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A Comprehensive Analysis on the Efficient Mechanisms to Detect Obstructive Sleep Apnea Using AI and Heuristic Algorithms

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ABSTRACT

Obstructive sleep apnea is a common problem arising in adults and children nowadays, determined by abnormalities in breathing gaps or incapability of air intake capacity during sleeping results in a decrease in oxygen level in blood. The brain detects this sudden decrease in the level of oxygen and sends a signal to wake the person up. Studies revealed the breathing stops for almost 10 seconds during a sleep apnea episode. There is no restriction on who can develop Obstructive Sleep Apnea(OSA), it can affect adults as well as infants. Our research primarily aims at assessing the various recent developments and studies made as a solution to this alarming problem. Their methodology and techniques have been studied and accuracy and sensitivity rates compared. A comprehensive and detailed study has been conducted on several research papers and studies done in the field of predicting sleep apnea. Sleep Apnea and classification of apneic signals have been mentioned in our study. The related researches have been studied extensively and compiled in our research work. The various techniques used by the researchers have been studied and tabulated along with the algorithm accuracies. It is observed that signal measurement along with AI algorithms has made significant advancements in OSA prediction. It is observed that Self Developed Algorithm on VAD showed the highest accuracy of 97%. PPG signal analysis and binary classification algorithm showed good accuracies of 86.67% and 86% respectively. AdaBoost, Decision Table and Bagging REPTree and SVM classifier also showed good accuracy of around 83% in the detection of Sleep Apnea episodes. The study highlighted the research works done to combat the rising problem of Obstructive Sleep Apnea. This comprehensive study of existing methods will help researchers to identify their drawbacks and find out more efficient solutions to them, which will help the humanity less prone to risks due to this alarming issue of sleep apnea.

Key Words: Obstructive Sleep Apnea, Polysomnography(PSG), FFT(Fast Fourier Transform), Sleep Apnea-Hypopnea Syndrome(SAHS), Frequency Modulated Continuous Wave(FMCW), piezoelectric, Heart Rate Variability(HRV), photoplethysmography (PPG)

INTRODUCTION

Obstructive Sleep Apnea is curable but very often the suffering person is unaware of this situation. If undetected, it may even drive a person into a coma or even death. Due to the seriousness of the issue, several researchers are coming up with ideas to find a solution to this problem. An extensive amount of study done in this field in the past decade reflects the need to assess this problem seriously and aim at deriving accurate solutions for the same. The prior research has been based on medical facilities based approaches. There is a deficit in remote healthcare approaches. In this paper, we aim to elucidate on this topic by giving various review on past papers. We intend to give a thorough analysis, including all the methods involved and the different techniques used in their respective papers. We also investigate the advantages and disadvantages involved in the methodologies. Sleep apnea is mistakenly taken lightly. The magnanimity of this disorder is sometimes life-taking. The main agenda is to spread the awareness, cause and cure of this disorder. The main indication of OSA is depicted by typical snoring at short intervals. Also, there happens to be a sense of fatigue and tiredness the following day.

SLEEP APNEA

This disorder is estimated to be prevalent among a population count of 200 million people.[1] In a study, there was an

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estimation that 4 per cent of men and 2 per cent of women in their middle-age life are more prone to this sleep apnea syndrome.[2] To avoid the time-consuming, expensive and strictly confined to limited professional work-force in the field of medical detection of sleep apnea through polysomnography; there have been several automated sleep apnea classification techniques devised in the past decade.

