IDENTIFICATION OF OBSTRUCTIVE SLEEP APNEA THROUGH SpO2 AND ECG SIGNAL FEATURES BY USING AN EFFICIENT NEURAL NETWORK SYSTEM

Ms.Dolypona Das¹, Mr.Vedanarayanan²

Abstract—Obstructive sleep apnea (OSA) is a common sleep disorder in which individuals stop breathing for sometime during their sleep. In this case, the upper airway is collapsed because of disrupted respiration. It occurs in 2 to 4% of middle-aged adults and in 1 to 3% of preschool children. Most of the sleep apnea cases are currently undiagnosed because of expenses and practical limitations of polysomnography (PSG) (Device used to detect sleep Apnea) at sleep labs, where an expert human observer is required. In the proposed system, an efficient neural network system is developed using SpO2 measurements obtained from pulse oximetry and ECG signal features to predict OSA. These measurements are given as inputs to the neural network system. By training the system we can detect whether the patient is suffering from OSA or not. This proposed method overcomes the practical difficulty of the patient being kept in the sleep lab for long time.

Keywords: sleep apnea; SpO2; ECG; OSA; polysomnography; features extraction; neural networks.

i) INTRODUCTION

A. Background

Sleep apnea is a kind of sleep disorder which is characterized by abnormal pauses in breathing of a subject during sleep. Each pause in breathing is called an ‘apnea’. The pause can last from at least ten seconds to minutes,
and may occur 5 to 30 times or more in an hour.

Excessive daytime sleepiness, impaired alertness and fatigue are the most common symptoms of sleep disorders [1]. Sleep apnea not only affects adults but also occurs in children in the age group of 1 to 5 years as well.

There are three forms of sleep apnea: Central (CSA), Obstructive (OSA), and Complex or Mixed sleep apnea (i.e. a combination of central and obstructive). It constitutes 0.4%, 84% and 15% of cases respectively for CSA, OSA, MIXED sleep Apnea. In CSA, breathing is inhibited by a lack of respiratory effort. In OSA, the upper airway is collapsed and the oxygen level in the blood drops because of disrupted respiration [2].

Patients suffering from OSA cannot concentrate, think or remember well during the day itself. It leads to more accidents in the work place and while driving. Symptoms for OSA at night time include snoring, gasping for air, insomnia, restless sleep. There are some serious daytime symptoms like daytime sleepiness, fatigue, headaches, irritability, depression and anxiety, sexual dysfunction which occur as a result of insufficient sleep at night.

OSA is a matter to be taken seriously. Untreated OSA increases the risk of heart attacks, strokes, high blood pressure and sudden death. It is estimated that only 10% of patients with OSA are being treated [3]. Some of the remaining 90% know that they have a problem, but they choose not to pursue treatment because of the inconvenience, expenses and practical limitations of Polysomnography (PSG) at sleep labs, where an expert human observer is required. The test for obstructive sleep apnea is polysomnography, also referred to as sleep study [4]. This test deals with measurement of different physical and physiological parameters while a subject is asleep. During attended polysomnography, a technician observes a person sleeping and monitors recording equipment in the setting of a sleep laboratory. A typical polysomnography test includes: an electroencephalogram (EEG), an
electro-oculogram (EOG), an electromyogram (EMG), measurement of oral and nasal airflow, measurement of chest and abdominal movement, audio recording of the loudness of snoring, blood oxygen levels (oximetry), and video monitoring of the subject during the study.

B. Paper organization

The rest of this paper is organized as follows. In Section (ii) we have discussed variety of sleep apnea detection methods. Section (iii) contains an overview of the system, including a description of the database of subjects, and the details of the analysis methodology including features extraction of the SpO2 and ECG signal. The Neural Network we used in this work is mentioned here. In Section (iv), we have explained the results of our system. Finally, Section (v) concludes the paper describing the usefulness of the system and highlights some directions for future research.

ii) LITERATURE SURVEY

Over years, several techniques have been discussed for identification of sleep apnea. Statistical features of nasal airflow, the thorax and abdomen signals, acoustic speech signal, oxygen saturation level, electrical activity of the brain (EEG), and electrical activity of the heart (ECG) are commonly used in the detection process.


In D. Avaraz et al. [6], 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. The spectral analysis of these two signals achieved 91% sensitivity, 83.3% specificity and 88.5% accuracy in OSA diagnosis.
J. Chung et al. [7] showed that thoracic and the abdominal signals were good parameters for the identification of sleep apnea. Using the mean of absolute amplitudes of the thoracic and the abdominal signals, the authors achieved good performance with a receiver operating characteristic value higher than 80%.

In R. Lin et al. [8], wavelet transforms and an artificial neural network algorithm were applied to the EEG signal to find a solution to the problem of identifying sleep apnea (SA) episodes. The system's identification results achieved a sensitivity of approximately 69.64% and a specificity of approximately 44.44%.

Based on spectral components of heart rate variability (HRV), frequency analysis was performed in paper proposed by M. Schrader et al. [9] to detect sleep apnea. Using Fourier and Wavelet Transformation with appropriate application of the Hilbert Transform, the sensitivity was 90.8%.

In M. Mendez et al. [10], a bivariate autoregressive model was used to evaluate beat-by-beat power spectral density of HRV and R peak area, where the sleep apnea classification results showed accuracy higher than 85%.

