REVIEW ON DETECTION OF OBSTRUCTIVE SLEEP APNEA

Akash Neelnaik[1], Mahalakshmi[2], Megha K[3], Namratha Bangera[4], Parveez Shariff B G[5]

[1]*Student, Electronics & Communication, AIET, Mijar, Karnataka, India*
[2]*Student, Electronics & Communication, AIET, Mijar, Karnataka, India*
[3]*Student, Electronics & Communication, AIET, Mijar, Karnataka, India*
[4]*Student, Electronics & Communication, AIET, Mijar, Karnataka, India*
[5]*Professor, Electronics & Communication, AIET, Mijar, Karnataka, India*

ABSTRACT

Sleep disorders are the most common health condition that can influence various aspects of life. Obstructive sleep apnea (OSA) is one of the serious sleep disorder, which causes the breathing to repeatedly start and stop during sleep. In many countries these kind of disorder is generally analyzed in sleep laboratories by the traditional detection process called Polysomnography. Most of the apnea disease are currently not analysed properly because of high cost of the test and the limitations of overnight sleep in the laboratories, where an expert human observer is needed to work over night. Multiple methods have been proposed to detect the physiological signals that are automatically analysed by different algorithms. In the proposed methodology different techniques are used for detecting the minute based analysis of OSA by Electrocardiogram (ECG) signal processing. Using the Physionet apnea ECG database, QRS complex is detected by pan Tompkins algorithm. Feature like Mean, Standard deviation and covariance is extracted from the output of the QRS complex. The classification algorithm is based on Support Vector Machines (SVM) and has been used to classify the apnea and nonapnea events from the features extracted. The software tool used for the detection of OSA is MATLAB platform. The main objective of the methodology is to detecting the OSA in a more accurate way to compute the sleep apnea score.

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

1. INTRODUCTION

Sleep apnea is commonly defined as the interruption of breathing during sleep. Normally there are three types of sleep apnea - obstructive, central, and mixed sleep apnea. Obstructive sleep apnea (OSA) is characterized by intermittent pauses in breathing during sleep caused by the obstruction and collapse of the upper airway of human body. This is typically accompanied by a reduction in blood oxygen saturation, and leads to the patient to wakening from sleep in order to breathe. More than 60 different sleep disorders, divided into seven categories, have been identified by the International Classification of Sleep Disorders. Sleep-related breathing disorders is the second category which includes central sleep apnea, obstructive sleep apnea (OSA) and sleep-related hypoxemia and hypoventilation. Central sleep apnea (CSA) is a neurological condition which causes the loss of all respiratory effort during sleep, and is also usually marked by decreases in blood oxygen saturation. Mixed sleep apnea combines components of both CSA and OSA, though treatment of the OSA portion often spontaneously leads to improvement in the CSA condition also.

Obstructive sleep apnea (OSA) is a potentially serious sleep disorder in which breathing is repetitively interrupted during sleep due to when your throat muscles intermittently relax and block your upper airway. This type of apnea occurs during sleep. An apnea is defined as complete cessation of breathing lasting 10 seconds or greater. A noticeable sign of hindering apnea is snoring. The common symptoms of obstructive sleep apnea include Excessive daytime sleepiness, Loud snoring Observed episodes of breathing cessation during sleep, Abrupt awakenings accompanied by gasping or choking, Awakening with a dry mouth or sore throat, Morning headache, Difficulty concentrating during the day, Experiencing mood changes, such as depression or irritability, High blood pressure, Night time sweating, Decreased libido.

OSA is the most common disorder in this group and is characterized by partial or complete obstruction and recurrent collapse of the upper airway, affecting ventilation during sleep. The symptoms of this disorder are excessive daytime sleepiness caused by no restorative sleep. Polysomnography (PSG) is that the gold commonplace for OSA diagnosing measure multiple sensors to record the breath flowing, metabolic process movement. Electro-oculogram (EOG), Electro-myogram (EMG), ECG and body position. Alternatively, OSA can be diagnosed if a frequency of obstructive respiratory events greater than or equal to 15 events/hour is detected, independent of associated symptoms. OSA severity can be defined as mild, moderate or severe. PSG provides accurate results but it is a slow and expensive process since it usually requires the patient to be in attendance at a sleep laboratory under the supervision of a specialized technician. The test could also be performed in the patient's home using portable PSG devices but the use of all the necessary sensors still result in an uncomfortable experience. Recorded signal data are scored manually to generate the clinical reports. Alternative devices have been developed with the aim of addressing these issues, monitoring the patients at home but with fewer sensors and employing automatic diagnosis algorithms.