MEASUREMENT OF APNEIC SIGNALS

Apneic intervals were evaluated by extracting features by studying the pattern in the phase of the respiratory signals and also the magnitude of the same, along with phase-locking value (PLV).[3] PLV is a measurement that can be used to study the abnormalities or changes in long-range synchronization of neural activity from Electroencephalogram(EEG) data. EEG is extensively used to detect wave patterns of the electrical performances of the brain which proved to be an important metric in OSA detection study. Data extraction involved the polysomnographic data of 100 subjects and oxygen saturation signals and Electrocardiogram (which is a mechanism to record electrical signals which are transmitted from the heart to electrodes, which efficiently allows measuring the signals produced by a heartbeat) signals for the whole night. Hilbert transform is used to determine the phases between two respiratory signals which is used to find the PLV between the two signals. This is followed by extraction of RR intervals, that is the time between continuous R-waves, from ECG signals and computation of Power Spectral Density using 256-point FFT, the two types of powers in Low-Frequency(LF), High-Frequency(HF), and Very-Low-Frequency (VLF) bands and Low-High Frequency power Ratio(LHR) (which is the ratio of LF over HF). Finally, SVM classifier has been used for OSA recognition; for specific features namely HRV, oxygen saturation using linear and second-order polynomial functions as kernels with C values such as (C=0.1,1,5,10). The overall accuracy was around 80%. But observation has been made by the authors that the accuracy goes up as C increases and the highest accuracy achieved at C = 5 or 10. However, it was not the same for linear classification of oxygen-saturation where accuracy decreased with increased C. The combined-signal classifier, implementing a second-order polynomial kernel with C = 5 yielded the maximum accuracy of 82.4% and sensitivity of 69.9%. Thus, it was concluded the combined-signal classifier proved to exhibit a higher accuracy than separate signal classifiers. Since second-order polynomial kernels provided higher accuracy, further accuracy improvement might be possible if higher-order polynomials are analyzed for optimum kernel selection. PLV has its disadvantage as it takes care of the second-order degree dependence between the vectors only. Kullback–Leibler divergence or the Kolmogorov–Smirnov test can be the alternatives. Moreover, The SVM has its disadvantage of long training time and added to its extraction of signals after 1 whole-night monitoring of a subject is also time-consuming and might seem unnecessary for several subjects.

TECHNIQUES TO CLASSIFY OSA

To automatically classify the respiratory signal to detect OSA, has elucidated on a self-developed algorithm.[4] Voice Activity Detection(VAD) has been used for classification of respiratory signals into positive or negative sleep apnea by checking for the apneic interval of fifteen seconds or more. Cepstral coefficient, spectral entropy, average magnitude difference function and signal energy are some of the important features of this algorithm. But there is an assumption that spectral of speech changes over short periods. After filtration of respiratory signal, the power with FFT is calculated for a signal after filtration followed by energy calculation in two window frames for all n/l frames where n is the number of sample in research and l is the window size. This technique compares every frame of signal energy to the threshold to determine whether an episode of silence is a sleep apnea episode or non-sleep apnea episode. For testing on various samples of breathing signals, volunteers were asked to before and after the 20 breathing cycles and the audio was recorded using a microphone. However, the quality and sound capturing capability of the microphone comes into consideration. There might be better and high-quality microphones which might prove to have better audio capturing feature. Again, determining the silence interval and checking if it is more than 15 seconds is commendable as it is a primary identifying feature of a sleep apnea episode. The accuracy is decently high being 97% as compared to other paper but needs to be improved and calibrated more efficiently.[3]

An efficient contactless technique for determining sleep apnea is developed where the abdomen and chest convulsions are tracked on mobiles and obstructive apnea, hypopnea and central apnea and also provides an estimation of the apnea-hypopnea value index is detected[5]. The contactless technique is extremely useful nowadays because the clinical polysomnography test can often be very irritable and complex to many individuals. The use of various sensors, chest and abdomen belt, movement sensors, and 5 EEG sensors is both labour and time-intensive. In the mobile application proposed in this study, the smartphone is transformed into an active sonar system to track chest and abdomen movements using Frequency Modulated Continuous Wave (FMCW). The biggest disadvantage is that the specific target range cannot be determined as there is a deficit in the marking of time which is imperative to enable the system to time with precision the transmission and recipient and transform them into range, in continuous basic wave radar-based devices in the absence of frequency modulation. This is primarily overcome by FMCW. The phone transmits FMCW signals which are then processed to detect the breathing. The distance to the human is first found out and then the breathing movements are tracked by performing in a shorter FFT and the reflected signals are monitored. Unlike papers[3,4], this study also aims at detecting types of apneic intervals occurring in a subject. Threshold values are used in this study namely threshold on the minimum distance between two consecutive peaks and minimum amplitude at which a peak can be detected. If the distance between consecutive peaks is greater than a time interval of 10 seconds, an event of central apnea is detected, while if the value of peak goes beyond the threshold maintaining its periodicity, it is marked as hypopnea event. In the cardiac chest movement signals, sudden fluctuation spikes are studied to identify the obstructive sleep apnea events when the peaks' amplitude grows by half. Accuracy being good, this study has a negative side which is the important requirement of a stable amplitude for the microphone. This requirement is very critical as amplitude changes are used to detect apnea events occurrence. But their study also revealed that the microphone experienced some unpredictable variations while transmitting and receiving signals. This can also result in improper predictions of sleep apnea events which can be misleading. However, this issue may be resolved by using an external microphone which can be connected to the smartphone via the cloud. Breathing pattern detection namely fine chest and abdomen movements due to breathing have given this study a better and stronger prediction of apnea event as compared to others.[3-5] Wearable chest bands having sensors fitted. These physiological signals can be monitored, thus being an important work in this particular domain.

