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Detection of Sleep Apnea Events via tracking Nonlinear Dynamic Cardio-Respiratory Coupling from Electrocardiogram Signals

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Abstract— **Obstructive sleep apnea (OSA) is a common sleep disorder that causes increasing risk of mortality and affects quality of life of approximately 6.62% of the total US population. Timely detection of sleep apnea events is vital for the treatment of OSA. In this paper, we present a novel approach based on extracting the quantifiers of nonlinear dynamic cardio-respiratory coupling from electrocardiogram (ECG) signals to detect sleep apnea events. The quantifiers of the cardio-respiratory dynamic coupling were extracted based on recurrence quantification analysis (RQA), and a battery of statistical data mining techniques were to enhance OSA detection accuracy. This approach would lead to a cost-effective and convenient means for screening of OSA, compared to traditional polysomnography (PSG) methods. The results of tests conducted using data from PhysioNets Sleep Apnea database suggest excellent quality of the OSA detection based on a thorough comparison of multiple models, using model selection criteria of validation data: Sensitivity (91.93%), Specificity (85.84%), Misclassification (11.94%) and Lift (2.7).**

I. Introduction

Obstructive sleep apnea (OSA) is a common sleep disorder that plays an important role in a person's chances of developing sleep insufficiency. Approximately 1 in every 15 Americans, or 6.62% of the total US population have been diagnosed with OSA. It is known that OSA increases mortality and also reduces quality of life and productivity. People experiencing OSA are more likely to suffer from chronic diseases such as hypertension, diabetes, depression, obesity, and cancer. An estimated 18 million people in the US have OSA and some 63 million suffering from OSA are yet to be clinically diagnosed [1].

OSA is characterized by periodic, complete or partial upper airway obstruction during sleep, causing intermittent cessations of breathing (apneas) or reductions in airflow (hypopneas) despite ongoing respiratory effort. Timely detection of sleep apnea events is vital for the treatment of OSA. Currently, a formal diagnosis test of OSA is to perform polysomnography (PSG) in a sleep laboratory. Although it is considered the standard test for the diagnosis of OSA, this approach suffers from several disadvantages, including that it requires an overnight stay in the sleep laboratory with all-night technologists and specialized equipment and facilities. The patient will also be hooked up to multiple probes while staying overnight. PSG is considered very expensive, inconvenient, uncomfortable and time consuming for both the patient and an evaluator.

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OSA monitoring and detection research has received considerable amount of attention in the literature. Several OSA detection approaches based on correlating the statistical patterns of heart rate, respiration rate, and oxygen saturation (SpO2) signals during OSA episodes have been attempted [2-4]. However, due to nonlinear nature of human signals, many OSA detection methods suffer from an inaccuracy of the detection resulting from nonlinearly underlying process of the signals. These methods do not capture variations in nonlinear dynamics of the signals responsible for detection of OSA events. Also, these methods attempt to look into each signal individually, they fail to capture a dynamic coupling and interrelationship of the signals that can be used to improve an accuracy performance of OSA detection.

In this paper, we present a novel approach based on nonlinear dynamic cardio-respiratory coupling to detect sleep events using electrocardiogram (ECG) signals. The advantage of this approach would lead to a cost-effective and convenient means for screening of OSA, compared to traditional PSG method. This approach enhances a quality of sleep apnea detection using nonlinear features from recurrence quantification analysis (RQA). By tracking nonlinear dynamics of cardio-respiratory system, one can effectively improve a detection quality of OSA events, compared to classical and advanced methods reported in the literature.

The remainder of this paper is organized as follows: Section II provides the background and review of relevant literature. Section III provides a research methodology for a detection of OSA events. Section IV presents the results. The last section, Section V is conclusion section.

