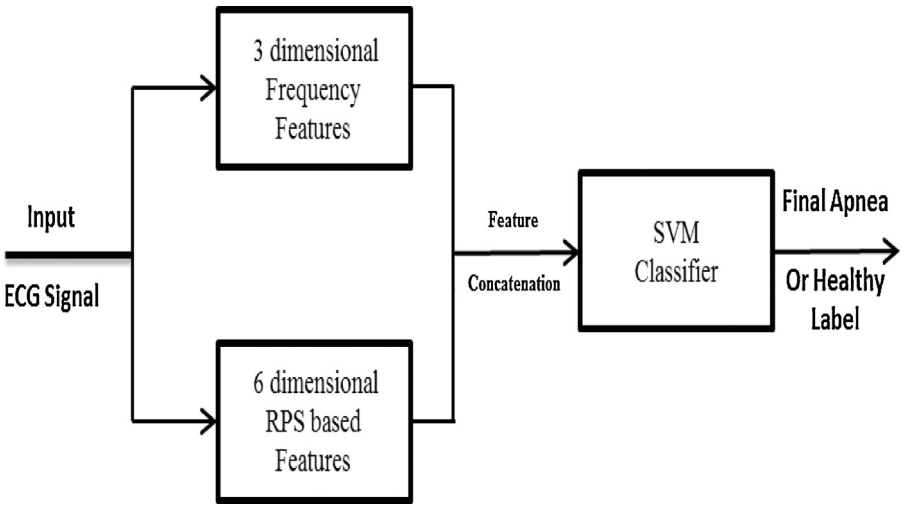

Fig. 1. The overall structure of proposed system.

heart rate variability (HRV) is clinically confirmed. Fluctuations in the frequency and time domain of ECG signal may reveal appropriate information on the dynamic characteristics lost with routine averaging or linear spectral methods. ECG signal is a quasi-periodic signal. So, we expect that we could extract useful information from ECG signal reconstructed phase space that are absent in usual frequency domain analysis.

In this research, in order to have the benefits of spectral domain analysis and reconstructed phase space simultaneously, we combined the spectral features with phase domain features to have better classification results for detection of sleep apnoea. Three spectral parameters are combined with 6 nonlinear parameters extracted from ECG signal. The resulted 9 dimensional feature vector is fed to a kernel based Support Vector Machine (SVM) system for classification.

2. The overall structure of the proposed method

As aforementioned, the proposed approach is based on the concatenation of frequency features and nonlinear features and classification of final feature set using a SVM based classifier. Fig. 1 shows the overall structure of proposed approach. As shown in Fig. 1, three dimensional frequency features have been combined with 6 dimensional non-linear RPS-based features. In next step, SVM classifier is applied to 9 dimensional final feature set and final label input data will be selected as healthy or Apnoea. Six nonlinear features have been used are Detrended Fluctuation Analysis (DFA), Correlation Dimension (CD), 3 Large Lyapunov Exponents (LLE's) and Spectral Entropy (SE). In Section 3, our feature set will be described completely.

3. Feature Extraction

In this section, our feature extraction approach will be described. In first part, the non-linear RPS-based features are explained and then introduced spectral domain features will be described.

3.1. Nonlinear RPS based features

Using non-linear analysis will help us to understand dynamical specifications of ECG signals. The first step in nonlinear analysis of time series is phase space reconstruction (state-space embedding), so we define ECG phase space reconstruction and then non-linear features are introduced. The main step in an embedding approach is obtained from Sauer and Yorke [15] work. They considered the Takens work and some other similar theories to show that every time-delay map with sufficient dimension is an embedding and guarantees the topological equivalence with the original generating system dynamic. In addition, they found that if d_0 be the dimension of the attractor obtained from a system using box-counting method, choosing $d > 2d_0$ guarantees that the reconstructed phase space of such a map is topologically the same as the true dynamics of the original system where d is the dimension of the reconstructed space [16]. Based on such a strong theory, we could use a time-delay based mapping from one-dimensional signal to the reconstructed phase space attractor. Suppose the samples of the ECG signal are given by $S = \{s_1, s_2, \ldots, s_n\}$, and $X = \{x_1, x_2, \ldots, x_N\}$ shows the trajectory points resulted from the embedding process, using time-delay based mapping

