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Developmental Strategies in Diagnosing Obstructive Sleep Apnea

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Abstract: ***A key mission in medical science is diagnosing a disease due to its criticality and accuracy in examining whether a patient is suffering from particular disease or not. Then, the most appropriate side of treatment can be decided. Obstructive Sleep Apnea (OSA) syndrome is the most widespread sleep disorder characterized by chronic episodes of reduction in the airflow or stoppage in airflow during sleep, being caused by blockage of upper airway. The intention of this review is to analyze already existing algorithms for detecting apnea all the way through usage of different sensors that have not been implemented on hardware. This study offers an exhaustive literature research value from 2003 to 2019 and setting a roadmap for bio-engineers and medical doctors thereby reducing research period and improving medical service efficiency concerning obstructive sleep apnea diagnosis.***

Keywords: ***Algorithms review, diagnosis approaches, obstructive sleep apnea, Sleep disorder.***

I. INTRODUCTION

In medical science, diagnosing a particular disease in precedence of its treatment is the major difficulty find. Hence diagnosis plays a significant role to examine whether or not a patient has a possible disease. The present work focuses on OSA diagnosis methods.

Sleep disorders are familiar health condition that affects various aspects of life. International Classification of Sleep Disorder have recognized more than 60 different types of sleep disorders and categorized them into seven groups. Obstructive sleep apnea belongs to second category and is characterised by frequent events of reduction or complete blockage of breathing during sleep and is due to collapse of upper airway. Apnea is the full obstruction of airway and hypopnea is the partial obstruction of airway when a person is asleep and breathing may be inadequate for 10 seconds or even longer. This lowers the level of oxygen in blood and in central nervous system. Brain senses this impaired breathing and arouses individuals from sleep so that the airway can be reopened. This awakening is so brief and breathing typically resumes with some gasping sounds and body jerk. A noticeable sign of this disorder is severe snoring and poor sleep quality.

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OSA individuals of about 25% reports excessive daytime sleepiness. Patients of greater proportion report un-refreshing sleep or fatigue [1]. Other important symptoms may include recurrent nocturnal waking due to gasping or choking sounds, nocturia, long existing morning headaches, and erectile dysfunction and poor concentration [2-4]. OSA affect people of all ages including childrens and its prevalence increases for aged people (50 years and above). Around 1 in 5 adult individual notices mild symptoms, while 1 in 15 individuals have moderate to severe symptoms of OSA. Obesity is a main risk factor and is seen in upto 70% of obese individuals.

American Academy of Sleep Medicine (AASM) has projected four levels of categorization for the sleep related disorder diagnostic devices [5]. Polysomnography (PSG level I study) is the gold model technique for diagnosing obstructive sleep apnea. It involves monitoring of seven or even more channels of data to record activity of different organ systems associated with sleep such as breathing airflow signal, respiratory movement, oxygen saturation (SpO2), Electrooculogram (EOG), electroencephalogram (EEG), electromyogram (EMG), electrocardiogram (ECG) signals and position of body[6]. OSA syndrome is detected if individual with indicated symptoms shows five or even more events of respiration per hour of sleep during night study of PSG [7]. Risk phase of apnea can be defined as normal (0-5 events/hour), 5≤AHI<15 events/hour is reported as mid, 15≤AHI<30 events/hour is reported as moderate and above 30 events/hour is reported as severe. Home based polysomnography (level II study) is used only for research purposes. Level III study involves recording minimum of 3 channels of data such as airflow, snoring, body posture, heart rate, respiratory excursion and oxygen saturation level but does not records sleep. Hence respiratory event index is used to estimate severity of OSA. Level IV study involves recording of less than or two channels of data. Oximetry is one channel while the other records heart rate, airflow or snoring.

PSG provides precise results but it is an expensive and very slow process. It usually requires the patient to be in the sleep laboratory under the supervision of expert technicians. Using portable PSG devices, the test can be carried out in patient's home but use of all necessary sensors makes uncomfortable experience. To address this issue, alternate devices (level IV study) have been developed to observe patients with fewer sensors and different diagnosis algorithms [8].

II. METHODS AND ALGORITHMS

In this section considerable amount of work has done to reassess papers that have offered algorithms based on analyses of respiration, ECG and pulse oximetry since these seems to be more potential approaches to detect OSA.