The system described in a computer-based diagnosis of sleep apnea involves the processing of the thoracic and abdominal excursion signals.[6] These signals can help detect obstructive and central sleep apnea attacks and syndromes. The most important contribution to this paper is that in between the two respiration signals, there exists a phase difference. These contribute to the identification and detection of sleep apnea and the grade of the same. Lessor no respiratory movements identify central sleep apnea. The novelty in the methodology involves on-line implementation of the whole system, thus playing a major role in clinical application. An innovative method is provided which classifies the signal system which has the capability of distinguishing between people inflicted with sleep laden disorders and people without them based on EEG and pupil size with an emphasis on the fact that pupil movements indicate alertness towards a situation.[7]

The thoracic and abdominal excursions' phase differences are estimated, a very important factor in detection, as it indicates the rank of airway hindrance.[6] A common phase between abdominal and thoracic indicates normal breathing whereas a counter phase indicates airway blockage. It is noted that identical frequency modulation is observed in the excursion signals of the thoracic and abdominal cavity, but they are found in a different phase. An on-line process is required where there is a low respiration rate is involved. In this process, the abdominal and thoracic breathing cycles' phase is determined discretely. It incorporated the channels used in PSG signals for thorax and abdomen, hence not utilizing the other available channels. The main reason for not selecting other signal channels was because the outputs of the signals are delayed by a chunk of seconds. A major reason is also that if the cardiovascular signals were included, they tend to superimpose with the other phenomena. Time-domain phase difference analysis methodology is used here, requires a greater number of signal periods. This would result in longer processing delay which would be not feasible for on-line signal analysis. When the extreme points of the two respiration signals are determined, the next objective is to find out the relation between them. If a common phase is detected between two periodic signals having identical frequencies, then it is found that the local extreme indexes are at the same time location. The period between these set of points is roughly around 50% of the time frame if the signals are found to be in their counter phase position.

An experiment is conducted on untreated OSA people, narcoleptic personalities and some healthy subjects[7]. An image sensor processes the pupil images via small infrared cameras. The image processor detects the pupil and has an output current is directly proportional to the pupil diameter. It also focuses on data pre-processing as a primary objective as the data comes with noise, i.e. such as eye and blinking movements. An algorithm was designed to remove the noise and to construct a continuum series, linear interpolation was used to position data in their resulting time spaces. A case of an anomaly in data is considered when the two adjacent time frame locus's change excessively or when the diameters of the pupil tend to zero. Theta Wave activity has been recorded to grow during sleep apnea episode attacks. Accordingly, the energy was calculated in an interval of 2s. They have also used ART2 NN's to recognize QRS waves. A sequence of ART2 NN's is imperative to derive the categorized output with utmost precision to achieve grouping of similar individuals in conjunction and to reduce the consequences of input order. It is to be noticed that ART2 NN's can enhance the precision of categorization over the individual ART2 network.

A study provided that in a good piecewise linearization method the tightness properties must be considered[6]. They include sharpness and locally ideal placements. To enhance computational efficiency selection strategies and effective breakpoints are immensely important. Thus, more work should be done to study the optimal positioning of the breakpoints. Thus, there is a high chance of diminishing the accuracy, as Piecewise Linear Approximation (PLA) was the initial phase. Moreover, the process is time-consuming which fails to serve the actual purpose. Thus a more dynamic and flexible method be applied. Whereas in another paper the drawback came as the experiment was done on a very small amount of individuals.[7] The less the number of data in a dataset the higher is a chance is to achieve maximum accuracy. Moreover, the algorithm developed by the researchers is a success to eradicate the noise in the pupil size data. But there can be a possibility of errors and it is cited that a lot of assumptions been taken to device the methodology. There might be an overlap with the user data and the unused data, hence removing the required data. Also, the time frame is not continuous and the preprocessing involves masking the actual data with a dummy to force it into continuous time interval. On the positive side, the ART2 NN's learns and adapts to an unstable domain with rapidity and solidity, unsupervised learning of priority behaviour, also determining the manifold of groups autonomously. Thus, as paper[7] uses an automated approach, whereas paper[6] is more prone to human errors. Thus to some extent, paper[7] is preferred.