$$X(n) = [S(n), S(n-\tau_d), \ldots, S(n-(d-1)\tau_d)] \quad (1)$$

where τ_d defines time lag value and d defines embedding dimension. So, to perform the embedding process, we have to properly estimate d, τ_d. We could estimate τ_d from the correlation among ECG samples. Narayanan [17] suggested using the mutual information measure for estimation of time lags between ECG samples as given by

$$I(T) = \sum_{n=1}^{N-T} P(s(n), s(n+T)).\log_2\left[\frac{P(s(n), s(n+T))}{P(s(n))P(s(n+T))}\right] \quad (2)$$

where $s(n)$ denotes ECG samples, P means probability function and I is the mutual information measure. The first minimum of $I(T)$ is the optimum time lag value. We found $\tau_d = 10$ as the best value for time lag. Fig. 2 shows the $I(T)$ calculated across the various time delay values. To obtain the best value of τ_d, we analyzed all ECG signals from database and the dominant value is selected as the best value of time lag parameter. After fixing $\tau_d = 10$, we have to determine the value of embedding dimension. We use the false neighbor's measure to determine the embedding dimension. False neighbors are points on reconstructed phase space, initially far apart to come near to each other. We should select embedding dimension in a manner that false neighbor's percentage becomes minimum [18]. Using this measure, we found $d = 8$ as the best value for embedding dimension of ECG signal. Fig. 3 shows a 3D reconstructed phase space attractor for a sample ECG Signal from our dataset.

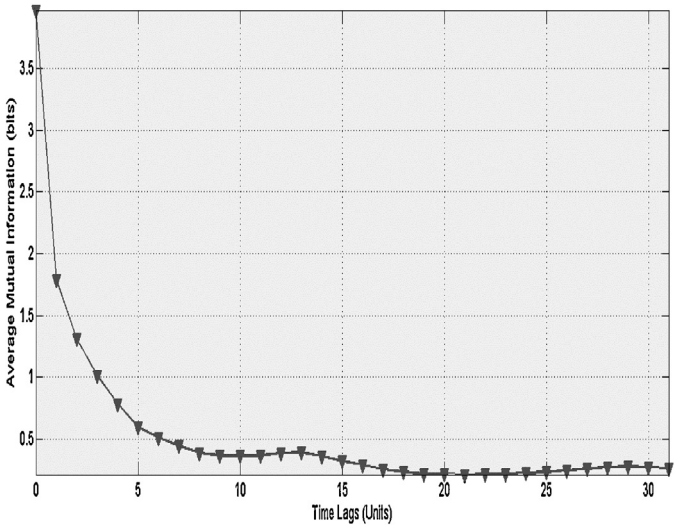

Fig. 2. Mutual information diagram across different time lags (first minimum is 10).

3.2. Detrended fluctuation analysis

The Detrended Fluctuation Analysis (DFA) is used to quantify the fractal scaling properties of short interval R-R interval signals. This technique is a modification of the root–mean–square analysis of random walks applied to non-stationary signals [19]. The root–mean–square fluctuation of an integrated and detrended time series is measured at different observation windows and plotted against the size of the observation window on a log–log scale. The root-mean square fluctuation of this integrated and detrended series is calculated using the equation

$$F(n) = \sqrt{\frac{1}{N}\sum_{k=1}^{N}[s(k) - s_n(k)]^2} \tag{3}$$

3.3. Correlation dimension (CD)

The quantitative measure of the nature of trajectory is called Correlation dimension (CD) and the ranges of CD signify various diseases [20]. The CD of the attractor is calculated for HRV data using the following formula:

$$CD = \lim_{r\to 0}\frac{\log C(r)}{\log(r)} \tag{4}$$

where the correlation integral $C(r)$ is given by

$$C(r) = \frac{1}{N^2}\sum_{x=1}^{N}\sum_{y=1, x\neq y}^{N}\Theta\left(r - \left|X_x - X_y\right|\right) \tag{5}$$

where X_x and X_y are points of the trajectory in the phase space, N is the number of data points in phase space, r is the radial distance around each reference point X_i and Θ is the Heaviside function. Fig. 4 shows $\log C(r)/\log(r)$ for an ECG Signal from a patient with apnoea. The slope of the line determines the CD parameters.

