

A Panoramic Study of Obstructive Sleep Apnea Detection Technologies

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Abstract—This study offers a literature research reference value for bioengineers and practitioner medical doctors. It could reduce research time and improve medical service efficiency regarding Obstructive Sleep Apnea (OSA) detection systems. Much of the past and the current apnea research, the vital signals features and parameters of the SA automatic detection are introduced. The applications for the earlier proposed systems and the related work on real-time and continuous monitoring of OSA and the analysis is given. The study concludes with an assessment of the current technologies highlighting their weaknesses and strengths which can set a roadmap for researchers and clinicians in this rapidly developing field of study.

Keywords: *sleep apnea, PSG, ECG, EEG, SpO₂.*

I. INTRODUCTION

Sleep apnea (SA) in the form of Obstructive sleep apnea (OSA) is becoming the most common respiratory disorder during sleep, which is characterized by cessations of airflow to the lungs. These cessations in breathing must last more than 10 seconds to be considered an apnea event. Apnea events may occur 5 to 30 times an hour and may occur up to four hundred times per night in those with severe SA [1].

The most frequent night symptoms of SA can include snoring, nocturnal arousals, sweating and restless sleep. Moreover, like all sleeping disorders, symptoms of sleep apnea do not occur just during the night. Daytime symptoms can range from morning headaches, depression, impaired concentration and excessive sleepiness which cause mortality from traffic and industrial accidents. However, these symptoms are not definitive to detect SA syndrome [2] [3].

In fact, SA is not a problem to be taken lightly, since it is associated with a major risk factor of health implications and increased cardiovascular disease and sudden death. It has been linked to irritability, depression, sexual dysfunction, high blood pressure (hypertension), learning and memory difficulties, in addition to stroke and heart attack [2][3]. Several treatments options for OSA patients include weight loss, positional therapy, oral appliances, surgical procedures and continuous positive airway pressure (CPAP). CPAP is a common and effective treatment especially for patients with moderate to severe OSA. CPAP devices are masks worn during sleep that improves oxygen saturation and reduces sleep fragmentation [4].

However, statistics show that around 100 million people worldwide, where in the US from 18 to 50 million people, are

suspected to have OSA, of which more than 80% remain undiagnosed [5]. The trouble of having examinations discourages patients prone to OSA undergo at the overnight clinical research through polysomnographic data. Polysomnography (PSG) is a complicated procedure and certain way of assessing the OSA problem. Complete PSG includes the monitoring of the breath airflow, respiratory movement, oxygen saturation (SpO₂), body position, electroencephalography (EEG), electromyography (EMG), electrooculography (EOG), and electrocardiography (ECG) [6]. However, PSG has received many criticisms from some researchers. This is due to several reasons, including first, the inconvenience since it requires the patient to be connected to numerous sensors and to stay in hospital for one night. Second, it is expensive. The average cost for a PSG is \$2,625 due to the need for the study to take place in a specially equipped medical facility, in addition to the requirement of having a sleep lab staff overnight, trained in ‘scoring’ the resultant measurements manually. Third, along wait list of up to 6 months is caused by limited availability of PSG [7].

According to the American Academy of Sleep Medicine (AASM), the Apnea-Hypopnea Index (AHI) is used to describe the number of complete and partial apnea events per hour of sleep and it is calculated to assess OSA syndrome severity. OSA severity is usually determined as follows: AHI 5-15 indicates mild, 15-30 indicates moderate and over 30 indicates severe OSA syndrome. Therefore, patients are diagnosed with OSA if they have five or more apnea events per hour of sleep during a full night sleep period [8].

However, new simplified diagnostic methods and continuous screening of OSA is needed, in order to have a major benefit of the treatment on OSA outcomes. In this study, we investigate the different current apnea researches which provide an alternative to the expensive PSG visual scoring method which is commonly used today to assess a patient’s sleep quality.

Much of the current apnea research is ranging from off-line computer-based systems for automatic evaluation of apneas by analyzing different signals stored in PSG records to comprehensive portable real-time devices that enable the patient to be diagnosed and receive feedback at home in order to alert of the apnea event and help the patient to recover.

In the following sections, we glance at a variety of sleep apnea detection and monitoring methods. Then, we conclude

our paper in section V, and highlight some directions for future research.

II. COMPUTER AIDED SLEEP APNEA DETECTION

Over the past few years most of the related research has focused on presenting methods for the automatic processing of different statistical features of different signals such as thorax and abdomen effort signals, nasal air flow, oxygen saturation, electrical activity of the heart (ECG), and electrical activity of the brain (EEG) for the detection of SA.