A. Based On Oximetry

Pulse oximetry is a method to measure the amount of haemoglobin (in percentage) saturated with oxygen. Among large number of polysomnographic recordings, [9] included recordings for individuals with age of ≥18 years and excluded individuals with parasomnia, chest wall diseases, lung diseases, anaemia and ischemic heart disease. Apnea Hypopnea Index with 0 to 86.5 events per hour from 230 polysomonographic recordings which met above criteria are categorized into 138 training sets and 92 test sets. Apneic event occurrence is denoted by three points A,B and C. Point A indicates the decrease in value of 1%≤SpO2≤3%. Point B indicates decrease in SpO2 signal to atleast 3% below point A. If SpO2 value returns to either 3% above point B or 1% below point A, it is marked as point C. The total time taken between point A and C should be ≥ 10seconds and ≤ 90seconds. From detection results AHI index are estimated using regression modelling.

[10] used two nonlinear characteristics such as and Lempel-Ziv complexity and Cumulative Tendency Measure methods to detect OSA. Three stage algorithm was used by [11] such as feature extraction, pre-processing with principal component analysis and statistical classifier.

The photoplethysmogram signal is monitored for decrease in amplitude fluctuations. With the features of Pulse Rate

Table-I: Comparitive Study Of Analyzed Algorithms

Source sensor	Year in which proposed	Technique or Methodology	Accuracy%	Advantages	Limitation
Oximetry	2018	Regression modelling	96.7%	Not only provides diagnostic information but also timing information of apneic events.	Difficult to categorise whether the detected apneic event is central apnea, obstructive apnea or mixed sleep apnea.
	2006	Lempel-Ziv complexity and Central Tendency Measure	87.2%	Improved sensitivity and specificity.	Small sample size.
	2010	Principal Component Analysis(PCA) and Linear Discriminant Analysis (LDA)	93.02%	Improved Classification performance due to the combination of nonlinear and spectral features from oximetry data.	Doubtful subjects are labelled as OSA Syndrome positive.
	2013	Pulse Rate Variability (PRV)	86.67%	PRV discriminate apneic events without need of additional signals.	1. Accuracy for fragment classification computed using leave-one-out method produced only smaller accuracies. 2. Limited subjects in database
	2014	Time varying characterization of PRV and SpO2	92.6%	Portable and less sleep disturbance.	Recordings are done only at hospital. Not suitable for home screening due to severe sensor displacement.
	2017	Artificial Neural Network classifier and Genetic Algorithm	97.7%	Identified that most of apneic event information are in time-frequency space and improved accuracy.	Multilayer Perceptron (MLP) structure is calculated using thumb rule and is subject dependent.
	2017	Deep Belief Network	UCDDB-85.26% Apnea ECG database-97.64%	Outperformed than other feature based approaches in both databases.	Unbalanced data due to prevalence of non apnea events and fixed Deep Belief Network structure.
Respiration	2013	k- Nearest Neighbour (kNN)	91.2%	Accurately detects apneic events from respiratory impedance signal.	Small sample set. Accuracy can be achieved higher if used with ECG analysis. Value of k has a greater impact on accuracy.
	2015	Ensemble classifiers-AdaBoost, Random subspace & Random Forest	98.68%	All three classifiers achieved good accuracy due to its robustness and stability. Amongst all, random forest achieved high accuracy of 98.68%.	-

Source sensor	Year in which proposed	Technique or Methodology	Accuracy	Advantages	Limitation
	2012	Support Vector Machine (SVM)	Independent test accuracy and Cross-validation accuracy -For apnea event 92.8% & 93.3%. For hypopnea event 89.6% & 90.1%.	Apneic event detection is not affected by less than two misclassifications.	Detection accuracy of hypopnea event is poor. Also, error occurs in seperating hypopnea from combined event (apnea+hypopnea).
	2013	Adaptive two stage classifier	Apnea- 94.9% Hypopnea- 91.8% Combined event- 96.5%	Automatically estimates AHI and can be implemented in type4 personal monitoring devices as per AASM guidelines.	Clinical validation study carried out on small datasets. Requires adjustment for different datasets hence unstable. Thermistor response to detect apnea events is poor
	2016	AdaBoost and ANFIS	AdaBoost- 98.43% ANFIS-98.68%	High detection reliability	Small dataset
	2013	Voice Activity Detection(VAD)	97%	VAD segments the breath signal into silence and sound segments and thus detected apnea events with good accuracy.	Real time apnea detection is not possible.
ECG	2017	Dual-tree complex wavelet transform and Logistic Boosting classifier	84.4%	High sensitivity (less missing detections). Doesn't involve denoising, preprocessing or rejections of artifacts.	-
	2016	Normal Inverse Gaussian (NIG) modelling, Tunable Q-factor Wavelet Transform (TQWT) and Adaptive boosting (AdaBoost).	87.33%	TQWT adjusts Q factor lower and higher to characterize non-apneic and apneic segments. Hence provides satisfactory performance.	Does not support larger data set. Apart from OSA, ECG signals are affected by many cardiac conditions. Data set used for validation purpose includes only healthy or apneic subjects.
	2016	TQWT and Random Under Sampling Boosting (RUSBoost)	UCDDB-91.94% Apnea ecg dataset- 88.88%	Computationally inexpensive. Does not experience mode mixing problems.	-

