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Sleep Apnea Detection Methods: A Review

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Abstract
Obstructive sleep apnea (OSA), one of the most widespread sleep-related disorders, is defined by a decrease in airflow while breathing during sleep and can have serious health effects. Most often, polysomnography is used in sleep labs to identify this condition, which is expensive and stressful for the patient. The expense, availability of sources, and highly dependent on one parameter, especially the apnea-hypopnea rate per hour (AHI) , limit current diagnostic testing procedures. Several systems have been developed to overcome this problem, using sensors to detect physiological signals that are then analyzed by algorithms, to conduct the examination and analysis in the patient's home. Reviewing articles that demonstrate the effectiveness of various technologies for ambulatory sleep apnea diagnosis is the goal of this study. Each article was assessed based on its diagnostic components, the degree of automation used, the level of evidence subtracted, and its quality grade.

Keywords: Obstructive Sleep Apnea, Polysomnograph, Apnea-Hypoapnea Index .

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الطرق المستخدمة لتشخيص حالات الاختناق اثناء النوم

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الملخص

حالات الاختناق اثناء النوم: هي من امراض النوم المنتشرة بصورة كبيرة حول العالم. وتحدث عندما ينغلق مجرى التنفس اثناء النوم. الطريقة التقليدية لتشخيص هذه الحالة هي استخدام جهاز تخطيط النوم في مختبر ومراكز النوم. يعتبر هذا الجهاز مرتفع الثمن والتقنية غير مريح للأشخاص الذين يخضون لها، إضافة إلى أن المؤشر الوحيد المستخدم واحدة لتشخيص الاختناق اثناء النوم وهي معدل توقف التنفس اثناء النوم. هناك الكثير من الانظمة طورت لتشخيص حلات الاختناق اثناء النوم بواسطة استخدام المستشعرات لتسجيل الاشارات الحيوية وتحليلها بواسطة الخوارزميات حيث يمكن استخدام هذه الأنظمة في المنزل.

ومدى فعاليتها في تشخيص الاختناق اثناء النوم حيث تم تقييم الابحاث اعتمادا على المؤشرات المستخدمة بالتشخيص ودرجة التدخل بالقياسات ودرجة الثقة والنوعية.

الكلمات المفتاحية: توقف التنفس، الاختناق الليلي.

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1 Introduction

At least 10% of people around the world suffer from the obstructive sleep apnea (OSA)[1][2], A significant portion of individuals with mild to severe illness go undetected [3][4]. OSA affects 14% of men and 5% of women in adults, particularly mild-moderate severity is on the rise and partly as a result of the rise in obesity in developed countries[5][6]. With estimates of the wider population prevalence approaching 50% for some nations, the overall prevalence is considered to be 1 billion[7]. This offers a diagnostic problem because the conventional diagnostic device was polysomnography (PSG) in a sleep center, which is time-consuming and costly[8]. Sleep disruption, quasi-sleep, and excessive daytime somnolence (EDS) are all symptoms of OSA, which is defined by repeated upper airway obstruction (UAO) during sleep that causes cycles of apnea and hypopnea [9]. Intermittent hypoxia (IH) is caused by the interruption of airflow and is considered to be a significant pathogenic mechanism for the severe effects of OSA, such as cardiovascular issues and death [10][11]. Due to its substantial correlation with cardiovascular disorders such as hypertension, arterial disease, heart disease, stroke, and diabetes, OSA adds to a significant health burden in society[12][13]. OSA is linked to a lower quality of life as a result of EDS[14], car accidents[15], depression, and cognitive impairment[16], regardless of age, sex, or fat.

A sleep study's apnea-hypopnea index (AHI) is used to measure the severity of OSA. But current research indicates a weak correlation between daytime symptoms and the level of OSA detected during a sleep study [17], therefore there is an increasing need for OSA diagnosis and treatment to adopt a more individualized approach in place of the AHI as the primary indicator of OSA[18].

Heart rate variation (HRV), pulse transit time (PTT), oxygen saturation (SpO_2), and the utilization of biomotion sensors are just a few examples of signs that may help with a more accurate and reliable diagnosis of OSA. Wearable technology and home sleep apnea monitoring could facilitate diagnosis and increase treatment compliance.