The validated database used to assess the detection algorithms in the related research studies is supplied online from the PhysioNet web site [9]. The Apnea Database available in PhysioNet has been created to support such studies. All apneas in the recordings are either obstructive or mixed and it does not contain episodes of pure central apnea or of Cheyne-Stokes respiration. The full overnight polysomnogram recordings were divided into a set of one-minute segments. Each segment was annotated based on visual scoring of disordered breathing during sleep and if at any time during that minute there was evidence of sleep apnea the segment was classified as “apnea”; otherwise it was classified as “normal”. Segments containing hypopneas were also classed as apnea [10].

Several studies show that the brain waves signal, Electroencephalogram (EEG), which indicates states of mental activity ranging from concentrated cognitive efforts to sleepiness [11], is able to diagnose SA. Wavelet transforms and an artificial neural network (ANN) algorithm were applied to the EEG signal in [12] to find a solution to the problem of identifying SA episodes. The EEG signals can be classified into four frequency bands of basis waves, namely as delta (δ), theta (θ), alpha (α) and beta (β). When an episode of SA occurs, the EEG signal shifts above the delta frequency band. Then, sleep EEG activity shifts from a delta wave to theta and alpha waves frequency bands in the range of 4~14 Hz once episode of SA ends. The system’s identification results achieved a sensitivity of approximately 69.64% and a specificity of approximately 44.44%. However, even though this study yielded promising initial results, it still requires improvement since the EEG signal characteristic of a SA is easily contaminated by artifacts, therefore, a preprocessor circuit is needed to eliminate EEG signal artifacts and enable the system to recognize SA episodes.

Many studies show that detection of OSA can be performed through the Electrocardiogram (ECG) signal due to cyclic variations in the duration of a heartbeat. This consists of bradycardia during apnea followed by tachycardia upon its cessation [13]. In our previous published research, we developed a model based on a linear kernel Support Vector Machines (SVMs) using a selective set of RR-interval features from short duration epochs of the ECG signal. The results show that our automated classification system can recognize epochs of SA with a high degree of accuracy, approximately 96.5% [14].

Arterial oxygen saturation (SpO_2) measured by pulse oximetry can be useful in OSA diagnosis as clinical experience indicates that an apneic event is frequently accompanied by a fall in the SpO_2 signal (oxygen desaturation) [15]. The study

carried out by Marcos et al. [16] provided an automated means for interpretation of SpO_2 signals, based on (LD) classifier and the linear combination of spectral and nonlinear features from SpO_2 recordings using principal component analysis (PCA). In addition, in [17] we further developed a Neural Network (NN) as a predictive tool for OSA using the SpO_2 signal features and evaluated its effectiveness.

It has been reported that, the snoring is a common finding in people with OSA. OSA is generally caused by a blocked of the airflow airway. Therefore, the snoring must become due to the vibration of soft tissues when the airflow stimulates the ill structure in the upper airway during sleep [18]. Of all methods for diagnosing OSA, the formants estimation method is most widely used. The formants information contains the essential acoustic properties of the upper airway. It has been discovered by studies that there is a correlation between the state of the upper airway and the first formant frequency. A narrower upper airway is usually led to a higher first formant frequency. Therefore, Andrew et al. [19] and [20] proposed fixed formant frequency thresholds to detect the hypopneic snores which must be higher than that of the typical ones.

Recently, based on the tracheal breathing sounds recording analysis during sleep, which can be used for respiratory flow estimation and distinguish the changes in breathing pattern recognition of the patient, the study in [21] reports a new fully automatic technology for OSA detection. Different parameters were investigated to distinguish the breathing level during each individual apnea event, including the total energy of the breath sound segments. After collection of data, each parameter was then fuzzified with a sigmoid function and the fuzzy output of the fuzzy functions are added together to classify the sound signals. The results show high sensitivity and specificity values of more than 90% in differentiating normal respiration from disordered breathing patients.

In the present studies, the researchers provide complementary information with combined different physiological signals, in order to obtain additional information to that provided by classical methods to evaluate sleep quality and detect apnea. In some studies, ECG and SpO_2 data have been bridged to analyze sleep data. As the blood oxygen saturation falls during apnea, the resultant increase in heart rate and blood pressure causes stress and potential injury to the parts of the cardiovascular system [22]. In [23], the authors analyze various feature sets and a combination of classifiers based on the arterial oxygen saturation signal measured by pulse oximetry (SpO_2) and the ECG. In this work, the Bagging with REP Tree classifier achieved sensitivity of 79.75%, specificity of 85.89% and overall accuracy of 84.40%.