The discomforts and inconvenience of the PSG procedure which is the traditional method for sleep apnea detection, and hence aims at an easily available, comfortable, and trustworthy alternative to the traditional methods are studied.[8] Real-time detection of sleep apnea and hypopnea using ECG and Spo2 signals has been developed by the researchers in the paper. Sleep apnea/hypopnea syndrome(SAHS) detection has been carried out several ways: once by only ECG signal and only SpO_2 signal, the other time using both, by ECG and SpO2 uses feature selection and another time using classifier combination. The features extracted are compared via different Machine Learning Algorithms to improve accuracy and sensitivity. Cost-sensitive weighting approach is also followed in this methodology. The ECG and SpO_2 signals are broken down into1minute segments, which is an efficient introductory approach to deal with the problem. Matrix Laboratory (MATLAB) is used for processing the signals and label a minute as apneic or non-apneic episode based on 5 seconds of apneic event occurrence. Basic statistical methods like mean, median and variance were calculated and used for further processing. The ODI index; the oxygen de-saturation index counts the number of times SpO_2 value drops below the fixed value which is between 2 to 5. TSA indicated the accumulative time SpO_2 stays dropped. Feature sets of the signals are monitored by an open-source software called WEKA. Several machine learning algorithms and classifiers namely, SVM, KNN, Decision Table and Decision Tree, multilayer perceptron, REPtree, FT trees have experimented within this study. Moreover, AdaBoost and ADtree have also been incorporated. Tenfold cross-validation approach has been used in the database and the 3 common evaluation metrics of specificity, accuracy and sensitivity have been used. To take care of computational overload, feature selection has been used. Comparison between different algorithms and classifiers result in some having higher sensitivity and accuracy over others. Hence, the classifier combination concept has been brought into this study for improvement in the overall performance. Results showed combined ECG and SpO2 feature set had higher accuracy as compared to the signals tested individually with their feature sets. For real-time detection, AdaBoost performed efficiently as compared to SVM and combining AdaBoost, Decision Table and Bagging REPTree gave the highest accuracy of 83.61. Further combinations can be explored from the comparisons provided in the paper, to have overall better accuracy and sensitivity.

Itinerant detection of the obstructive sleep apnea syndrome (OSAS) has been brought to light in a research paper whose study is based on pulse photoplethysmographic (PPG) signal.[9] A proposal is there that decrease in variations in the amplitude of the can prove to be an OSAS discriminator. Heart rate variability (HRV) analysis can be thus used to detect the apneic event. HRV needs electrocardiogram as an additional requirement. It is a disadvantage because of discomfort due to sensors over the patient. It can disrupt normal sleeping habits. Hence, Pulse rate variability is more focussed on in this study as opposed to HRV in paper.[8] The amplitude fluctuations are known as DAP which is used in this study to detect apneic episodes.DAP detection on the database involved the preprocessing stage of suppression of mean by RMS method and the concept of the threshold. Linear and adaptive are the 2 divisions of pulse detector. Filtering is done to avoid false detection of abnormal hikes in PPG pulses as regular pulses with the help of an adaptive threshold. Clustering of DAP events into apneic and non-apneic based on SaO2 decrease and airflow decrease for a specific time interval of 5 seconds is done. Feature selection using the wrapper method approach was performed to work with the one giving the most accuracy. Classification with an accuracy of 86.67% is commendable however use of the only SaO2 is not only sufficient for apneic episode detection.

Several studies on sleep apnea detection involve methods primarily include determining a list of applicable attributes and developing a classification model to fit the features to perform an automatic diagnosis. Measuring signal strength in wireless networks to monitor breathing and a device called BodyBeat uses microphones having piezoelectric mechanism on the surface of the body, which is used in monitoring sounds of food intake, respiration, etc. in the body are some of the latest trends developed to monitor sleep apnea[10,11]. The medication used in this cited paper, states that it acts as a promoter of consciousness, thus not letting the body achieve full Rapid eye movement sleep. The consciousness of the body increases the inherent capability of detecting any choking and thus, saving from the effects of sleep apnea and other choking nasal disorders like narcolepsy[13]. Classification models in use include k-Nearest Neighbour (KNN), Support Vector Machine (SVM), SVM and smartphone-based auto-adjustable pillow system, neural network and NN with the amount of oxygen being carried by the RBC cells, and linear discriminant analysis (LDA).[1,3,12,14] There have been several sensors, signal analysis to predict sleep apnea. Choi et al. used thoracic and piezoelectric sensors and data from 179 polysomnographic recordings and used convolutional neural networks (CNN).[15] In another study, the abdominal and chest motions from 5804 recordings were selected and analysed.[16] Respiration signals obtained from ECG were also utilized in many studies. A combination of AdaBoost with Decision Stump and Bagging along with features gathered from ECG and SpO_2 signals and SVM with feature extraction from heart-beat signals have been used to detect OSA.[8,17] In another study, the subject is handed over a mobile sensor and an ECG sensor to wear and be monitored every night at the place of stay of the individual. The sensor collects the data and mobile records it.[18] Binary classification is implemented on the annotations to detect positive or negative apneic intervals. The model used a multilayer model for better monitoring. Data, Decision and Action together determine the apnea episodes if any. Classification is accomplished using DEREx tool and gives an accuracy of around 86% which is fair. However, if the hardware part can be thought of by replacing with an alternative, then this application can be reaching out to subjects on a wider scale. And, DEREx proves to have higher accuracy as compared to AdaBoost or Bagging and SVM in this study comparison. In the last 10 years, apnea monitoring using Heart Rate Variability (HRV) based on ECG has been developed extensively.[19]