3.4. Lyapunov exponents

We could define Lyapunov exponent of a system as the value of the rate of separation of two close trajectories in the phase space with initial separation δZ_0 diverge

$$\left|\delta Z(t)\right| \approx e^{\lambda t}\left|\delta Z_0\right| \tag{6}$$

where λ is the Lyapunov exponent of the system. As the rate of separation is sensitive to initial condition, we could use the maximum Lyapunov exponent as the final measure.

There are several proposed schemes for calculation of Lyapunov exponents. One approach is presented in [18]. This method is based on projecting the data points in each neighborhood into the most densely populated regions of the phase attractor. Usual methods for estimating Lyapunov exponents are difficult to implement and unreliable for short length data. So, we followed a method proposed by [21] which is fast and reliable. Next to embedding process, we locate the nearest neighbors of each point in reconstructed phase space by searching for the points with minimizes the Euclidian distance to the point of interest.

$$d_j(0) = \min_{X_j}\left\|X_j - X_{\hat{j}}\right\| \tag{7}$$

LLE is then estimated from the mean separation rate of the nearest neighbors.

$$\lambda_1(i) = \frac{1}{i\cdot\Delta t}\cdot\frac{1}{(M-i)}\sum_{j=1}^{M-i}\ln\frac{d_j(i)}{d_j(0)} \tag{8}$$

where $d_j(i)$ is the pair of close points after i discrete-time steps, and Δt is the inverse of sampling frequency. In this paper, three largest Lyapunov exponents of the involved ECG signals are used. As the best dimension of reconstructed phase space was selected as 8, to obtain three largest Lyapunov exponents we should calculate 8 Lyapunov Exponents from Eq. (8) and then select three largest exponents. These three features were selected based on Fischer Discrimination Analysis. Linear discriminant analysis and the related Fisher's linear discriminant are methods used in statistics and machine learning to find a linear combination of features which characterize or separate two or more classes of objects or events. The resulting combination may be used by a linear classifier or more commonly for dimensionality reduction of features before applying to a more complex classifier. Fisher discriminator analysis for a two-class problem leads to Eq. (9) which evaluates Fisher's measure or F-ratio,

$$F_{\text{ratio}}(W) = \frac{W^T S_B W}{W^T S_W W} \tag{9}$$

where S_B is the between class scatter matrix, S_W is the sum of scatter matrixes and W is consisted of the largest eigenvectors of ${S_W}^{-1}S_B$. Fisher's measure or "F-ratio" defines the ratio between classes scattering to within class scattering of data points. Higher value of F-ratio for a group of samples from different classes implies more discrimination power among the involved classes. So F-ratio value could be a measure to find a properly pruned version of the original features. So, in order to choose appropriate Lyapunov exponents with maximum discrimination ability, a complementary test was done to confirm the results obtained by this measure. By deleting Lyapunov exponents which have the smaller F-ratio, we could reduce the size of the LE's feature vector. Using this measure, finally three largest Lyapunov exponents were selected.

3.5. Spectral entropy

Spectral entropy quantifies the spectral complexity of the time series. Application of Shannon's channel entropy gives an estimate of the spectral entropy of the process, where entropy is given by

$$E = \sum_k p_k \log\left(\frac{1}{p_k}\right) \tag{10}$$

where p_k is the probability density function (PDF) value at frequency k. The spectral entropy $\mathbf{E}\,(0 < E < 1)$ describes the complexity