Because of the desaturation event that activates the sympathetic nervous system, the relationship between periodic changes in the SpO_2 profile and in the EEG pattern due to apnea events during the night was investigated in [24]. The combined spectral analysis of these two signals achieved 91% sensitivity, 83.3% specificity and 88.5% accuracy in OSA diagnosis.

The first successful preliminary attempts to directly assess the interactions of power spectral of sleep EEG and ECG signals in detecting OSA events is presented in [25].

Consistency between these two signals over different frequency bands (0-128 Hz) were evaluated before, during and after an OSA terminations event (with/without arousals) in non-REM as well as REM sleep.

III. HOME-RECORDING FOR SA DETECTION

Nowadays, much of the current apnea research is being done on providing portable devices that monitor those experiencing apnea during the day. The device could act as an inexpensive and convenient way for doctors to diagnose SA patients and as a means for collecting data on apnea sufferers to determine the severity of the condition once diagnosed. More specifically, this may help in the initial assessment of patients with suspected OSA in order to prioritize patients. Patients with utmost need of treatment will go through complete PSG recordings within a sensible time frame; meanwhile those who are free of apnea symptoms will avoid the cumbersome procedure [26].

Various portable monitor devices already exist in the market. ApneaLink™ Plus Home Sleep Apnea Test Device is one of the carriage able in home sleep test diagnostic devices that records up to four channels of information: respiratory effort, pulse, oxygen saturation and nasal flow. The patient can sleep normally while ApneaLink™ Plus monitors his/her sleep, checking breathing patterns and the amount of oxygen in his/her blood and recording possible apneas or other breathing abnormalities [27]. Also, SleepStrip™ may be a simple and effective tool for OSA diagnostic strategy. This device has to be worn for a minimum of five hours of sleep, and the actual device is placed on the individuals face where the two flow sensors (oral and nasal thermistors) are placed in just below the nose and above the upper lip to capture the breath of individual patient. For all samples combined, sensitivity and specificity values ranged from 80-86% and 57-86% respectively [26].

Also, WM ARES is a home sleep test device that records heart rate, airflow, respiratory effort and oxygen saturation [28]. When the patient wakes in the morning, after removing the tube from the nose and the tape and sensor from the finger, he/she returns the device to the clinician for analysis. The device contains a detailed record of the patient's personal sleep patterns, which can be downloaded, analyzed and processed in the clinician's computer. The clinician will then identify if the person is suffering from sleep apnea.

In [29], a new screening test for OSA was implemented on a Personal Digital Assistant (PDA) platform to perform the test at home during the patient's nightly rest. The Bluetooth ECG sensor, made by Corscience [30] is integrated into this platform, and the algorithm running on the PDA calculates an index that quantifies the magnitude of the heart beats rate variability power spectrum alterations. After the patient's first night using the device at home, the collection of test results are transmitted directly from the PDA to the hospital via the internet either by a WiFi connection, or by GPRS/UMTS connection. Once the healthcare staffs have evaluated the results, they will notify the patient whether the collected test results are conclusive or not. If the results are conclusive the patient should return the device. If needed; however, the patient may be asked to repeat the test again to collect additional data the following night. However, there is a loss of efficiency in

the use of the wireless network because normal ECGs are also sent, which implies a high cost.

The portable device hardware design of an FPGA for home preliminary screening of SA syndromes in [31] stores a combination of three signals data of three sensors, namely the nasal air flow and the thorax and abdomen effort signals of overnight sleep on a Secure Digital card. Later, the sleep specialist at the clinic uses an algorithm for the evaluation and detection of SA. The device is relatively inexpensive and simple to use to diagnose more cases of SA.

Habul et al. [32] developed a diagnostic device for initial test at home that measures three vital signals, namely "the respiratory rate measurement, the oxygen concentration in blood and chest oscillations. The system architecture is divided into 5 parts, the microcontroller, the external communications, data storage, power management, and signal conditioning part. The data will be transmitted wirelessly and stored on the storage device. After the patient has finished sleeping, the next morning he or she can bring the data received on the storage device to a clinic's office, where the physician can interpret the data and determine what the patient's condition is. However, the device will reduce the cost for the patient because the patient does not have to pay for an overnight stay at the sleep center" [32].