II. Background And Review Of Relevant Literature

Respiration studies have increasingly assumed importance in the field of biomedical analytics research. Respiration signal analysis is beginning to be applied to address a variety of issues ranging from cardiac diagnostics [5] and sleep studies [6], to sports medicine [7]. As the respiration pattern is evidently affected during apnea, understanding respiration pattern becomes vital in order to detect the occurrence of OSA [8]. With recent advances in wearable health systems and healthcare cost reduction, significant efforts [9, 10] have been made to address the extraction of respiration waveforms from ECG data, hence number of sensors and total examination cycle can be reduced. Different methods, such as heart rate variability [11] and wavelets [12] have been used to derive respiration signals.

Recently, Empirical Mode Decomposition (EMD) [13] technique has been investigated to address the limitations of conventional EDR methods in the presence of noise. EMD is used to decompose an ECG signal into a finite number of

components called intrinsic mode functions (IMFs). EMD allows perfect reconstruction of the ECG signal using IMFs. This property of EMD leads to an application of determining trend and noise from an original ECG signal. Many studies [14, 15] indicate that EDR obtained from EMD has highest correlation with the real respiratory signal compared to results obtained from other methods.

This present approach has been developed using RQA which is nonlinear feature extraction method. We developed a method to derive respiration data from ECG signals using EMD. This EDR method based on EMD technique is a cost-effective way to obtain respiration data for OSA detection without using excessive cardio-respiratory sensors. The RQA features of EDR signals based on EMD, and heart rate variability (HRV) extracted from ECG signal are applied as the inputs for OSA detection using a battery of statistical data mining techniques. This research is aimed to create an automated detection method of OSA events which can capture a nonlinear dynamic underlying cardio-respiratory system resulting in a quality enhancement of OSA detection.

III. Research Methodology

In this research, the ECG data and apnea annotations were obtained from Physionet database. The ECG signal was recorded for more than eight hours at a sampling rate of 100 Hz. Because the frequency characteristics of extracted features (R-R interval, HRV, and respiratory) are very low, less than 5 Hz, the obtained ECG data is suitable for our analysis. The annotations were derived by human experts on the basis of simultaneous related signals (i.e., SpO2, chest and abdominal respirations, airflow, and ECG) used for screening OSA. The apnea annotations were recoded into a binary representation, and were considered a target variable for prediction analysis. Apart from ECG and apnea annotations, heart rate represented in beats per minute (BPM) was also estimated by calculating the RR intervals in the ECG signal. To detect OSA, the respiration rate derived by applying EMD on ECG signals and HRV derived from the variation of RR intervals were processed using RQA. Three models of different RQA features were developed for a detection comparison as shown in Table I. The overall procedure of the detection approach includes three main steps: Data Processing, Feature Extraction and Detection as shown in Fig. 1.

TABLE I. Summary of models

Model	Inputs
I	RQA features of respiration rate
II	RQA features of HRV
III	RQA features of both HRV and respiration rate

The following subsections present the details of EDR based on EMD, RQA and data mining techniques for the detection of OSA.

A. ECG Derived Respiration (EDR) Based On EMD

The EMD method aims to represent a nonlinear and nonstationary signal $x(t)$ as a superposition of a finite number of components called intrinsic mode functions (IMF) as

$$x(t) = \sum_{n=1}^{L} s_n(t) + r_{L+1}(t) \quad (1)$$

where $s_n(t)$ are the IMFs and $r_{L+1}(t)$ is the residual from the decomposition. The IMFs provide local characteristic time scales and adaptive basis for EMD. Consequently, IMFs can be used to capture drifts and nonlinear modes of any nonlinear and nonstationary processes, including ECG signals. Also, the adaptive basis of EMD does not require parametric functional form for the original series. The characteristic of IMF is that it has only one extreme between zero crossings, and has a mean value of zero. The following procedure of EMD called sifting process is used to extract IMFs from an ECG signal $x(t)$:

