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Original Article

Validation of an automated algorithm for detecting apneas and hypopneas by acoustic analysis of breath sounds ☆

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ABSTRACT

Background: Sleep-disordered breathing (SDB) is common and is associated with increased risk for cardiovascular disease. However, most patients remain undiagnosed due to lack of access to sleep laboratories. We therefore tested the validity of a single-channel monitoring setup that captures and analyzes breath sounds (BSs) to detect SDB.

Methods: BS were recorded from 50 patients undergoing simultaneous polysomnography (PSG). Using custom-designed automatic software, BS were subjected to a set of pattern recognition rules to identify apneas and hypopneas from which the acoustic apnea–hypopnea index (AHI-a) was calculated. Apneas and hypopneas from PSG were scored blindly by three technicians according to two criteria; one relying solely on the drop of the respiratory signal by >90% for an apnea and by 50% to 90% for a hypopnea (TV50 criteria), and another that also required a desaturation or an arousal for a hypopnea (American Association of Sleep Medicine [AASM] criteria). PSG AHI (AHI-p) was calculated for each technician according to both criteria.

Results: There was no significant difference between AHI-p scores according to TV50 and AASM criteria. AHI-a was strongly correlated with AHI-p according to both TV50 ($R = 94\%$) and AASM criteria ($R = 93\%$). Bland–Altman plot analysis revealed that 98% and 92% of AHI-a fell within the limits of agreement for AHI-p according to TV50 and AASM criteria, respectively. Based on a diagnostic cutoff of AHI-p $\geqslant 10$ for SDB, overall accuracy of AHI-a reached 88% and negative predictive value reached 100%.

Conclusion: Acoustic analysis of BS is a reliable method for quantifying AHI and diagnosing SDB compared to simultaneous PSG.

1. Introduction

Sleep-disordered breathing (SDB) is associated with poor sleep and hypersomnolence that causes daytime fatigue and increases the risk for motor vehicle accidents [2]. Obstructive sleep apnea (OSA), which is the most common type of SDB, also increases the risk for developing hypertension, heart failure (HF), and stroke [3,4], and of death from cardiovascular diseases [5]. Patients with untreated SDB consume twice as many healthcare resources for treatment of cardio-respiratory diseases as subjects without SDB [6]. In contrast, treating SDB alleviates hypersomnolence, lowers blood pressure, and improves cardiovascular function in patients with hypertension or HF [7–11]. Therefore, widespread diagnosis and treatment of SDB could have a considerable beneficial medical and public health impact [12]. Unfortunately, it has been estimated that up to 85% of individuals with SDB remain undiagnosed due to the lack of awareness of the disease and lack of accessibility to a sleep laboratory [2]. Therefore, there is an increasing demand for developing reliable yet simple instruments to diagnose SDB that are more accessible and less costly than polysommnography (PSG).

Several attempts have been made toward creating portable monitors for SDB that are less expensive and more available than PSG and can be used in the patients' homes. Most of these devices

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reproduced a subset of PSG channels in a more compact form such as nasal flow, oximetry, and thoracoabdominal effort [13]. This approach, though resulting in relatively less expensive montages than PSG still requires a combination of channels to achieve an acceptable accuracy [14]. However, it is well-known that the more the channels are added to a portable monitor, the more difficult it is to use and the higher the failure rates will be in unattended settings [13].

Breath sounds (BSs) have recently emerged as a rich source of data on respiratory patterns. Several groups have shown that acoustic analysis of BSs can be used to identify pathological respiratory sounds such as wheezing [15] and crackles [16], as well as identification of snoring site [17,18]. In the quest for a reliable and simple home monitor for SDB, acoustic analysis of BSs also has been used to distinguish normal BSs and simple snoring from those resulting from SDB [19–23]. Although such techniques could have utility in screening for SDB, in medical practice, knowledge of disease severity in terms of frequency of apneas and hypopneas per hour (apnea–hypopnea index [AHI]) usually is taken into account when recommending treatment. Hence, to improve accuracy and reliability of acoustic analysis of BSs for diagnosing SDB, respiratory sound analysis should be able to identify individual apneas and hypopneas. Therefore, the objective of our study was to develop and test the accuracy of acoustic analysis of overnight BS recordings to detect the presence and quantify the severity of SDB.

2. Methods

2.1. Subjects

We studied 50 consecutive subjects at least 18 years of age. Subjects were referred for PSG due to a history suggestive of SDB including at least two of the following symptoms, a history of loud habitual snoring, restless sleep, morning headaches or excessive daytime sleepiness. No exclusion criteria were imposed.

