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Automated detection of sleep apnea from electrocardiogram signals using nonlinear parameters

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Abstract
Sleep apnoea is a very common sleep disorder which can cause symptoms such as daytime sleepiness, irritability and poor concentration. To monitor patients with this sleeping disorder we measured the electrical activity of the heart. The resulting electrocardiography (ECG) signals are both non-stationary and nonlinear. Therefore, we used nonlinear parameters such as approximate entropy, fractal dimension, correlation dimension, largest Lyapunov exponent and Hurst exponent to extract physiological information. This information was used to train an artificial neural network (ANN) classifier to categorize ECG signal segments into one of the following groups: apnoea, hypopnoea and normal breathing. ANN classification tests produced an average classification accuracy of 90%; specificity and sensitivity were 100% and 95%, respectively. We have also proposed unique recurrence plots for the normal, hypopnea and apnea classes. Detecting sleep apnea with this level of accuracy can potentially reduce the need of polysomnography (PSG). This brings advantages to patients, because the proposed system is less cumbersome when compared to PSG.

Keywords: ECG, sleep apnoea, apnea, hypopnoea, correlation dimension, Hurst exponent, ANN

(Some figures in this article are in colour only in the electronic version)
1. Introduction

On average, humans spend one third of their time sleeping. During sleep the body restores and develops itself (Gumustekin et al 2004). Therefore, sleep is an essential part of our life. In order for one to function well at work or at play, both an adequate amount and sufficient quality of sleep is necessary. In particular, sleep quality is reduced by sleep apnoea.

During apnea breathing stops completely or takes less than 10% of a normal breath for a period of 10 s or more and as a result there will be at least a 4% drop in oxygen in the blood (Mindell and Owens 2003, Norman et al 2007, Nabili and Verneuil 2010). During hypopnea the breathing decreases to 69–10% of normal breath and oxygen content in the blood decreases by 4% or more during this duration (Mindell and Owens 2003, Nabili and Verneuil 2010). Apnea index (AI) indicates the severity of sleep apnea: the number of apnea events per hour. Apnea/hypopnea index (AHI) is the number of apnea and hypopnea episodes per hour: 5–15 = mild, 15–30 = moderate, above 30 severe.

There are three types of sleep apnea: (i) central sleep apnea (CSA), (ii) obstructive sleep apnea (OSA) and (iii) mixed sleep apnea. The brain does not send signal to muscles to breath during CSA. During OSA, the muscles become unsuccessful to take sufficient breath and airflow gets obstructed. Mixed sleep apnea is due to combination of both CSA and OSA, obstructive sleep apnoea is the most common (Nabili and Verneuil 2010). It was noted that the prevalence of sleep apnoea for men and women is 4% and 2%, respectively, on a global scale (Young et al 1993).

Electrocardiography (ECG) records bioelectrical potentials at the body surface (Garvey 2006) and hence it provides plenty of physiological information of the heart such as its electrical activity (Acharya et al 2007). Changes in ECG signals can be related to sleep apnoea and these changes are caused by neuroautonomic and mechanical factors (Mendez et al 2008). These changes are cyclic variations in both heart rate and ECG amplitude/morphology.

Many studies have documented the usefulness of ECG to detect sleep apnoea, but most of these studies focus on OSA detection. There are three main techniques to detect sleep apnoea from ECG, namely time domain (e.g. moving averages), frequency domain (e.g. Hilbert transform) and ECG morphology-based (e.g. ECG pulse energy) techniques (Penzel et al 2002).

Maier et al did a comparison of three methods for extraction of respiratory events from single-lead and multi-lead ECG (Maier et al 2007). 90 patients were brought into this study and the results showed that respiratory information retrieved from multi-lead ECGs can significantly improve ECG-derived respiration (EDR) quality. Central apnoea detection from the median envelope of lead-pair loop-angles was achieved with 85% sensitivity and 89% specificity.

