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Accurate method for home-based diagnosis of obstructive sleep apnea: a review

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ABSTRACT

Overnight polysomnography is the gold standard for the detection of obstructive sleep apnea-hypopnea syndrome (OSAS). However, it is expensive and needs attending personnel. The study of simplified sleep apnea monitoring is one of the recent trends for sleep medicine research. The proposed clinical prediction rules employ the vital and social statistics, symptoms, craniofacial traits, and obesity-related measures for initial screening of OSAS in an ambulatory setting. However, most of them are partially or completely clinical and not home-based. One disadvantage of this sort of screening methods is their inability to asses OSAS severity. Another approach of initial OSAS screening is a usage of just one or two physiological signals such as electrocardiography (ECG), pulse oximetry, snoring, nasal airflow, or even speech sound. In this study, we aimed to review the different strategies and to compare their performances, reported by means of their sensitivity–specificity and accuracy for OSAS incidence and severity. OSAS severity is determined by apnea-hypopnea index (AHI) value. Based on the data obtained from the related articles, the most accurate methods of AHI estimation exploit ECG and pulse oximetry signals.

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Introduction

Obstructive sleep apnea-hypopnea syndrome (OSAS) is a widespread breathing disorder during sleep, and a potentially fatal condition affecting millions people worldwide. A study of the American adult society showed the OSAS prevalence of 2-4 % in two decades ago (1). However, its outbreak is increasing internationally along with obesity and aging (2). According to later observances in some Asian countries, it affects 7.5-27 % of adult population (3,4).

OSAS patients literally face frequent periods of airway blockage (apnea) or narrowing (hypopnea) during sleep. The termination or decrease in respiratory airflow results in the loss of oxygen (hypoxemia) and the increase of CO2 (hypercapnia) in blood stream. These phenomena trigger the reaction of the central nervous system called arousal. During arousals the respiration resumes without reaching the conscious wakefulness (5). The frequent arousals and the inability to achieve or maintain the deeper stages of sleep could lead to excessive daytime sleepiness (EDS), non-restorative sleep (6), and automobile accidents (7). OSAS may also lead to type 2 diabetes (8), impaired cognition, and psychiatric symptoms such as personality changes, decreased memory, erectile dysfunction (impotence), and depression (9).

Through the apnea-associated short-term cardiovascular consequences, sleep apnea forms a risk factor for arterial and pulmonary hypertension, cardiovascular diseases such as coronary artery disease, congestive heart failure, and stroke (6). Each of these conditions significantly worsens the quality of life, yet many of the patients remain unrecognized for years (10).

The standard clinical method for the identifi-

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cation of sleep apnea is nocturnal recordings of different electrophysiological signals in sleep laboratories called polysomnography (PSG). The apnea-hypopnea index (AHI) obtained through PSG uses to characterize OSAS severity. The AHI is the number of apnea and hypopnea events occurring per hour of sleep (11). Initial screening of OSAS is of great value, since PSG is an expensive, time-consuming, and labor-intensive procedure. According to the results of initial screening, we could refer only the suspected moderate or severe OSAS patients to sleep laboratories. Hence, not only the efficiency of public health system enhances but also the imposed medical and economic burden on the patients decrease.

Literature review

Initial OSAS screening employs a variety of different strategies ranging from non-polysomnographic parameters to easily-acquired biomedical signals. Obesity–related measures such as body fat distribution, neck circumference, body mass index (BMI), craniofacial characteristics, and body and trunk positions have been investigated (12-14). The reviewed studies have assessed the craniofacial characteristics through cephalometrics, computed tomography, magnetic resonance imaging, and acoustic reflection. In spite of disagreements and debates, previous researches closely related some alterations in the oral cavity such as retroposition of the maxilla, shortening of the mandibular body, inferiorly-displaced hyoid bone, retrognatism, dental occlusion class II and narrow, arched hard palate to the incidence and severity of OSAS (13).

Clinical forecasting rules based on the vital and social statistics, symptoms, and body mass index identify 76% to 96% of OSAS patients and 13% to 54% of non-OSAS ones (15). The United States Department of Health and Human Services has reviewed the effectiveness of the available models and the morphometric model by Kushida gave near perfect categorical decision (i.e. discrimination between OSAS and non-OSAS subjects) (16). This model combines the maxillary and mandibular measurements with BMI and neck periphery and provides a rapid, accurate, and reproducible method for predicting whether patients in an ambulatory setting are at risk for OSAS or not (17). This clinical predictive model was tested on Caucasian and Indian patients, where it was found that patients with values equal to or more than 67, typically had OSA (12,17). The important deficiency of this sort of screening methods is their categorical decision and inability to asses OSAS severity.