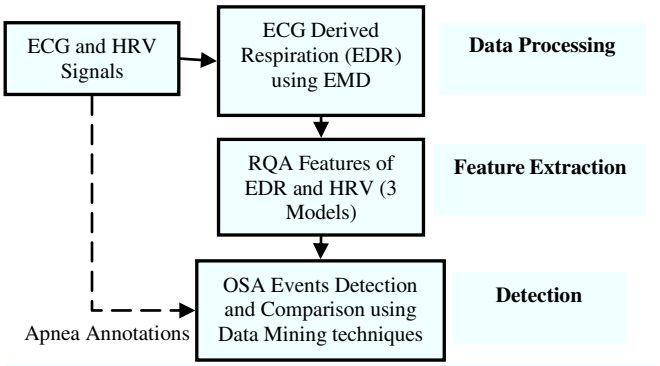

Figure 1. Overall procedure of the prediction approach

1) Identify all local minima and maxima ($x^*_{\max}(t_i)$ and $x^*_{\min}(t_j)$) of $x(t)$, where $i = 1, \ldots, n$ and $j = 1, \ldots, m$

2) Use a cubic spline interpolation to define an upper $u(t)$ and lower envelope $v(t)$ from the extreme points as

$$u(t) = \oplus u_i(t) \quad t \in (t_i, t_{i+1}) \text{ and } i = 1, \ldots, n \quad (2)$$

where $\oplus$ represents a direct sum,

$$u_i(t) = \frac{z_{i+1}}{6\tau_i}(t - t_i)^3 + \frac{z_i}{6\tau_i}(t_{i+1} - t)^3 + C_i(t - t_i) + D_i(t_{i+1} - t) \quad (3)$$

$$\tau_i = t_{i+1} - t_i, C_i = \frac{x^*_{\max}(t_{i+1})}{\tau_i} - \frac{\tau_i}{6} z_{i+1}, D_i = \frac{x^*_{\max}(t_i)}{\tau_i} - \frac{\tau_i}{6} z_i \quad (4)$$

$$\tau_{i-1} z_{i-1} + 2(\tau_{i-1} + \tau_i) z_i + \tau_i z_{i+1} = 6\left(\frac{x^*_{\max}(t_{i+1}) - x^*_{\max}(t_i)}{\tau_i} - \frac{x^*_{\max}(t_i) - x^*_{\max}(t_{i-1})}{\tau_{i-1}}\right) \quad (5)$$

The process to define lower envelope $v(t)$ is similar to (2)-(5) when $v(t) = \oplus v_i(t) \quad t \in (t_j, t_{j+1})$ and $j = 1, \ldots, m$

3) Compute the mean envelope $m(t)$

$$m(t) = [u(t) + v(t)]/2 \quad (6)$$

4) Compute the IMFs $s_p(t)$ iteratively through a series of reductions

$$h_k(t) = r_{p-1}(t) - m_k(t), \quad k = 1, \ldots, K_{\max}, p = 1, \ldots, P, \quad r_0(t) = x(t) \quad (7)$$

Here, $h_k(t)$ is treated as the series, and $m_k(t)$ is computed as the mean of the upper and lower envelopes of $h_k(t)$. The process

will repeat all the steps until the following stoppage criterion (*SD*) is reached

$$\frac{\sum_{t=0}^{T}|h_{k-1}(t)-h_k(t)|^2}{\sum_{t=0}^{T}h_{k-1}^2(t)} < SD^* \quad (8)$$

5) Obtain the residue $r_p(t)$

$$r_p(t) = r_{p-1}(t) - s_p(t) \quad (9)$$

The process continues till the number of the extreme points of $r_p(t)$ is not larger than two. As EMD allows a perfect reconstruction of the original ECG signal, $x(t)$, using IMFs and residue as given in (1), this property of EMD is used for the estimation of respiration from IMFs of ECG signal. Since the frequency characteristic of respiration lies in the range of 0.2-0.33 Hz, the EDR based on EMD is estimated from a summation of IMFs lying in the respiration range.