A study was done to compare 13 ECG-based sleep apnoea detection algorithms (Penzel et al 2002). The top algorithms utilized frequency-domain features to acquire heart rate changes and respiration effects on ECG waveforms. Four of the algorithms attained perfect scores in differentiating patients with and without apnoea. Two of the algorithms attained an accuracy of more than 90% in detecting apnoea during every minute of ECG recording.

Roche et al (2002) have used algorithms based on heart-rate variability (HRV) in diagnosing patients who were likely to have OSA. They report a diagnostic sensitivity of 87% for the total power spectral density. Furthermore, the team discovered a close connection with disease status for both percentages over the total power spectral density and power spectral density of the interbeat interval increment of very low frequencies.

A study done on ECG-based detection of OSA to support the hypothesis that since there is a larger reduction in breathing during apnoea events in contrast to hypopnoea events, the ECG
physiological predictors' changes during apnoea events should be more prominent compared to hypopnoea events. Therefore, the detection of hypopnoea events is a tougher task compared to detection of apnoea events (Nilsen et al 2008). This study also looked into the possible benefits of using two ECG leads compared to using a single ECG lead. The results revealed that the differentiating ability of the model from the apnoea data set was significantly greater compared to the model from the hypopnoea data set. The results also suggest that using additional ECG leads increases the accuracy of the measurements.

Using ECG, a group of researchers investigated the automatic classification of sleep apnoea epochs (de Chazal et al 2000). This study is based on the collection of 70 single-lead ECG signals where half of them were used for training while the other half were used for independent testing. It was noted that features based on power spectral density estimates of the $R$-wave maxima and $R–R$ intervals are the most discerning. Classification of about 89% was attainable.

A study was done on whether or not the extraction of ECG characteristics, such as HRV and peak $R$ area, can be an alternative in diagnosing sleep apnoea (Mendez et al 2007). The authors studied 50 ECG recordings; they were split equally into training and testing data sets. More than 85% of accuracy in classifying apnoea events and normal events was attained.

de Chazal et al analysed an automated classification algorithm. The system handles short-duration epochs of surface ECG recordings which were attained from PSG studies. They tried to determine whether or not an epoch belongs to a period of sleep disordered respiration or normal respiration (de Chazal et al 2004). The algorithm was trained and tested on 70 overnight ECG data which contained normal and OSA subjects. The data were split evenly into training and testing data sets. The results were largely positive. Depending on the length of epochs, the classifier accurately classified between 87% (15 s epochs) and 91% (60 s epochs) of the epochs in every test set.

This study utilizes nonlinear signal analysis to implement a system that is capable of detecting sleep apnoea from ECG signals automatically. The proposed automated detection system can provide an alternative to laboratory PSG in the future. The nonlinear parameters involved are correlation dimension (CD), fractional dimension Hurst exponent (H), largest Lyapunov exponent (LLE), fractal dimension (FD) and approximate entropy (ApEn). ECG recordings are analysed and a classifier is used to classify the different forms of respiratory events.

The information contained in ECG data is discussed in section 2 while both different ECG signal analysis methods and recurrence plots are discussed in section 3. The classifier used is discussed in section 3. Section 4 explains the results while section 5 presents the discussion on the results of the work. Finally, section 6 concludes the paper.

2. Data

The data for this study comes from two groups: normal and suspected sleep apnea. 450 sets of apnoea ECG data, 130 sets of hypopnoea ECG data and 130 sets of normal breathing ECG data were gathered from the two groups for this study. MATLAB (MathWorks, USA) and Chaos Data Analyzer (Sprott and Rowlands 1995) were the two types of software used for data analysis.

The suspected sleep apnea group is composed out of 25 subjects, which were recruited at random from patients at the Sleep Disorders Clinic at St Vincent’s University Hospital, Ireland (Goldberger et al 2000). The data acquisition was approved by the Hospital’s Ethics Committee and written and informed consents were taken for all subjects. Every subject went through a standard overnight, attended PSG. After which an experienced sleep technologist
carried out sleep staging according to Rechtschaffen and Kales (1968) rules and interpreted the respiratory events.

