REVIEW ON EFFICIENT CLASSIFIER FOR THE DETECTION OF SLEEP APNEA

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Abstract- Sleep disorders are the most common condition of health and can affect various aspects of life. One of the serious sleep disorders is sleep apnea (SA), which causes the breathing to start and stop repeatedly during sleep. In many countries this kind of condition is normally studied by the conventional detection procedure called Polysomnography in sleep laboratories. Most apnea disease is currently not properly analyzed due to high test cost and overnight sleep limitations in laboratories where an expert human observer is needed to work overnight. Multiple methods were proposed to detect the physiological signals which are analyzed automatically by different algorithms. The different techniques used in the proposed methodology are used to detect the minute Electrocardiogram (ECG) based SA study of the signal processing. Using the Physionet apnea ECG database, pan Tompkins algorithm detects QRS complex. Feature such as Mean , Standard deviation and covariance are drawn from the QRS complex output. The classification algorithm is based on Decision tree and student's t-test was used from the extracted features to distinguish apnea and non-apnea cases. MATLAB framework is the software method used for the effective classifier for sleep apnea detection. The methodology's main aim is to find the efficient classifier for the detection of sleep apnea.

Keywords: -*Sleep apnea, Electrocardiogram (ECG), QRS complex, Support Vector Machine (SVM).*

I INTRODUCTION

The general concept of sleep apnea is the absence of breathing during sleep. Sleep apnea is typically classified into two main groups- obstructive and central. Obstructive sleep apnea (OSA) is characterized by irregular breathing delays during sleep, caused by upper airway obstruction or collapse. It is usually followed by a decrease in the concentration of blood oxygen, which contributes to sleep waking to breathe.

Central sleep apnea (CSA) is a neurological disease that causes the loss of all respiratory activity during sleep, and is typically often characterized by reductions in saturation of blood oxygen. Mixed sleep apnea combines both CSA and OSA components, while spontaneous treatment of the OSA portion frequently leads to improvement in CSA condition as well.

Obstructive sleep apnea (OSA) is a potentially severe sleep disorder where breathing is interrupted repeatedly during sleep when the throat muscles relax intermittently and block your upper airway. This type of apnea happens while sleeping. An apnea is defined as the complete 10-second or greater cessation of breathing.

Snoring is a common symptom of obstructive sleep apnea.

Common sleep apnea symptoms include prolonged daytime sleepiness, heavy snoring, recurrent periods of breathing cessation during sleep, sudden awakenings followed by gasping or trembling, waking with a dry mouth or sore throat, morning headache, trouble focusing throughout the day, mood changes such as depression or irritability, high blood pressure, sweating during night.

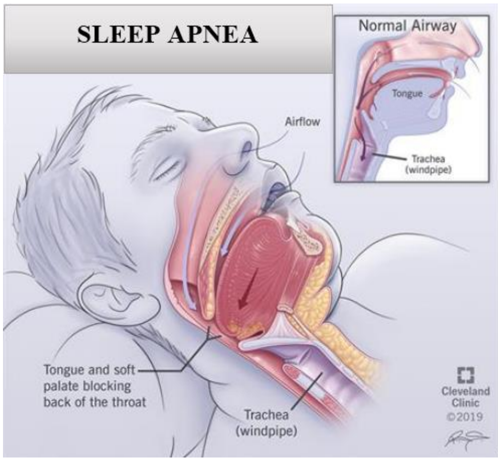

Figure 1.1: Schematic of the causes of SA

II BACKGROUND SURVEY

A literature review has been undertaken which covers papers published between 20013 and 2018. The search was performed using the IEEE explorer, literature cited in the papers and numerous journals included.