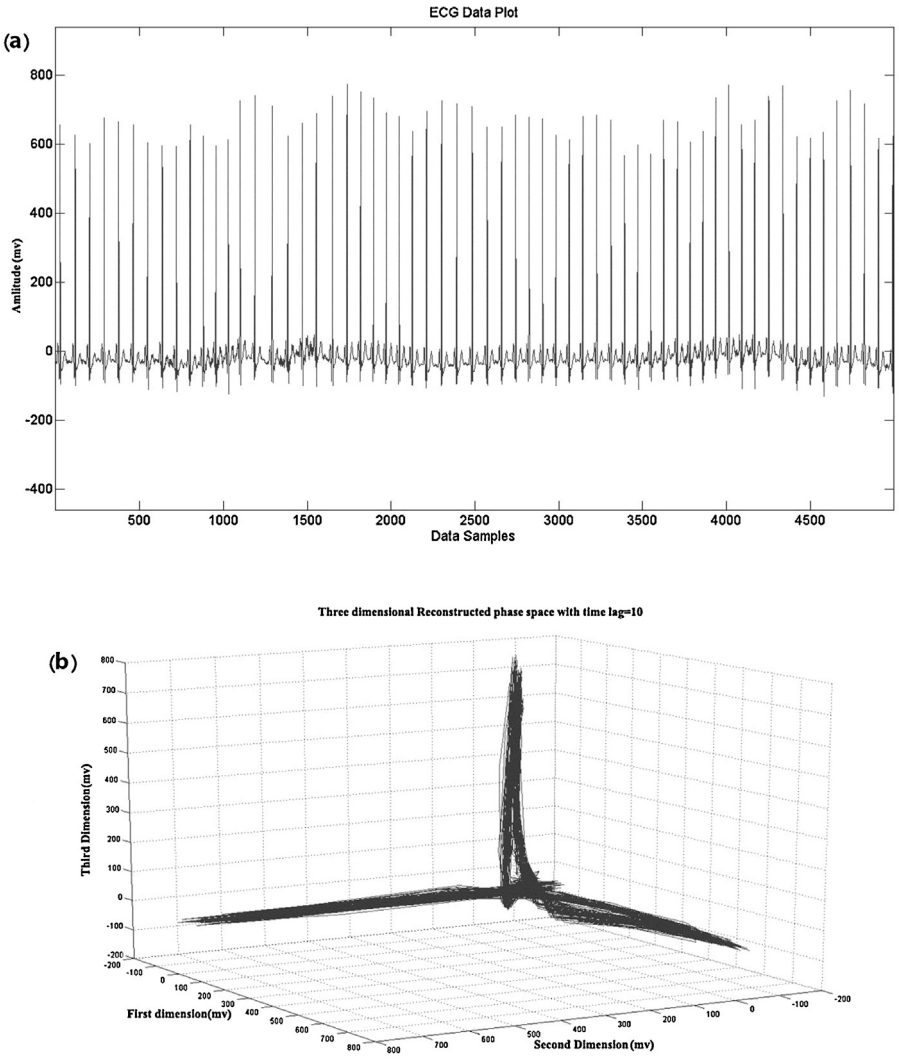

Fig. 3. (a) Electrocardiograph signal, and (b) three dimensional reconstructed phase space.

of the HRV signal. This spectral entropy **E** was computed for the various types of cardiac signal [22].

3.6. Spectral features

Different researches verify that heartbeat intervals show significant fluctuations based on physical activities of the brain stem cardiovascular centers [23,24]. During sleep stage, especially deep sleep, the influence of internal parameters such as spontaneous body movements and rapid eye movement on the cardiovascular centers is minimal.

Togo et al. [25] divided Heart Rate Variation (HRV) signal into three main categories: Very Low Frequency band (VLF: .003–.04 Hz), Low Frequency Band (LF: .04–15 Hz) and High Frequency Band (HF: >0.15 Hz). By using wavelet analysis, they founded both stationary and non-stationary periodic patterns in the VLF range, the presence of which has been discussed but has not been fully established. Although, they explained that there is an endogenous rhythmic component in human HRV in the VLF range. Fig. 5 shows three different frequency bands for ECG signals of a patient with apnoea.

Based on this idea, we calculated spectral density for these three bands as our three spectral features. In order to achieve better classification results, we normalized these features and called them NVLF, NLF and NHF. As will be described in experiments results, these spectral features show good discrimination performance between patients with apnoea and healthy one.