Table 1 shows the details of the data used for this study. The last three columns indicate the number of data used for this study. Each data length is 900 samples.

In another group at University College Dublin, 14 subjects with no known medical conditions were recruited from the general population (12 males and 2 females, age: 27 ± 4 years, BMI: 25 ± 4 kg m⁻²). Sleep staging signals were recorded overnight with the use of a set of Grass amplifiers (from Astro-Med Inc., USA) during the subjects’ sleep. With the use of the Somnolyzer 24 x 7 system (Anderer et al 2005), sleep staging was carried out using Rechtschaffen and Kales (1968) rules.

3. Methods

3.1. Preprocessing

The original signal sampling frequency was 256 Hz. Then the signal is passed through a low pass filter of cut-off frequency 15 Hz to remove unwanted high frequencies present in the ECG
signal. High pass filter with cut-off frequency 0.3 Hz was used to suppress baseline wander present in the ECG signal. Median filter was used to extract baseline wander of the processed ECG signal, and then subtracted from the processed ECG signal to effectively remove all baseline wander.

3.2. ECG signal analysis methods

Using nonlinear methods will help us to understand ECG signals in a more effective way. The different nonlinear parameters, CD, LLE, FD, H and ApEn, are explained below.

3.2.1. State-space reconstruction. The first step in nonlinear time series analysis is state-space (phase-space) reconstruction. One-dimensional data $y(n)$ where $n = 1, 2, \ldots, N$ is viewed in an $m$-dimensional Euclidean space, $\mathbb{R}^m$. An attractor is created by a path that joins the vectors in the state space and this attractor maintains the topological properties of the original unidentified attractor.

The method of delays is a popular way to reconstruct the state space (Takens 1981). According to this method, $m$-dimensional vectors, $x_n$, in the state space are produced from the time-delayed samples of the original signal, $y(n)$, as follows:

$$ x_n = [y(n), y(n-d), y(n-2d), \ldots, y(n-(m-1)d)] $$

where $d$ indicates embedding delay, and $m$ indicates the embedding dimension (i.e. number of coordinates).

3.2.2. Estimation of embedding dimension ($m$). The minimal sufficient embedding dimension, $m$, can be achieved by using a method called false nearest neighbour (FNN) (Kennel et al 1992). For this study $m$ was obtained as 10. Figure 1 illustrates the estimation of the embedding dimension for the study data using the frontal node numbering method.

3.2.3. Estimation of delay time ($\tau$). Fraser et al have suggested using time delayed mutual information to find out the reasonable time delay (Fraser and Swinney 1986). Nonlinear
correlations in the time series are taken into consideration when mutual information method is used. Mutual information function for the ECG signal used in this study is given in figure 2. It can be observed that the mutual information reaches its first minimum at $\tau = 10$. A time delay of 10 was obtained for the ECG signals used.

3.2.4. Approximate entropy. ApEn can be defined as the logarithmic likelihood that the data trends which are similar to each other will remain similar for the next comparison with an extended pattern. Thus ApEn offers a measure of regularity. The index for overall ‘complexity’ and ‘predictability’ of the time series is represented by ApEn.

Let us consider ECG signal $X(n)$, $n = 1, 2, 3, \ldots, N$. A series of patterns of length $e$ (embedding dimension which is the smallest integer for which the patterns do not intersect with each other) is derived from $x(n)$. ApEn is given by

$$\text{ApEn}(e, r, N) = \frac{1}{(N - e + 1)} \sum_{i=1}^{N-e+1} \log C_i^e(r) - \frac{1}{(N - e)} \sum_{i=1}^{N-e} \log C_i^{e+1}(r).$$

(2)

The correlation integral $C_i^e(r)$ is given by

$$C_i^e(r) = \frac{1}{(N - e + 1)} \sum_{j=i}^{N-e+1} \Theta(r - ||X_i - X_j||)$$

(3)

where $r$ was chosen to be 0.2 times the standard deviation of the ECG signals, and $e$ was chosen to be 10.

