Obstructive Apnea Hypopnea Index Estimation by Analysis of Nocturnal Snoring Signals in Adults

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Study Objective: To develop a whole-night snore sounds analysis algorithm enabling estimation of obstructive apnea hypopnea index (AHI_{est}) among adult subjects.

Design: Snore sounds were recorded using a directional condenser microphone placed 1 m above the bed. Acoustic features exploring intra- (mel-frequency cepstral coefficients, pitch density) and inter-run (running variance, apnea phase ratio, inter-event silence) snore properties were extracted and integrated to assess AHI_{est}.

Setting: University-affiliated sleep-wake disorder center and biomedical signal processing laboratory.

Patients: Ninety subjects (age 53 ± 13 years, BMI 31 ± 5 kg/m²) referred for polysomnography (PSG) diagnosis of OSA were prospectively and consecutively recruited. The system was trained and tested on 60 subjects. Validation was blindly performed on the additional 30 consecutive subjects.

Measurements and Results: AHI_{est} correlated with AHI (AHI_{PSG}; r² = 0.81, P < 0.001). Area under the receiver operating characteristic curve of 85% and 92% for thresholds of 10 and 20 events/h, respectively, were obtained for OSA detection. Both Altman-Bland analysis and diagnostic agreement criteria revealed 80% and 83% agreements of AHI_{est} with AHI_{PSG}, respectively.

Conclusions: Acoustic analysis based on intra- and inter-snore properties can differentiate subjects according to AHI. An acoustic-based screening system may address the growing needs for reliable OSA screening tool. Further studies are needed to support these findings.

Keywords: Snoring, acoustic analysis, obstructive sleep apnea

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INTRODUCTION

Obstructive sleep apnea (OSA) is a chronic disorder affecting 2% to 7% of adults and can lead to considerable morbidity.1 Partial or complete collapse of the upper airway during sleep has different effects on the human body, ranging from noisy breathing (simple snoring)2 to cardiovascular morbidity.3 Snoring is the most common symptom of OSA, occurring in 70% to 95% of patients.4 The estimated prevalence of self-reported snoring in the general population extended over a wide range from 16% to 89%5-8; this prevalence depends on awareness, age, culture, and biased bed partner complaints.9,10 Nevertheless, self-reported snoring is considered a poor predictor of OSA because of the great prevalence of self-reported snoring in the general population.4,11,12

Little is known about acoustic characteristics of snoring events in adults. Earlier studies investigated snoring sound intensity,13 spectral,14-16 and pitch-related17,18 features. Fiz et al.19 used computerized snore detection algorithm enabling full-night analysis. The majority of those studies focused on intra-snore properties by analyzing snore-by-snore events. It is possible that the biological instability of the upper airway formation across the night, and especially during obstructive events, may lead to alterations in inter-snore properties, i.e., between clusters of snore events and across the night. This perspective of snore analysis was not sufficiently explored. Analysis of sequential properties of snores across the night as a measure of inter-snore properties revealed that OSA patients have greater variances of snore duration, separation, and average power. However, inconclusive findings were reported regarding the prediction of AHI by inter-snore measures.20

It is possible that the snoring signal carries essential information able to discriminate between patients of different OSA degrees of severities and simple (non-OSA) snorers. In the current study, we developed and validated a snore analysis algorithm enabling estimation of apnea hypopnea index (AHI_{est}) based solely on analysis of snoring signals acquired by a non-contact microphone. In this study we explored and combined inter- and intra-snore properties to determine AHI_{est} in patients referred for polysomnography (PSG) and compared it to AHI determined by PSG (AHI_{PSG}).

METHODS

Setting

University affiliated sleep-wake disorder center and biomedical signal processing laboratory.

Subjects

We recruited 90 consecutively and prospectively adults (aged 19 to 87 years, 33/57 women/men) referred to the Sleep-Wake Unit of Soroka University Medical Center for PSG OSA.
Figure 1—Block diagram of the study protocol. System-design study (n = 60 subjects) in which an acoustic screening algorithm for obstructive sleep apnea was designed. First, (A) The snore detection algorithm (trained by manually segmented events) was applied to isolate snore signals; (B) Five acoustic features were extracted; (C) The features together with polysomnography results, used for model training; (D) Model parameters used. Validation study was performed on 30 subjects by same initial procedures. The extracted acoustic features matched to the model (trained by the system-design data), in order to assess estimation for the subjects’ OSA severity.