Source sensor	Year in which proposed	Technique or Methodology	Accuracy	Advantages	Limitation
	2013	Quadratic Discriminant Analysis, Linear Discriminant Analysis	QDA-89% LDA-87%	Cepstrum coefficients provides improved screening of OSA	-
	2004	Heart Rate Variability (HRV) spectral components and Linear Discriminant Analysis	For 3 variables- 96.7% For 30 variables- 92.0%	Promising way to detect OSA by ECG.	Detection rate can be improved
	2015	Extreme Learning Machine , Empirical Mode Decomposition	83.77%	Provides feasibility to portable sleep monitoring devices.	Number of hidden neurons affects the detection accuracy. Reduced performance due to mode mixing between intrinsic-mode function levels.
	2017	Variational Mode Decomposition (VMD) and SVM classifier	97.5%	Improved accuracy over empirical mode decomposition	-
	2012	Hidden Markov model	99.23%	Removes artifacts and achieved higher accuracy over other approaches.	-
Combined approaches	2003	Power spectral analysis	89%	Cost effective and can be incorporated into the existing system used in hospitals without any additional cost.	-
	2012	Classifier combination	82%	Classification performance is balanced and improved.	-
	2015	Linear Discriminant Analysis (LDA)	87%	Performed well in minute by minute apnea location task and in per subject global diagnosis.	Absence of subjects with cardiac disturbances and between 5 to 10 events per hour.

	2009	Logistic regression	88.5%	Median frequency and spectral entropy provides rich information in OSA diagnosis when used SaO2 with EEG signal.	Study data could be larger since individuals with OSA positive were predominant.
	2017	Multi-modal approach and Support Vector Machine	96.64%	Multi-modal technique performed for SpO2 and ECG signals with feature level fusion achieved highest accuracy of classification with SVM than all other scenarios.	Accuracy decreased when SVM used with single modal approach.

UCDDB- University College of Dublin sleep apnea DataBase

Variability, Linear Discriminant Analysis classifies the data in [12]. [13] measured number of desaturation events per hour, , length of trace and the time with oxygen saturation less than 90% and then classified apnea events based on physiology. Combination of time and frequency domain characteristics obtained from PRV and SpO2 signals were used by [13]. Artificial Neural Network were employed by [14] to identify features of blood oxygen saturation and achieved 97.7% accuracy.[15] uses 3 layer learning model - first two layers for Boltzmann machine and third is a soft max layer.

B. Based On Respiration

A novel approach was proposed by [16] in which a coil of wire was first strapped around the rib cage of an individual. Then, respiratory signal is obtained by measuring the impedance of a coil. Peak to peak time, Peak height stability value, flat lining and long pauses occurrence were extracted and applied to kNN. [17] employed time frequency method by applying Hilbert Huang transform to nasal airflow signal. The airflow signal is decomposed into minimum, maximum and average by wavelets and skewness, entropy and energy were obtained by [18] and used three classifiers such as AdaBoost, Random forest and Random subspace. To detect OSA, [19] used oronasal airflow signal. The signal was filtered at first by butterworth filter and then segmented into features. With the three extracted features, apneic datas are classified by Support Vector Machine classifier. [20] Used airflow signal with same filter and performed two steps. First, to detect sleep disorder and the other is to classify either as apnea or hypopnea. [21] Extracted the statistical features of airflow signal by decomposing it by Daubechies wavelet. Classifiers such as Adaptive Neuro Fuzzy Inference System and AdaBoost are used to classify the data amongst which the best performance is achieved by ANFIS. [22] Utilized characteristic moment waveform to detect respiratory rate by segmenting the sound of breathing signal during sleep.