In this study, ApEn determines the regularity of the ECG signals. An increase in regularity and predictability of the ECG signal will cause ApEn to decrease. The method by Pincus and Keefe (1992) was used. ApEn results for various respiratory events are listed in table 2.

3.2.5. Correlation dimension. The quantitative measure of the nature of trajectory is called correlation dimension (CD) and the ranges of CD signify various diseases (Grossberger and Procassia 1983). The CD of the attractor is calculated for HRV data using the following formula:

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

(4)
3.2.6. Largest Lyapunov exponent. LLE determines sensitivity of the system to initial conditions and it signifies the measure of predictability. If a positive Lyapunov exponent exists, it will signify chaos.

The method proposed by Rosenstien et al (1993) was used in this study. This method looks for the nearest neighbour of each point in phase space and traces their separation over certain time development. The LLE is calculated using a least-squares fit to ‘average’ line defined by

\[ y(n) = \frac{1}{\Delta t} \langle \ln (b_i (n)) \rangle \]  

where \( b_i (n) \) represents the distance between the \( i \)th phase-space point and its nearest neighbour at \( n \)th time step, and \( \langle \cdot \rangle \) denotes the average over all phase-space points. LLE results for various respiratory events are listed in table 2.

3.2.7. Hurst exponent. Evaluation of the self-similarity and correlation properties of a signal is done using \( H \). The method analyses the smoothness of a fractal time series based on the asymptotic pattern of the rescaled range of the process. \( H \) is defined as

\[ H = \log (R/S) / \log (T) \]  

where \( T \) represents the sample of data time length, \( R/S \) represents the corresponding value of rescaled range, \( R \) represents the difference between the maximum deviation from the mean and minimum deviation from the mean and \( S \) represents the standard deviation (Dangel et al 1999). \( H \) results for various respiratory events are listed in table 2.
3.2.8. Fractal dimension. FD determines the complexity of dynamic signals. A fractal is a group of points which, when looked at smaller scales, looks similar to the whole group (Mandelbrot 1982). FD is a powerful tool for transient event detection. FD has been used in ECG and EEG analysis to recognize and differentiate specific states of physiologic functions (Acharya et al 2005).

Let $S$ be a compact subset of a metric space. For each $\varepsilon > 0$, let $N(\varepsilon)$ be the smallest number of circles of radius $\leq \varepsilon$ needed to cover $S$. Let’s say

$$\delta = -\lim_{\varepsilon \to 0^+} \frac{\log N(\varepsilon)}{\log \varepsilon}$$

exists; then $\delta$ is called the FD of $S$. In this research, Higuchi’s algorithm has been used to evaluate FD (Higuchi 1988). FD results for various respiratory events are listed in table 2.

3.3. Recurrence plots

Recurrence plots aim to expose non-stationarity of time series like heart rate signals (Acharya et al 2006). Recurrence plots were originally introduced by Eckmann et al (1987, VRA software) as graphical methods for diagnosing both drift and hidden periodicities during time progression, which are imperceptible otherwise.

Say $x_i$ is the $i$th point on the orbit in an $m$-dimensional space. The recurrence plot is an array of dots in an $N \times N$ square, where a dot is positioned at $(i, j)$ whenever $x_j$ is close enough to $x_i$. In order to create a recurrence plot, an $m$-dimensional orbit of $x_i$ is created. The ball of radius $r$ centred at $x_i$ in $\mathbb{R}^m$ contains an adequate amount of other points $x_j$ of the orbit. Lastly, a dot is plotted for every point $(i, j)$ for which $x_j$ is in the ball of radius $r$ centred at $x_i$. Thus, a recurrence plot is created.

The plots will be symmetrical along the diagonal $i = j$, because $x_i$ is near to $x_j$ and vice versa. The average recurrence plots of apnoea, hypopnoea and normal ECG signals are shown in figure 5.