Jarvis et al.[1] suggested that the sleep apnea disorder be based on their Electro-Cardiograms (EGCs). The approach is a simple algorithm using the characteristics present in the ECG spectrogram. Additionally describe extensions that allow evaluation of whether a subject experiences apnea on a minute-by - minute basis. Recognition rates are reached for the screening of patients with apnea up to 91 per cent and 84.55 per cent for minute by minute quantification. This means that the intrinsic dynamics of the system , which controls the heart of the cardiac cycle during apnea, change. This paper outlines a tool that could be clinically applied to classify patients with SA

Chazal et al.[2] proposed a method for the automatic electrocardiogram (ECG) processing to detect obstructive apnea. The system screens single-lead ECG night time recordings for the occurrence of severe sleep apnea and offers a minute-by - minute study of disordered respiration. A broad independently tested collection of 70 ECG recordings obtained from normal subjects and subjects with obstructive and mixed sleep apnea was used in the study, each of approximately eight hours in length. Of such recordings, 35 were used for training and 35 were retained for independent research.A broad variety of features were considered based on pulse cycles and a respiratory signal derived from the ECG. Comparison was made of classificators based on linear and quadratic discriminants. To optimize classifier performance, feature selection and regularization of classifier parameters were employed. Results show that a 100 percent success rate and a minute-by - minute classification accuracy of over 90 percent could separate the normal recordings from the apnea recordings.

Marcos et al[3] proposed a new entropy measure known as kernel entropy (KerEnt), which quantifies the irregularity in a series, to be applied to recordings of nocturnal oxygen saturation (SaO2). The study included a total of 96 participants suspected of having sleep apnea- hyponea syndrome (SAHS): 32 SAHS-negative participants and 64 SAHS-positive subjects. Their SaO2 signals were handled separately, using KerEnt. Our findings show that SAHS-positive subjects are associated with a greater degree of irregularity. Statistical analysis showed important differences between SAHS-negative and SAHS-positive community KerEnt values.The diagnostic utility of this parameter has been studied through the analysis of the receiver operating characteristic (ROC). A Correct description Of 81.25 percent (sensitivity 81.25 percent and specificity 81.25 percent). Repeated apnea during a sleep raises SaO2 data irregularity. KerEnt can measure that effect to detect SAHS

Xie et al[4] proposed that, in order to find an effective and reliable alternative to polysomnography (PSG), this paper explores real-time detection of sleep apnea and hyponea syndrome (SAHS) by electrocardiograph (ECG) and peripheral oxygen signal saturation, individually and in combination. In our work on classification we provide ten machine learning algorithms. It is shown that in terms of diagnostic capability our proposed SpO2 features outperform the ECG features. More specifically , we propose a combination of classifiers to further enhance the efficiency of classification by harnessing the complementary knowledge given by individual classifiers.With our selected SpO2 and ECG apps, the classifier combination using Ada Boost with Decision Stump, Bagging with REP Tree, achieves sensitivity, precision and accuracy for a minute real-time SAHS detection over approximately 82 percent.
Total overnight recordings of 25 sleep-disordered-breathing offenders.

Braojos et al[5] indicated that wireless sensor nodes have recently been developed to provide a reasonable amount of computational power, so that sophisticated algorithms for signal processing can now be implemented even in these extremely low power platforms. WSNs' increasingly popular area of operation is telehealth care, which facilitates the continuous monitoring of subjects even outside of the medical setting. In recent years , the design of solutions for automated and remote electrocardiogram analysis (ECG) has drawn significant research interest, and various algorithms have been proposed to delineate normal and abnormal heart rhythms.They tested some of the most effective strategies to filter and delineate the ECG signal. A 78.5 per cent accuracy was achieved.