B. Recurrence Quantification Analysis (RQA)

RQA is a method of nonlinear data analysis that quantifies the number and duration of recurrences of a dynamical system presented by its phase space trajectory using recurrence plots. In this study, the EDR signals contain dynamical information that is useful for a detection of OSA. An equivalent state space (attractor) of EDR signals can be reconstructed from the delayed coordinates of the measurement $y(t)$ as

$$f(t_i) = [y(t_i), y(t_i+\tau), y(t_i+2\tau), ..., y(t_i+(m-1)\tau) \quad (10)$$

where m is the embedded dimension and τ is the time delay. The minimal sufficient embedding dimension m to unfold the attractor is determined by false nearest neighbor method [16]. The optimal time delay τ is selected to minimize mutual information function $M(\tau)$, defined as

$$M(\tau) = \int_t p(t,t+\tau)\log\frac{p(t,t+\tau)}{p(t)\,p(t+\tau)}dt \quad (11)$$

where $p(t,\tau)$ is the joint density function, and $p(t)$ and $p(t+\tau)$ are marginal density functions of $y(t)$ and $y(t+\tau)$, respectively. The recurrence plots provide a convenient means to capture the topological relationships existing in the *m*-dimensional state space by calculating the distance from each state to all others $D(i,j) := \|v(i)-v(j)\|$, where $\|\cdot\|$ is a norm (e.g., the Euclidean norm) and mapping the distance to a color scale. Some of the important RQA features and their equations are summarized as shown in Table II.

C. Data Mining Methods

In order to uncover the underlying patterns of cardio-respiratory system for a detection of OSA, several data mining methods are used. There are five data mining techniques used in this research, including neural network, autoneural, regression, decision tree and ensemble models. In this research, the neural network model has one hidden network layer consisting of three neurons. The weight function in each neuron is automatically optimized based on the discovered patterns from given training data. Autoneural is used as an automatic tool to search for an optimal setting for a neural network model.

Decision tree model will ranks each RQA feature input from their contributions to the final output to the tree. Then, the output would be selected based on the rules created by each leaf of the tree. Ensemble model could be used to combine other modeling methods, such as a neural network and a regression, and then forms the rules based on the prior models for a better final model solution. The performance of these models are assessed using four model selection criteria as shown in Table III.

TABLE II. RQA feature description (Marwan 2007)

RQA Features	Equations
Recurrence Rate	$RR(\varepsilon)=\frac{1}{N^2}\times\sum_{i,j=1}^{N}R_{i,j}(\varepsilon)$
Determinism	$DET = \frac{\sum_{l=l_{\min}}^{N} lP(l)}{\sum_{l=1}^{N} lP(l)}$
Mean diagonal line length	$L = \frac{\sum_{l=l_{\min}}^{N} lP(l)}{\sum_{l=l_{\min}}^{N} lP(l)}$
Longest diagonal length	$L_{\max} = \max(\{l_i\}_{i=1}^{N_l})$
Entropy	$ENTR = -\sum_{l=l_{\min}}^{N} p(l)\ln P(l)$
Laminarity	$LAM = \frac{\sum_{v=v_{\min}}^{N} vP(v)}{\sum_{v=1}^{N} vP(v)}$
Trapping time	$TT = \frac{\sum_{v=v_{\min}}^{N} vP(v)}{\sum_{v=v_{\min}}^{N} vP(v)}$
Maximal length of vertical lines	$V_{\max} = \max(\{v_l\}_{l=1}^{N_v})$

* Recurrence time type 1 and 2, Entropy, Clustering coefficient and Transitivity are not shown here.

TABLE III. Model selection criteria

Model Selection Criteria	Description
Misclassification Rate	Rate at which misclassification occurs in the validation data
Lift	Model improvement provided by the model with respect to the baseline (random guess probability)
Sensitivity	Ratio of true positives to the sum of true positives and false negatives
Specificity	Ratio of true negatives to the sum of true negatives and false positives

IV. RESULTS

As shown in Fig. 1, the first step of the procedure is data processing step. The respiration data was derived from an ECG signal. Using EMD technique, the ECG signal was decomposed into 12 IMFs (I1-I12) and residual (R) as shown in Fig. 2. Since EMD property allows perfect reconstruction of the ECG signal using IMFs, this property is very useful to isolate respiration data from the original ECG signal. The IMFs that lie in the frequency range of respiration include IMF8 to IMF 12 and the residual (I8 to I12 and R in Fig. 2). A summation of these IMFs provides the EDR signal as shown in Fig. 3 (a).

