Obstructive Sleep Apnea Detection Methods Based on Heart Rate Variability Analysis: Opportunities for a Future Cinc Challenge

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Abstract

The effects of sleep-related disorders, such as obstructive sleep apnea (OSA), can be devastating either in children or adults. Misdiagnosis may lead to severe cardiovascular diseases. Besides, OSA consequences are often related to bad job performance, and road accidents. Nowadays, polysomnography (PSG) is still considered the gold standard for OSA diagnosis, but the required facilities are extremely high, thus reducing availability worldwide. For this reason, simpler and cost-effective diagnosing methods have been proposed in the late years. In this regard, the heart rate variability (HRV) has been demonstrated to strongly reflect apnea episodes during sleep. Hence, this work reviews the latest advances in the evaluation of OSA from the HRV perspective to consider its potentialities for a future revisited CinC Challenge.

1. Introduction

Sleep apnea syndrome is a disorder in which breathing is repeatedly arrested during sleep. To appraise its severity, an apnea/hypopnea index (AHI) is determined as the number of apnea and hypopnea events per hour of sleep. Prevalence is considered high, ranging from 9 to 38% (AHI $\leq$ 5) in the general population, and it is greater in people suffering from obesity, particularly in men [1]. Two types of sleep apnea syndromes may be found in the literature, i.e., central sleep apnea (CSA) and obstructive sleep apnea (OSA). CSA is characterized by a decrease or abeyance of ventilatory effort, whilst OSA is characterized by repetitive episodes of obstruction of the upper airway [2].

Both varieties are usually associated with a significant decrease in blood oxygen saturation (SpO2) [2]. As a consequence, breathing pauses for a few seconds, which leads to a decrease of blood oxygen and an increase of CO_2. This causes the central nervous system activation that results in arousals during sleep [3]. These arousals cease the process of sleep and brings oxygen level back to normal. Furthermore, OSA is often associated with a characteristic snoring pattern that is alternatively followed by silent episodes that usually last 20 to 30 seconds [2]. These episodes, may be noticed by a bed partner. Moreover, arrhythmias and hypoxemia may occur during the aforementioned stages, leading to severe cardiovascular diseases likewise high blood pressure, heart attacks and strokes [4].

Patients suffering from OSA also describe feelings of excessive sleepiness, disorientation, grogginess, and lack of coordination. The daytime sleepiness can be incapacitating, resulting in job loss, road accidents, marital or family problems, and poor school performance [2]. Misdiagnosis can lead patients to being labeled as lazy or as having a primary mental disorder, such as depression. Notwithstanding, polysomnography (PSG) is still currently asserted as the gold standard for OSA diagnosis. PSG recordings typically involve oral-nasal airflow, blood oxygen saturation, chest-abdominal breathing movements, and body position when accompanied with electroencephalogram, electromyogram, and electrocardiogram (ECG). All needed devices put on the patient's body scarcely conveys a reliable sleep. Although this method may provide further information about eventual sleep disorders, its complexity and cost limits the global coverage.

In this regard, heart rate variability (HRV) plays a critical role since it strongly reflects apnea episodes during sleep [5]. In comparison with other magnitudes, such as oral-nasal airflow [6] or the rapid eye movement, HRV is easier to obtain from ECG or photoplethysmography (PPG), and brings accurate results [7]. In the view of more comfortable and cost-effective tools released in the late years, i.e., the single-lead ECG [8] and pulse oximetry devices [9], HRV has become a sort of a new standard in researching. Therefore, because PSG is complex and time-consuming, the search for simpler methods in OSA detection has become a major goal. In this context, this work reviews the latest advances in the evaluation of OSA from the HRV perspective to consider its potentialities for a future revisited CinC Challenge.

2. Methodology

A literature research has been conducted by consulting the following databases: Web of Science, PubMed, Elsevier's ScienceDirect, IEEEXplorer, Springer, and Scopus. The employed key terms were *sleep apnea*, *detection*, and *heart rate variability*. These key terms were combined in advanced searching tools, e.g., "sleep apnea AND heart rate variability" such that 119 articles were found in the period within 2009 and the present. Afterward, a comparison between target key-terms and articles key-terms was performed excluding those articles that mismatched with the topic. Another exclusion criterion was ignoring all articles that were not published in scientific journals, i.e., conferences and congresses. Eventually, 18 articles remained as potential candidates. These articles were fully read and studied as well as some of their inner references. Ultimately, the classification performances and standard procedures were extracted to establish the expected results criteria. However, due to similarities between some methods, only 7 papers were considered in this survey, since they obtained the most promising results in terms of accuracy (Ac), sensitivity (Se), and specificity (Sp).