3.4. Surrogate data

The aim of surrogate data is to examine the original ECG signal for any presence of nonlinearity. Nonlinearity must be present before any nonlinear analysis algorithms can be applied on the ECG data.

The values computed for the original ECG data are compared against the surrogate data and if there is a significant difference in nonlinear parameters values, this will indicate that nonlinearity is present in the original ECG signal (Theiler et al 1992). The technique of using surrogate data in nonlinear analysis is acquired by phase randomization of the original data with spectral properties almost the same as those of the given data. Surrogate data possess Fourier decomposition containing randomized phase components with identical amplitudes as the empirical data decomposition. This can be acquired with the use of Chaos Data Analyzer (Sprott and Rowlands 1995).

3.5. Back-propagation algorithm

An artificial neural network (ANN) classifier was used to analyse the performance of the five nonlinear parameters (H, LLE, CD, FD, ApEn) in an automated pattern recognition system. The computational goal of an ANN system is to produce a solution to a specific type of nonlinear optimization problem (Lippman 1989).
In order to train the ANN, we used a supervised learning algorithm named back-propagation algorithm (BPA) (Lippman 1989). This algorithm is best suited for feed-forward networks and it is used for automatic detection of unidentified data. BPA uses an iterative gradient which is created to lessen the mean square error between the actual output and the wanted output (Lippman 1989). The layered neurons between input and output layers are called hidden layers or nodes, as shown in figure 3. When BPA is in process, weights connected to the hidden layers are altered constantly, hence enabling the pre-selected neural network to learn.

In this study, a four-layered feed-forward neural network with two hidden layers and 11 neurons was employed to process the data in each layer (refer to figure 3). A learning constant \( \eta = 0.9 \) (step-size control) was selected by trial and error. The binary outputs are 0 0, 0 1 and 1 0.

Sensitivity and specificity are the most commonly used statistics used to explain a diagnostic test. Sensitivity measures the amount of positives in a certain population of patients with the disease while specificity measures the amount of negatives in a certain population of patients without the disease (Fletcher 2005).

As the false negative (FN) value falls, the level of sensitivity increases hence the probability of detecting the disease will increase. In order for the level of specificity to increase, the false positive (FP) value must be lowered. The positive predictive value (PPV) of a test describes the probability of a patient who is correctly diagnosed with positive results (Stein 1998). In this work, apnea or hypopnea is considered as positive and normal as negative.

300 sets of training data were used for apnoea class. 90 sets of data were used for hypopnoea class and the same amount of data was also used for normal breathing class with 900 samples for each epoch. During the testing stage, 40 sets for data hypopnoea, 40 sets of normal breathing class and 150 sets of apnoea were used. H, LLE, CD, FD and ApEn were used as the input features. Three-fold cross-validation was performed. The average of three tests is considered as the actual results (accuracy, sensitivity, specificity).
4. Results

4.1. Analysis of nonlinear parameters

Table 2 presents the different mean values of H, LLE, CD, FD and ApEn for apnoea, hypopnoea and normal breathing ECG signals. It can be observed from the table that the differences are statistically significant ($p < 0.0001$).

An indication of disorder in ECG signals is represented by ApEn. Hypopnoea and apnoea ECG signals have a greater ApEn value than the normal breathing (0.538 ± 0.094) ECG signals. This is due to the chaotic nature of the abnormal signals (apnoea and hypopnoea). It can also be observed that ApEn values of both hypopnoea (0.854 ± 0.081) and apnoea (0.8306 ± 0.154) ECG signals are relatively close to each other.

From table 2 it can be seen that normal breathing ECG signals are more predictable when compared to the abnormal ECG signals. This is due to the higher value of H for normal breathing (0.616 ± 0.026) ECG signals. This also shows that apnoea (0.222 ± 0.026) and hypopnoea (0.208 ± 0.018) ECG signals are very unpredictable.