In using vision based analysis to diagnose OSA in [33] there has been effective use of two SONY infrared camcorders (DCR-HC-30E) that work together in order to capture 10 video clips from three different angles. General body movement is continuously monitored and updated in a 2D breathing activity template. After collection of video data, offline analysis is used to detect abnormal breathing and to facilitate diagnosis of OSA.

Furthermore, after a careful meta-analysis of literature for twenty-five various tools and devices used to screen and detect SA by Ross et al. [34], it was discovered that only two of these were done at home, all others were performed under supervision in the sleep laboratory. The studies results gave sensitivity values ranging from 78-100% and specificity values ranging from 62-100%. However, the related issues such as reliability, compliance, prices and safety, equipment failure rates were largely ignored.

IV. REAL-TIME SYSTEMS FOR CONTINUOUS DETECTION AND SCREENING OF SLEEP APNEA

Although the systems in [26-34] provide home based OSA diagnosis, but all of them record the physiological sleep data of patients to memory card. Then, the patient must load these data into medical center computers where physicians use specialized software to analyze the data. Meanwhile, some patient can experience life threatening episodes by not receiving proper feedback notification from a medical center. Hence, to reduce the waiting times, as an alternative proposal to that scenario, the real time monitoring systems that promotes not only a transmission of physiological data but also a real time analysis of these data in order to alert of the apnea event and help patients to recover is performed in researches that appear in [35-40].

Sechang et al. [35] propose a wireless OSA monitoring system, which enables the patient to be diagnosed and receive

feedback at home. The system supports monitoring five different biomedical signals continuously, namely, electrocardiogram with dry electrodes, body position, nasal airflow, abdomen/chest efforts and oxygen saturation. A wireless transmitter unit in the system sends the measured signals from sensors to a receiver unit with Zigbee communication. The receiver unit, which has two wireless modules, Zigbee and Wi-Fi, receives signals from the transmitter unit and retransmits signals to the remote monitoring system with Zigbee and Wi-Fi communication, respectively.

In [36] the implementation of HealthGear, a real-time monitoring wearable system with a blood oximeter to monitor the patient's blood oxygen level and pulse is presented. The three main hardware components of HealthGear's include: an oximetry sensor, a data transmission module and a smart phone. The sensor is connected wirelessly via Bluetooth to a smart phone which collects, analyzes and transmits the stored physiological data, and presenting it to the patient in an understandable way. The after mentioned study addresses with 20 participants how HealthGear manages to acquire, process, store, and display the medical information.

The study in [37] develops a wearable biomedical system embedded in a comfortable glove. The work is based on the photoplethysmographic (PPG) signal coming from a standard SpO₂ wrapped sensor placed in one of the fingers for the continuous monitoring of SA patient at home. The real-time monitoring is performed through the glove communications with an internet gateway connected with a remote station. When the number of SA events crosses a guard level, the alarm is released.

More recent works [38, 39] implement real-time monitoring systems that detect apneic events while the patient is sleeping. This monitoring system constitutes of SpO₂ values analysis from the Medical, Inc., 4100 Digital Pulse Oximeter. The oximeter uses the Bluetooth serial line profile to send SpO₂ current values every second to the PDA. The classifier of apnea episodes has been built using the Bagging method that uses the decision tree ADTree as base classifier. However, it must be taken into consideration that the classifier has only been trained and tested with the eight records of Apnea-ECG Database from the Physionet website that contain SpO₂ records, and when validated against Apnea-ECG Database, provides an accuracy of 93%. Moreover, the system is limited to the detection of SA, but proposed system can be used for the detection of a variety of sleep disorders.

Another recent work, Apnea MedAssist [40], was implemented on Android operating system (OS) based smartphones. The smartphone provides initialization, configuration, and synchronization of Bluetooth connectivity to an off-the-shelf one Lead ECG sensor used for recording heart activity on a per 1-min epoch basis. The fully automated processing platform on a smartphone, which was implemented to process ECG and generate input features for the SVM classifier to recognize OSA events, shows a high degree of accuracy for both home and clinical care applications. However, to increase the accuracy to the ones considered here,

more extracted input features from ECG or other biomedical sensors such as SpO₂ can be added.

V. CONCLUSIONS

Table 1 provides a summary of all related work with respect to performance measures, signals employed, technique used, test set and size, decision method chosen to signify if there is an apnea on a specific signal interval or not, whether it is run in real time, offline or portable, hardware used in the implementation, and more extra features such as the cost.