2. BACKGROUND SURVEY:

A literature review covering papers published between 20013 and 2018 was undertaken. The search was conducted using the IEEE explorer, cited literature in the included articles and various journals. Bijoy Laxmi Koley [1] presents a methodology suitable for carriage able device in home care applications for monitoring the adaptive sleep apnea in real time. This methodology is to spot the occurrence of apnea or hypopnea events with the help of Oronasal airflow signal and the main objective is to reach clinical standards in the estimation technique of apnea solemnity. To detect apnea or hypopnea events on the basis of personalized breathing patterns this method uses combined adaptive two stage classifier model. For the recognition of sleep occasions, Optimum arrangement of time, frequency, and nonlinear measures, extracted from converging portions of typical 8s were nourished to Support vector machine based classifiers model to recognize de the conceivable origin of the segments, i.e., either from normal or abnormal events, and then to detect an event the decision of the classifier model on the time sequenced successive segments.

Nuno Pombo et al [2] have introduced a reasonable and efficient implementation for recognizing minute based examination of sleep apnea by Electrocardiogram (ECG) signal processing. The Physionet apnea ECG database have been used in this methodology, using this database, a median filter was applied for the recording of ECG signal in order to obtain the ECG-derived respiration (EDR) and the Heart Rate Variability (HRV. For training, testing and validation of an artificial Neural Network (ANN) the subsequently obtained features were used. By randomly dividing the data until it reaches a good performance using a k-fold cross validation training and testing tests were obtained. This auspicious early stage result may tends to complementary studies which includes alternative features selection methods and other classification model. The study has presented a model for detecting minute base analysis of sleep apnea based on ECG signal. As per the results presented, the observation is the trained network exhibited it propriety, feasibility and accuracy for the detection of sleep apnea. According to results, the ANN classification has spare accuracy for apnea detection and identification (82,120%).

Chia-Ching Chou et al [3] have presented a real-time Obstructive Sleep Apnea discriminant method from frequency analysis of and Heart Rate Variability and ECG-Derived Respiratory is propound. By comparing to the traditional techniques like Polysomnography which requires various physiological signals which will be measured from patients, the proposed method uses only ECG signals to determine in the time interval in OSA. So as to be doable to be executed in hardware to accomplish the real time detection and versatile application, the simplified Lomb periodogram is exploited to perform the frequency analysis of HVR and EDR in this application. The test results of this work show that the overall precision can be adequately increased with values of Sensitivity (Se) of 95.7%, Specificity (Sp) of 91%, and Accuracy of 93.2% by integrating the HRV and EDR indexes.

Rahul K. Pathinarupoth et al [4] have told that sleep apnea is the kind of disease condition affecting as much as 9% of women and 24% of men in US population. In present, the most exercised clinical method for diagnosis of sleep apnea is the utilization of polysomnography, which is both tedious and badly designed for patients. Polysomnography is one of the apnea monitoring technique where patients requires to get admitted to the health center and have to sit for one entire day in the patients. It likewise requires the manual mediation of a prepared professional to order the estimations collected. More readily, the use of multiple physical attached sensors like oxygen saturation sensor, respiratory rate monitors, ECG monitors, ECG leads, and wrist autograph have been proposed in the review