4. SVM classifier

In order to discriminate Apnoeas from healthy ones, Support Vector Machine (SVM), which is known as a useful technique in the field of statistical learning theory [25], is employed. This technique has been widely used in different signal processing, pattern recognition and classification applications [26,27]. Classifying data is a common task in machine learning. Suppose some given data points each belong to one of two classes, and the goal is to decide which class a *new* data point will be in. In the case of support vector machines, a data point is viewed as a p-dimensional vector, and we want to know whether we can separate such points with a $(p-1)$-dimensional hyperplane. This is called a linear classifier. There are many hyperplanes that might classify the data. One reasonable choice as the best hyperplane is the one that represents the largest separation, or margin, between the two classes. So we choose the hyperplane so that the distance from it to the nearest data point on each side is maximized. If such a hyperplane exists, it is known as the *maximum-margin hyperplane* and the linear classifier it defines is known as a *maximum margin classifier.* After choosing the maximum margin hyperplane and margins, data Samples on the margin are called the *support vectors*. Because of SVM good performance,

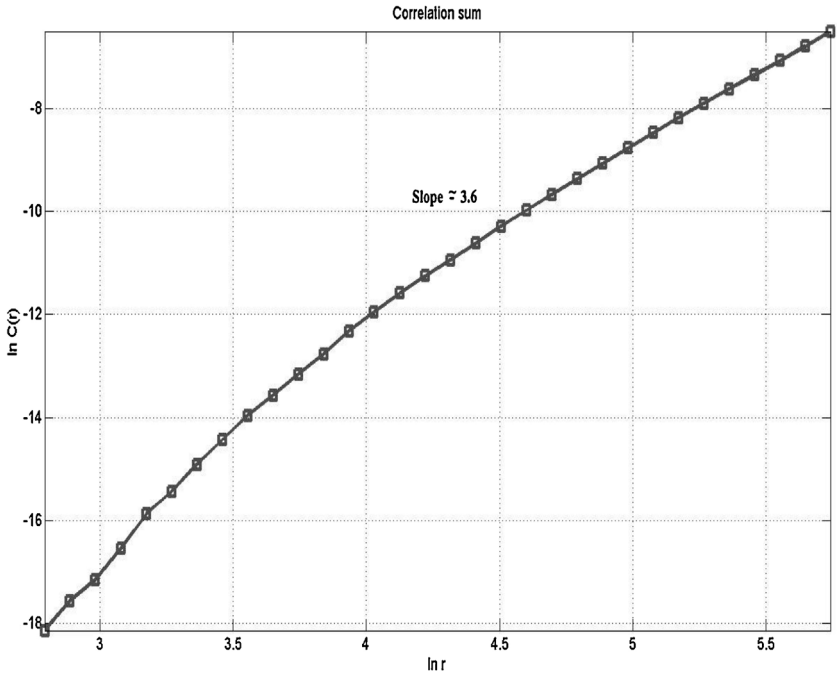

Fig. 4. The $\log C(r)/\log(r)$ diagram for an ECG Signal from a patient with apnoea.

especially in the case of two-class discrimination problems, this technique has been selected as the classification method in this research for discrimination of apnoea. If the training data with k number of samples is represented by $\{x_i, x_j\}$, $i = 1, 2, \ldots, k$ where $x \in R^n$ is n-dimensional vector and $y \in \{+1, -1\}$ is the class label of data. In SVM, the goal is to find a hyper-plane that separates the data with the minimum error. In this research, a kernel–SVM formulation, with *Gaussian radial basis kernel* functions [28] is used. Gaussian radial basis functions flexible kernels that allow smooth, curved decision boundaries. Gaussian radial basis kernel is defined as

$$k(x_i, x_j) = e^{-\lambda\left\|x_i - x_j\right\|^2}, \lambda > 0 \quad (11)$$

Sometimes this kernel parameterized as $\lambda = 1/2\sigma^2$

5. Experiments

In order to evaluate the performance of proposed approach for classification of apnea from normal stages, experiments were done in two main categories. In first part, some statistical tests are done on extracted features from ECG signal to evaluate the discrimination ability of these features for apnoea and healthy classes. In second part of experiments, classification tests using SVM classifier were done.

