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Sleep Apnea Syndrome Detection Techniques Using ECG Signal Recordings – A Survey Approach

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Abstract— A type of sleep disorder or syndrome which is characterized by the breaks in respiratory breathing process or occurrences of uncommon or superficial breathing during sleep is called sleep apnea disorder. Since for the last few years various signals [such as Polysomnographic signals, EEG signals, Respiratory signals, ECG signals etc] have been used for the detection of sleep apnea syndrome or disorder. But ECG signal recordings have been found effective and efficient for the diagnosis process. Various models and algorithms have been developed using ECG signal recordings to detect sleep apnea disorder. This paper focus on the survey of different techniques developed to detect sleep apnea disorder and a comparative analysis has been prepared between the different techniques used.

Keywords— Sleep, ECG, Sleep Apnea, RR interval, epochs, classifier.

I. INTRODUCTION

A. Sleep and Sleep Apnea

Sleep may be stated as naturally reiterate resting state of human body during which suspension of consciousness takes place. Sleep represents a composite, highly coordinated pattern of distinct physiological variables [1]. Polysomnography [PSG] is a method which used to describe physiological sleep and the different stages of physiological, for the diagnoses of various types of disorders of sleep which includes restless legs syndrome, narcolepsy, parasomnias REM behavior disorder and sleep apnea [1, 2].

Sleep apnea is defined as the blockage of complete or near complete airflow for at least10 seconds. Sleep apnea consists of three types: Central, Obstructive and Mixed. In Central sleep apnea interruption of breathing occurs by the lack of respiratory effort. In Obstructive sleep apnea interruption of breathing occurs by the physical blockage of airflow in spite of respiratory effort. Mixed sleep apnea is the combination of both obstructive and central sleep apneas. In mixed sleep apnea, transition from obstructive to central features takes place during the events of apnea [3].

Sleep apnea is identified as a problem by others witnessing the apnea affected individual during its occurrences or is suspected due to its bad effects on the human body [4]. Most of the sleep apnea cases go undiagnosed because of the operating cost, inconvenience and unavailability of diagnosis and testing machines. So there are many methods developed which uses the features of ECG signal for the detection of sleep apnea. As ECG signal recording is one of the well-organized and easier technologies for the detection of sleep apnea disorders.

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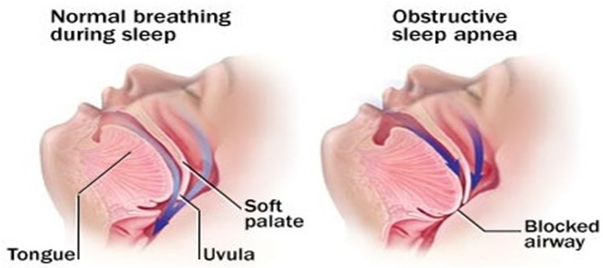

Fig. 1 Normal airway and Obstructive sleep apnea [2]

II. ELECTROCARDIOGRAM [ECG]

The ECG is a very diagnostic tool which is designed for the recording of the electrical activity of the heart which happens due to the depolarization and repolarization of the heart chambers named as atria and ventricles [5]. The ECG signal recording is measured by putting the electrodes on the human body in the designed pattern. The information produced by ECG machine gets plotted on the specially designed ECG paper containing small squares. ECG recordings are analyzed by a heart cardiologist who can examine the characteristics and features of the ECG signal to extract the information regarding the status of the patient's heart and diagnosis the disease if the patient have.ECG recording signal mainly contains the PQRST waves in the single normal cardiac cycle [6]. The very first wave is the P wave which corresponds to the atrial depolarization, the second wave is the Q wave which corresponds to the septal depolarization, the third and the largest wave is the R wave which corresponds to the ventricular depolarization and the fourth wave is the S wave which corresponds to the depolarization of the Purkinje fibers. The fifth wave is the T wave which depicts the ventricular repolarization. Sometimes ECG recording consists of U wave which occurs when the ECG machine picks up the repolarization of Purkinje fibers [7].