Srinivasan Murali et al [5] have proposed that OSA is one of the sleep disorders but only 10% of the cases are diagnosed. In addition, there is an absence of devices for long term checking of OSA, since current frameworks are excessively cumbersome and intrusive to be utilized consistently. In this ambience, ongoing studies have demonstrated that it is conceivable to detect it automatically depending on single lead ECG recordings. Even in non-invasive smart wearable sensors this approach can be used to measure and process the bio-signals. This methodology mainly focuses on the implementation, optimization and integration of an algorithm for the detection of OSA for proper health-care. It depend on frequency domain analysis while focusing an ultra-low power embedded wearable gadget. As it must impart its resources utilization with other computations. Present results are based on publicly available signals show a classification accuracy of 83.2% for offline and online analysis. This methods give better classification accuracy than the other best offline algorithm when using the same features for classification. Because of the significant amount of population affected and the counter effects of OSA on health conditions and also on this topic many studies has been recently conducted. In particular one of the attempt to detect OSA by single lead ECG recordings to identify new and solid methods for screening OSA with a less intrusive setup than current solutions.

Daniel J. Bratton et al [6] have told that OSA is the casual factor in the pathogenesis of vascular dysfunction and hypertension, this is the condition which can advance expansion and consequent aortic analyzation and rupture. The objective of the methodology used in this review is to summaries the current literature on the possible association between OSA and aortic disease and delineate the underlying mechanisms. Relevant studies were found by finding out terms together with “obstructive sleep apnea” together with “aortic aneurism, dissection, and dilation” in the MEDLINE and EMBASE databases. Observational studies systematically reported that OSA is very current among patients with arterial blood vessel aneurysms and arterial blood vessel dissections. Patients with co-occurring OSA and Marfan’s syndrome moreover as patients at the additional severe finish of the spectrum of OSA appear to be particularly liable to arterial blood vessel wellness. Several mechanisms are discussed concerning the link between OSA and aortic disease: nocturnal negative intrathoracic pressure surges leading to mechanical stretching of the aorta and ultimately aortic distension; arousal-induced reflex sympathetic activation with sequent cardiovascular disease and intermittent drive related to involuntary system activation and consequently augmented aerophilous stress. Further well controlled studies are needed in order to define the exact role of OSA as a risk factor for aortic disease.

Dionisije Sopic et al [7] intended that Continuous monitoring of patients suffering from cardiovascular diseases and, in particular, Myocardial Infarction (MI) places a considerable burden on health-care systems and government budgets. One of the major challenges in this area is to design ultralow energy wearable devices for long-term monitoring of patients’ vital signs. In this work, we present a real-time event-driven classification technique, based on support vector machines (SVM) and statistical outlier detection. The main goal of this system is to keep up a high classification accuracy whereas reducing the quality of the classification formula. This technique leads to a reduction in energy consumption and thus battery lifetime extension. This experimental analysis demonstrates that our period classification theme outperforms the present approaches in terms of energy consumption and battery lifetime by a factor of 3, while maintaining the classification accuracy at a medically-acceptable level of 90%.In this paper author have addressed the problem of early detection and prediction of myocardial infarction through the use of a wearable device. In order to monitor the patients on a long-term basis, we have proposed a two-level real-time event-driven classification technique that reduces the energy consumption while maintaining a high classification accuracy.

3. BASICS OF ECG

ECG consists of graphical recording of electrical activity of the centre over time. It is most recognized biological signal, and with non-invasive method; it's ordinarily used for diagnosing of some diseases by inferring the signal. Cardiovascular diseases and abnormalities alter the graphical record wave shape; every portion of the graphical record wave carries info that's relevant to the practicing in inbound at a correct diagnosing. The medical instrument signal taken from a patient is mostly get corrupted by external noises, hence necessitating the need of a proper noise free ECG signal. A signal acquisition system, consist of several stages, including signal acquisition though hardware and software instrumentation, noise or other characteristics filtering and processing for the extraction of information. Electrocardiography signals recorded on a long timescale (i.e., several days) for the purpose of identifying intermittently occurring disturbances in the heart rhythm. An ECG gives two major kinds of information. First, by activity time intervals on the graphical record, a doctor can determine how long the electrical wave takes to pass through the heart. Finding out however long a wave takes to travel from one a part of the centre to subsequent shows if the electrical activity is traditional or slow, fast or irregular. Second, by activity the number of electrical activity passing through the centre muscle, a cardiologist may be able to find out if parts of the heart are too large or are overworked. There’s no pain or risk related to having associate degree cardiogram. The machine only records the ECG. It doesn’t send electricity into the body.

