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A highly Reliable and Fully Automated Classification System for Sleep Apnea Detection

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Abstract: Sleep apnea (SA) in the form of Obstructive sleep apnea (OSA) is becoming the most common respiratory disorder during sleep, which is characterized by cessations of airflow to the lungs. These cessations in breathing must last more than 10 seconds to be considered an apnea event. Apnea events may occur 5 to 30 times an hour and may occur up to four hundred times per night in those with severe SA [1]. Nowadays, polysomnography (PSG) is a standard testing procedure to diagnose OSA which includes the monitoring of the breath airflow, respiratory movement, and oxygen saturation (SpO2), body position, electroencephalography (EEG), electromyography (EMG), electrooculography (EOG), and electrocardiography (ECG). Therefore, a final diagnosis decision is obtained by means of medical examination of these recordings [2]. However, new simplified diagnostic methods and continuous screening of OSA is needed in order to have a major benefit of the treatment on OSA outcomes. In this regard, a portable monitoring system is developed to facilitate the self-administered sleep tests in familiar surroundings environment closer to the patients' normal sleep habits. With only three data channels: tracheal breathing sounds, ECG and SpO2 signals, a patient does not need hospitalization and can be diagnosed and receive feedback at home, which eases follow-up and retesting after treatment.

Keywords: *Sleep Apnea, PSG, ECG, RR interval, SpO2, VAD, features extraction, SVMs.*

1. Introduction

Sleep is the circadian rhythm which is among the most crucial needs in our day to day activities. Getting enough hours of sleep indicate repaired blood pressure, heart rate, and relaxed muscles and tissues [3].A sleeping disorder occurs when one cannot sleep and has symptoms like excessive daytime sleepiness and fatigue. Sleep Apnea (SA) is among the very common respiratory sleeping disorders characterized by cessations of airflow to the lungs or having a very low breath. The cessations lasting in more than 10 seconds considered as apnea event might occur 5 to 30 times in an hour and up to 400 per night [1]. Clinically, sleep apnea is divided into Obstructive Sleep Apnea (OSA) and Central Sleep Apnea (CSA). OSA, being the most common SA, is generally caused by a collapse of the upper respiratory airway. CSA is a neurological condition where brain fails to appropriately control breathing [2] [4].

Statistics show that out of 18 million Americans suffering from OSA, around 10 million remain undiagnosed [5]. The undiagnosed cases are due to inconvenience, expenses and unavailability of testing. The Polysomnography (PSG) is the current and traditional testing process which is a standard procedure ordered for all sleep disorders. This testing records the breath airflow, respiratory movement, oxygen saturation, body saturation, body position, electroencephalogram (EEG), electroculogram (EOG), electromyogram (EMG), and electrocardiogram (ECG) to determine the sleep stages [6].

To summarize, PSG needs to be replaced by more convenient detection methods and faster treatment. In this regard, a fully automated classification system that can recognize epochs of sleep apnea (SA) with high accuracy is presented. The objective of the system is to alert a patient who might be subject to an apnea attack.

2. Related Works

In the present studies, the researchers provide complementary information with combined different physiological signals, in order to obtain additional information to that provided by classical methods to evaluate sleep quality and detect apnea. In some studies, ECG and SpO2 data have been bridged to analyze sleep data. As the blood oxygen saturation falls during apnea, the resultant increase in heart rate and blood pressure causes stress and potential injury to the parts of the cardiovascular system [7]. In [8], the authors analyze various feature sets and a combination of classifiers based on the arterial oxygen saturation signal measured by pulse oximetry (SpO2) and the ECG. In this work, the Bagging with REP Tree classifier achieved sensitivity of 79.75%, specificity of 85.89% and overall accuracy of 84.40%.

Because of the desaturation event that activates the sympathetic nervous system, the relationship between periodic changes in the SpO2 profile and in the EEG pattern due to apnea events during the night was investigated in [9]. The combined spectral analysis of these two signals achieved 91% sensitivity, 83.3% specificity and 88.5% accuracy in OSA diagnosis.

The first successful preliminary attempts to directly assess the interactions of power spectral of sleep EEG and ECG signals in

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detecting OSA events is presented in [10]. Consistency between these two signals over different frequency bands (0-128 Hz) were evaluated before, during and after an OSA terminations event (with/without arousals) in non-REM as well as REM sleep.

3. Proposed Methodology

In this research, a fully automated classification system that can recognize epochs of sleep apnea (SA) with high accuracy is presented. The classification methodology on downloaded data is based on Support Vector Machines (SVMs) using the RR-interbeat interval series in the Electrocardiography (ECG) signal and a Neural Network (NN) using Oxygen saturation (SpO2) signal measurements obtained from pulse oximetry. Furthermore, a portable monitoring system is developed to facilitate the self-administered sleep tests in familiar surroundings environment closer to the patients' normal sleep habits. With only three data channels: tracheal breathing sounds, ECG and SpO2 signals, a patient does not need hospitalization and can be diagnosed and receive feedback at home, which eases follow-up and retesting after treatment.