Time series variability can be determined by CD. It can be seen from table 1 that hypopnoea (4.595 ± 0.454) ECG signals have the highest variability compared to apnoea (3.849 ± 0.637) and normal breathing (2.663 ± 0.223) ECG signals.

In order to have more self-similarity in the ECG signal, a higher FD values need to be attained. The highest FD values are seen in the normal breathing group (−1.077 ± 0.008) while apnoea (−1.486 ± 0.060) and hypopnoea ECG signals (−1.527 ± 0.028) have slightly lower FD values.

Indication of the divergence rate of trajectories in the phase space can be reflected by LLE. Table 2 shows that apnoea (0.057 ± 0.022) ECG signals have the highest LLE value when compared to the other two types of ECG signals, hypopnoea (0.048 ± 0.018) and normal breathing (0.035 ± 0.025).

The mean variance plots, shown in figure 4, are presented with group means with 95% confidence intervals of apnoea, hypopnoea and normal breathing ECG signals based on the five different parameters. Note that A represents apnoea, B represents hypopnoea and C represents normal breathing.

4.2. Analysis of classification results

An average of 90% classification accuracy was achieved for the ANN classifier (refer to table 3). The sensitivity, specificity and PPV for the ANN classifier are 100%, 95% and 98.97%, respectively (refer to table 4). Table 5 shows the confusion matrix of the proposed system and the overall classification accuracy is 89.1%:

$$\text{Overall accuracy} = \frac{\text{Correctly classified}}{\text{Total number of epochs used for classification}} = \frac{135 + 38 + 32}{230} = 89.1\%.$$  

4.3. Analysis of surrogate data

The surrogate data method is widely used to test for nonlinearity in the time series. It indicates some linear stochastic process as a null hypothesis, and simulates surrogate data sets that are consistent with some null hypothesis (Kunhimangalam et al 2008). To analyse the nonlinear
Automated detection of sleep apnea from electrocardiogram signals using nonlinear parameters

Figure 4. Mean variance plots of features used: (a) Hurst exponent; (b) largest Lyapunov exponent; (c) correlation dimension; (d) fractal dimension; (e) approximate entropy.
Table 3. Results of classification for the ANN classifier.

<table>
<thead>
<tr>
<th>Classes</th>
<th>Training</th>
<th>Testing</th>
<th>ANN (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td>90</td>
<td>40</td>
<td>100</td>
</tr>
<tr>
<td>Hypopnoea</td>
<td>90</td>
<td>40</td>
<td>90</td>
</tr>
<tr>
<td>Apnoea</td>
<td>300</td>
<td>150</td>
<td>80</td>
</tr>
<tr>
<td>Average</td>
<td></td>
<td></td>
<td>90</td>
</tr>
</tbody>
</table>

Table 4. Sensitivity, specificity and PPV results for the ANN classifier.

<table>
<thead>
<tr>
<th>Classifier</th>
<th>True positive (TP)</th>
<th>True negative (TN)</th>
<th>False positive (FP)</th>
<th>False negative (FN)</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>Positive predictive accuracy (PPV)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANN</td>
<td>190</td>
<td>38</td>
<td>2</td>
<td>0</td>
<td>100%</td>
<td>95%</td>
<td>98.97%</td>
</tr>
</tbody>
</table>

Table 5. Confusion matrix of the classifier.

<table>
<thead>
<tr>
<th>Classes</th>
<th>Normal</th>
<th>Apnea</th>
<th>Hypopnea</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td>38</td>
<td>0</td>
<td>0</td>
<td>38</td>
</tr>
<tr>
<td>Apnea</td>
<td>0</td>
<td>132</td>
<td>8</td>
<td>140</td>
</tr>
<tr>
<td>Hypopnea</td>
<td>2</td>
<td>18</td>
<td>32</td>
<td>52</td>
</tr>
<tr>
<td>Total</td>
<td>40</td>
<td>150</td>
<td>40</td>
<td>230</td>
</tr>
</tbody>
</table>

characteristics of sleep ECG signals, ten sets of surrogate data were generated for each of the three classes. Then the FD is estimated on both the surrogate data set and original data in this work. We have observed that the FD values for the original data and the surrogate data differ more than 60% indicating that the underlying null hypothesis is rejected and nonlinearity is detected.