5.1. Database

Whole ECG recording for Apnoea and normal subject are obtained from physionet.org for the Computers in Cardiology 2000 challenge. Like this research, the goal of this challenge was to detect

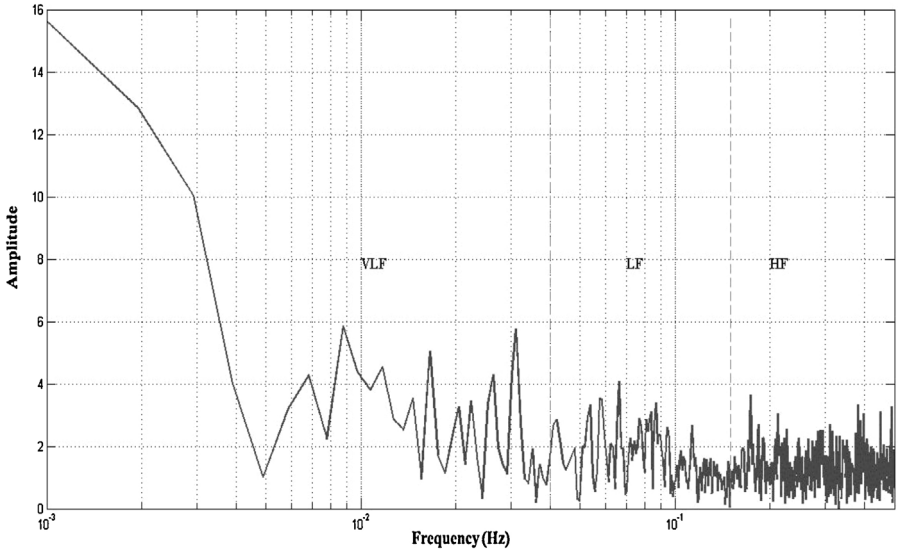

Fig. 5. VLF, LF and HF frequency bands for an ECG Signal from a patient with apnoea.

apnoea based on single ECG lead signals [8]. The data consists of 70 records, divided into a *learning set* of 35 records and a *test set* of 35 records. Recordings vary in length from slightly less than 7 h to nearly 10 h each. Each recording includes a continuous digitized ECG signal, a set of apnea annotations (derived by human experts on the basis of simultaneously recorded respiration and related signals), and a set of machine-generated QRS annotations. All apneas in these recordings are either obstructive or mixed. Minutes containing hypopnea are also scored as minutes containing apnoea. Each recording includes a set of reference annotations, one for each minute of the recording that indicate the presence or absence of apnea during that minute.

5.2. Statistical tests

Before classification stage, we calculated mean and standard deviation measures for different features. ANOVA (Analysis Of Variance) is selected as 0.001 in these experiments. ANOVA is a particular form of statistical hypothesis testing heavily used in the analysis of experimental data. A statistical hypothesis test is a method of making decisions using data. When we have only two samples we can use the *t*-test to compare the means of the samples but it might become unreliable in case of more than two samples. If we only compare two means, then the *t*-test (independent samples) will give the same results as the ANOVA. It is used to compare the means of more than two samples. Table 1 shows mean ± std of the 1 min ECG segments spectral parameters (NVLF, NLF, and NHF). As Table 1 verifies, there were significant differences between the normal and apnoea groups in PSD parameters. Also, similar tests are done for four categories of nonlinear features (LLE, CD, DFA and SE). Fig. 6 shows BOXPLOT diagrams of these features distribution. As shown, DFA and CD parameters show more discrimination ability in comparison with other features. These simple statistical tests proved that proposed feature set have appropriate discrimination ability for detection of apnoea groups from normal ones. Now, the results of classification using SVM classifier are explained.

Table 1
Power spectral density parameters distribution for apnoea and normal groups.

