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Various Methods for Identification of Obstructive Sleep Apnea Using Electrocardiogram Features

Remalli Rohan[1*], D. Santhosh Kumar [1], and Srinivasa Rao Patri[1]

[1]Dept. of E.C.E, VNR VJIET, Telangana, India.
remallirohan@gmail.com, santhoshkumar_d@vnrvjiet.in, srinivasarao_p@vnrvjiet.in

Abstract: **Sleep is critical to health and well-being. Poor quality sleep is analogous with a wide range of negative outcomes ranging schizophrenia to cardiovascular syndromes. Sleep disturbances may increases several unresponsive outcomes including daytime sleepiness, degraded cognitive performance, irritability, obesity and depression. Occurrences of breaks in the respiratory breathing process during sleep are called "Obstructive Sleep Apnea". Abundant algorithms and models have been designed, proposed and developed using Electrocardiogram features to detect sleep apnea syndrome. The ECG signal represents the electrical activity of heart. Mostly the cardiac diseases can happen due to sleep apnea which needs to be diagnosed in the critical stage. This survey paper aims to bring the different techniques to identify sleep apnea syndrome by using the ECG features, because ECG features have been found most effective and efficient to detect the sleep apnea disorders. In this paper a comparative analysis has been prepared between the different techniques used.**

Index Terms: **Apnea-hypopnea index (AHI), Electrocardiogram (ECG) features, Heart Rate Variability (HRV), Obstructive Sleep Apnea (OSA) and Sleep.**

I. INTRODUCTION

Sleep is important for psychological and physical recreation. The average life span human sleep is about one-third of their lives. The body cannot function properly without enough sleep. Sleep disorders are a common health condition which can affect countless features of life. Mainly sleep disorders are categorized into 6 types: sleep-related movement disorders, insomnia, sleep-related breathing disorders, circadian rhythm sleep wake disorders, sleep-related movement disorders, parasomnias, central disorders of hyper somnolence [1]. According to the America Academy of Sleep Medicine (AASM) sleep apnea is described as a blockage in airflow lasting for at least 10 seconds, and may occur multiple times per hour [2].

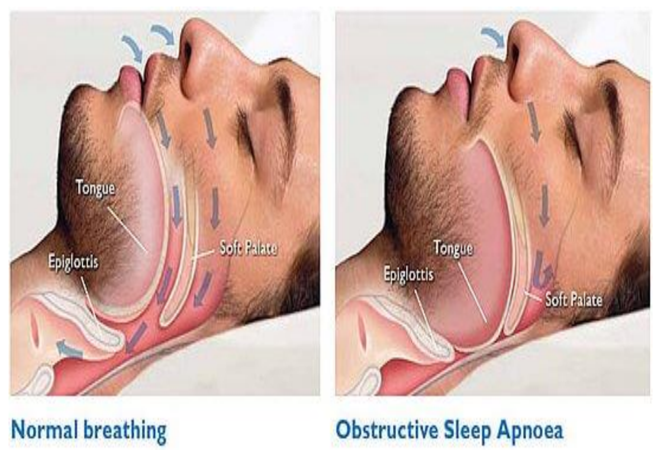

Fig. 1. Normal Breath and Obstructive Sleep Apnea Syndrome Breathing.

Obstructive sleep apnea (OSA) comes under sleep-related breathing disorder as shown in the figure 1 [3]. OSA is a widespread disorder and it is distinguished by a reduction of respiratory breathing airflow during sleep. In many countries this syndrome is generally identified in sleep laboratories by using the polysomnography signals. The polysomnography is the gold standard tool for analyzing the various sleep signals from one to another sleep stages. Various sensors are used to record the signals like Electrocardiogram (ECG), Electroencephalogram (EEG), Electromyography (EMG), Electrooculography (EOG), respiratory signals; blood oxygen saturation, breath airflow, body position and various parameters are collected for the classification of different syndromes.

OSA can be identified if a frequency of obstructive respiratory events is greater than equal to 15 events / hour. In clinical exercise, the intensity of apnea / hypopnea disorder is evaluated using the apnea hypopnea index (AHI). Sleep apnea is further divided as further into 3 categories based on their frequencies: mild OSA ($5 \leq$ AHI <15 events / hour), moderate OSA ($15 \leq$ AHI <30 events / hour) and high OSA (AHI ≥ 30 events/hour) (Fabio Mendonca et al, 2018). Age is also an important risk factor for the enlargement of OSA.