2.2. Acquisition of BSs

BSs were recorded by a unidirectional condenser microphone embedded in the center of a loose fitting face frame, which kept the microphone in a fixed location approximately 3 cm in front of the subject's face as shown in Fig. 1. Digitized sound data were transferred to a computer using a USB preamplifier and audio interface (M-Audio, Model MobilePre USB) with a sampling rate of 22,050 Hz and resolution of 16 bits.

2.3. Polysomnography

Subjects underwent overnight PSG using standard techniques and scoring criteria for sleep stages and arousals from sleep [24,25]. Thoracoabdominal movements and tidal volume were measured by respiratory inductance plethysmography (RIP) [26]. Airflow was measured by nasal pressure cannulae [26] and arterial oxyhemoglobin saturation (SaO_2) by oximetry. Apneas and hypopneas were scored according to two different criteria. The first was the American Academy of Sleep Medicine (AASM) criteria which defines an apnea as a drop in the respiratory signal, in our study the electronic sum of thoracoabdominal movement was defined by $\geqslant$90% lasting $\geqslant$10 s [27], and a hypopnea as an event that satisfies either of the following two conditions: a drop of the respiratory signal by $\geqslant$30% lasting $\geqslant$10 s and accompanied by either a $\geqslant$4% desaturation or terminated by an arousal, or a drop of the respiratory signal by $\geqslant$50% lasting $\geqslant$10 s and accompanied by either a $\geqslant$3% desaturation or terminated by an arousal [27]. For the second criteria, apneas were similarly defined, but hypopneas were defined as a 50% to 90% reduction in thoracoabdominal sum lasting $\geqslant$10 s, regardless of any desaturation or arousal as previously described [28], which we refer to as TV50. This analysis was done because our acoustic recording setup does not include oximetry. The AHI was quantified as the number of apneas and hypopneas per hour of sleep. The protocol was approved by the Research Ethics Board of Toronto Rehabilitation Institute.

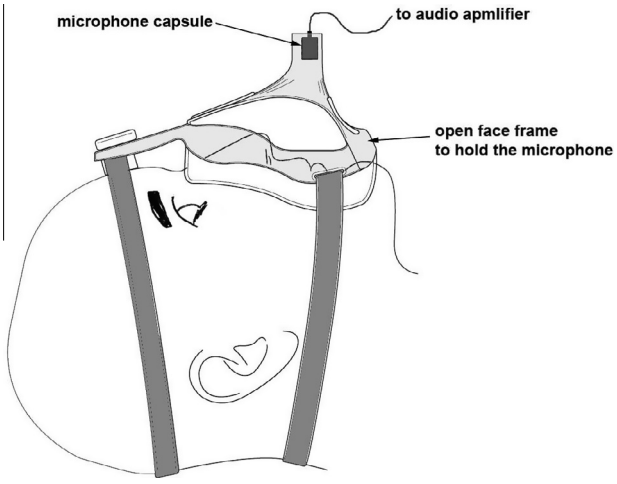

Fig. 1. Illustration of the face frame and location of the microphone.

2.4. Development of the automated algorithm

Our approach for detecting apneas and hyponeas in our study is to scan BSs waveforms for apnea-specific and hypopnea-specific features. The features were derived from the basic definitions of apneas and hypopneas and their pathophysiological properties. The algorithm was developed to detect respiratory events based on the way a sleep technician would manually identify them in other traces such as nasal airflow or thoracoabdominal effort (i.e., by finding a baseline and the characteristics of signal reductions from the baseline). For this purpose, raw BS waveforms are preprocessed to obtain a more uniform version, which is then subjected to a set of mathematical rules each to examine a certain feature as described hereafter.

2.4.1. Transformation of the raw acoustic signals

The aim of this step was to convert the raw acoustic signals into waveforms proportional to BS amplitude with a uniform baseline. To do this we used the technique of adaptive segmentation and normalization whose mathematical and physiological bases were previously described [29] and briefly mentioned in this section. Initially, the envelope of BSs was formed by the summation of absolute values of the raw sound signal samples within 400-millisecond long moving windows (L) overlapping by 75%.[1] The resulting envelope models individual breathing cycles and is referred to as breathing envelope (BE) as presented in Fig. 2. Transient outliers in BE, such as coughs and transient loud snorting were removed. BE models all the remaining BSs including inspiration, expiration, and regular snoring.

Subsequently, a second envelope that traces the longer term variations was formed by interpolating the maxima of BE to create another envelop that is equal in length to BE. This latter is referred to as effort envelope (EE), as illustrated in Fig. 2b. EE was

[1] The values used in this work are slightly modified from the ones used earlier in [29]