Obstructive Sleep Apnea Detection Using SVM-Based Classification of ECG Signal Features

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Abstract— **Sleep apnea is the instance when one either has pauses of breathing in their sleep, or has very low breath while asleep. This pause in breathing can range in frequency and duration. Obstructive sleep apnea (OSA) is the common form of sleep apnea, which is currently tested through polysomnography (PSG) at sleep labs. PSG is both expensive and inconvenient as an expert human observer is required to work over night. New sleep apnea classification techniques are nowadays being developed by bioengineers for most comfortable and timely detection. This paper focuses on an automated classification algorithm which processes short duration epochs of the electrocardiogram (ECG) data. The presented classification technique is based on support vector machines (SVM) and has been trained and tested on sleep apnea recordings from subjects with and without OSA. The results show that our automated classification system can recognize epochs of sleep disorders with a high accuracy of 96.5% or higher. Furthermore, the proposed system can be used as a basis for future development of a tool for OSA screening.**

Keywords: Sleep apnea, PSG, ECG, RR interval, feature extraction, SVM.

I. INTRODUCTION

A. Background

Over the average lifespan, humans sleep for about 1/3 of their lives. A sleeping disorder is when one cannot sleep, causing the body to lose function. Just as the body's benefits of rest can range from physical to emotional and psychological effects, lack of sleep can damage the body physically, emotionally and psychologically. Till date, 84 kinds of sleep disorders have been discovered, including the most common ones such as insomnia, sleep apnea, narcolepsy and restless leg syndrome [1].

Sleep Apnea (SA) is the instance when one either has pauses of breathing in their sleep, or has very low breath while asleep. This pause in breathing is known as an apnea, and can range in frequency and duration. The lack of breathing during sleep is known as a hypopnea [2]. Sleep apnea is classified into two different types. The first type is Obstructive Sleep Apnea (OSA), which is more common, occurring in 2% to 4% of middle-aged adults and 1% to 3% of preschool children [3], and is generally caused by a collapse of the upper respiratory airway. The second one is Central Sleep Apnea (CSA), which is caused by an absent or inhibited respiratory drive. Most cases of CSA are mixed, meaning that it is often along with OSA cases, and the CSA only cases appear exceedingly rarely [4]. Despite how

common it is, most cases go undiagnosed and can be attributed to 70 billion dollars loss, 11.1 billion in damages and 980 deaths each year [5].

Most sleep apnea cases go undiagnosed because of the inconvenience, expenses and unavailability of testing. The traditional testing process includes a polysomnography (PSG), which is a standard procedure for all sleep disorder diagnosis. It records the breath airflow, respiratory movement, oxygen saturation, body position, electroencephalogram (EEG), electrooculogram (EOG), electromyogram (EMG), and electrocardiogram (ECG) [6].

B. Contribution and Paper Organization

It is clear that the mere dependency on PSG needs to be taken away from the laboratory for simpler detection and faster treatment of sleep apnea. Instead, automated, at-home devices that patients can simply use while asleep seem to be very attractive and highly on-demand. We propose a novel methodology in this paper that combines most effective RR-interval based features of the ECG signal based on the ones suggested by Chazal et al., and Yilmaz et al. This work relies on Support Vector Machines (SVM) for classification. Performance assessment of the combination of these two approaches is done by measuring the classification performance in determining the presence of apnea for different epoch lengths.

The rest of this paper is organized as follows. In Section II, we glance at a variety of sleep apnea detection methods. Section III contains an overview of the system, and details on the analysis methodology of the paper. We describe the steps to determine RR-interval and features extraction for different epoch lengths in the same Section. In Section IV, we present the results of our system, and then we provide a comparison with other SA detection works. Finally, Section V concludes this paper regarding the potential usefulness of our system, and highlights some directions for future research.