Most of the OSA cases go undiagnosed because of the operating cost, unavailability and testing machines of polysomnography and the whole machine unit cannot be implemented in the home environment. In order to overcome these issues, methods have been developed which uses the features of ECG signal for the identification of obstructive sleep apnea. Long term health issues connected with untreated obstructive sleep apnea are:

- Hypertension
- Obesity
- Depression
- Cardiac arrhythmia
- Myocardial infarction
- Diabetes
- Heart failures
- Stroke
- Worsening of attention deficit hyperactivity disorder (ADHA)

II. Electrocardiogram (ECG)

ECG signals are the most important and powerful tool used to diagnosis and treatment for any heart rate diseases. Any syndrome of heart rate in the morphological samples is the indication of cardio arrhythmia. ECG recordings mainly contain PQRST waves in the signal as shown in the figure2.

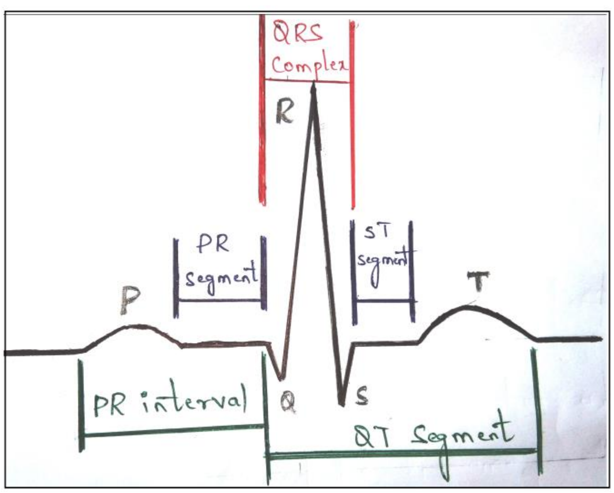

Fig. 2. ECG Waveform.

The very first P wave occurs in the signal which correlates to the atrial depolarization, the second wave is the Q wave which is correspondence to the septal depolarization, R wave is the third and largest wave which resembles the ventricular depolarization, and the fourth wave is the S wave which is correspondence to the depolarization of Purkinje fibers. The last wave is the T wave which is resembles to ventricular repolarization. Sometimes ECG waves also consist of U wave which occurs when ECG machine considers the repolarization of Purkinje fibers [5]. Table1 shows, ECG wave's duration and amplitudes which helps to identify the QRS complexes in the signals

Table- I: ECG Features Amplitudes and Durations

ECG Features	Amplitude (mV)	Duration (ms)
P wave	0.1-0.2	60-80
PR- segment	-	50-120
PR intervals	-	120-200
QRS complexes	1	80-120
ST -segment	-	100-120
T-wave	0.1-0.3	120-160
ST interval	-	320
RR interval	-	(0.4-0.2)s

III. Literature Survey

Over a last few years, various researchers have proposed new methods, algorithms; techniques have been developed for identification of obstructive sleep apnea syndrome. Mostly the database referred are from Physionet apnea-ECG, MIT-BIT Polysomnography, sleep data from various hospitals are listed in the table 2, which gives a brief comparison between the different approaches and performance analysis.

Martin O. Mendez et al, (2007) suggested a bivariate autoregressive model to evaluate beat-by-beat power spectral density of Heart Rate Variability (HRV) and R peak area to detect OSA from ECG based features. This model was applied on the physionet database, data was split into 2 sets of training and testing data and classified the events of sleep apnea syndrome from the normal sleep signal by using the K-NN supervised learning classifier and achieve d a very good results.

Daniel Alvarez et al, (2009) studied that oxygen saturation blood (SAO_2) and electroencephalogram (EEG) signal recordings may help in providing the essential details for the pinpointing the OSA behavior. By considering the classical spectral parameters based on the relative power in specified frequency bands ($A_{f\text{-bands}}$), peak amplitudes (PA), median frequency (MF) and spectral entropy (SE) were applied to obtain the spectral information. Two features [PA and MFsat] of oximetric and 3 features [A_{delta}, A_{alpha} and SE_{eeg}] of EEG spectral analysis were extracted and automatically selected to provide the OSA syndrome performance results.

Ahsan H. Khandoker et al, (2009) by using wavelet based features analysis of ECG signal recordings to identify the obstructive sleep apnea and Hypopnea events. Where total 82535 epochs of ECG, each epochs of 5-s duration during sleep, 1638 epochs of ECG from 689 hypopnea events, 3151 epochs of ECG while 1862 apnea events were collected from 17 patients for the train sets. By using the two-staged feed forward neural networks model and leave-one-patient-out, cross validation were used for training. During the first state of classification events were normal breathing and at 2nd stage hypopnea was classified from the sleep apnea.