The second step of the procedure is feature extraction step. In this step, the RQA technique was used to extract RQA measures from the EDR signal. Dimension (M = 7) and Time

Delay (τ = 5) was determined by false nearest neighbor method. Fig. 3(b) shows a recurrence plot of the EDR signal from the first step. The result of recurrence plot of EDR signal yielded 13 features which were fed as an the inputs to the data mining models. The last step of the procedure is the detection step. As mentioned in Section III, three models of different RQA measures were developed for a detection comparison. The RQA measures of EDR and HRV signals were extracted and used as inputs for data mining modeling to detect OSA events. The results of selected data mining methods for each model are shown in Table III.

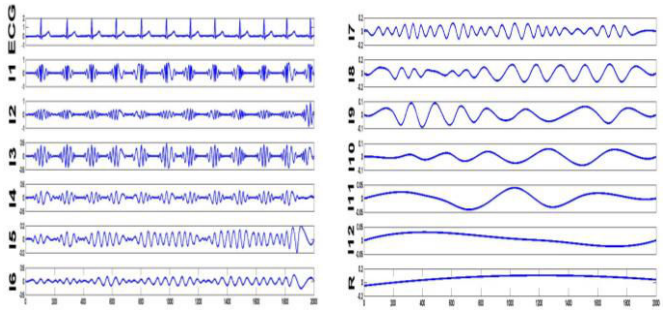

Figure 2. ECG and 13 IMFs of ECG signal using EMD

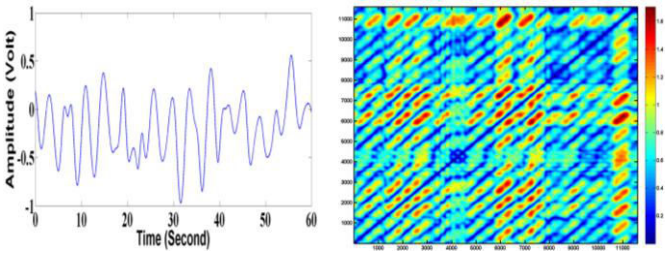

Figure 3: (a) The EDR signal and (b) recurrence plot

TABLE IV. Summary of models' performance

Model	Methods	Sensitivity	Specificity	Misclassification Rate
I	Ensemble	87.05%	75.29%	20.00%
II	AutoNeural	96.47%	84.70%	14.00%
III	AutoNeural	91.93%	85.84%	11.94%

Model	Methods	Lift	AHI
I	Ensemble	1.75	25.19
II	AutoNeural	1.25	27.27
III	AutoNeural	2.70	26.23

As shown in Table IV, using data mining techniques, Ensemble method was selected for Model I, and AutoNeural was selected for Model II and III. Model III which uses RQA features of both EDR and HRV signals as the model's inputs, provides the lowest misclassification rate for a detection of OSA. A combination of sensitivity and specificity of model III indicates the robustness of the model. Moreover, the lift value also indicates that this model is the best detection model in terms of model improvement with respect to the baseline (random guess probability). In addition to four model selection criteria reported, the apnea-hypopnea index (AHI) that shows sleep apnea severity is also reported in Table IV. The given data has an original AHI of 22.20. Using our approach, the AHI of model I to III is ranging from 25.19 to 27.27.

V. Conclusions

In this paper, we present a novel approach based on nonlinear dynamic cardio-respiratory coupling to detect sleep apnea events using electrocardiogram (ECG) signals. This detection based approach provides an automated detection of sleep apnea events, and enhances a detection quality using recurrence quantification analysis (RQA) and a battery of statistical data mining techniques. The test results suggest that the AutoNeural model using RQA features of EDR and HRV as inputs provides the best detection performance in terms of misclassification rate (11.94%), specificity (85.84%), and lift (2.7).

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