3. Sleep apnea detection methods

In order to organize all the entries of the survey, methods were classified according to the physiological nature of the signal used to extract HRV. Thus, the methods included in this review are based on electrocardiogram (ECG), and pulse oximetry.

3.1. Methods based on ECG

In 2018, Zarei and Asl proposed an automatic OSA detection algorithm based on discrete wavelet transform (DWT) and entropy features [10]. They employed two different databases, the Apnea-ECG, from Physiobank [11], and the St. Vicent's University Hospital/University College of Dublin Sleep Apnea Database [12], both available on Physionet's official repository. They segmented the recordings into 60-seconds intervals and then applied DWT to decompose them into several time-frequency scales. Furthermore, they employed complexity measures such as approximate entropy, conditional entropy and similarity, to assess the presence of irregularity within recordings. As a result, 108 features were extracted. Eventually, they applied a sequential feature selection (SFS) algorithm and assessed several machine learning classifiers. In this case, support vector machine (SVM) best performed, obtaining an Ac of 95.7%, Se of 95.8% and Sp of 95.6% as per detected patient, and an Ac of 94.6%, Se of 94.4%, and Sp of 95.7% as per detected apnea episode during sleep with only 18 features after SFS.

In 2017, Dong et al. developed model based on frequency networks [13]. They also employed the Apnea-ECG database [11] together with a private dataset. Firstly, they performed a 5-min recording segmentation. Then, they employed the Lomb-Scargle periodogram (LSP) [14] to obtain the power spectral density (PSD) of HRV. The particular point in this work, was the use of dynamic time warping (DTW) to assess similarity between time-frequency series. Thus, a network of HRV segment frequencies was formed up with conventional nodes. Such nodes were connected by means of a threshold value determined by the DTW distance. Thus, as a result of using only 3 network features, they obtained and Ac of 90.1%, Se of 88.3% and Sp of 90.5% to detect OSA patients (OSA diagnosis).

In 2016, Cheng et al. conducted a series of experiments in 2-dimensional fractal space based on heterogeneous recurrence analysis [3]. They used the Apnea-ECG database as well [11]. They formed up a state space from the HRV time series using the Takens' delay embedding theorem [15]. The resulting attractor was segmented into multiple sub-regions to facilitate the extraction of local heterogeneous recurrence properties. Moreover, the recurrent patterns between regions were labeled through a multidimensional categorical indexing tree together with a fractal representation of these [16]. Ultimately, a regularized logistic regression model was used to combine the extracted features, thus reaching Ac of 83.0, Se of 83.0% and Sp of 82.0%, as per detected apnea episode.

3.2. Methods based on pulse oximetry

In July 2019, Bozkurt et al. proposed a method based on PPG by combining multiple machine learning techniques and non-linear features [17]. The initial data was recorded with a PSG device at the Sleep Laboratory of the Department of Pulmonary Diseases at Sakarya Hendek State Hospital. Thereafter, HRV was derived from the PPG peaks, similarly to former ECG recordings. Therefore, they extracted several features from the PPG and the HRV series, which added up to 86 features. Nevertheless, they applied F-score to reduce the number of candidate features. Ultimately, they formed up an ensemble classifier based on the majority vote of several conventional classifiers. Classification results were shown for two different number of selected features. They finally obtained an Ac of 93.0, Se of 93.0% and Sp of 96.0% with only 4 features as per detected patient. It is worth saying that even if apnea was detected, they intended to detect arousals during breathing arrests.