Lorena S. Correa et al, (2009) suggested an identification method based on spectral analysis, and applied on the 3 ECG-desired respiratory signals [EDR]. Which are obtained from R wave area [EDR1], heart rate variability [EDR2] and R peak amplitude [EDR3] from the 8 patients. The central, mean, first quartile frequencies were determined from the spectrum every 1 min for each EDR. A threshold based decision was made for each frequency parameter based on the R wave, sensitivity and specificity was 90% was achieved compared to the other parameters.

A.F. Quiceno-Manrique et al, (2009) heart rate variability analysis method is used to identify obstructive sleep apnea in ECG recordings. Fluctuations of oxygen saturation in blood which causes variations presents in the rate of heart, which can be help to implement by means of time-frequency analysis which belongs to Cohen’s class. By using the dynamic features extracted from the time-frequency distribution able to detect the OSA from normal signals.

T Sidik Mulyono et al, (2010) proposed a regression model to identify sleep apnea disorder by using principal component regression (PSR) analysis. And tried to model linear correlations between 11 input features (which are statistical values obtained from heart beat intervals in ECG signal recordings) and AHI (Apnea hypo apnea index) divided into 3 stages of patients (heavy apnea, middle apnea and normal). The results gave 79.5% of accuracy of RSME and correlation value R.

Sani M. Isa et al, (2011) Sleep apnea was detected by using electrocardiogram by implementing principal component analysis (PCA). R-R intervals were given as input, each epoch with 1 min duration. Chazal and Yilmaz proposed combinational features, transformed into orthogonal features with the help of PCA. For model selection cross validation, random sampling and test on train data were used and tested. For classification K-NN, Naïve Bayes and Support vector machine with Radial basis function (RBF) kernel gives the best classification accuracy results.

Majdi Bsoul et al, (2011) proposed a real time sleep apnea monitor system termed as “Apnea Med Assist” for identifying obstructive sleep apnea with a high accuracy for both clinic and home care applications. This developed system uses single lead ECG to extract the set of features and with the help of support vector classifier (SVC) apnea events were detected. This system is also implemented on the android platform based on smart phones.

Laiali Almazaydeh et al, (2012) proposed an automatic classification algorithm which process epochs of short duration of electrocardiogram data. To differentiate the sleep apnea on subjects having OSA or normal breath based on the R-R interval based features and classified by using the SVM classifier and achieved the accuracy of 96.5%.

Baile Xie and Hlaing Minn (2012) used 10 machine learning algorithms to detect real-time sleep apnea and hypopnea disorder based on the electrocardiography (ECG) recordings and saturation of peripheral oxygen (SpO_2) signals both in combinational and individual sets. By using the classifiers combination of AdaBoost with decision stumpy, bagging with REPTree and K-NN. Among these classifiers bagging with REPTree achieved a highest accuracy in detecting the OSA events.

Md Juber Rahman et al, (2018) used 17 time and frequency domain features and nonlinear heart rate variability (HRV) features to identify the severity of OSA events. And also Poincare plot features for detecting the sleep apnea from single lead ECG are used. Philip de Chazal et al, (2003) detected Obstructive sleep apnea from the single lead Electrocardiogram which is an automated processing in identifying the apnea syndrome from normal berating signal. A wide variety of time and frequency domain measurements of HRV are used for the feature extraction from the ECG derived respiratory signals.

Bulent Yilmaz et al, (2010) by extracting the R-R intervals based features and classified the OSA epoch from single lead ECG. Serein AI-Ratrout and Abdulnasir Hossen (2018) proposed a procedure for identification of OSA on the MIT standard database, extracting the features which are depend on wavelet packed decomposition technique of HRV and apnea was classified by using the linear SVM.

Gregoire surrel et al, (2018) developed a hardware sensor device which is wearable, accurate and energy efficient system for monitoring in online and detect the obstructive sleep apnea syndrome on long-term basis. The time domain analysis was computed for sleep apnea score. And the signals were classified as an obstructive sleep apnea by using the SVM classifier. This wearable device can achieve a battery lifetime of days for continuous screening of OSA.

Lili Chen et al, (2014) proposed an automatic-segmentation based screening technique with a single channel of electrocardiogram signal for identification of obstructive sleep apnea. This method is implemented in 3 aspects: first the signal is automatically segmented and local median filter is applied, to eliminate unwanted R-R intervals in the 2nd stage and in last stage the signals are classified by adding additional admission information and plugged into SVM classifier to detect the OSA from normal breathing signal.