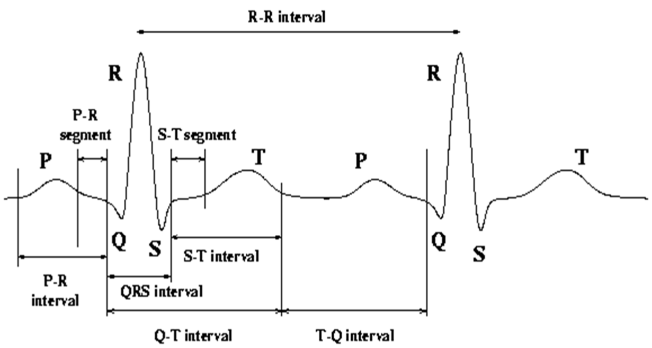

Fig. 2 Basic ECG Waveform [5]

III. RELATED WORK DONE TILL NOW

Over the last few years, various methods have been developed for diagnosis of sleep apnea disorder. Various statistical features and characteristics of different signals such as the thorax and abdomen effort signals, nasal air flow, oxygen saturation, acoustic speech signal, electroencephalogram(EEG) i.e. electrical activity of the and electrocardiogram[ECG] i.e. electrical activity of the heart are usually used for the detection of sleep apnea disorder[8].

P de Chazal et al [9] developed a method which investigates automatically the prediction of epochs of sleep apnea from the ECG signal. The author used linear Discriminates classifier model to classify the features that were derived from the ECG signal. The Philipps-University database of sleep apnea was used for the analysis. The features considered for the analysis were Mean

RR interval, First and second serial correlation coefficients of the RR intervals ,Standard deviation of the RR interval, Other time domain measures of RR intervals such as NN50 and pNN50, Mean PR interval , Allan variance of the RR intervals evaluated at various time scales, 0 Standard deviation of the PR intervals ,0 Count- [or rate-]-based spectrum of the RR intervals, 0 Interval based spectrum of the RR intervals, Serial correlation coefficients of the PR intervals ,0 R-wave amplitude spectrum for the analysis. It was found that features based on the power spectral density estimates of RR intervals and R wave maxima to be the most analytical. Results of this classification gave accuracy of approx. 89%.

Martin O. Mendez et al [10] proposed a bivariate autoregressive model to measure beat-by-beat power spectral density of HRV and R peak area. The model was applied on the Physionet database. K-Nearest Neighbor (KNN) classifier was used for classify events of apnea from the normal ones, on a min-by-min basis for each recording. Analysis data were divided into two sets, testing and training set with 25 recordings each. The results obtained from classification gave accuracy greater than 85% in both testing and training.

Daniel Álvarez et al [11] studied that oxygen saturated blood (SaO_2) and the electroencephalogram (EEG) signal recordings could help in providing integral information for the diagnosis of the obstructive sleep apnea (OSA) disorder. Parameters that were based on the relative power in specified bands band of frequency [i.e. Af-band] or peak amplitudes [PA] were used to distinguish the frequency content of EEG and SaO_2 signal recordings. Further, the spectral entropy (SE) and the median frequency (MF) were also applied to obtain the additional spectral information. The author applied a forward stepwise logistic regression (LR) procedure with cross validation leave-one-out to acquire the optimal spectral set of features. Two features extracted from the oximetric spectral analysis (i.e. PA and MFsat) and three features extracted from the EEG spectral analysis (i.e. Adelta, Aalpha and SEeeg) were selected automatically and provide 83.3% specificity , 91.0% sensitivity and 88.5% accuracy.

Ahsan H. Khandoker et al [12] used wavelet analysis based features of ECG signal recording to detect sleep apnea index (AI) or hyperpnoea index (HI). Total of 82535 epochs of ECG with each of 5-s duration while normal breathing during sleep, 1638 epochs of ECG while 689 hyperpnoea events, and 3151 epochs of ECG while 1862 events of apnea were collected from 17 apnea affected patients in the training set. Two staged feed forward neural network model was chosen which used ECG signal recoding features with the technique of leave one patient, out cross-validation. During first stage, events [hyperpnoea and apnea] were classified from events of normal breathing. During second stage, hyperpnoea were classified from sleep apnea. Test was performed on 16 subjects independently. The independent test and cross validation accuracies of hyperpnoea and apnea detection were approx 76.82% and 94.84% respectively.