4.4. Analysis of recurrence plots

The recurrence plot of a normal breathing ECG signal has more white squares than the recurrence plots of both apnoea and hypopnoea ECG signals. This shows that the normal breathing ECG signals show more symmetry and periodicity than the other two types of ECG signals at lower scale. It can also be said that recurrence plots of apnoea and hypopnoea ECG signals are more rhythmic than the recurrence plot of normal breathing at higher scale. It can also be observed that the amount of frequency, periodicity and rhythm within the two abnormal ECG signals are almost the same due to their close similarity in the recurrence plots.

Finally, the amount of correlation can be observed by analysing the grey colour bar of the recurrence plots. At one end of the colour bar, white indicates low correlation while at the other end of the colour bar, black indicates high correlation. The colour of the recurrence plot for normal breathing ECG signals leans towards the white portion of the colour bar. In contrast, the recurrence plot colour of apnea and hypopnea ECG signals leans more towards the black portion of the colour bar. The colours of apnea and hypopnea ECG signal recurrence plots are very similar. Thus, it is clear that the normal ECG signals have a lower correlation than abnormal breathing ECG signals. Furthermore, apnoea and hypopnoea ECG signals have
Figure 5. Recurrence plots: (a) apnea; (b) hypopnea; (c) normal ECG signals.
almost the same amount of correlation. Recurrence plots of apnoea, hypopnoea and normal breathing ECG signals are shown in figure 5.

5. Discussion

From table 2 it can be observed that the nonlinear parameters namely H and FD decreased during apnoea and hypopnoea respiratory events, which indicates that apnoea and hypopnoea ECG signals are both highly chaotic and highly variable. It can also be observed that apnoea ECG signals are slightly less chaotic and have a slightly lower variability than hypopnoea ECG signals.

The reflex activation of dilator muscles, when reacting to airway obstruction, tends to fail in OSAS patients. This failure is due to ventilatory control defects, retardation in reflex activation and defects in arousal mechanisms (Byron et al 2006). Airway obstruction during sleep in OSAS patients can also be caused by a narrow anatomical structure of the pharynx at any level and anatomic abnormalities such as soft palate elongation and macroglossia. Any of these causes can lead to the occurrence of hypopnoea and apnoea. As a result, CD indicates high variability and ApEn indicates highly chaotic ECG signals in both abnormal respiratory events.

Kowallik et al (2001) did a study on the correlation between breath to breath variability and AHI in OSA patients. The main aim of the study was to analyse the amount of breathing disturbance during non-occluded breathing. The team discovered that breathing in OSA patients is characterized by two qualities, breathing disruptions and a greater variation in the pattern of normal-length breaths.

The recurrence plots, shown in figures 16 to 18, indicate that normal breathing ECG signals have lower periodicity and frequency than abnormal ECG signals. However, a study on evaluating a new automated measure of cardiopulmonary coupling (CPC) during sleep,
Automated detection of sleep apnea from electrocardiogram signals using nonlinear parameters

Table 6. Results of the OSA classification accuracy using different bio-signals.

<table>
<thead>
<tr>
<th>Author</th>
<th>Input signal</th>
<th>Accuracy (%)</th>
<th>Number of classes</th>
</tr>
</thead>
<tbody>
<tr>
<td>de Chazal et al (2003)</td>
<td>ECG</td>
<td>90</td>
<td>2 (Normal apnea)</td>
</tr>
<tr>
<td>Mietus et al (2000)</td>
<td>ECG</td>
<td>93.3</td>
<td>2 (Normal apnea)</td>
</tr>
<tr>
<td>Corthout et al (2008)</td>
<td>ECG</td>
<td>90</td>
<td>2 (Normal apnea)</td>
</tr>
<tr>
<td>Mijović et al (2001)</td>
<td>Tachograms</td>
<td>89</td>
<td>2 (Normal apnea)</td>
</tr>
<tr>
<td>Várady et al (2002)</td>
<td>ECG</td>
<td>90</td>
<td>2 (Normal apnea)</td>
</tr>
<tr>
<td>Current study</td>
<td>ECG</td>
<td>90</td>
<td>3 (Normal apnea hypopnea)</td>
</tr>
</tbody>
</table>