Feature	Apnoea	Normal	ANOVA
NVLF	0.472 ± .112	0.279 ± .082	$p < .001$
NLF	0.245 ± .145	0.295 ± .954	$p < .001$
NHF	0.324 ± .104	0.461 ± .160	$p < .001$

5.3. Classification results

Three measures namely accuracy, sensitivity and specificity were used to assess the performance of the SVM classifier. Accuracy indicates overall detection accuracy, sensitivity is defined as the ability of the classifier to accurately recognize a true apnea case whereas specificity would indicate the classifier's ability not to generate a false negative (normal subject, false apnea case). These measures are defined as follows.

$$\text{Accuracy} = 100 \times \frac{TP + TN}{M} \tag{12}$$

$$\text{Sensitivity} = 100 \times \frac{TP}{TP + FN} \tag{13}$$

$$\text{Specificity} = 100 \times \frac{TN}{TN + FP} \tag{14}$$

where M, T, TN FP and FN are the number of input samples, the number of correct recognition with negative label, the number of false recognition with positive label and the number of false recognition

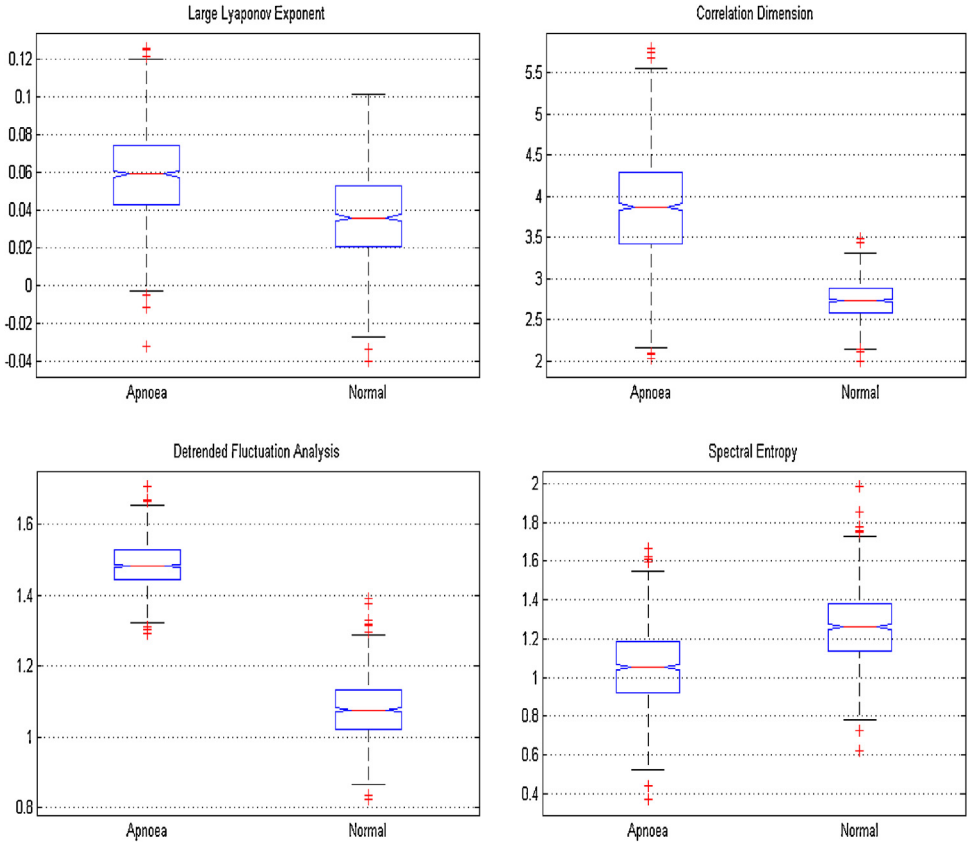

Fig. 6. Nonlinear parameters distribution diagram for apnoea and normal groups.

Table 2
SVM classification results using power spectral density parameters and proposed feature set.

Feature set	N	TP	TN	FP	FN	Accuracy	Specificity	Sensitivity
PSD features	6711	2730	2145	845	991	72.64%	73.36%	71.73%
RPS based features	6711	2840	2748	491	632	83.26%	81.79%	84.84%
PSD features + RPS based features	6711	3215	3147	195	154	94.80%	95.42%	94.16%

with negative label, respectively. For 16,711 min (total number of minutes for the 35 subjects during sleep), about 10,000 samples used for training of SVM classifier and remained part used in test stage. Table 2 shows the classification results for Power Spectrum Density (PSD) parameters and combined proposed feature set.