Koley et al[6] presented a novel methodology for adaptive, real time sleep apnea monitoring, suitable for portable devices used in home care applications. With the assistance of the Oronasal airflow signal, this approach detects apnea or hypopnea events and seeks to follow clinical expectations in the apnea gravity evaluation process.This uses an adaptive two stage classifier model that is dynamically combined to diagnose apnea or hypopnea events based on individual breathing patterns. For event detection, Optimum range of time , frequency and nonlinear measurements, derived from overlapping segments of typical 8s were fed to help vector-based classifier model to classify potential segment origin, i.e., whether from usual or abnormal (apnea / hypopnea) episodes, and then the classifier model 's decision on the time sequenced successive segments was used to detect the occurrence. On clinical testing online the efficiency of the proposed real-time algorithm is validated. Average accuracies of hypopnea, apnea and combined event detection were found to be 91.8 percent, 94.9 percent and 96.5 percent respectively as compared to polysomnography-based respective indices on unseen subjects during online study, which are very appropriate.

Fan et al[7] have proposed an effective method for detecting obstructive sleep apnea (OSA) in real time from the frequency analysis of ECG-derived respiratory (EDR) and heart rate variability (HRV). Compared to conventional polysomnography (PSG), which involves multiple measured physiological signals from patients, the proposed method of detection of OSA uses only ECG signals to assess the time interval of OSA. In this report, the simplified Lomb Periodogram is used to perform the frequency analysis of EDR and HRV in order to be feasible to implement in hardware to achieve the real-time detection and portable use.The experimental results of this study suggest that the overall accuracy can be effectively improved by combining the EDR and HRV indexes with Specificity (Sp) values of 91%, Sensitivity (Se) values of 95.7%, and Accuracy of 93.2%.

Pinho et al.[8] presented an appropriate and efficient implementation for the detection of minute-based sleep apnea analysis by Electrocardiogram (ECG) signal processing. To obtain the Heart Rate Variability (HRV) and the ECG-derived respiration (EDR) a median filter was applied to the recordings using the Physionet apnea-ECG database. The subsequent extracted features were used for artificial Neural Network (ANN) preparation, testing , and validation. Training and testing sets were obtained by dividing the data randomly until a k-fold cross validation achieves good performance. This promising early stage result could lead to complementary studies including alternative selection methods of features and/or other model of classification. The study outlined an ECG-based model for detecting minute-based sleep apnea analysis. It was observed that the qualified network showed suitability, feasibility and precision for sleep apnea detection according to the findings provided. The ANN classification has sufficient accuracy for the detection and diagnosis of sleep apnea (82.120 per cent), according to results

Sopic et al[9] intended that continuous monitoring of cardiovascular disease patients, and in particular myocardial infarction (MI), would put a substantial burden on health care facilities and government budgets. The rise of wearable devices soothes this burden, allowing long-term monitoring of patients in ambulatory settings. One of the biggest challenges in this area is designing wearable ultralow-energy devices for long-term monitoring of vital signs of patients. In this work, we present a technique of classification based on real-time event-driven vector support machines (SVM) and statistical outlier detection.

Chaiwisood et al[10] developed health monitoring systems and smart home projects for the elderly so that they can live as much as possible independently of themselves. This work aims to create a small system capable of transmitting signals and electrocardiogram (ECG) to monitor the elderly 's movement including warnings of fall incidents. The ECG R- peak detection algorithm consists of preprocessing the signal and the sensitivity of the ECG beat detector is 69.9% and the specificity is 90%.

Haitham et al[11] proposed a classifier for supporting vector machines (SVM), using a linear and second-order polynomial kernel. The respiratory features had the highest sensitivity for the minute classification while the highest specificity was provided by the oxygen saturation. The performance of the polynomial kernel was always better and the highest accuracy of 82.4 percent (Sen: 69.9 percent, Spec: 91.4 percent) was achieved with the combined feature classifier. For topic classification, the polynomial kernel had a significant increase in the accuracy of oxygen saturation as both the oxygen saturation (Sen: 100%, Spec: 90.2%) and the combined function (Sen: 91.8%, Spec: 98.0%) achieved the maximum accuracy of 95%.Further analysis of the SVM with certain types of kernels may be useful to customize the classifier with the proper features for an OSA automatic detection algorithm.