Table-II: Comparison of Different Approaches and Performance Analysis of Previous Work

Authors	Data input	Features	Classifiers	Performance results		
				Acc* %	**Sen* %**	**Sep* %**
Martin O. Mendez et al., (2007)	Apnea ECG database Physionet	• Power spectral density of HRV. • R-R intervals.	K-Nearest Neighbor.	> 85	-	-
Daniel Alvarez et al., (2009)	Sleep unit of Hospital, Spain	• Two features from oximetric and three features from EEG spectral analysis.	Forward stepwise logistic regression	88.5	91	83.3
Ahsan H. Khandoker et al., (2009)	Institute of breathing and sleep Austin Hospital	• Events of Hypopnea • wavelet based features of ECG	Two-staged feed forward Neural Networks	94.84	91.68	98.87
A.F. Quiceno-Manrique et al., (2009)	Apnea ECG database Physionet	• Dynamic features like spectral centroid • energy of spectral centroid • cepstral coefficients	K-NN	92.67	-	-
Sani M. Isa et al., (2011)	Data base of ECG signal	• Combinational features of Chazal and Yilmaz	K-NN, Naïve Bayes and Support vector machine with Radial basis function (RBF)	99.54	-	-
Majdi Bsoul et al., (2011)	Apnea ECG database Physionet	• Time domain and spectral domain	SVM	96	-	-
Laiali Almazaydeh et al., (2012)	Apnea ECG database Physionet	• R-R interval	SVM	96.5	92.9	100
Baile Xie and Hlaing Minn (2012)	UCD sleep apnea data base from Physionet	• electrocardiography (ECG) recordings • saturation of peripheral oxygen (SpO_2)	Bagging with REFTree	84.40	79.75	85.89
Md Juber Rahman et al., (2018)	Apnea ECG database Physionet	• 17 features of time and frequency domain • Poincare plot	Ensemble classifier	87.5	100	83.33
Philip de Chazal et al., (2003)	Larger data base of PSG measurements by Philipps university.	• Time and frequency of HRV	Quadratic discriminant	92.5	-	-
Bulent Yilmaz et al., (2010)	PSG recordings	• R-R intervals	K-NN, Quadratic discriminant	89	-	-

			analysis (QDA) and SVM			
M Schrader et al., (2000)	Apnea ECG database Physionet	• heart rate variability, • frequency analysis, • Fourier and wavelet transform	-		90.8	-
Lin et al., (2006)	MIT-BIH database Physionet	• Wavelet transform EEG signal	ANN	-	69.64	44.44
Serein AI-Ratrout and Abdulnasir Hossen (2018)	MIT database	• Wavelet packet decomposition of heart rate variability	Linear SVM	93.34	90	100
Gregoire surrel et al., (2018)	Apnea ECG database Physionet	• R-R intervals • Time domain analysis	SVM	88.2	-	-
Ahsan H. Khandoker et al., (2009)	Apnea ECG database Physionet, Research unit data base and UCD sleep apnea database	• HRV • R-R intervals	SVM	92.85	-	-
Lili Chen et al., (2015)	Apnea ECG database Physionet	• R-R intervals	SVM	97.41	-	-
Hoa Dinh Nguyen et al., (2014)	Apnea ECG database Physionet	• HRV • 72 features of RQA	SVM	84.14	93.74	65.88
Changyue Song et al., (2016)	Apnea ECG database Physionet	• Temporal dependence with segments	Discriminative hidden Markov model	97	-	-
Hong Ji Lee et al., (2013)	13 healthy subjects , data from lab	• QRS features	SVM	98.4	-	-
Zhao Dong et al., (2018)	Apnea ECG database Physionet	• HRV • R-R intervals	-	90.1	88.29	90.5
T. Sunil Kumar and Vivek Kanhangad (2018)	Apnea ECG database Physionet	• Gabor filter responses	Least square SVM	93.31	-	-
Heenam Yoon et al., (2018)	45 healthy subjects from hospital	• R-R intervals From ECG signals	Threshold heuristic rules And 5 fold cross validation	89.97	68.71	93.75
Rajendra Acharya U et al., (2011)	PSG databse	• Approximate entropy • Largest lyapunov	A-NN	90	100	95