2 Conventional measures

PSG serves as the standard for the research of sleep and is the gold standard for the detection of OSA[8]. PSG is a time-consuming procedure that involves recording EEG, EOG, EMG, ECG signals in order to assess several aspects of sleep, including stages of sleep, arousals, movement, and sleep-related irregular heartbeats.

Airflow is detected using a thermistor and a nasal pressure sensor, while thoracic motions are found by respiratory inductive plethysmography. It is also possible to monitor heartbeats and oxygen levels using pulse oximetry . PSG is usually done out in a sleep lab with a technician present.

The development of alternate methods of testing, such as portable Home sleep apnea testing (HAST), is a result of the increased occurrence of OSA[19], the time-consuming setup, and worries that PSG diagnosis is ineffective [20].

3 Home sleep apnea testing(HAST)

HSAT is more inexpensive, practical, and can be done in the patient's home. Respiratory effort, airflow, heart rate or ECG, arterial oxygen saturation, snoring, body posture, and movement are among the four to seven factors that the HSAT will monitor. The diagnosis accuracy of newer technology has increased, and several instruments have now been verified against PSG[21]. HSAT may also record multiple nights of sleep, which is helpful because a night-to-night fluctuation is a characteristic of OSA and is typically more significant in people with mild severity[22][23]. Due to HSAT's inability to measure total sleep duration (TST) and detect arousal, these devices often underestimate the AHI regardless of their simplicity, raising the risk of a false-negative result[24][25]. Less physiological variables are assessed, which can cause results to be misunderstood and may cause parasomnias, insomnia, and other accompanying sleep disorders such as limbs motions to go unnoticed. The American Academy of Sleep Medicine (AASM) cautions against using HSAT as a technique for population screening, but does endorse it for the diagnosis of OSA in certain groups[26].

4 Modern technologies in OSA diagnosis

New, innovative technology enables more complex algorithms and systems to acquire in-depth information. Classical PSG is still the "gold standard," but modern techniques like wearable, Wi-Fi, unique sensors, and remote monitoring provide intriguing proposed solutions to PSG. Combining these techniques can have the potential to improve patient care and make diagnostic tests easier to read, resulting in a quicker diagnosis and, eventually, more effective therapy for OSA patients.

4.1 techniques based on oximetry

Oliver et al. [27] presented a system called HealthGear that consists of an oximetry sensor that transfers signals to a smartphone via Bluetooth for analysis. In order to find intensity peaks, the OSA detection algorithm computes a graph of the mean-oximetry signal and examines the frequency range from 0.015-0.04 Hz.

Alfredo et al.[28] designed a system that transmits oximeter measurements to a Personal Digital Assistant (PDA) via Bluetooth. Each SpO2 signal fragment followed a categorization procedure that involved analyzing five alternate decision and obtaining the majority result. **Zhang et al**.[29] suggested a continuous diagnosis and therapy strategy. The SpO2 level is measured by a pulse oximeter, and the signals is transmitted via Bluetooth to a smartphone where it is analyzed by an algorithm that looks for desaturation episodes. The closest local maximum SpO2 grade and local minimum SpO2 grade are first detected. If the minimum was less than the first threshold and the maximum minus the minimum was larger than the second threshold, an episode was deemed to have occurred.

Garde et al.[30] demonstrated a portable technique that utilization a mobile phone with a pulse oximeter. The proposed device records SpO2 levels, the software analyses the signals on time and frequency domain. An autoregressive model was used in statistical analysis of the time domain to calculate the power spectral density (PSD). As a classifier, a linear discriminant analysis (LDA) was employed.

Grade et al.[31] employed the same tool, however, the photoplethysmography (PPG) and SpO2 values are provided by the pulse oximeter.

Angius et al.[32] used a wireless method to collect data from a monitoring station and measure the photoplethysmography signal from the SpO2 detector. The system consists of two primary components that are located in the patient's house and the Remote Monitoring Station (RMS) .

The technology created by **Fábio M et al.**[33] could wirelessly transmit the oxygen saturation and pulse rate signals to the processing unit, where an application could record and analyze the information. The system, shown in figure 1, is made up of a computer, Bluetooth modules, an FPGA, and a pulse oximeter.