A large body of literature is about the biomedical signal processing techniques for simplified OSAS detection. The prospective aim of most of these techniques is the development of home-based systems. They employ signals such as the electrocardiogram (ECG) (18,19), electroencephalogram (EEG) (20), airflow (21), snoring and speech signals (22,23), abdominal movement (24), and pulse oximetry (24-27). Some attempts have diagnosed OSAS with a combination of the mentioned biomedical signals (28,29).

Khandoker et al. proposed the recognition of individual apnea and hypopnea events by the resultant cyclic variations in heart rate (18). For individual differentiation of apnea and hypopnea events from normal breathing, they estimated the surrogate apnea index (AI)/hypopnea index (HI). They suggested that wavelet analysis (30) of short-term (5 seconds in duration) ECG signals provided useful information regarding the effect of apnea and hypopnea on cardiac electrical activities. Power in the frequencies higher than 20 Hz distinguished electromyogram (EMG) from respiratory muscle activity (31). They found that the 16–32 Hz band of ECG signals reflected the difference in the intensity of respiratory effort during apnea and hypopnea events (18).

They exploited a two-staged feed forward neural network model (32) for the classification of events. The classifier differentiated respiratory events from normal breathing events at the first stage, and designated the type of respiratory events (hypopneas from apneas) at the second stage. The first stage has shown a sensitivity of 91.68%, specificity of 98.87%, and accuracy of 98.48%, and that of the second stage has revealed the sensitivity of 87.22%, specificity of 87.03% and accuracy of 88.71%. Independent test was performed on 16 ECGs containing 483 hypopnea and 1352 apnea events. The cross validation and independent test accuracies were 94.84% and 76.82% for training set, and 94.72% and 79.77% for test set, respectively.

Research interest toward real-time or on-line apnea monitoring has increased recently. The implemented online methods through Global System for Mobile communication (GSM) or any communication network can be in touch with a medical practitioner or sleep center for real-time monitoring and assessment of OSAS.

Bsoul et al. implemented a real-time OSAS detection system using a single lead nocturnal ECG signal. The real-time capability comes from the use of 1-minute ECG segments for analysis. They used the support vector machine (SVM) for classifying breathing events as apnea or hypopnea. Their suggested that method exploited the ECG waveform changes accompanied by apneic events (19). The morphologic changes in the ECG

waveforms allowed deriving a signal proportional to the respiratory movement. In the literature, various methods were proposed to extract the surrogate ECG-derived respiratory (EDR) signal (33,34) based on R-wave amplitude, R-wave duration, QRS complex area, T-wave amplitude, or T-wave area. The authors used the T-wave method, which was more suited to the low sampling rate of their data (<250 Hz). They exploited the R-wave amplitude method for recordings with undetected (or inverted) T-wave.

Another ECG-derived respiratory signal is respiratory sinus arrhythmia (RSA). RSA is the heart rate variability in synchrony with the respiration; studies have found that the R–R interval in the ECG is shortened during inspiration and prolonged during expiration. This measure could be useful for evaluating parasympathetic nerve activity (35) and it is also used in the mentioned on-line method (19).

This on-line method uses either the general adult subject-independent model or subject-dependent one for AHI prediction. The subject independent classifier can be used for the initial screening or when no previous sleep study (PSG data) are on hand. The subject-dependent classifier utilizes the subjects` PSG data in a custom designed classifier to reach better performance.

For the general adult subject-independent model, they have not reported the sensitivity-specificity pair, but their system achieved an accuracy of up to 89.88%. The best performance of their subject-dependent model was specificity of 84.98% to 85.9%, sensitivity of 95.1% to 96.17%, and corresponding accuracy of up to 89.3%.

Until now, the application of the ECG-based algorithm for apnea scoring is restricted to nonclinical populations. Given the high prevalence of sleep apnea and long-waiting lists at sleep laboratories, many hospitals that do not have sleep unit may want to start performing portable ECG recording on symptomatic patients (18).

Blood oxygen saturation (SpO2), measured by pulse oximetry, is another choice for OSAS screening. The researchers are extensively interested in this signal, because it could be easily and non-invasively acquired and is suitable for portable monitoring. Apneas and hypopneas are usually accompanied by noticeable desaturation events. Consequently patients with OSAS tend to show unstable SpO2 signals (36,37). Several quantitative measures are available to quantify such irregular behavior of SpO2; e.g. the number of oxyhemoglobin desaturations below a certain threshold (usually a 3% or 4% decline from baseline) (38,39), cumulative time spent below a certain saturation level (40), and the saturation variability index (41,42). Many researchers have quantified the variability of SpO2 by means of spectral and nonlinear measures (43).