		exponent • Hurst exponent • Fractal dimension • Correlation dimension				
Babaeizadesh S et al., (2011)	Sleep health center in Boston	• Peak-to-trough QRS amplitudes and HRV	Receiver operating characteristics-thresholds	71	60	82
Poupard L et al., (2012)	118 patients database	• HRV statistics	Threshold	-	97	72
Richard Singhathip et al., (2010)	26 subjects	• HRV statistics	Receiver operating characteristics-thresholds	93	-	-
Roche F et al., (2004)	28 subjects	• Spectral	Threshold	-	78	70
Ahsan H. Khandoker et al., (2009)	Apnea ECG database Physionet	• wavelet	SVM	100	-	-
Benali Medjahed Oussama et al., (2015)	Apnea ECG database Physionet	• 11-time domain • PCA	SVM	-	96	-
Thomas RJ et al., (2007)	Apnea ECG database Physionet	• spectrograms	Threshold	-	86	95
Liu D et al., (2012)	Apnea ECG database Physionet	• Hilbert huang transform	Receiver operating characteristics-thresholds	79	73	71
Carolina Varon et al., (2015)	Apnea ECG database Physionet and KU Leuven sleep lab	• Wavelet • HRV	Threshold	85	85	85
Maier C et al., (2014)	Apnea ECG database Physionet	• Time-domain features	Threshold	-	86	86
Ciara O'Brien et al., (2007)	UCD sleep disorder clinic	• Spectral and statistics	Linear discriminant	83	79	85

[a] Acc = Accuracy, Sen. = Sensitivity and Sep = Specificity.

Hoa Dinh Nguyen et al, (2014) developed an online sleep apnea syndrome detection method based on Recurrence Quantification Analysis (RQA) by considering heart rate variability data. The RQA features are used for the classification and to speed up the real-time classification performance of the system. Two binary classifiers that are SVM and Neural Networks (NN) are used to detect and differentiate sleep apnea from normal breathing signal.

Changyue Song et al, (2016) suggested a novel based detection method to identify obstructive sleep apnea by considering the temporal dependences within segmented signals from ECG recordings. To validate the sleep apnea signals from normal breathings sounds a discriminative hidden markov model was employed and secured 97.1% of accuracy.

Hong Ji Lee et al, (2013) developed and examined a system that estimates the body postures on bed by using unconstrained ECG measurements. Input data is extracted by placing the 12 electrodes on a 13 healthy subjects and from these subjects QRS complexes features were extracted and applied to linear discriminant analysis, SVM with linear and radial basis function and artificial neural networks with one and 2 layers. Among these classifiers SVM gives a very good performance results.

Giovanna Sannino et al, (2014) detected and monitored real time obstructive sleep apnea episodes by an automatic rules consisting of heart rate variability parameters in a mHealth system. Da Woon Jung et al, (2017) aimed to develop a new predicting obstructive sleep apnea by using electrocardiogram taken during the sleep on set period. By using the regressive model trained and validated to get the good performance results.

Zhao Dong et al, (2018) current technique found on the frequency network analysis, and proposed to detect obstructive sleep apnea based on the heart rate variability from nocturnal ECG signals automatically. It is implemented firstly measuring the power spectral density of HRV segment with lamb-scargle method, the dynamic time warping distance (DWT) was implemented. The formed DWT matrix was converted to binary matrix.

T. Sunil Kumar and Vivek Kanhangad (2018) obstructive sleep apnea was detected from the single lead ECG signal of 1 min duration, based on the one-dimensional (1-D), phase descriptor (PD) based approach. Phase descriptor is enumerated using phase information and features are extracted from Gabor filter and signals are classified as OSA by the utilization of least-squares support vector machines

Heenam Yoon et al, (2018) developed automatic slow wave sleep analysis for healthy and obstructive sleep apnea subjects by using R-R intervals from an electrocardiogram. This method was appraised based on 5 fold cross validation and achieved a very good results in differentiating a person from healthy subject or an OSA subject.

CONCLUSION

Over the last decades, ECG and obstructive sleep apnea syndrome detection has attracted lots of interest for the researchers. In this present review paper, we have analyzed papers from an engineering and medical background. It is observed that ECG based OSA disorder identification is difficult, because ECG signals are complex and the OSA includes changes in it. In this survey paper shows that there is an interconnection between the changes in ECG signal and obstructive sleep apnea syndrome events. Based on the same data, mostly Support vector machine classifiers are used in order to differentiate between sleep apnea disorder signals to normal breathing signals.

Another observation is seen that for the feature extraction mainly R-R intervals, heart rate variability and time and frequency features are used yield good performance results. Various automated models, techniques and algorithms were developed for the detection of obstructive sleep apnea syndrome events based on the ECG signal features, which helps in selecting the best detection technique or algorithm for identifying the sleep apnea syndrome events with high performance results while implementing in various real time home applications.

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