The study in B. Xie et al. [11] assesses the analysis of various feature sets and a combination of classifiers based on the arterial oxygen saturation signal measured by pulse oximetry (SpO2) and the ECG in order to evaluate sleep quality.

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%.

In Laiali Almazaydeh et al. [12], had developed and validated a Feed forward neural network (BPN) using SpO2 measurements obtained from pulse oximetry to predict OSA. The results show performance of 85% and high diagnostic performance with an
accuracy of 93.3% correct detection rate (sensitivity 87.5% and specificity 100%).

iii) METHODOLOGY

Database- The database for SpO2 and ECG signals are collected from SRMC- Medical University Hospital.

SpO2 signal- SpO2 is the amount of oxygen being carried by RBC (red blood corpuscles). It can be defined as the ratio of oxyhaemoglobin to the total concentration of haemoglobin present in the blood.

Figure 1. Filtered SpO2 signal

The above graph is a filtered SpO2 signal where x-axis represents time in ms and y-axis denotes the amplitude of the signal in volts. The SpO2 signal is obtained from the main ECG signal after it has been separated. The main ECG signal is separated into SpO2 and ECG signal.

ECG signal- ECG is a trans-thoracic interpretation of the electrical activity of a human heart. It is detected by electrodes which are attached to the outer surface of the skin and recorded by a device kept outside the body. The recording thus produced is termed as electrocardiogram.

Figure 2. Filtered ECG signal

The above graph is a filtered ECG signal with one RR peak. This signal is obtained from the main ECG signal after it is separated into SpO2 and ECG signal at a frequency of 128 Hz.

Work Flow-

Figure 3. Work flow
First we take an ECG signal. Then we separate SpO2 and ECG signal from the main ECG signal. Using Back Propagation Neural Network (BPN), we extract the features of the signals. We train the BPN network. Then we take an ECG signal for testing and give it to the BPN network to check whether the patient is suffering from OSA or not.

iv) RESULTS

After separating SpO2 and ECG signal from the main ECG signal, we extract the features of the signals using Back Propagation Neural Network (BPN). The features are delta index, oxygen indices, mean, standard deviation, variance, median, mode, and covariance. The resulting graph for delta index is given below:

The resulting graph for oxygen indices:

The mean, standard deviation, variance, median, mode, covariance of ‘input ECG signal’ is listed below:

<table>
<thead>
<tr>
<th>Feature</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>127.6464</td>
</tr>
<tr>
<td>standard deviation</td>
<td>24.5602</td>
</tr>
<tr>
<td>Variance</td>
<td>603.2025</td>
</tr>
<tr>
<td>Median</td>
<td>124</td>
</tr>
<tr>
<td>Mode</td>
<td>124</td>
</tr>
<tr>
<td>Covariance</td>
<td>603.2025</td>
</tr>
</tbody>
</table>

The mean, standard deviation, variance, median, mode, covariance of ‘filtered ECG signal’ is given below:

<table>
<thead>
<tr>
<th>Feature</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.1937</td>
</tr>
<tr>
<td>standard deviation</td>
<td>5.0469</td>
</tr>
<tr>
<td>Variance</td>
<td>25.4716</td>
</tr>
<tr>
<td>Median</td>
<td>0</td>
</tr>
<tr>
<td>Mode</td>
<td>0</td>
</tr>
<tr>
<td>Covariance</td>
<td>25.4716</td>
</tr>
</tbody>
</table>

Table 1. input ECG signal

Table 2. filtered ECG signal
covariance of ‘SpO2 signal’ is given below:

<table>
<thead>
<tr>
<th>SpO2 signal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
</tr>
<tr>
<td>standard deviation</td>
</tr>
<tr>
<td>Variance</td>
</tr>
<tr>
<td>Median</td>
</tr>
<tr>
<td>Mode</td>
</tr>
<tr>
<td>Covariance</td>
</tr>
</tbody>
</table>

**Table 3. SpO2 signal**

The mean, standard deviation, variance, median, mode, covariance of ‘filtered ECG signal with RR peak’ is given below:

<table>
<thead>
<tr>
<th>Filtered ECG signal with RR peak</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>mean</td>
<td>280.3929</td>
</tr>
<tr>
<td>standard deviation</td>
<td>172.9344</td>
</tr>
<tr>
<td>variance</td>
<td>2.9906e+004</td>
</tr>
<tr>
<td>median</td>
<td>264.7266</td>
</tr>
<tr>
<td>mode</td>
<td>1.1719</td>
</tr>
<tr>
<td>covariance</td>
<td>2.9906e+004</td>
</tr>
</tbody>
</table>

**Table 4. filtered ECG signal with RR peak**

After the BPN is trained, we take an ECG signal of a patient for testing and directly give to the trained BPN network to check if he/she is suffering from OSA or not. The result is positive and the accuracy obtained by the method is **97.3154%**.

```matlab
>> ANNClassification(Delta,phi1,100,D,S,As,00); NORMAL
Accuracy in percentage
97.3154
```

v) CONCLUSIONS AND FUTURE DIRECTIONS

The accuracy of the proposed system gives a better result than the existing system. The accuracy of the existing system is 93.3% whereas the accuracy for the proposed system is 97.3154%.
In this work, we discussed about the possibility of the detection of obstructive sleep apnea from the SpO2 and ECG signal features.

This study has resulted into a high performance and an improved accuracy of the Neural Network.

A future direction to this work is to apply our methodology to a larger population to validate the results.

vi) REFERENCES


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