A preliminary design of our system is shown in Figure 1. The full architecture starts first with a questionnaire where the patients answer to SA related questions to see where their SA risk stands. Then, the system is setup containing a small microphone integrated with a large stethoscope-like diaphragm in place with a soft band that is secured gently around the patient's neck to record the breathing sounds. The system utilizes the classifier for classifying the breath of the patient. It takes into the account the breath a patient has for a period of time. The average values allow us to figure out the peak intake of air via the windpipe, and also the peak exhale of air. These two values let an expert, a doctor or the patient himself/herself know how the classifier is going to monitor the breathing based on the above threshold values. Due to the fact that the blood oxygen level reduces after the body lacks the intake of oxygen over a period of time, SpO2 module will enable us to collect additional data using the simple finger clip-on wireless pulse oximetry sensor, in addition to the pulse rate measurement. These physiological signals will be connected wirelessly via Bluetooth to the person's mobile phone or personal computer for processing and storage to detect the abnormalities and activate the alarms to the patient and/or to a control center or a hospital. Moreover, it could release the oxygen from the oxygen cylinder in case it is available in the patient's bed room.

At the same time, the data can be uploaded to a cloud application to keep health information along with the individual's personal information record, and transmitted to a hospital for sleep data analysis. The cloud system will offer access to a large pool of sleep data for further investigations by researchers to enhance their used mechanisms and tools. The details of the overall methodology shown in Figure 2 are discussed in the subsequent sections.

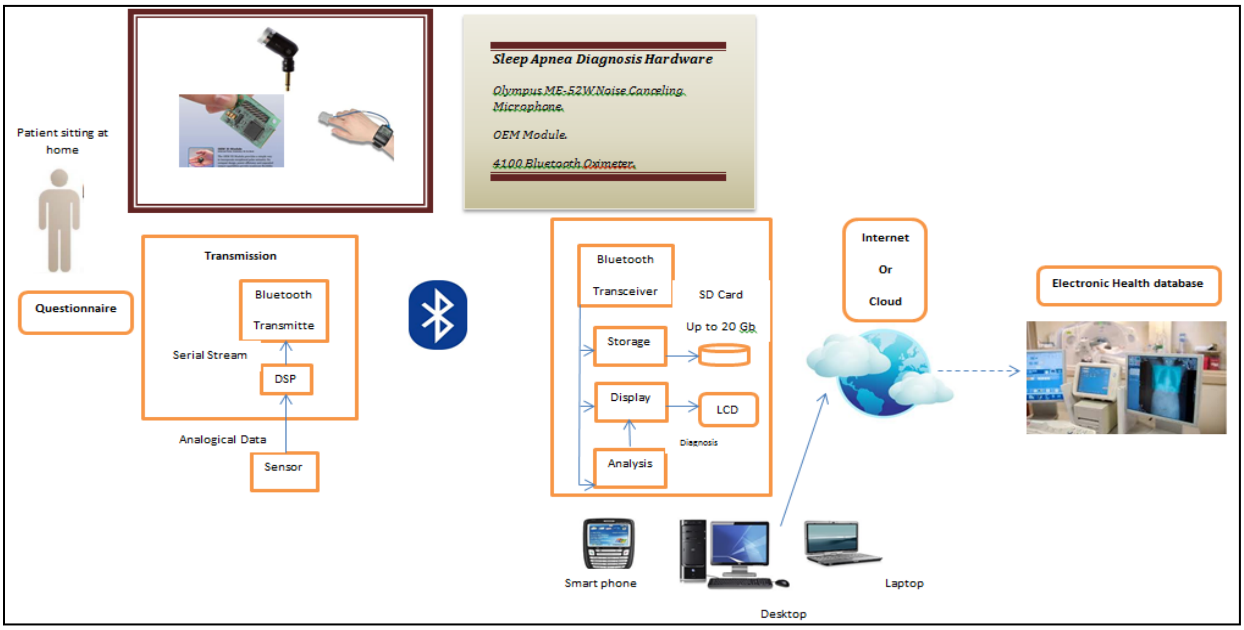

Figure 1. Schematic diagram of the system

3.1. A. Analysis of ECG Signal

In this work, the design involves acquiring the electrocardiogram (ECG) signal. The ECG is a representation of the electrical activity of the heart; each activity has a distinctive waveform. 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]. This signal is then processed to cancel the noise and detect RR-interval. Then, a combination of the most effective set of RR-interval based features of the ECG signal is calculated for classification is calculated for classification. The features considered are a novel hybrid of features extracted from [6] and [11]. The following are the most effective set of RR-interval based features of the ECG signal for apnea detection:

- 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 classification results confirm the improved accuracy compared to the [6] and [11] techniques alone.