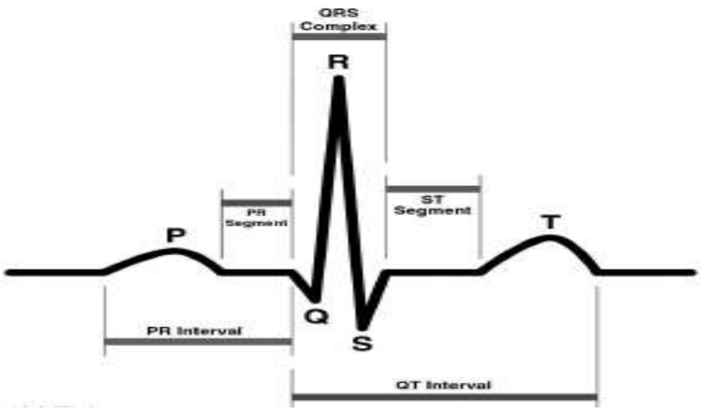

Fig 1: Waveform of ECG signal

4. METHODOLOGY

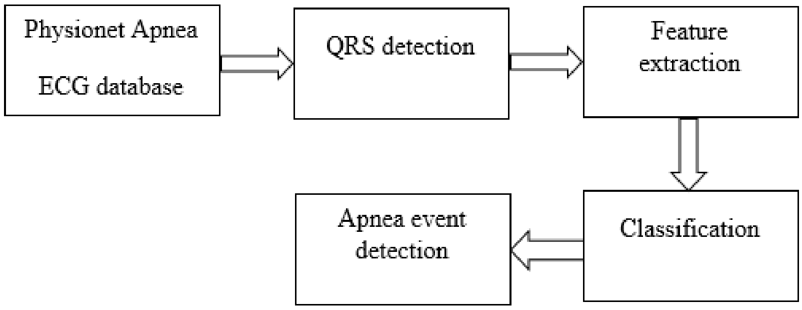

Fig 2: shows basic methodology of Obstructive Sleep Apnea detection.

4.1 Database:

Standard database is available on site called Physionet. Physionet provides free access to large collections of recorded physiologic signals (Physiobank) and related open source software (PhysioToolkit). Here data from the Apnea ECG database (Physiobank ATM) were used, which includes recordings of many common and life-threatening arrhythmias. The data consist of 70 records, divided into a learning set of 35 records (a01 through a20, b01 through b05, and c01 through c10), and a test set of 35 records (x01 through x35), all of which may be downloaded from this page. Recordings vary long from slightly but seven hours to just about ten hours every. Each recording includes a continuous digitized ECG signal, a set of apnea annotations and a set of machine-generated QRS annotations. Several files are associated with each recording. The .hea files are (text) header files that specify the names and formats of the associated signal files; these header files are required by the software package on the market from this web site. The .apn files are (binary) annotation files, containing associate degree annotation for every minute of every recording indicating the presence or absence of symptom at that time; these are on the market for the 35 learning set recordings only.

4.2 QRS Detection:

The QRS advanced detection algorithmic rule uses optimized Bandpass-filtering to scale back false detection. The new method called Modified Pan-Tompkins algorithm based on the slope and amplitude of ECG signal is used for the work to detect QRS complex. The purpose of pre filtering is to scale back numerous noise elements so as to attain improved detection responsibility. The QRS detection reliability of an algorithm was tested with a noisy stress ECG signal. The usefulness of the proposed method is shown by applying the algorithm to signal from Apnea ECG database to obtain the number of heart-beats per minute which helps to diagnose the heart disease.

4.3 Feature Extraction:

The main objective of ECG Feature extraction process is to derive a set of parameters that best characterize the ECG signal. These parameters ought to contain most data regarding the graph signal. Hence, the selection of these parameters is an important criterion to be considered for proper classification. The parameters includes Standard deviation, Mean and Covariance of ECG signal etc.