Different diagnostic models are available for the detection of OSAS based on logistic regression (25), linear discriminant analysis (44), and neural networks (45,46). All the aforementioned methods, however, provide either a categorical decision for each subject (OSAS/non-OSAS) or an indirect estimation of AHI based on overnight SpO2 recordings. Regardless of the type of decision, regression methods suffer from a basic deficiency; they all assume that the predictable outcome (i.e. the OSAS severity) is dependent on one or more features that are statistically independent from each other (47,48). This strong assumption might not be true for many of the biological features.

Burgos et al. implemented real-time OSAS detection systems using an ensembled classifier and the SpO2 signal (49). More recently, Xie et al. developed a real-time detection of OSAS using a classifier combiner and both ECG and SpO2 signals (50). However, the previous works tried to identify apneic periodes in terms of fragments of the signal on minute-by-minute basis, but did not identify the events. The number of apneic events may not be the same as the number of 1-minute epochs, because one epoch may contain multiple events and a long apnea event may be prolonged in several epochs. Therefore, the identification of events is desirable for direct estimation of AHI.

Koley et al. proposed an online apnea and hypopnea event detection system that provided a direct estimation of AHI by counting the total number of identified events (26).

Properly-trained classifiers can perform apnea/hypopnea event detection. This involves presenting the feature vector extracted from the specified data segment (termed the longer segment) to the SVM_N_AB classifier model for the prediction of possible class normal (N) or abnormal (AB). If the decision of the classifier is AB, then that longer segment of the SpO2 signal is further fragmented into shorter overlapped segments. Features are again extracted from these fragments of shorter duration and are presented to the SVM_S_D_R classifier model for the classification of desaturation (D), re-saturation (R), and steady (S) states of the SpO2 Signal.

In careful investigation of the SVM_N_AB classifier model alone (System-I) and the SVM_S_D_R classifier model alone (System-II), the authors observed that System-I identified some of the non-event-related long-duration drops in SpO2 as events. However, this system is robust in detecting events with the duration of more than 20 seconds. On the other hand, System-II

overestimates the AHI by detecting short-duration fluctuations of SpO2 as events, but it is robust to reject long-duration drops in SpO2 as events, often incorrectly identified by System-I. When the output of SVM_S_D_R fed to SVM_N_AB (System-III), classification accuracy enhances but at the expense of comparatively higher computations. The authors reported separate sensitivity–specificity pairs for abnormal, desaturation (D), re-saturation (R), and steady (S) states of the SpO2 signal but just tabulated the achieved accuracies for the overall event-detection process. The highest sensitivity–specificity pair was (96.7%-94.5%) for R detection while the lowest values (87.5%-81.7%) went to the abnormality detection. They achieved average event detection accuracies of 96.7% and 93.8% for the offline and the online tests.

In contrast to other works, this study used overlapping segments of SpO2 signal and then categorized these segments into different classes with the help of classifiers. Finally, with the help of time sequence decisions of the classifiers, a rule-based system was employed to identify the event, which basically took the reference of the typical time domain signature produced in SpO2 during the apnea/hypopnea event.

Conclusion

Clinical prediction rules identify 76% to 96% of OSAS patients and 13% to 54% of non-OSAS ones based on the vital and social statistics, symptoms, craniofacial traits, and obesity-related measures. These clinical predictive models are useful for the initial screening of OSAS in an ambulatory setting. However, most of them are partially or completely clinical and not home-based. Another deficiency of this sort of screening methods, which is even more important, is their categorical decision and inability to asses OSAS severity. They are unable to designate the suspected moderate or severe OSAS patients for further monitoring at sleep laboratories.

Simplified monitoring of sleep apnea severity (ascertained by the AHI value) is viable using just one or two physiological signals such as ECG, pulse oximetry, snoring, nasal airflow, or even speech sound. Comparing their sensitivity–specificity pair and accuracy for both OSAS incidence and severity, the most accurate methods of AHI estimation, exploit ECG and pulse oximetry signals. The most recent and accurate strategy exploits pulse oximetry signal with highest sensitivity–specificity pair of (96.7%-94.5%) and average event detection accuracy of 96.7%.

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Conflict of Interest

The authors declare no conflict of interest.

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