based on single-lead ECG signals, reports that sleep apnoea correlates with both low-frequency oscillations in heart beat and low-frequency variations in ECG signals (Thomas et al 2005). The cause of low-frequency variations in ECG signals is due to the motion of the chest wall during respiration. CPC utilizes Fourier-based methods to analyse the inter-beat (R–R) interval series and its linked EDR signal. CPC presents two CPC regimes. One of which is high-frequency coupling (0.1–0.4 Hz band) which correlates with respiratory sinus arrhythmia. The other regime is low-frequency coupling (0.01–0.1 Hz band) which is associated with sleep apnoea.

Table 6 relates the OSA classification accuracy for OSA of eight different systems projects. All these projects employed linear discriminant analysis. The last row in table 6 shows the results reported in the current study. In contrast to all previously reported methods, our system evaluates a three-class problem (normal, apnea, hypopnea). However, the reported results of the current studies are among the best when compared with previously reported results.

In this study, a novel method is proposed to detect apnoea, hypopnoea and normal breathing ECG signals using nonlinear parameters such as H, CD, FD and ApEn. We obtained the similar performance for our classifier even for the three-fold stratified cross-validation method. However, the performance of the method can be improved further, using more training data, better features and better classifier.

6. Conclusion

Sleep apnoea is a very common sleep disorder that can be characterized by an abnormally high level of AHI during sleep. ECG signals are useful in the detection of sleep apnoea. Studying ECG signals with nonlinear parameters will greatly aid the understanding of the underlying system dynamics.

Classification of apnoea, hypopnoea and normal breathing ECG signals was done using the ANN classifier. The detection of respiratory (apnoea, hypopnoea or normal breathing) ECG signals was achieved with an overall accuracy of 89.1%; sensitivity of 100%, specificity of 95% and PPV of 98.97% were also achieved. Also, unique recurrence plots are proposed for normal, hypopnea and apnea classes. The significance of this study arises from the fact that it can be used as an adjunct tool by sleep physicians to diagnose sleep apnoea.

The accuracy of the proposed method depends on both the amount and quality of the training data, training thoroughness as well as parameters used to characterize the input. More research has to be done on the use of sleep EOG, EMG or EEG signals to detect sleep apnoea. In this way we hope to support sleep physicians better in their task of sleep apnoea diagnosis.
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References

Anderer P et al 2005 An e-health solution for automatic sleep classification according to Rechtschaffen and Kales: validation study of the somnolyzer 24 x 7 utilizing the siesta database Neuropsychobiology 51 115–33
Data analysis software http://www.mathworks.com/ (last accessed on 18 August 2009)
Fletcher S W 2005 Clinical Epidemiology: The Essentials (Baltimore, MD: Williams & Wilkins)
Higuchi T 1988 Approach to an irregular time series on the basis of the fractal theory Physica D 31 183–206

Mietus J E, Peng C K, Ivanov P Ch and Goldberger A L 2000 Detection of obstructive sleep apnea from cardiac interbeat interval time series Comp. Cardio. 27 753–6


Pincus S M and Keefe D L 1992 Quantification of hormone pulsatility via an approximate entropy algorithm Am. J. Physiol. 262 E741–54


Stein J H 1998 Internal Medicine (St Louis, MO: Mosby)

Takens F 1981 Detecting strange attractors in turbulence Dynamical Systems and Turbulence ed D Rand and L S Young (Berlin: Springer)


VRA software (accessed on November 2010) http://home.netcom.com/~eugenek/download.html