Lorena S. Correa et al [13] proposed a detection method which was based on spectral analysis was applied on the three ECG derived respiratory (EDR) signals. These were derived from R wave area [i.e. EDR1], heart rate variability [i.e. EDR2] and the R peak amplitude (i.e.EDR3) of ECG signal recordings in 8 patients having sleep apnea disorder. The central, mean, first and peak frequencies were determined from the spectrum at every min for each EDR signal. A threshold-based decision was made for each frequency parameter on every one min segment of the three EDR signals. When the value of its frequency was below a set threshold level then classified it as 'sleep apnea' otherwise 'not sleeps apnea'. Results obtained show that EDR1, (based on R wave area) gave better performance in diagnosing apnea with sensitivity and specificity near about 90% while EDR2 [based on heart rate variability] gave similar specificity but lower sensitivity (approx. 78%) and EDR3 (based on R peak amplitude) gave lowest sensitivity and specificity near about 60%.

A.F. Quiceno-Manrique et al [14] used heart rate variability analysis for the diagnosis of sleep apnea, due to the fluctuations produced by oxygen saturation present in blood which cause variations in the rate of heart. With the help of implementing time frequency analysis distribution such variations present in the rate of heart could be assessed which belongs to Cohen's class. In this paper, dynamic features were extracted from the time frequency distributions for detecting obstructive sleep apnea using ECG signals which were recorded while sleeping. A methodology was applied to determine the pertinence of each and every dynamic feature, before implementing knn classifier which was used to detect the pathologic and normal signals. The proposed method in the paper can be used as a diagnostic tool for diagnosis of OSA with very good accuracy of up to 92.67%.

Sidik Mulyono et al [15] proposed a regression model to recognize sleep apnea disorder with the help of principal component regression (PCR) analysis. The author tried to model correlations between 11 input features linearly [which were the analytical values extracted from beat intervals of heart in ECG signal recordings], and the apnea hypo apnea index (AHI) that gave three levels of patient i.e. normal, middle apnea and heavy apnea. The results demonstrated that the interaction value of R and RMSE approx. gave 79.5% accuracy.

Sani M. Isa et al [16] used Electrocardiogram (ECG) signal to detect sleep apnea by implementing in Principal Component Analysis (PCA) classifier. The input was RR intervals per epoch statistics with 1 minute duration. The features which were proposed by Chazal and Yilmaz were transformed from combination to orthogonal features with the help of PCA. While selecting model random sampling, Cross validation, and train data were tested. The results obtained using classification using Naïve- Bayes classifier, kNN classifier, and Support Vector Machine (SVM) classifier showed that features produced by PCA gave better performance accuracy as compared to features which was proposed by Chazal and Yilmaz. The results showed that the Chazal features were linear, but PCA and Yilmaz features were non-linear. The QRS detection process gave an average accuracy of determining RR-interval was 99.54%.

Majdi Bsoul et al [17] proposed a real time sleep apnea monitoring system called 'Apnea Med Assist" for detecting obstructive sleep apnea events with a high accuracy for both clinical care and home applications. The fully developed automated system used single channel ECG of patient to extract sets of features and used the support vector machine classifier (SVC) for the detection of sleep apnea events. The "Apnea MedAssist" was implemented on the android platform based on smart phones, used either the subject dependent SVC model or general adult subject independent SVC model and achieved a sensitivity of 96% for the subject independent SVC.

Laiali Almazaydeh et al [18] proposed an automated classification algorithm which evaluate epochs of short duration of the electrocardiogram (ECG) data. This algorithm was based on support vector machines (SVM) classifier and had been trained and tested on recordings of sleep apnea on subjects having OSA or not having OSA. The Physionet database of Apnea ECG signals was used for the analysis. The algorithms were implemented in MATLAB toolset. The results produced from this algorithm showed high accuracy of approx. 96.5%.

Baile Xie et al [19] used 10 machine learning algorithms to detect real time sleep apnea and hypopnea syndrome which were based on electrocardiograph (ECG) signal recordings and saturation of peripheral oxygen (SpO_2) signals, both in combination and individually. The author proposed a combination of classifiers to further increase the performance of classification by applying the corresponding data obtained from the different classifiers individually. The author used St. Vincent's University College/ University Hospital Dublin Sleep Apnea Database (CD database) for the detection of sleep apnea. The combination of classifier using AdaBoost with Bagging with REPTree ,Decision Stump, and either Decision Table or kNN achieved specificity, sensitivity and accuracy all around approx 82% for a min based real time sleep apnea and hypopnea syndrome detection.