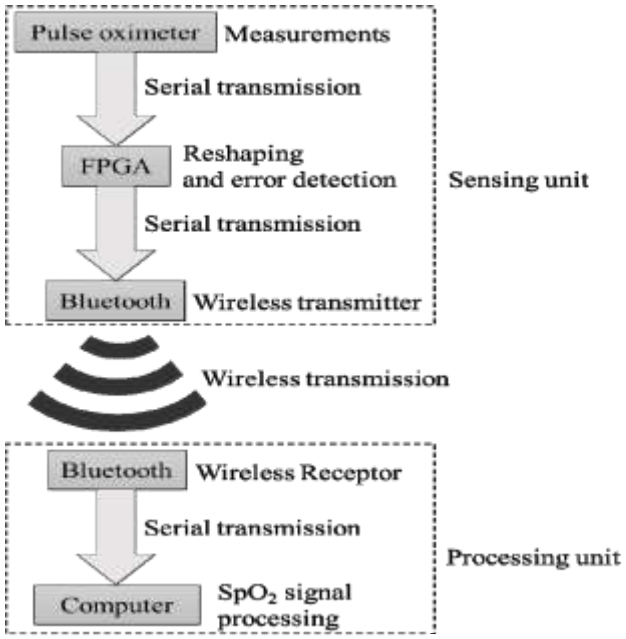

Figure 1. architecture of developed system [33].

4.2 techniques based on respiration analysis

study of breathing can obviously shows the presence of OSA because Obstructive Sleep Apnea is distinguished by a dramatic reduction in breathing. Depending on ballistocardiography (BCG), **Mac et al**.[34] created a non-invasive technique for analyzing physiological data and identifying body movement associated with breathing. Each breath intensity is categorized by an algorithm as normal, arousal, or apnea. **Shin et al.**[35] additionally made use of the strategy of using an air bed with a balance tube depended on BCG as the sensing unit. An auto-correlation function was used to calculate the mean respiration rate, and variance analysis was used to identify OSA. An air bed and balance tube, a pressure sensor, analogue filters, an A/D converter, and a digital processor or personal computer make up the system.

Hwang et al.[36] built a polyvinylidene fluoride film-based sensor on top of a mattress, and the output signal changes in accordance with the respiratory phases. To identify OSA, an adaptive threshold was applied to the respiratory signal's standard deviation. The sensor, which was made up of a 41 array and intended to be positioned beneath the subject's back.

Jin et al.[37] measured the flow of nasal air using a micro-electro-mechanical systems (MEMS) sensor and an efficient algorithm for detecting apnea, . A threshold window was specified before the resulting signal was compared to it. A wearable apnea device with high-level integration SOC (system-on-chip) that integrates a MEMS sensor and a bespoke IC is shown in Figure 2. Such a device can be exceedingly user-friendly and cause the patient little discomfort.

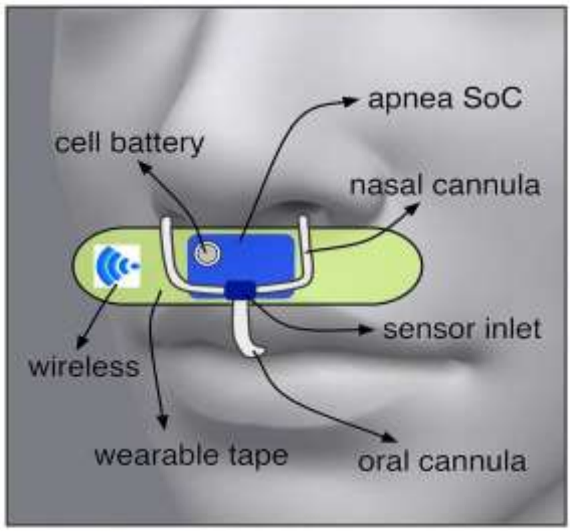

Figure 2. A sleeve that can be worn that has a tiny sleep apnea detection device[37]

John et al.[38] employed a piezoelectric sensor to detect changes in pressure and then used mathematics to depict the subject's breathing rate in the frequency domain.

Crupi et al.[39]used a vest with piezoresistive fibers to measure breathing activity using a recording device and thoracic plethysmography. To find the flow rate of nose air**, . Senthil et al**. [40] used a electrical mechanical capacitive pressure sensor. **Nam et al.** [41] evaluated the breathing pattern using a pressure sensor that was mounted on the bed and wirelessly transmitted the information to a computer. The user's physiological information, such as respiration, heart rate, and activity rate, were collected using a pressure sensor. A typical bed had the pressure sensor fitted in it. Based on breathing data obtained by a pressure bed sensor, the sleep-wake cycle was calculated.