Acoustic Features

Five acoustic features (i.e., individual measurable heuristic properties of the snore signal) were extracted (see supplemental material for detailed and formulated features’ descriptions): (1) Mel-Cepstability is a measure of the entire night spectrum’s stability, defined as the sum of variances of 12 Mel Frequency Cepstrum Coefficients (common representation of the audio spectrum) normalized by the total energy of the snores. (2) Running Variance quantifies the inter-snore variability of the snore’s energy across the night. All the snores were clustered into groups according to their proximity and the within-group variance was evaluated; then the global mean was calculated for each patient. (3) Apneic Phase Ratio represents the relative duration when the upper airways are collapsed, defined as the relative number of snore groups with energy variance larger than a specific threshold. (4) Inter-Event Silence counts the acoustic energy pattern of obstructive apneic events, i.e., silence between 2 sound events. (5) Pitch Density is a measure of the stability of the tissue’s vibration frequency.

Data Collection

Prior to nocturnal in-laboratory PSG all subjects completed a validated self-administered sleep questionnaire. The Epworth Sleepiness Scale (ESS) was used to evaluate daytime sleepiness. Apneas and hypopneas were defined using the American Academy of Sleep Medicine criteria. An apnea was defined as a decrease in airflow ≥ 80% from baseline for ≥ 10 sec. A hypopnea was defined as a decrease in airflow ≥ 50% airflow reduction and ≥ 4% desaturation for ≥ 10 sec. Apnea hypopnea index (AHI) was calculated as the number of respiratory events per hour of sleep.

Acoustic signals were recorded using a non-contact directional condenser microphone with a frequency range of 20–20,000 Hz (RODE, NTG-1), placed 1 m above the bed and connected to an audio recording device (Edirol R-4, Bellingham, WA, USA). Each recorded signal was digitized (PCM, 16 bits per sample, 44,100 Hz), down sampled to 16 KHz, and synchronized with PSG study onset. This procedure enables reliable acquisition of full-night audio signal and ensures that all the snores (and other low intensity audio events) are recorded, minimizing the possibility for false periods of silence detection.

Data and Statistical Analyses

Acoustic and statistical analyses were performed using MATLAB (R-2010b, The MathWorks, Inc., Natick, MA, USA). Both the system design study (n = 60) and the validation study (n = 30) had similar data handling protocols (Figure 1). Performance characteristics were conducted separately for the design study and the validation study.

Statistical power (α = 0.05) was calculated for the validation set based on AHI values extracted from the system design data set. A sample size of 25 subjects was calculated to provide ≥ 95% power to detect significant differences between OSA (AHI > 10) vs. non-OSA subjects (AHI ≤ 10). Therefore, 30 subjects were recruited for the validation study. PSG data were compared between non-OSA and OSA subjects and between design and validation study groups using student t-test or \( \chi^2 \) test. The square of the correlation coefficient (R²) between each of the 5 acoustic feature values and the AHI was calculated. In case of nonlinear relations (as in apneic-phase-ratio and pitch density), a nonlinear transformation was applied prior to correlation evaluation. Using multivariable regression, fed by the entire set of features, we estimate the OSA severity (AHI).
i.e., estimate equation that binds the proposed features (independent variables) to $\text{AHI}_{\text{EST}}$ (dependent variable).

Comparing $\text{AHI}_{\text{EST}}$ with $\text{AHI}_{\text{PSG}}$ was done by: (1) Altman Bland plot to determine diagnostic agreement between the gold standard $\text{AHI}_{\text{PSG}}$ and $\text{AHI}_{\text{EST}}$. (2) The diagnostic agreement approach was used to assess the accuracy of our system. 

Diagnostic agreement is defined when $\text{AHI} > 40$ on both assessments, or if $\text{AHI}_{\text{PSG}} < 40$ and $\text{AHI}_{\text{EST}}$ was within 10 events/h; overestimate and underestimate are defined when $\text{AHI}_{\text{PSG}}$ is 10 events/h more or less than $\text{AHI}_{\text{PSG}}$ (both < 40 events/h), respectively.

The classification performances were estimated using the resubstitution method (optimistic estimation) and the leave-one-out validation (pessimistic estimation) method, which provides an indication for possible over-fitting, i.e., whether the complexity of the classifier is suitable for the quantity of data. For the classification ($\text{AHI} < 10/20$ event/h), sensitivity and specificity were obtained, together with the un-weighted Cohen kappa coefficient ($\kappa$). Performance for different working points was obtained from a receiver-operating curve (ROC) and the area under this curve (AUC). Data are presented as mean ± SD. The null hypothesis was rejected at the level of 5%.

