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Do Anthropometric Parameters Change the Characteristics of Snoring Sound?

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Abstract— Snoring sounds is commonly known to be associated with obstructive sleep apnea (OSA). There are many studies trying to distinguish between the snoring sounds of non-OSA and those of OSA patients. However, OSA is only one of the conditions that affect the structure of upper airway. In this study, we investigated the effect of anthropometric parameters on the snoring sounds. Since snoring sounds are non-Gaussian signals by nature, we derived its Higher Order Statistical (HOS) features and investigated the statistical significance of the anthropometric parameters on each of these features. Data were collected from 40 patients with different levels of OSA. Tracheal respiratory sounds collected by a microphone placed over suprasternal notch, were recorded simultaneously with full-night Polysomnography (PSG) data during sleep. The snoring segments were identified semi-automatically from respiratory sounds using an unsupervised snore detection algorithm. The bispectrum of each SS segment was estimated. We calculated two common HOS measures, Skewness and Kurtosis, plus a new feature called Projected Median Bifrequency (PMBF) from the SS segments. Then, we investigated the statistical relationship between these features and anthropometric parameters such as height, Body Mass Index (BMI), age, gender, and Apnea-Hypopnea Index (AHI). The result showed that gender, BMI, height, and AHI are the parameters that do change the characteristics of snoring sounds significantly.

I. Introduction

SNORING is a very common disorder that increases with age. Overall, 20-40% of the general population snore during sleep [1]. By age of 60, snore prevalence increases to 60% in male and 40% in female gender [2]. It is commonly known to be associated with obstructive sleep apnea (OSA) [3]. There are many studies [4-7] trying to distinguish between the snoring sounds of non-OSA and those of OSA patients. However, OSA is only one of the conditions that affect the structure of upper airway. Hence, the aim of this study was to investigate the effect of anthropometric parameters on the snoring sounds.

Different tasks such as investigation of obstruction in the upper airway [8, 9], assessment of the outcome of surgical treatment [10-12], classification of snorers as simple snorer or OSA patients [13, 14], and automatic detection and classification of snoring episodes [15, 16] utilize acoustical analysis of snoring sounds.

Most of the signal processing techniques used for snoring sound analysis, such as autocorrelation/autocovariance function [13, 15], power spectrum density (PSD) [17-19], and autoregressive (AR) modeling [13, 18] are based on a linear model of snoring sound. These 2nd order statistical techniques such as spectral analysis assume that the signal-generating process is Gaussian and linear; moreover, the signal's phase information is ignored.

If the signal of interest, i.e. snoring sounds, violates one of the above assumptions, one should take into account an alternative technique. Higher order statistics (HOS) techniques reveal information on not only amplitude of a signal, but also its phase. Furthermore, if a signal generated from a non-Gaussian process is received along with additive Gaussian noise, a transformation to higher order cumulant domain would be blind to the noise; hence, achieving a cleaner estimate in noisy environments.

HOS analysis was used in [20] as a tool for screening OSA among snorers. However, to date, there was no study investigating the relationship between HOS properties of snoring sounds and anthropometric parameters of snorers. This paper discusses this relationship. The bispectrum of each snoring sound (SS) segment of data were estimated. We derived a new feature called Projected Median Bifrequency (PMBF), and also calculated skewness and kurtosis values of the SS segments. Then, we investigated the statistical relationship between theses features and anthropometric parameters of 40 snorers using Kruskal-Wallis Analysis of Variance (KWAV).

II. Method

A. Data Recording

Forty individuals (8 females, 33 to 67 years old) with an average age of 49.8±10.7 years, who were referred to full-night Polysomnography (PSG) at the Health Science Center, Winnipeg, participated in this study. The study was approved by the Biomedical Research Ethics Board of the University of Manitoba. Simultaneously with the PSG, the participants' respiratory sounds signals were recorded by a microphone (ECM-77B with high-performance frequency response of 40 Hz-20 KHz) placed over the suprasternal notch of trachea. Table I shows the participants'

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anthropometric information. The apnea/hypopnea index (AHI) of each subject was determined by the PSG study; 8 individuals had AHI≤5 (simple snorers) and 32 had OSA with various degrees of severity (AHI values from 5.7 to 125.7).