3.2. Analysis of SpO2 Signal

SpO2 is the amount of oxygen being carried by the red blood cells in the blood. SpO2 goes up and down according to how well a person is breathing and how well the blood is being pumped around the body [12].

SpO2 measured by pulse oximetry can be useful in OSA diagnosis. Significant changes can be found in patients affected by OSA because of the recurrent episodes of apnea, which are frequently accompanied by oxygen desaturations [13].

In this work, three of SpO2 features act as inputs to the classifier and the diagnosis is the target. These three features are detailed as follows, respectively:

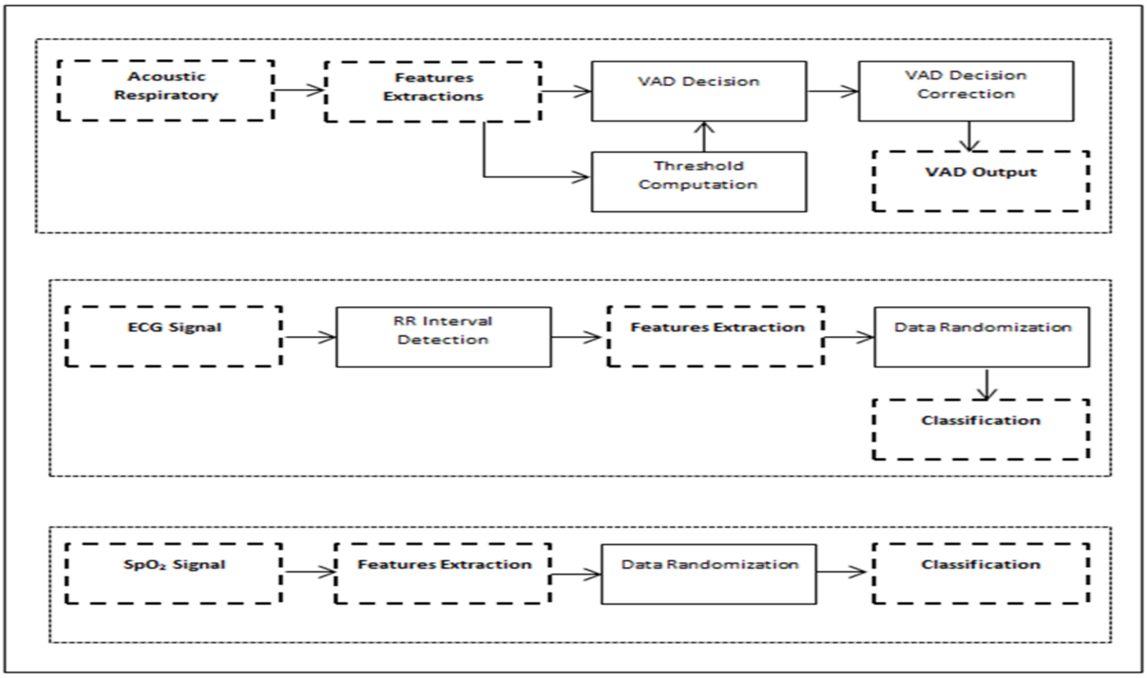

Figure 2. Schematic diagram of the proposed methodology

- Delta index (Δ index): This is a common measure to detect the apneic events by measuring SpO2 variability. Levy et al. [13] calculates Δ index as the sum of the absolute variations between two successive points, divided by the number of intervals. It is usually computed for 12-sec. intervals.
- Oxygen desaturation indices of 3% (ODI3): This measure is obtained by calculating the number of times per hour with values of SpO2 greater than or equal to 3% from the baseline. The baseline is set initially as the mean level in the first 3 minutes of recording [14].
- Central tendency measure with radius 0.5 (CTM50): This measure is applied in [14]. CTM50 is computed by selecting a circular region of radius 0.5 around the origin, counting the number of points that fall within the radius, and dividing by the total number of points.

3.3. Analysis of Respiratory Signal

This work introduces an automated approach towards identifying the presence of SA based on the acoustic signal of respiration. The characterization of breathing sound was carried by Voice Activity Detection (VAD) algorithm, which is used to measure the energy of the acoustic respiratory signal during breath and breath hold.

VAD relies on measurement of features from speech which yield highly in differentiating between voiced and unvoiced segments, where the regions of voice information within a given audio signal are referred to as 'voice-active' segments and the pauses between talking are called 'silence' or 'voice-inactive' segments. Therefore, the performance trade-offs of VAD algorithm are made by maximizing the detection rate of active speech while minimizing the false detection rate of inactive segments [15].