**RESULTS**

Patients

We approached 90 potentially eligible patients. Eleven patients reported that they snored < 3 nights/week, and 16 reported that they “don’t know” how many days a week they snore. No significant differences were found between system design ($N = 60$, m/f 36/24) and validation ($N = 30$, m/f 21/9) groups in age, BMI, snoring, ESS, AHI, associated morbidities, or tobacco smoking (Table 1).

Snore Detection

During system design, a snore detection algorithm was trained and tested using large amounts of manually labeled events (121,400 snoring events and 77,400 noise events). Very good performance rates of 87% to 92% correct snore detection and 6% to 10% false positive were achieved using resubstitution and cross-validation methods. Finally, the mean number of detected snoring events was 1267 (range 127–4030) and 1295 (range 146–3519) per subject in the system design and validation study, respectively ($p = 0.46$; Table 1).

Feature Extraction

Table 2 presents for each feature its values and its correlation with AHI for both groups. No significant difference was found between groups (all $p > 0.3$). All 5 selected acoustic features were found to be significantly correlated with AHI (all $p < 0.01$). The most correlated feature was the inter-event silence. The running variance feature was found to be higher in adjacent to apnea events, as exhibited in Figure 2A.

Estimated Apnea and Hypopnea Index ($\text{AHI}_{\text{EST}}$) was calculated by multivariate linear regression model (trained by the system design group), fed by the 5 features as the independent variables. $\text{AHI}_{\text{EST}}$ was found to be correlated with $\text{AHI}_{\text{PSG}}$ (study design: $r^2 = 0.81$, P < 0.001; validation: $r^2 = 0.71$, P < 0.001). Scatter plots of AHI by $\text{AHI}_{\text{PSG}}$ versus $\text{AHI}_{\text{EST}}$ are
shown in Figure 3A; examining this figure, one can see that there is a slight trend towards a plateau at AHI > 30 events/h in the validation study. Examining the Bland and Altman plots (Figure 3B) comparing \( \text{AHI}_{\text{psG}} \) versus \( \text{AHI}_{\text{Est}} \) showed no consistent bias, i.e., the mean difference was only 0.5 and 3.5 events/h for system design and validation, respectively. The plots also show that the \( \text{AHI}_{\text{psG}} \) corresponded more closely to \( \text{AHI}_{\text{Est}} \) when the mean AHI was < 30 events/h in the validation study. Finally, using the diagnostic agreement approach, we found 80% to 83% diagnostic agreements with PSG (Table 3A).

It should be noted that combining the 5 features into one model improves the correlation of AHI estimation (compared to each feature by itself).

**Patient Classification**

Using the Bayes classifier, we classified the subjects into 2 groups using a threshold of AHI > 10 (events/h) and AHI > 20. In the validation study, the classification rates were 87% (80%) sensitivity (specificity) for AHI > 10 and 89% (78%) for AHI > 20. For both AHI thresholds, Cohen \( \kappa \) was 0.667 (CI 0.39-0.93),
which is considered as good agreement.\textsuperscript{30} Full performance evaluation is represented in Table 3B. ROC curves corresponded to the same AHI cutoffs (Figure 4) for the system design (upper panel) and validation (lower panel) studies. The AUC were all > 0.85, showing high sensitivity and specificity in screening for OSA.

**DISCUSSION**

We propose innovative approach for AHI\textsubscript{EST} based solely on snoring sound signals. Our data suggest that acoustic analysis can differentiate subjects according to AHI. An acoustic-based screening system may address the growing needs for OSA screening diagnosis tools.

