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Obstructive Sleep Apnea Prediction During Wakefulness

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***Abstract*— In this paper, a novel technique based on signal processing of breath sounds during wakefulness for prediction of obstructive sleep apnea (OSA) is proposed. We recorded tracheal breath sounds of 35 people with various severity of OSA and 17 non-apneic individuals; the breath sounds were recorded in supine and upright positions during both nose and mouth breathing at medium flow rate. Power spectrum, Kurtosis and Katz fractal dimension of the recorded signals in every posture and breathing maneuver were calculated. We used one-way ANOVA to select the features with most significant differences between the groups followed by the Maximum Relevancy Minimum Redundancy (mRMR) method to reduce the number of characteristic features to three, and investigated the separability of the groups based on the three selected features. The results are encouraging for classification of patients using the selected features. Once being verified on a larger population, the proposed method offers a fast, simple and non-invasive screening tool for prediction of OSA during wakefulness.**

I. INTRODUCTION

OBSTRUCTIVE Sleep Apnea (OSA) is a common respiratory disorder. By definition, sleep apnea is the cessation of airflow to the lungs (during sleep) that lasts for at least 10 seconds and is associated with more than 4% drop of the blood's Oxygen saturation (SaO_2) level. Sleep apnea causes daytime sleepiness, poor job performance, and increased risk of accidents and lack of concentration [1-3]. Sleep apnea occurs more in males with a higher prevalence in elderly [4]. It is also common in people with high blood pressure, smokers and those with narrowed airway due to tonsils or adenoids[5].

The current Gold Standard diagnostic tool for sleep apnea is Polysomnography (PSG) during the entire night. The standard PSG consists of recording various biological signals including EEG, ECG, EMG of chins and legs, nasal airflow, electro-oculogram (EOG), abdominal and thoracic movements [6]. It is an expensive test for health care system with a very long waiting time (especially in Canada) for patients to receive the assessment. Therefore, many studies have sought developing alternative, non-invasive and portable OSA monitoring tools.

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While there have been many studies and developed technologies to detect OSA during sleep, few studies attempted to predict OSA during wakefulness [7-10]. In [7] a method based on Ultrafast Magnetic Resonance Imaging from pharyngeal airway was proposed both during wakefulness and sleep. Although, their results were highly accurate during sleep; they achieved only 46% accuracy during wakefulness.

Recently, a group of researchers investigated the correlation of speech disorder and OSA [8, 9] . The acoustic features of 18 OSA and 10 non-OSA speakers were compared, and substantial differences were found [8]. Then, by combining feature selection technique and Gaussian mixture model (GMM)-based classifier patients with OSA were detected [9]. Although good results were achieved, the feature space dimension was too high for their database size (over-fitting) and they didn't provide physiological reasons for the calculated features.

On the other hand, it has been shown that patients with OSA may have a defective ability to dilate the pharynx during inspiration [11]. In addition, the tracheal breath sound intensity of people with OSA was shown to increase in supine position compared to that of the control group [10]. Considering that people with some degrees of upper airway obstruction are more prone to develop OSA, we hypothesize that there must be noticeable differences among the nose and mouth breathing sounds characteristics recorded from people with different OSA severity in supine and upright positions.

Our feasibility study of the above hypothesis has shown encouraging results [12]. In this study, we increased the number of subjects to 52 (as opposed to 16 in [12]), and investigated features that were statistically different between OSA patients with different severity. The severity of OSA was determined by full-night PSG assessment.

We recorded tracheal breath sound signals during nose and mouth breathing maneuvers in both supine and upright positions. The Power Spectrum Density (PSD) [13], Fractal Dimension (FD) using Katz algorithm [14] and Kurtosis [15] of the tracheal breath sound signals in each respiratory phase of each signal, recorded in each position and breathing maneuver, were calculated. We used one-way analysis of variance (ANOVA) [16] to select the features with most significant differences between the groups followed by the Maximum Relevancy Minimum Redundancy (mRMR) method to reduce the number of characteristic features to three, and investigate the separability of the groups based on the three selected features.