II. RELATED WORK

Several methods have been suggested for identification of sleep apnea over the past few years. Statistical features of different signals such as nasal air flow, the thorax and abdomen effort signals, acoustic speech signal, oxygen saturation, electrical activity of the brain (EEG), and electrical activity of the heart (ECG) are commonly used in the detection.

Ng et al. [7] showed that thoracic and the abdominal signals were good parameters for the identification of the

occurrence of sleep apnea. Using the mean of absolute amplitudes of the thoracic and the abdominal signals, they have achieved a good performance with a receiver operating characteristic value higher than 80%.

Depending on the hypothesis that speech signal properties of OSA patients will be different than those not having OSA, Goldshtein et al. [8] developed a gaussian mixture model-based system to classify between the OSA and non-OSA groups. They achieved a specificity and sensitivity of 83% and 79% for the male OSA and 86% and 84% for the female OSA patients, respectively. Their technique relied on vocal tract length and linear prediction coefficients features.

The study in [9] assessed analysis of a comprehensive feature set based on blood oxygen saturation (SaO$_2$) from nocturnal oximetry in order to evaluate sleep quality. The three features of SaO$_2$ signal which are delta index, central tendency measure and oxygen desaturation index are evaluated. Central tendency measure accuracy was higher than those provided by delta index and oxygen desaturation index. With central tendency measure the sensitivity was 90.1% and the specificity was 82.9%.

The relationship between periodic changes in the oxygen saturation (SaO2) profile and in the EEG pattern due to apnea events during the night was investigated in [10]. The spectral analysis of these two signals achieved 91% sensitivity, 83.3% specificity and 88.5% accuracy in OSA diagnosis.

In [11], the authors analyze various feature sets and a combination of classifiers based on the arterial oxygen saturation signal measured by pulse oximetry (SpO$_2$) and the ECG in order to evaluate sleep quality and detect apnea. With selected features of the SpO2 and ECG signals, the Bagging with REP Tree classifier achieved sensitivity of 79.75%, specificity of 85.89% and overall accuracy of 84.40%.

Wavelet transforms and an artificial neural network (ANN) algorithm were applied to the EEG signal in [12] to find a solution to the problem of identifying sleep apnea episodes. The system's identification results achieved a sensitivity of approximately 69.64% and a specificity of approximately 44.44%.

Many studies show that detection of obstructive sleep apnea can be performed through heart rate variability (HRV) and the ECG signal.

Quiceno-Manrique et al. [13] proposed a simple diagnostic tool for OSA with a high accuracy (up to 92.67%) using time-frequency distributions and dynamic features in ECG signal. Moreover, based on spectral components of heart rate variability, frequency analysis was performed in [14] using Fourier and Wavelet Transformation with appropriate application of the Hilbert Transform, where the sensitivity was 90.8%. In addition, in [15] a bivariate autoregressive model was used to evaluate beat-by-beat power spectral density of HRV and R peak area, where the classification results showed accuracy higher than 85%. The technique in this work also relies on features of the ECG signal.

III. METHODOLOGY

In this work, we focus on the ECG signal features to detect sleep apnea. The block diagram of the overall methodology used in this study is shown in Figure 1.

A. Subjects

The database of ECG signals used is available from the *PhysioNet* web site [16]. The *Apnea-ECG Database* contains 70 recordings, containing a single ECG signal varying in length from slightly less than 7 hours to nearly 10 hours each. The sampling frequency used for ECG acquisition was 100 Hz, with 16-bit resolution, and one sample bit representing 5μV. The standard sleep laboratory ECG electrode positions were used (modified lead V2) [6].
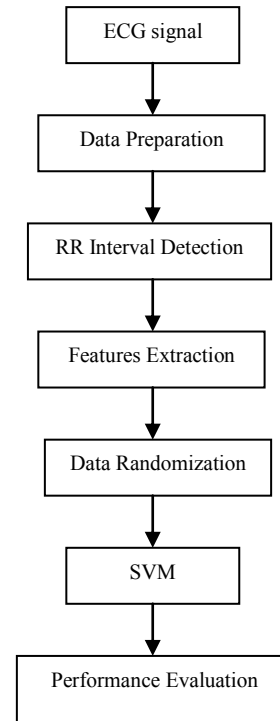

Figure 1. Schematic diagram of the system.