4.4 ECG classification:

The extracted features is been classified by applying the result of feature extraction to the classifiers. Different types of classification techniques are used to classify ECG data under the extracted features. The ECG beats after segmentation is re-sampled. It contains one or more classifier units which select one of the required classes in response to the input feature vector. Consequently, going through the last classification step, ECG signals representing heart beats are classified into either normal beats or abnormal beats. Classification process of ECG signals utilises many classification techniques comparing to all the other techniques Support Vector Machine (SVM) is most used ECG classifier.

5. RESULT

Table -1: Results of different techniques

Name	Feature extracted	Classifier and accuracy
1. B. L. Koley et al	Mean	SVM classifier (96.5%)
2. M. da Silva Pinho et al	Mean, SD	ANN classification (82.12%)
3. C.-C. Chou	PSD	EDR and HRV (93.2%)
4. R.K. Pathinarupothi	Mean	LSTM-RNN (85%)
5. Srinivasan Murali,G	Mean	Thompson filter (83.2%)
6. D. Sopic	Entropy, Signal Energy	SVM 90%

The above table gives the overall view of the techniques used in the background survey **.**In this results author B.L Koley and D Sopic has obtained the accuracy of 96.5% and 90% respectively for the SVM classification method. Author Siva et al has got 82.1% accuracy for the feature like mean and Standard deviation by ANN classification method.C-Cchou has obtained 93.2% of accuracy for the methods like EDR and HRV by extracting Power spectral density feature. By using LSTM-RNN classifier author R.K Pathinarupothi has got 85% of accurate value. Srinivasan Murali G has obtained 83.2% of accuracy for Thompson filter classification with extracted mean feature.

6. CONCLUSION

In conclusion the overall survey on obstructive sleep apnea detection presents an ECG-based model for detecting minute based analysis of sleep apnea. According to the results, the trained network revealed it suitability, feasibility and accuracy for sleep apnea detection. The approximate accuracy obtained for almost all the papers included in literature is 88.2%, 83.2% etc. for different classifiers and feature extraction techniques. By considering all the results obtained from the literature papers we conclude that the proposing methodology for the detection of OSA is to obtain the accuracy more than the present techniques are providing.

7. REFERENCES

[1] B. L. Koley and D. Dey, “Real-time adaptive apnea and hypopnea event detection methodology for portable sleep apnea monitoring devices,” IEEE Trans. Biomed. Eng., vol. ffr, no. 12, pp. 3354–3363, Dec. 2013.

[2] M. da Silva Pinho, N. Pombo, N. M. Garcia, “Sleep apnea detection using a feed forward neural network on ECG signal,” in Proc. IEEE 18th Int. Conf. E-Health Netw., Appl. Serv., 2016, pp. 1–6.

[3] C.-C. Chou,S.-H. Fan, W.-C. Chen, W.-C. Fang, “Real-time obstructive sleep apnea detection from frequency analysis of EDR and HRV using lomb periodogram,” in Proc. IEEE 37th Annu Int. Conf. Eng. Med. Biol. Soc. , 2015, pp. 5989–5992.

[4] R. K. Pathinarupothi, R. Vinaykumar, E. Rangan, E. Gopalakrishnan, K. Soman, “Instantaneous heart rate as a robust feature for sleep apnea severity detection using deep learning,” in Proc. IEEE Int. Conf. Biomed. Health Inform. 2017, pp. 293–296.

[5] Srinivasan Murali,G. Surrel, F. Rincon, D. Atienza, “Low-power wearable system for real-time screening of obstructive sleep apnea,” in Proc. IEEE VLSI (ISVLSI) Comput. Soc. Annu. Symp, 2016, pp. 230–235.

[6] Daniel. J. Bratton, T. Gaisl, M. Kohler, “The impact of obstructive sleep apnoea on the aorta,” Eur Respiratory J, vol. 46, no. 2, pp. 532–544, Jun. 2015.

[7] D. Sopic, A. Aminifar, A. Aminifar, D. Atienza, “Real-time classification technique for early detection and prevention of myocardial infarction on wearable devices,” in Proc. 13th IEEE Biomed. Circuits Syst. Conf., 2017, pp. 1–4.