In 2018, Haoyu et al. developed an internet of medical things scheme based on SpO2 (extracted from PPG) and supported with HRV [18]. In this work, HRV and SpO2 were both extracted from the St. Vicent's University/University College of Dublin Apnea database, and a private dataset previously recorded as well. All recordings were scored on a one-minute basis by clinical experts, therefore, these were divided into 1 minute-length segments. In the first place, several statistical features were extracted from HRV and SpO2. In the case of HRV, they extracted the mean, the standard deviation, and the square root of the mean of the sum of the squares pertaining to differences in adjacent RR intervals. Furthermore, they adopted the method proposed by Bsoul et al. [5] to extract the rest of the SpO2 features. Again, among these, they were the minimum, the variance, the mean, and a correlation coefficient regarding SpO2 samples for every segment of signal. Eventually, the best performance were obtained employing a SVM approach and using two features from HRV and other two from SpO2. As a result, they claimed an Ac of 98.5, Se of 95.8% and Sp of 98.9% as per diagnosed patient.

Also in 2018, Garde et al. developed a pulse oximetry-based OSA screening method [19], which has been validated with the "Sleep" dataset from the British Columbia Children Hospital and a private dataset. All data comprised both PSG and PPG recordings collected at the same time. Firstly, they segmented PPG signals into 2-minute frames. Then, SpO2 and pulse rate variability (PRV), a surrogate form of HRV, were extracted from every segment. PRV represents a surrogate form of HRV, similarly to what Bozkurt e al. did the following year. In this regard, pulse to pulse intervals (PPI) were obtained by means of a peak detection algorithm. In the frequency domain, each PPI was re-sampled at 4 Hz to compute its PSD. Regarding SpO2, conventional time-frequency domain parameters were extracted in addition to the delta index, which represents the SpO2 variability. In this case, they employed multivariate logistic regression models. For each classifier, a stepwise selection method was applied to select the most relevant features and finally train the model. As they assessed classification in terms of AHI, there were different results of Ac for each case. However, for the minimum AHI to be considered apnea (AHI $\geq$ 5), they obtained Ac of 82.0%, Se of 85.0% and Sp of 79.0% as per diagnosed patient.

In 2015, Garcia-Ravelo et al. introduced a novel approach based on permutation entropy [20]. The CinC Challenge 2000's Database [21] was selected. They conducted signal segmentation with 1-min margin between frames. Then, RR intervals were extracted after an R-peak detection algorithm followed by an adaptive filtering to remove artifacts. They extracted different features from different analyses based on PE, cepstrum coefficients, and PSD measurements. Regarding PE, the features were extracted by encoding the RR intervals in symbols. Relative frequency was calculated for each symbol and then PE was obtained through its original expression [22]. They also derived respiration from the ECG recordings, and then computed PSD. Finally, two classifiers were employed. The best performance was obtained by using 20 features combined with quadratic discriminant analysis, thus obtaining values of Ac, Se, and Sp of 84.6%, 75.1%, and 90.5%, respectively, as per detected apnea episode.

Year	**Authors**	**# Feat.**	**Ac (%)**
2019	Bozkurt et al. [17]	4	93,00
2018	Zarei and Asl [10]	18	95,71
2018	Haoyu et al. [18]	4	98,54
2018	Garde et al. [19]	5	82,00
2017	Dong et al. [13]	3	90,10
2017	Martín-Gonzalez et al. [8]	3	84,76
2016	Cheng et al. [3]	11	85,00
2015	García-Ravelo et al. [20]	20	84,60
2010	Bsoul et al. [5]	111	100
2009	Khandoker et al. [7]	28	92,90

Table 1. Summary of authors and overall accuracy

4. Conclusions

The proposed HRV-based OSA detectors have reported promising results, but additional research is still required to consider them as potential alternatives to PSG. In fact, some authors associated HRV features with OSA severity (i.e. the number of apnea episodes per hour) [19, 23]. On the other hand, others used HRV features to detect OSA in a minute-by-minute basis [24]. Although accuracy values between 80 and 95% have been reported in both cases, a high number of HRV features, along with other parameters derived from the ECG, have had to be combined with advanced classifiers. As a reference, former studies have been included in Table 1 to compare the number of employed features in each case. Because short databases have only been used for validation of these methods, more efforts are still required to obtain a realistic view of their generalization capability, and thus of their performance in wider contexts. Consequently, OSA detection is still an interesting opportunity for a future revisited CinC Challenge.

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