From such results, we can see that most of the approaches make use of the whole signal in order to perform the analysis, and the validation provided by the tests have been performed on the Apnea-ECG Database. Furthermore, we can categorize the various systems that deal with OSA monitoring, that is, those portable commercially available as well as research proposals into off-line and real-time systems. The main categories include (A) Off-line systems that help to diagnose SA using the automatic computer analysis on downloaded recorded data. For example, Zhao et al. [18], ApneaLink™ Plus [27], and other portable commercial systems that only record the signals (SpO₂ and airflow) to perform off-line analysis. These systems still have various limitations resulting from the fact that the classification is not performed in the place where the signal is acquired. (B) Systems that perform local real-time OSA monitoring. For example, MedAssist [40] lies within this category.

In general, the diversity of the studies designs and objectives were very high and the methodological rigor of these studies as assessments of diagnostics and monitoring tests was low. Thus, to enhance the utility of this literature, we are working on developing a portable monitoring system to facilitate the self-administered sleep tests in familiar surroundings environment closer to the patients' normal sleep habits. Therefore, the patient does not need hospitalization and can be diagnosed and receive feedback at home, as it eases follow-up and retesting after treatment. In this system, the sleep data will be sent wirelessly via Bluetooth to a nearby smartphone for processing and storage. Moreover, the data can be uploaded to cloud and transmitted to a hospital to keep the individual's health records. This not only will assist physicians and patients in planning for sleep apnea treatment, but will also offer access to a large pool of sleep data for investigations in this challenging field through providing benchmark data that can be used by researchers to enhance their used mechanisms and tools.

After the successful design and implementation of the OSA system, it is planned to be experimentally tested in order to evaluate its accuracy and practicality. The tests will take place in a local hospital for a set of patients who have symptoms of OSA. In addition, a different set of other subjects without SA symptoms will test the system to verify its false positive accuracy.

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TABLE 1 Comparison Current OSA Detection Techniques

Research work	Performance [%]			Signal analyzed	Techniques employed	Decision method	Test set & size	Realtime/Of fline/ Portable	Hardware used
	Se	Sp	Acc						
Lin et al. [12] 2006	69.64	44.44	NA	EEG	Wavelet Transforms & ANN	Threshold (delta wave frequency)	slp59 EEG recording from the MIT-BIH sleep database	Offline	NA
Almazaydeh et al. [14] 2012	100	92.9	96.5	ECG	Feature Extractions	SVM classifier	70 ECG recording from physionet	Offline	NA
Marcos et al. [16] 2010	97	79.3	93	SpO ₂	Spectral and nonlinear features	LDA classifier	214 SpO ₂ signals	Offline	NA
Almazaydeh et al. [17] 2012	87.5	100	93.3	SpO ₂	Feature Extractions	NN	8 SpO ₂ recording from physionet	Offline	NA
Zhao et al. [18] 2011	90	91.67	NA	Snoring	Formant frequency	Personalized threshold	12 simple snores (7 males, 5 females) and 30 OSA patients (27 males, 3 females)	Online	a non-contact unidirectional microphone placed about 0.3m above the patient's mouth simultaneously with their full PSG study
Yadollahi et al. [21] 2009	90	90	NA	Tracheal breathing	Total energy of the breath sounds segment	fuzzy functions	40 patients	Online	Sony (ECM-77B) Microphone
Xie et al. [23] 2012	79.75	85.89	84.4	Spo ₂ and ECG	Features set	Bagging with REP Tree classifier	25 subjects PSG recording	Offline	NA
Alvarez et al. [24] 2009	91	83.3	88.5	Spo ₂ and EEG	Spectral analysis	Forward stepwise logistic regression (LR)	148 subjects PSG recording	Offline	NA
Shochat et al. [26] 2002	80-86	57-86	NA	Airflow	NA	NA	402 patients	Online, Portable	oral and nasal thermistors
Wang et al. [33] 2006	NA	NA	NA	Body movement	Video information	A continuously updated 2D breathing activity template	2 subjects	Online	Two SONY infrared camcorders (DCR-HC-30E)
Angius et al. [37] 2008	NA	NA	NA	PPG	Frequency analysis	Guard level (fixed threshold)	20 volunteers	Remote realtime	SpO ₂ wrapped sensor, remote station
Burgos et al. [38,39] 2010	NA	NA	93	SpO ₂	Features set	decision tree ADTree classifier	8 records from Physionet	Realtime, portable	Medical, Inc., 4100 Digital Pulse Oximeter, PDA
Bsoul et al. [40] 2011	96	NA	NA	ECG	Features measure	SV classifier	ECG recording from physionet	Realtime, portable	ECG sensor, smartphone, server

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