C. Based On ECG

Electrocardiogram waveforms are analyzed to detect sleep disorders. ECG signals are segmented in [23] and frequency sub bands are generated from dual tree wavelet transform. Logistic boosting classifier is used to detect apnea situations. [24] Followed same method but used tunable Q factor wavelet transform and adaptive boosting classifier. [25] Divided the ECG signals into segments each of 1 minute duration and extracted spectral and statistical features from each segments. Random under sampling boosting is used as classification model to classify apnea events. Cepstrum features from RR series are fed into LDA and QDA classifiers in [26]. Frequency information such as low, high, ultra-low and very-low frequency, high were used by [27] to classify using LDA. Different decomposition methods such as Empirical- Mode Decomposition (EMD) [28] and Variational-Mode Decomposition (VMD) [29] are utilized to decompose electrocardiogram signals into variational mode functions and finite intrinsic mode functions. [30] Presented a different approach using multi source information of ECG signal in combination with index based cross correlation. Breathing results in modulation in the amplitude of T and R waves. [31] analyzed that sleep disorders can be predicted using Morphology of ECG and heart rate by cardio-pulmonary coupling. Multi resolution wavelet transforms are used by [32] to separate ECG into alpha, beta, delta and theta spectral components and these coefficients were fed as input into neural networks. [33] Presented a detection algorithm that divides the spectral power in VLF band of RR series and calculates power ratio based coefficients. SVM and Gaussian mixture model classifiers are tested and best results were obtained using SVM. Signals such as RR and EDR (ECG derived respiration) are decomposed by [34] using 14-levels of Daubechies wavelet and fed into SVM to classify OSA events. [35] Used coefficients of RR series with SVM classifier and Hidden Markov Model. [36] Used three stages to classify apnea data. First stage, ECG data are analysed for changes in EDR and HRV. In second stage, power spectral density was used to obtain features from EDR and HRV. Then, Hill climbing algorithm is used to select best features. In third stage, SVM classifier is used to classify apnea and normal data.

D. Based On Combined Approaches

OSA can be detected by considering only SpO2 signals but [37] used both heart rate and SpO2 signals from pulse oximeter. Peaks in the frequency band of both signals are used to classify apnea events. A different approach was presented by [38] where a combination of ECG and SpO2 signals was used. The features derived from these signals are analysed using correlation based subset selection and fed into three different classifiers. Combination of SpO2 and RR series are employed by [39] in which features in both frequency and time domain were extracted from RR series. Then LDA classifier was used to classify segments either apnea or normal. [40] Performed fusion at feature level of two signals such as SpO2 and ECG by employing multimodal techniques. The resultant signals are tested by kNN, SVM and Naive Bayes classifiers. PPG and nasal airflow signals were used by [41] to detect arousals and presented apnea hypopnea index and respiratory disturbance index.[42]Developed a sleepcare kit with photoplethysmography (PPG),

nasal tube of PPG equipment to measure breathing signals and IMU sensor to determine posture. The measured datas are analyzed to detect apnea or hypopnea in real time.

III. RESULTS AND DISCUSSION

Thus a wide survey on previous works has been carried out covering different approaches in detecting OSA. Summary of papers presented and corresponding algorithms used is shown in table I. The table is categorised into four sections, related to different approaches analysed. By analysing algorithms, the highest accuracy was reported by [14] based on oximetry, [18] and [21] using respiration analysis, [35] based on ECG and [40] with combined approaches. Maximum sensitivity was reported by [12] and [14] using oximetry analysis and by [29] using analysis of ECG signals. [36] Used ECG signals and achieved 100% results for best classification, specificity and sensitivity. It is observed that based on single sensor approach, OSA is detected with highest accuracy by ECG signals since these electrocardiogram signals achieved best classification results. Most algorithms using electrocardiogram signals were tested on clear signals obtained from public databases. This could add a way to improve diagnosis. Combined approaches did not add to relevant advancement of classification capability. Algorithms with single source sensor to detect OSA are preferred due to their reduced complexity for hardware implementation. Classifiers such as kNN, SVM and NN were used in majority of works. Some work achieved good performance with high complexity. The key aspect is to obtain a method with good performance and reduced complexity.

IV. CONCLUSION

This review provides an overall analysis of existing algorithms to produce a robust tool for diagnosis of OSA. This can be a future direction for researchers to implement the analyzed algorithms in hardware and more research on self learning the classified features. The key aspect is to obtain a method with good performance and reduced complexity. With this intent, a special interest is to develop a home diagnosing device with reduced numeral of sensors and reduction in cost of diagnosis. Adapting proposed algorithms in efficient hardware and self learning the features is the key challenge identified. This work is essential, since it help patients by creating awareness and perhaps prevention too among peoples.

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