**Acoustic Features**

In the current study, several acoustic features were examined and followed by implementation of novel ideas. The majority of earlier studies focused on a limited number of selected features and, as such, essential information was not sufficiently explored. Earlier studies mainly investigated intensity levels,\textsuperscript{19} pitch analysis,\textsuperscript{18,20} and formant frequencies\textsuperscript{14-16} of snoring sounds. Also, higher order spectral-based algorithms,\textsuperscript{31} sub-band energy distributions, and sequential properties\textsuperscript{20} were investigated in the context of snoring and sleep apnea. These acoustic features have been shown to be in statistical associated with OSA, but none of these studies have estimated AHI based on acoustic analysis of snoring across the night. In our study, we selected five acoustic features that best explain the relations between snoring and AHI. The selected features capture the energy dynamics and frequency information that is hidden in the snoring sounds. Some of the features (mel-cepstability and pitch density) contain intra-snore information, and the others (running variance, apnea phase ratio, and inter-event silence) contain the inter-snore information. Our data indicate that the inter-event silence was the best feature for predicting AHI (as a single feature, Table 2); nevertheless, estimation of AHI solely by this feature results in poor prediction of AHI and therefore poor system performance. The unique combination of these five features gives a powerful multidimensional feature vector that is highly correlated with the AHI. Use of the multivariate approach was found, as expected, to outperform each of the single-feature performances.

Body posture during sleep may affect the acoustic characteristics of snores,\textsuperscript{12} such as snoring intensity. Since body posture can change several times during sleep, we selected acoustic features that are minimally affected by sound intensity. For example, the mel-cepstability feature, a spectrum based feature (based on the cepstrum coefficient),\textsuperscript{21} is not affected by sound intensity; the Inter-event silence feature is based on the event detection algorithm, which has an adaptive energy threshold; the pitch density is based on the autocorrelation function,\textsuperscript{22} and as such is not affected by sound intensity. However, it is possible that not only the sound intensity is affected by body posture, but also other acoustic properties. Further study should investigate the effect of sleep position on AHI\textsubscript{EST}.

Our data show greater variances in snore characteristics among patients with AHI > 10, both in frequency domain (mel-cepstability) and across the night (running variance). These findings support the thought that OSA is associated with functional abnormalities of the upper airways indicating collapsibility.\textsuperscript{33} However, all the aforementioned studies explored jointly all the snores of a subject without referring to the snore timeline across the night, as we did in this study. Our study shows for the first time transient variations in the acoustic signal adjacent to obstructive events (Figure 2A). Such a perspective found expression in the apneic phase ratio feature, which quantifies temporary ascension of feature variation around obstructive events, caused, probably, by biological alterations of airway patency during efforts to restore ventilation.\textsuperscript{34}

**Estimated AHI (AHI\textsubscript{EST})**

One of the merits of this study is the ability to estimate AHI based solely on snoring signal using a non-contact directional microphone. Across a wide range of OSA severities, the AHI\textsubscript{EST} is strongly correlated with the AHI\textsubscript{PSG}. To our knowledge, none of the previous reports proposed estimation of AHI by snoring analysis and validated their results. Van Brunt et al.\textsuperscript{13} however, sought an acoustical signature event, defined as a loud sound preceded by a period of silence (as can be seen in Figure 2B), and quantified apnea events accordingly. A major limitation of their approach was the great sensitivity to artifact noises and the need for process automation that was not performed and is essential for across-night snoring analysis. Our study improves Van Brunt’s approach by applying an event detection algorithm, applying acoustic filtration, which enables avoiding misdetection of apnea due to slight breath hidden by background noise, and tracing for other indicators for obstructive events, such as transient ascension of variances. Taken together, the proposed method to evaluate AHI\textsubscript{EST} is an accurate and reliable approach for the detection of OSA having very good agreement with AHI\textsubscript{PSG}.

**Study Strengths and Limitations**

To our knowledge, this is the first study exploring acoustic properties of snoring using two different subject groups, i.e.,
One of the main goals of sleep medicine today is to improve access to OSA diagnosis and treatment. On the other hand, resource availability (supply) is governed by the cost of obtaining a diagnosis, the number of facilities available, the number of sleep and allied health specialists, the policies governing reimbursement for ordering and interpreting results, and the level of adherence to practice guidelines. At present, resource availability is limited relative to demand. While multichannel sleep apnea monitoring devices can be used at home, there are a number of constraints for their use; these include cost-effectiveness limitations, reduced availability of technical and specialist expertise, and complexity for patient use at home.

**Summary**

This study provides evidence that snoring analysis based on intra- and inter-snore properties can differentiate adult habitual snorers according to AHI. An acoustic-based system may address the growing needs for OSA screening diagnosis tools. Further studies are needed to determine data reproducibility of this system and its cost-effectiveness as a potential screening tool for OSA.

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**DISCLOSURE STATEMENT**

This was not an industry supported study. The authors have indicated no financial conflicts of interest.