Carolina Varon et al [20] used four easily measureable features. Three features were generally used before but fourth feature were newly proposed in the paper. From the three well known features, two were measured from the time series of RR interval and another one from the approx. respiratory signal which was derived from the ECG with the help of principal component analysis (PCA). The fourth and new feature was proposed in this paper and it was computed with the help of the principal components of the QRS complexes. RBF kernel in the least squares support vector machines [LS-SVM] classifier, these four features used gave an accuracy on the Physionet database of apnea higher than 85% for a independent classification subject, and higher than 90% in case of specific approach of patient.

TABLE 1 COMPARATIVE ANALYSIS BETWEEN DIFFERENT TECHNIQUES USED

Author	Year	Paper Title	Results
P de Chazal et al [9]	2004	Automated Detection of Obstructive Sleep Apnea at Different Time Scales Using the Electrocardiogram	classification accuracy of approx. 89%
Martin O. Mendezet al [10]	2007	Detection of Sleep Apnea from surface ECG based on features extracted by an Autoregressive Model	Classification accuracy was greater than 85% in both testing and training data
Daniel Álvarez, et al [11]	2009	Spectral analysis of electroencephalogram and oximetric signals in obstructive sleep apnea diagnosis	forward stepwise logistic regression (LR) procedure provided 83.3% specificity , 91.0% sensitivity and 88.5% accuracy
Ahsan H. Khandoker et al [12]	2009	Automated Scoring of Obstructive Sleep Apnea and Hypopnea Events Using Short-Term Electrocardiogram Recordings	The independent test and cross validation accuracies of hyperpnoea and apnea detection were approx 76.82% and 94.84% respectively.
Lorena S. Correa et al [13]	2009	Sleep Apnea Detection based on Spectral Analysis of Three ECG - Derived Respiratory Signals	EDR1, (based on R wave area) gave better performance- with sensitivity and specificity near about 90% EDR2 (based on heart rate variability) gave similar specificity but lower sensitivity (approx. 78%) EDR3 (based on R peak amplitude) gave lowest sensitivity and specificity near about 60%.
A.F. Quiceno-Manrique et al [14]	2009	Detection of obstructive sleep apnea in ECG recordings using time-frequency distributions and	Accuracy of up to 92.67%.

		dynamic features	
Sidik Mulyono et al [15]	2010	Principal Component Regression Analysis on Automatic Sleep Apnea Detection from ECG Data	correlation value of R and RMSE approx. gave 79.5% accuracy
Sani M. Isa et al [16]	2011	Sleep Apnea Detection from ECG Signal: Analysis on Optimal Features, Principal Components, and Nonlinearity	PCA gave better performance accuracy in determining RR-interval was approx 99.54%
Majdi Bsoul et al [17]	2011	Apnea MedAssist: Real-time Sleep Apnea Monitor Using Single-Lead ECG	“Apnea MedAssist” provided sensitivity of 96% for the subject independent SVC
Laiali Almazaydeh et al [18]	2012	Detection of obstructive sleep apnea through ECG signal features	Automated classification algorithm gave high accuracy of approx. 96.5%.
Baile Xie et al [19]	2012	real time sleep apnea detection by classifier combination	Achieved specificity, sensitivity and accuracy all around approx 82% for a min based real time sleep apnea and hyperpnoea syndrome detection.
Carolina Varon et al [20]	2013	Sleep apnea classification using least-squares support vector machines	least squares support vector machines (LS-SVM) classifier, gave an accuracy on the Physionet apnea ECG database higher than 85% for a independent classification subject, and higher than 90% in case of specific approach of patient.

IV. CONCLUSIONS

In this survey approach, various automated algorithm, models and techniques for the detection of sleep apnea syndrome episodes with the help of ECG signal recordings have been studied. This survey approach helps in selecting the best detection model or algorithm for the diagnosis of sleep apnea disorder events with the highest specificity, sensitivity and accuracy. For the same purpose a comparative analysis has been prepared between the different methods used.

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