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II. METHOD

A. Data

Fifty two individuals (37 males) suspected of having OSA, who were referred to the Sleep Disorder Center at Misericordia Health Center, Winnipeg MB, gave written consent to be enrolled in this study. The study was approved by the Ethics Board of the University of Manitoba. All of the study participants went through full night PSG assessment. Based on their apnea/hypopnea (AHI) scores (determined by the PSG), we grouped them into non-OSA (AHI < 5), mild OSA (5≤ AHI < 15), moderate OSA (15≤ AHI < 30) and severe OSA (30≤ AHI). The average age, body mass index (BMI) and AHI values of the participants are summarized in Table I.

Tracheal breath sound signals were collected by a Sony microphone (ECM-77B) embedded in a chamber (diameter of 6mm) placed over the suprasternal notch of trachea using double-sided adhesive tapes. The sound signals were amplified, band pass filtered (0.05-5000 Hz), and digitized at 10240 Hz. The recordings were done in two different body positions: upright and supine. In each body position breath sounds were recorded during two breathing maneuvers for at least five full breaths in each trial. The two breathing maneuvers were breathing through the nose and then through the mouth with a nose clip in place at medium flow rate.

A. Pre-Processing

Inspiration is an active process, while expiration is a passive process. Therefore, the inspiration and expiration phases were analyzed separately. The signals were band pass filtered (150-800 Hz) to reduce the effect of heart sound and background noise. The onset of each phase was calculated using our method detailed in [17]. Given that we did not record respiratory flow, to ensure the phase labels, we always started each recording at the inspiration phase.

TABLE I
AVERAGE AGE, BODY MASS INDEX (BMI), AHI VALUES OF THE PARTICIPANTS.

Groups	# of Subjects	AGE	BMI	AHI
AHI<5	17	40.3 ±8.0	26.5 ± 5.7	1.3± 1.7
AHI>5 & AHI<15	13	47.8 ±9.6	30.8 ± 6.3	11.4± 2.8
AHI>15 & AHI<30	7	50.6 ±6.8	29.2 ±3.1	23.8± 4.4
AHI>30	15	49.9 ± 10.4	38.4 ±5.5	76.7± 40.3

B. Feature Extraction

For each respiratory phase in each breath, the PSD (using Welch method) [13], FD (using Katz algorithm [14]) and Kurtosis [13-15] were calculated in 50ms windows (with 50% overlap with the adjacent windows) over the 150-800 Hz; they were called P^{b_i}, FD^{b_i} and $Kurt^{b_i}$ respectively, where b_i represent the breath number 1 to 5. Then, the average curves of the P^{b_i}, FD^{b_i} and $Kurt^{b_i}$ were calculated over five breath phases denoted as Ave^{Pow}, Ave^{FD} and Ave^{Kurt}. The variance and median values of these average curves, denoted as Var_{pow}^{ave}, Med_{pow}^{ave}, Var_{FD}^{ave}, Med_{FD}^{ave}, $Var_{Kurt}^{ave}$and Med_{Kurt}^{ave}, were calculated and used as the features to investigate further.

Having recorded in two positions and at each position by two breathing maneuvers, for each subject we have had 4 recorded sound signals that by analyzing inspiratory and expiratory phases separately would result in 8 signals per subject. In addition, we investigated the differences between nose and mouth breathing in each position as well as the difference between the positions in each nose and mouth breathing signals. Therefore, extracting the 6 features from each signal in the above mentioned conditions would result in 96 features per subject in total.

C. Feature Selection

First, we divided the study participants into two groups: severe OSA (AHI>30) and non-OSA (AHI<5). Then, one-way ANOVA test were run on each of the 96 features separately. Twenty one features were found to be statistically significantly different (p <0.05) between the severe OSA and non-OSA groups. Second, we divided the study participants into groups of AHI>15 and AHI<15, and ran the one-way ANOVA test again on the original 96 feature set. This time, 17 features were found to be statistically significantly different (p <0.05) between the mentioned groups. Then, out of the 21 and 17 features that were found to be statistically significantly different between the groups, we selected the common features (12) for further analysis.