B. ECG

ECG is considered as one of the most efficient features to detect sleep disorders. Cyclic variations in the duration of a heartbeat, also known as RR intervals (time interval from one R wave to next R wave) of ECG have been reported to be associated with sleep apnea episodes. This consists of bradycardia during apnea followed by tachycardia upon its cessation [6]. RR-interval is defined as the time interval between two consecutive R peaks. The RR interval time series generated for each ECG beat can be written as follows [17]:

$$rr(i) = r(i+1) - r(i), \qquad i = 1, 2, ..., n-1 \quad (1)$$

Several researches have been conducted to recognize sleep apnea using the features derived from the RR interval such as median, mean, inter-quartile range (IQR), and the standard deviation of the change in RR intervals [6][17][18].

C. Data Preparation

To select the data, we chose the ECG records which have continuous apnea data for a certain period of time, followed by a regular (normal) data representation for a period of time, or vice versa. The data preparation is used for training the SVM classifier (see subsection III.G).

The next step in our procedure after data selection is data partitioning. In our work, three cases of partitioning were analyzed, as follows:

- *Case* 1. The apnea and regular data are partitioned into 10 second pieces.
- *Case* 2. The apnea and regular data are partitioned into 15 second pieces.
- *Case* 3. The apnea and regular data are partitioned into epochs of 30 second pieces.

Since apnea is defined as a pause in breathing, and can last from a few seconds to minutes (almost >=10 sec); we investigate the three above cases to determine the best accuracy that can be achieved.
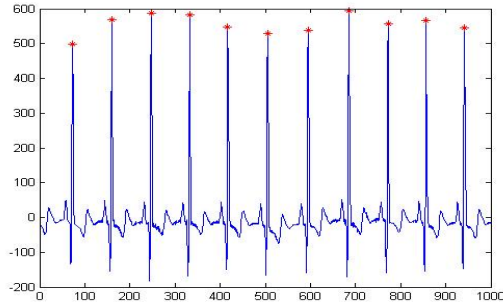

Figure 2. Detection of R- Peak.

D. RR Interval Detection

We need to distinguish the R waves from the other waves of the ECG signal. Therefore, we developed the following two conditions, in which R-peak was detected. An R peak will be identified if both conditions 1 and 2 are satisfied:

 1) It has to be a local maximum, which is detected by a *local max* function within a window of 150ms.
 2) The *local max* peaks must be at least 2 standard deviation above the mean.

Once the R-peak was determined, RR intervals were computed. The RR interval is the peak to peak time period from two continuous peak signals as shown in Equation 1. Figure 2 shows the detection of R-peaks.

E. Features Extraction

Our technique relies on an effective combination of ECG signal features which is a novel hybrid of features extracted from [6] and [19]. The following ECG features which are most effective for apnea detection are calculated:

- Mean epoch and recording RR-interval.
- Standard deviation of the epoch and recording RR-interval.
- The NN50 measure (variant 1), defined as the number of pairs of adjacent RR- intervals where the first RR-interval exceeds the second RR- interval by more than 50 ms.
- The NN50 measure (variant 2), defined as the number of pairs of adjacent RR-intervals where the second RR-interval exceeds the first RR interval by more than 50 ms.
- Two pNN50 measures, defined as each NN50 measure divided by the total number of RR-intervals.
- The SDSD measures, defined as the standard deviation of the differences between adjacent RR- intervals.

- The RMSSD measures, defined as the square root of the mean of the sum of the squares of differences between adjacent RR- intervals.
- Median of RR-intervals.
- Inter-quartile range, defined as difference between 75th and 25th percentiles of the RR-interval value distribution.
- Mean absolute deviation values, defined as mean of absolute values obtained by the subtraction of the mean RR-interval values from all the RR-interval values in an epoch.