Hummel et al[12] used a reported breath sound from 29 patients which isolated 45 segments with obstructive only and 40 segments with central respiratory only. Afterwards, 10 acoustic characteristics were extracted and used to classify the essential breath sounds: inspiration, expiration, and snoring. The basic sounds were extracted from a 2nd set of 6 sound-specific features, designed based on SA pathophysiology. Using a leave-one-out cross validation scheme, these 6 functions were used to train and evaluate a linear SVM classificator. The outstanding 91.8 per cent accuracy was achieved.

Gopal et al[13] suggested a T-test method for selecting the function from the RR and QRS complex intervals. A Neuro Fuzzy detection method has also been introduced to reduce the classification of misses. A neurofuzzy method is a flippant learning that uses learning algorithms derived from the theory of neural networks. The required ECG signal is taken from the database at Physionet. In analyzing sleep apnea, the artificial intelligence based detection method reduces the false positive rate. The accuracy of the test classifiers was 88%, 76.7%.

Garcial et al[14] suggested a method for diagnosing OSA is polysomnography (PSG) but this technique involves a great deal of resources, such as a complex signal collection system and the involvement of a diagnostic specialist. For the experiments the RR sequence obtained from the electrocardiogram is used. An adaptive filtering procedure is applied for automatic removal of artefacts. Epochs of five minutes are used to extract characteristics from the RR intervals. Depending on the domain they were derived, features may be divided into three classes. The accuracy obtained was 0.88 with the aid of Logistic Regression, the sensitivity is 67.9 percent, and the specificity is 90 percent.

Rezaei et al[15] The detection of sleep apnea using parameters derived from the ECG is non-invasive and cheap. The ECG-derived features that are to be used in conjunction with existing standard features to improve sleep apnea detection. The features they provided were derived from the use of Poincare RR interval plots. Global features are based on the number of points in Poincare plot above, below and the identity line. In addition, local features are based on point-to - point variations with respect to the identity line (i.e., Poincare plot time information).

IV RESULT

Author	Database	Approach: Features	Approach: Classifier	Accuracy (%)	Sensitivity (%)	Specificity (%)
Maier et al [4]	MIT-BIH Arrhythmia	Time	-	85.5	-	-
		Mean				
Chazal et al [8]	MIT-BIH Arrhythmia	Polynomial Kernel	Linear SVM Classifier	90	78.5	-
Marcos et al [12]	European Sleep Apnea	Polysomnography	-	81.25	81.25	81.25
Koley etal[15]	MIT-BIH Arrhythmia	Polysomnography	-	91.8	-	-
Fan et al [16]	Myocardial Infarction	Frequency Analysis of EDRand HRV	-	93.2	95.7	91
Pinho et al [20]	MIT-BIH Arrhythmia	Time Domain-Median	Neural Network Classifier	82.12	-	75
Sopic et al [23]	Myocardial Infarction	Frequency Domain-Mean, Median	SVM Classifier	90	-	-
Chaiwisood et al [25]	European Sleep Apnea	R Peak Detection	-	65.8	-	-
Haitham et al [26]	MIT-BIH Arrhythmia	Polynomial Kernel	SVM Classifier	95	98	90
Hummel et al [27]	Myocardial Infarction	Time Domain-Mean	Linear SVM Classifier	91.8	-	-
Gopal et al [28]	MIT-BIH Arrhythmia		T Test Method ,Fuzzy Classifier	85.4	73.5	-
Garcial et al [29]	Physionet	Polysomnography	-	88	67.9	-
Rezaei et al [30]	Physionet	Poincare Plot	SVM	88.89	77.7	100

V CONCLUSION

The results showed that the trained network was appropriate, feasible and reliable for an effective classifier for sleep apnea detection. For various classifiers and feature extraction techniques, the average accuracy obtained for almost all papers included in the literature is 88.2 percent, 83.2 percent, etc. By taking into account all the results obtained from the literature papers, we conclude that the proposed methodology for an efficient classifier for sleep apnea detection is to obtain more accuracy than the present techniques.

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