6. Discussion

The goal of this research was to use signal processing techniques for detecting sleep apnoea from the single lead ECG signal instead of the expensive and complicated whole-night polysomnography. Some studies have used nonlinear signal processing methods to study biological signals, such as heart rate variations and the respiration pattern in obstructive sleep apnea syndrome. In this work, we used the combination of two types of features:

- Frequency domain Features
- ECG signal reconstructed phase space features

The idea of frequency domain analysis is based on this fact that HRV pattern for OSA subjects were more regular during apnea due to cyclic bradycardia and tachycardia with time period around the apnea-arousal duration. The cyclic behavior can also be detected by evaluating the power in the very low frequency band of the RR signal. So, we extracted three features from power spectral density for VLF band (.003–.04 Hz), LF band (0.04–0.15 Hz) and HF band (>0.15 Hz). We normalized these parameters based on their amplitude and used NVLF, NLF and NHF features. As shown in Table 1, we have the most discrimination ability for NVLF.

Also as ECG signal has quasi-periodic specification, we tried to extract appropriate information from reconstructed phase space. In first stage, using time delay based method; 1-dimensional ECG signal should be mapped into a multi-dimensional subspace. Using mutual information measure and false neighbors approach, we found 10 as best time lag value and 8 for embedding dimension. Correlation Dimension (CD), Detrended Fluctuation Analysis (DFA), 3 Large Lyapunov Exponents (LLEs) and Spectral Entropy (SE) are used as our other feature sets. As shown in Fig. 6, it can be observed that most of the non-linear parameters increased during apnoea events except for spectral entropy thus indicating that apnoea ECG signals are highly chaotic and have high variability.

Mietus et al. presented an automated technique to detect and quantify OSA from single-lead ECGs based on periodic oscillations detection in cardiac inter-beat intervals that are frequently associated with extended cycles of sleep apnoea [29]. This method utilizes Hilbert transform of the sinus inter-beat interval time series. Their algorithm produced a classification accuracy of 93.3% for both sleep apnoea and normal subjects and accurately detected the presence or absence of sleep apnoea in 84.5% of the testing data.

Corthout et al. did a study on the automatic screening of OSA solely with the use of ECG signal based on empirical mode decomposition (EMD) and wavelet analysis [30]. Linear discriminant analysis was used as the classifier. Classification of ECG signals as apnoea types or non-apnoea types was proven to be very accurate (with an accuracy of 90%) on a minute-by-minute basis.

In this present study, a novel method is proposed to detect apnoea from normal breathing ECG signals using non-linear parameters such as CD, FDA and SE and power spectral density parameters. Using these proposed features, we achieved about 94.8% classification accuracy. In order to analysis the proposed feature set discrimination ability, as done in Section 2 for LLE features, we calculated the F-ratio for all the 9 features in the proposed feature set. This test showed that by deleting any of features from final feature set, the discrimination power and the classification performance of final system decreases. So, based on this test results we selected the final feature set selected as mentioned in the previous sections.

7. Conclusion

Sleep apnoea is a very common sleep disorder. ECG signals are useful in the detection of sleep apnoea. Study of the ECG signals using non-linear parameters method will greatly aid in the understanding of the inner dynamics of the system. Classification of apnoea and normal breathing ECG signals was done using a SVM classifier with radial basis Gaussian kernels.

Whole ECG recording for Apnoea and normal subject are obtained from physionet.org for the Computers in Cardiology 2000 challenge. The data consist of 70 records, divided into a *learning set* of 35 records and a *test set* of 35 records. Totally 16,711 min of data used for test and train of SVM classifier. Finally proposed feature set achieved an accuracy of 94.80%, sensivity of 94.16% and specificity of 95.42%. The significance of this study is that it provides a viable alternative for sleep physicians when it comes to diagnosing sleep apnoea due to its less cumbersome nature as compared to PSG.

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