Rodriguez et al.[42] examined the tracheal turbulence that brought on the breathing events. An acoustic chamber was used to detect the turbulence, and the analysis was carried out in 2 steps, the first in the system and the second in a PC .

4.3 techniques based on ECG

The electricity of the heart can be captured via an electrocardiogram. Patients with OSA have changes in heart rate variability (HRV).

Yilmaz et al. [43] proposed a method that records and analyzes the data using a Holter device while applying Hilbert transform and derivative-based QRS detection.

Bsoul et al. [44] employed a single-channel ECG. To process the data, it is Bluetooth-transmitted to a smartphone. The T waves were found using an automated wavelet-based analysis approach based on the undecimated lifting scheme. These waves serve as the foundation for estimating the parameters of respiration, and "a support vector machine (SVM)" was used to identify the data using their time- and spectral-feature information.

Salem et al. [45] implemented a wireless strategy as well. The RR interval was computed on a smartphone using the ECG data. The series were subsequently modified to produce Normalized time series, and the data were classified using the z-test analysis of the root mean square of the mean of the squared difference between subsequent Normalized intervals.

Surrel et al.[46] employed single-lead ECG analysis in a similar manner in addition to the goal of getting the RR interval and diagnosis OSA by the relative power on a chosen band that maximizes the accuracy relative to the total signal power.

4.4 techniques based on sound

Specific noises can be utilized to identify apneic episodes. **Kaniusas et al**.[47] and colleagues employed this idea .A microphone was positioned close to the thorax to record snoring noises, and breathing events were then classified. The classified events were subjected to histogram analysis and adaptive thresholds in order to identify OSA**. Hiroshi et al.**[48] used a compressing sound spectrograph method to analyze tracheal noises. To measure OSA, a tracheal sound-respiratory disturbance index was suggested.

Zhao et al.[49]suggested an alternative method in which the mike was putted above the objective mouth to record snoring sounds. The snorer's first formant frequencies were split into two clusters by the K-means clustering technique using a custom threshold.

Several researchers utilized mobile phones to record sounds. Mel-frequency cepstral coefficients and a K-means clustering technique were applied to the recorded sound by **Lu-Ping et al.**[50]in order to identify apnea. **Han et al.**[51] and **Ren et al**.[52] used SVM as a classifier with the same objective.

A phone was utilized by **Nandakumar et al**.[53] as an acoustic system. The microphone picked up sound waves that were reflected from the phone speaker. In order to estimate the breathing signal, a frequency waves was sent out, and an algorithm looked at the reflections that arrived at various intervals, concentrating on the reflection patterns caused by breathing.

4.5 techniques based on combined approach

To identify OSA, it is possible to combine different methods. Sound and oximetry were used by Yadollahi et al.[54] to identify OSA. Breathing sounds were captured and classified. Analysis was done on the voice section that matched oxygen concentration signal decreases. A sigmoid function was used to fuzzily each parameter, and the results were then measured against to a basline.

Heneghan et al.[55] used the method, in which a mobile system captures ECG and SpO2. Using the RR interval time series, the program examines features of electrocardiogram signal by analysing the size of QRS amplitude, oxygen concentration levels, and cyclic fluctuations in heart rate. The data were categorized using an LDA.

Embedded sensors in neck cuffs were employed by **Rofouei et al**.[56] to record breathing sounds and SpO2. To detect times of not respiration and reduction in the oxygen concentration level, the detection algorithm received the information through Bluetooth. The system is made up of multiple sensor nodes, a CPU, and a Bluetooth transceiver that are all assembled into a neck cuff together with a desktop computer or a cell phone. For data aggregation, the data from a laptop or a cell phone can be uploaded to the cloud.

The neck-cuff system is seen in Fig. 15.a, along with views of the system from the user's front and back. In section b, these elements are fully described.

Using a microphone affixed to the patient's neck, **Al-Mardini et al**.[57] calculate the breathing effort. The data is gathered and the AHI is calculated using a smartphone. The Oxygen Desaturation Index was calculated using the smartphone-connected pulse oximeter (ODI). AHI and ODI are averaged, and an algorithm calculates the occurrence of OSA by comparing the result to a threshold.

Behar et al.[58]introduced Sleep application, a smartphone application that uses characteristics collected from audio recorded from an external speaker placed adjacent to the nose and PPG recorded by a pulse oximeter connected to the application by Bluetooth as inputs of an classification model.