On the next stage, a search algorithm was needed to find the best subspace of features. We used the Maximum Relevancy Minimum Redundancy (mRMR) method [18] to select the best 3-D subspace to maximize separation of the subjects with AHI<15 from subjects with AHI>15; this separation is the most challenging as there is no gap of AHI between the groups. The selected features by the mRMR method jointly have the largest dependency on the target class. This procedure is called Max-Dependency:

$$maxD(S,c), D = I(\{x_i, i = 1, \ldots, m\}; c), \quad (1)$$

where, I represents mutual information; $(\{x_i, i = 1, \dots, m\}; c) = I(S, c)$, and takes the following form:

$$I(S_m, c) = \int \dots \int p(x_1, \dots, x_m, c) \log \frac{p(x_1,\dots,x_m,c)}{p(x_1,\dots,x_m)p(c)} dx_1 \dots dx_m dc \quad (2)$$

In the Max-Relevance approach, $D(S, c)$ in (1) is approximated with the mean value of all mutual information values between individual features x_i and the class c:

$$\max D(S, c), D = \frac{1}{|S|} \sum_{x_i \in S} I(x_i; c) \quad (3)$$

As the dependency among these m features could be high, minimal redundancy criterion was defined to reduce redundancy:

$$\min R(S, c), R = \frac{1}{|S|^2} \sum_{x_i \in S} I(x_i; x_j). \quad (4)$$

By combining (3) and (4), the minimal-redundancy-maximal-relevance criterion is defined as:

$$\max \Phi(D, R), \Phi = D - R \quad (5)$$

In order to find the subset S_m, we used incremental search method. Suppose that we chose S_{m-1}; the mth feature is chosen from the set $\{X - S_{m-1}\}$ by maximizing the following condition:

$$\max_{x_j \in X - S_{m-1}} [I(x_j; c) - \frac{1}{m-1} \sum_{x_i \in S_{m-1}} I(x_i; x_j)] \quad (6)$$

Applying the above mentioned method resulted in the following 3 best features:

- $MPUNI: Med_{pow}^{ave}$ of the Upright position, Nose breathing, Inspiratory phase
- $MKSNI: Med_{Kurt}^{ave}$ of the Supine position, Nose Breathing, Inspiratory phase
- $VKUNI: Var_{Kurt}^{ave}$ of the Upright position, Nose breathing, Inspiratory phase

These features were calculated for every subject, and used to investigate whether they can cluster patients with different severity of AHI.

III. Result & Discussion:

Figure 1(a) shows mean and standard deviation of the MPUNI calculated for participants with AHI<15 and AHI>15. The results show the patients with higher AHI have higher MPUNI values. This result is congruent with physiological facts about airway structure in people with OSA. It is known that people with OSA disorder usually have smaller and more collapsible pharynx than healthy individuals [19-23]. Individuals with OSA have been shown to increase their pharynx dilator muscle activities during wakefulness to compensate pharyngeal problems [24]. On the other hand, it has been shown that the average power of tracheal breath sound is representative of the pharyngeal pressure [25]. Hence, the increase in the dilator muscle activities in OSA patients during wakefulness might be average power of the upright nose breathing, which has been shown to be higher for people with OSA.