The first seven features are proposed by Chazal et al. [6], while the three latter feature are proposed by Yilmaz et al.[19], who claimed that RR interval mean, standard deviation, and range are sensitive to outliers, and thus classification performance deteriorates when only these features are included.

Our hybrid technique includes a combination of the most effective set of RR-interval based features of the ECG signal for classification. The classification results confirm the improved accuracy compared to the two above techniques.

F. Support Vector Machines

We use Support Vector Machines (SVM) as a classification (also known as supervised learning) method in order to investigate apneaic epoch detection. In our implementation, we use a linear kernel function to map the training data into kernel space. In the optimization process, we use a method called sequential minimal optimization to find the separating hyperplane.

For data randomization, we separate the apnea and non apnea data. We then separate training data and testing data, with 80% for the training and 20% for the testing. After the signals are separated, we perform the training for SVM.

IV.   RESULTS

A. Performance Evaluation

We evaluated the effectiveness of our model on the different records in the Apnea-ECG database. MATLAB toolset was used for signal processing and classification.

Two statistical indicators, Sensitivity (*Se*) and Specificity (*Sp*) in addition to the Accuracy (*Acc*) have been used to evaluate the performance of our classification system. Table I, II and III show the classification results for the three cases mentioned in the data partitioning step. Our model was based on a linear kernel SVM using various RR-interval features of the ECG signal. The three cases used here are: (*i*) 10 seconds data partitioning, (*ii*) 15 seconds, and (*iii*) 30 seconds. The accuracy of our approach is 86.1%, 96.5%, and 95%, respectively. From Table II, SVM with linear kernel using 15 second epochs shows the best classification accuracy with high successful rate of correct prediction.

TABLE I
10 sec. (Accuracy is 86.1%)

Input\Output	Regular	Apnea
Regular	**97.2%**	2.78%
Apnea	25%	**75%**

TABLE II
15 sec. (Accuracy is 96.5%)

Input\Output	Regular	Apnea
Regular	**100%**	0%
Apnea	7.1%	**92.9%**

TABLE III
30 sec. (Accuracy is 95%)

Input\Output	Regular	Apnea
Regular	**100%**	0%
Apnea	10%	**90%**

B.   Comparison with other techniques

We performed a comparison with other SA detection works. Table IV represents comparative results. As can be seen, our system has achieved a comparable or better performance.

TABLE IV
Comparison of Sleep Apnea Detection Approaches.

Method	Approach	Performance [%]		
		Se	Sp	Acc.
Chazal et al. [6]	Measure of minutes of sleep disordered respiration	NA	NA	91
Alvarez et al. [9]	SaO2	90.1	82.9	NA
Alvarez et al. [10]	SaO2 and EEG signal	91	83.3	88.5
Xie et al. [11]	SpO2 and ECG	79.75	85.89	84.40
Lin et al. [12]	EEG signal	69.64	44.44	NA
Q-Manrique et al. [13]	ECG signal	NA	NA	92.67
Schrader et al. [14]	Fourier and Wavelet Transformation of HRV	90.8	NA	NA
Mendez et al. [15]	Bivariate autoregressive model of HRV	NA	NA	85
Yilmaz et al. [19]	RR-interval based classification	NA	NA	89
Proposed	**Features extraction of ECG signal**	**92.9**	**100**	**96.5**

V.   CONCLUSIONS AND FUTURE WORKS

In this work, we studied the possibility of the detection of sleep apnea or hypopnea events from the ECG signal variation patterns during sleep. We further developed a model using the ECG signal features and evaluated its effectiveness. We evaluated our model on three different epoch lengths. From the experimental results, we conclude that SVM with linear kernel shows the best accuracy with 15 second epoch length.

As a future work, we plan to do performance optimization for feature selection, and then incorporate this work into a real- time monitoring system that acquires and analyzes the ECG signal of subjects during sleep.

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