The most important part in VAD classifier is feature extraction, from which different regions in the audio signal can be separated. Common features used in the VAD detection process are cepstral coefficient [16], spectral entropy [17], zero-crossing rate [18, 19], least square periodicity measure [20], and average magnitude difference function [21]. Another important and widely used feature in this regard is signal energy, which is presented in this work, and compared with the dynamically calculated threshold.

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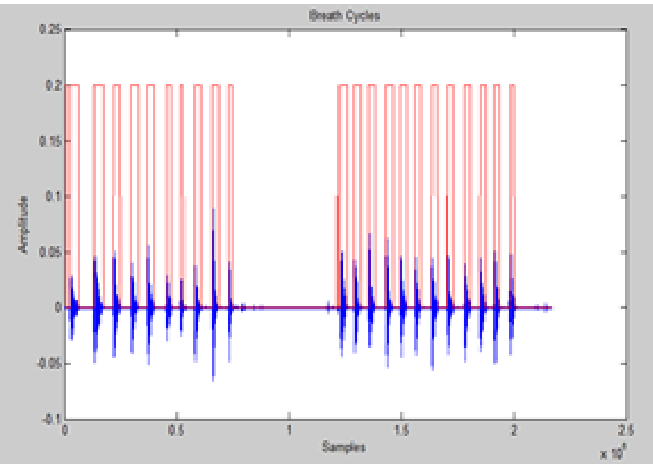
widely used feature in this regard is signal energy, which is presented in this work, and compared with the dynamically calculated threshold.

In the implemented work, in the first step, the respiratory signal is filtered to remove the undesired low frequency components. Then, the power with different window sizes of the Fast Fourier Transform (FFT) is calculated for the filtered signal [22]. Since VAD aims to differentiate voice and silence, where silence is mostly referring to background noise, the noise level at every frame needs to be computed. For this purpose, a threshold THR value needs to be determined for comparing the signal value against noise. The VAD technique eventually makes a decision by comparing every frame of signal energy against the THR value. It is important to note that transitional periods from active voice to silence may also affect the decision.

The outcome of the VAD technique is the separated speech and silence phases which can be fine-tuned for identifying breath versus breathing cessations for apnea detection.

4. Results and Discussion

To build our model, we used MATLAB toolset. The data records were imported as MATLAB matrices (.mat) from physionet web site [23]. We evaluated the effectiveness of our model on the Apnea database, using different records available in that database. The results show that our automated classification system can recognize epochs of SA with a high degree of accuracy, approximately 97.1%. Moreover, The performance of our classification algorithm is tested on real human respiratory signals which is given to the classification system as the input, and the coding is developed in such way that it calculates the fundamental feature of the respiratory signal, which is the energy. The threshold is then applied to the extracted energy feature and the binary decision is made. VAD=1 is declared if the energy feature exceeds the threshold. Otherwise, VAD=0 is for no breath or when silence (cessations of breathing) is present. Figure 3 shows the results obtained from the segmentation technique of the input signal which splits the acoustic signal of respiration into silence and voiced phases. The start point and end point of a respiratory signal which contains breathing phases is determined in this work. Hence, the apnea events that are silence phases lasting 15s or longer can be detected. Therefore, the experimental results show that the VAD is useful as a predictive tool for the segmentation of breath into sound and silence segments.



The work results provide motivating insights towards future developments of convenient and effective OSA screening setups.

Figure 3. Segmentation acoustic signal of breath

5. Conclusion

In this work, we studied the possibility of the detection of SA events from three different signals variation patterns. With the implemented system the patient does not need hospitalization and can be diagnosed and receive feedback at home, as it eases follow-up and retesting after treatment. In this system, the sleep data will be sent wirelessly via Bluetooth to a nearby smart-phone for processing and storage. Moreover, the data can be uploaded to cloud and transmitted to a hospital to keep the individual's health records. This not only will assist physicians and patients in planning for sleep apnea treatment, but will also offer access to a large pool of sleep data for investigations in this challenging field through providing benchmark data that can be used by researchers to enhance their used mechanisms and tools.

The presented framework will establish a simple and helpful at-home OSA screening system, while keeping in mind the cost, efficiency, the portability as well as the comfortability of the patient.

In addition to the nighttime data collection, in our system future improvement we will offers daytime data collection through continuously monitoring of the person's lifestyle and habits that factor into the condition of his/her sleep and could be vital signs to derive meaningful physiological parameters of interest. It allows the user to keep track of the day by asking him/her to enter the data in different ways, such as filling out a quick survey form available on our application. Some of the patterns that could be monitored and logged throughout the day include eating heavy or light meals, drinking alcohol, exercising frequency, and lifestyle such as smoking and sleeping schedule. To sum up, our continuous monitoring system has the advantage that patients can continue living a normal life with support of patient mobility, and will also help to prevent such a life threatening disease from creating further health complications.

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