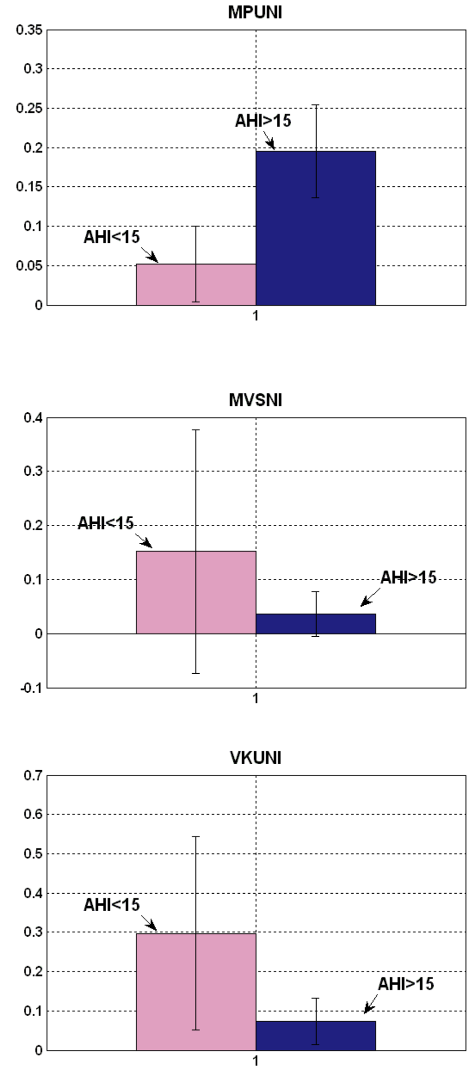

Fig. 1. (a) The mean and standard deviation of the MVSNI for participants with AHI<15 and AHI>15;(b) the mean and standard deviation of the MPUNI for the mentioned groups; (c) the mean and standard deviation of the MPUNI for the mentioned groups.

Figure 1(b) and Fig. 1(c) show mean and standard deviation of the MKSNI and VKUNI, calculated for participants with AHI<15 and AHI>15. Figure 2 (a) and (b) show the 3-D scatter plot the three selected best features of subjects with AHI<15 and AHI>15 and subjects with AHI<5 and AHI>30, respectively. As it can be seen, data points with lower AHI are more concentrated in the top left corner of scatter plot, while the data points with higher AHI are distributed toward the opposite corner. In addition, the subjects in Figure 2 (b) are either form non-apneic subjects (AHI<5) or patients with severe OSA (AHI>30); there is a gap between the AHI of each group. Therefore, Fig. 2 (b) shows more distinguishable clusters of subjects.

Furthermore, it can be seen that, MKSNI and VKUNI are providing somehow the same information. In other words, the

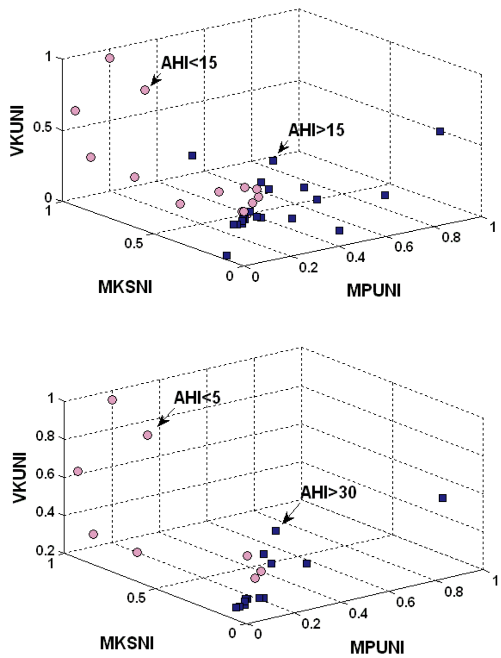

Fig. 2. (a) The 3-D scatter plot (MPUNI, MKSNI, VKUNI) for subjects with AHI<15 and AHI>15. (b) The 3-D scatter plot (MPUNI, MKSNI, VKUNI) for subjects with AHI<5 and AHI>30.

groups can be distinguished by these two features with almost same accuracy. Hence, using a 2-D classification with MPUNI and VKUNI features must result in the same accuracy as a 3-D classification.

IV. Conclusion

In this study a novel method using breath sound analysis has been proposed for OSA prediction during wakefulness. Three features representing average power and variation in the kurtosis of the sound signals at different positions were shown to be characteristic features to provide a reliable screening tool for OSA and predicting its severity. The proposed method was tested on 52 subjects and the pilot results are very encouraging to show a good seperability between the groups with different levels of OSA. The results of this study pave the way for a simple, non-invasive, and inexpensive screening tool for patients suspected of OSA to identify the level of OSA severity during wakefulness within a few minutes of breath sounds recording.

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