5 Discussion

Obstructive sleep apnea (OSA), a potentially dangerous disease, is distinguished by frequent breathing stops during sleep. The standard for diagnosing OSA is polysomnography (PSG), however, it is expensive, uncomfortable for patients, and necessitates an overnight stay in the hospital. Researchers have experimented with numerous homebound and affordable ways for detecting OSA in an effort to free patients from the limitations imposed by PSG. Various methods have been used to identify OSA. In order to provide an idea of the performance of the devices under study, a comparison of the results obtained is offered, taking into account the challenges that arise when comparing methodologies because of the various settings and populations employed for the research. Table.1 shows the comparison between techniques. The research studies produced the best results when oximetry and sound analysis were combined, followed by respiration analysis, which was employed, either independently or in combination, by all commercial devices that claim to have the highest diagnostic performance. According to this study, portable monitors can be used to diagnose OSA earlier on, resulting in a significant decrease in diagnostic costs and the time it takes to get a sleep study. They can also make sleep research more accessible to the general public by lowering the wealth of the participants in the sleep clinics and laboratories and providing access to individuals with low income and/or poor mobility. According to the severity level determined by the home diagnostic test, patients could be ranked in order of need for PSG. Although recent research has several methodological problems, the results are reliable and suggest that portable monitors can be utilized as a first-line OSA diagnosis tool. However, because to factors that cannot be controlled in the subject's home, such as misuse of the device, these devices are more susceptible to mistakes.

Research	Quality	Categorize	Population	epoch-based Sensitivity	subject-based Sensitivity	automatisation

The attempt to find physiological indicators which differentiating those who have a medically serious problem is growing as a result of the growing understanding that AHI is a subpar indicator of the existence of OSA and the transition to mobile devices for diagnosis and treatment. Although currently available technologies have not yet achieved that goal, it is anticipated that cellphones and wearable technology will play an important part in these advancements. Biomarkers and other techniques may also be useful, particularly in identifying pertinent comorbidity. The most likely combinations of signals to succeed in displacing traditional tests like PSG for most patients are those that can be non-invasively evaluated in an ambulatory context. There are a variety of ways to enhance the diagnostic system Based on respiration analysis, such as enhancing the piezoresistive sensor's dependability or adding other sensors, like an abdomen respiratory sensor and/or pulse oximetry, to better distinguish respiratory episodes. Every body movement during the sleeping will impact the signal. It is challenging to calculate HR and RR from information acquired from just a pressure sensor while a patient is moving around on a bed.

Alfredo et al.[28]	c	O_1	3	92	-	Full-automatic
Zhang et al.[29]	b	O_1	40	96	-	Full-automatic
Garde et al.[30]	a	O_1	68	-	80	Full-automatic
Garde et al.[31]	a	O_1	160	79	-	Full-automatic
Mack et al.[34]	b	E_4	13	89	-	Semi-automatic
Shin et al.[35]	b	E_4	13	88	-	Full-automatic
Hwang et al.[36]	b	E_4	26	73	100	Full-automatic
Jin et al.[37]	b	R_2	5	-	100	Full-automatic
Crupi et al.[39]	d	E4	-	98	-	Semi-automatic
Nam et al.[41]	d	E_4	10	-	-	Full-automatic
Rodriguez et al.[42]	c	R_2	30	89	-	Full-automatic
Yilmaz et al. [43]	d	C_3	-	-	-	Full-automatic
Bsoul et al. [44]	c	C_3	35	96	-	Full-automatic
Salem et al. [45]	c	C_3	70	-	-	Full-automatic
Surrel et al.[46]	c	C3	70	-	-	Full-automatic
Kaniusas et al.[47]	c	A_1	30	-	-	Full automatic
Hiroshi et al.[48]	b	A_1	383	-	93	Full automatic
Zhao et al.[49]	b	A_1	42	-	90	Full automatic
Nandakumar et al.[53]	b	A_1	37	-	-	Full-automatic
Yadollahi et al.[54]	a	O_1	40	-	82	Full-automatic
Heneghan et al.[55]	a	C_3	59	51	94	Full-automatic

Al-Mardini et al.[57]	b	S_3	15	-	100	Semi-automatic
Behar et al.[58]	c	S_1	121	81	-	Full-automatic

Table 1. Evaluation of the research devices.

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