METHODOLOGY TO ANALYZE SLEEP APNEA SIGNALS

As discussed, different papers had their approach towards targeting this serious issue of sleep apnea. Use of sensors, signal analysis, classifiers, FFT analysis, HRV monitoring, AI techniques has been in recent use as alternatives of the traditional PSG. The methodology used in different papers in our study have been tabulated in Table 1:

Table 1: Different methods used in studied papers

Paper Number	Method Used
1	SVM and auto-adjustable pillow system
3	SVM classifier
4	Self Developed Algorithm, VAD
5	FMCW and FFT Analysis
6	Piecewise Linearization
7	Adaptive Resonance Theory 2 Neural Network
8	AdaBoost, Decision Table and Bagging REPTree
9	PPG Signal, Classification based on primarily SAO2 amount
11	Piezoelectric mechanism
12	K-Nearest-Neighbour(KNN)
12,14	NN
15	Piezoelectric sensors and CNN
17	SVM on heart-beat signals
18	Binary Classification using DEREx
19	HRV monitoring using ECG

Table 1 depicts the algorithms which have been implemented in various papers, successfully predicted sleep apnea with a high accuracy rate. In algorithms used in 1, 3, 4, 12, primarily used machine learning algorithms with proper hyperparameter tuning. 4, a self-developed algorithm provided with the highest accuracy rate. 7, 12, 14, 15 algorithms used complex deep learning methodologies and had good results. Also, 5, 6, 17, 19 are primarily the electrical methodologies used to calculate and predict sleep apnea using Fourier analysis on Heart Beat signals, snoring, ECG signals.

COMPHENSION ON THE RESULTS

The key findings of our paper throw light upon all the existing methods that have been extensively researched and deployed to detect sleep apnea. Applications of AI, as we have found, are gradually replacing the traditional OSA detection techniques. Researchers are making use of several complex analytical algorithms as we have seen in our study, to find alternatives to the existing treatments. Some show higher accuracy using ensemble methods, while some use primarily signal analysis and result in impressive outcomes, while again some combine sensors and AI to yield better results. However, in general, it can be observed signal analysis along with AI algorithms has higher accuracy in OSA prediction. The comparison of the different methods used in our studied papers and their accuracy obtained is illustrated in Table 2:

Table 2: Comparison of accuracies between studied papers

Paper Number	Accuracy
3	82.4%
4	97%
8	83.61%
9	86.67%
18	86%

As depicted from the above table (Table 2), it is observed that Self Developed Algorithm on VAD used in paper 4, showed the highest accuracy of 97%. The VAD design includes processing of the input signal followed by feature extraction and final VAD computational decision. Paper 9 using PPG signal analysis and paper 18 using a Binary Classification algorithm showed impressive accuracies of 86.67% and 86% respectively. AdaBoost, Decision Table and Bagging REP-Tree in paper 8 and SVM classifier in paper 3 also showed good accuracy of around 83% in the detection of Sleep Apnea episodes.

CONCLUSION

The existing methods have enhanced the possibility of detection of sleep apnea and therefore reduce life-risk of an individual. Using different kinds of Machine learning and deep learning algorithms, IOT devices, sensors and signals have opened new doors to discover more and develop more accurate and better solutions to add on to the existing methods. A comprehensive study of existing methods will help researchers to identify their drawbacks and find out more efficient solutions to them, which will help humanity less prone to risks due to this rising problem.

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