TABLE I
ANTHROPOMETRIC INFORMATION OF PARTICIPATING INDIVIDUALS

Group	Number of subjects	Age	Body mass index	AHI
OSA	32 (7 females)	49.6± 10.8	34.5± 6.8	34.7±35
Simple Snorers	8 (1 females)	50.6±11.2	30.4± 3.7	2.2±1.4

As known, the respiratory sounds of a snorer consist of breath, loud vibratory sounds (perceived as snore by humans), and/or small segments of silence [15]. We call the part of respiratory sound containing snore (or loud vibratory sounds) as Snoring Sound (SS) segment. The length of each SS segment varies within and between the subjects.

The automatic algorithm proposed in [16] was used to extract the SS segments in a semi-automated manner. An example of the selection method is as the following: the PSG data provided information about the time (e.g. 3:00-3:45 am) when the patient X was snoring. Given this information the snore detection algorithm proposed in [16] was run either on the entire interval (if < 15 minutes) or on a 15-minute interval (if > 15 minutes). The snoring intervals shorter than 5 minutes were neglected. Overall 18143 of SS segments from all patients were analyzed, which on average corresponded to 9.1±3.8 min of snoring intervals per patient.

The extracted SS segments for each patient were used to estimate the bispectrum and derive the desired features. It should be noted that the bispectral analysis was only performed on the SS segments.

B. *Higher order statistics (HOS)*

Assume that $s(n)$ is an extracted SS segment (in general a random process). The key assumption underlying the HOS analysis is that the process $s(n)$ is stationary in some sense [21]. Snoring sounds are non-stationary in nature [18]. Hence, all the HOS measures such as bispectrum and bicoherence should be calculated on a short time-windowed version of the signal to ensure wide-sense stationarity of the SS segments.

1) *Definition of Bispectrum and Bicoherence*

The 2[nd] and 3[rd] order cumulants of a zero-mean stationary process are defined by:

$$c_2(k) = E\{s^*(n)s(n+k)\}, \qquad (1)$$

$$c_3(k,l) = E\{s^*(n)s(n+k)s(n+l)\}, \qquad (2)$$

where $s(n)$ is a zero mean stationary process, $k,\ l,$ and m are different time increments, * refers to complex conjugate operator, and c_2 and c_3 denote 2[nd] and 3[rd] order cumulants respectively [22]. The 2[nd] and 3[rd] order polyspectrum are defined as the Fourier transform of c_2 and c_3, respectively [22]:

$$P(f) = \sum_{k=-\infty}^{+\infty} c_2(k)e^{-j2\pi fk}, \qquad (3)$$

$$B(f_1,f_2) = \sum_{k=-\infty}^{+\infty}\sum_{l=-\infty}^{+\infty} c_3(k,l)e^{-j2\pi f_1 k}e^{-j2\pi f_2 l}, \qquad (4)$$

where $P(f), B(f_1,f_2)$ represent the PSD and bispectrum, respectively. In practice, the number of sound samples is finite; hence, the HOS measures need to be estimated from available data. In this study, the direct approach [21], which is an extension of the Welch technique for power spectrum density estimation, was used to estimate the bispectrum ($\hat{B}(f_1,f_2)$).

The discrete bispectrum has many symmetries in (f_1,f_2) plane. It is only needed to calculate $\hat{B}(f_1,f_2)$ in the non-redundant region or principal domain (D) which is defined as: $D = \{0 < f_1 \leq \frac{f_s}{2}, 0 < f_2 \leq f_1,\ 2f_1 + f_2 \leq f_s\}$ [23].

C. *Feature Extraction*

Suppose that we estimated the bispectrum ($\hat{B}(f_1,f_2)$) in D. This section details on deriving PMBF defined in section I.

1) *PMBF*

Median Bifrequency (MBF) is the bifrequency where the summation of absolute values of $\hat{B}(f_1,f_2)$ becomes half of the summation of absolute value of $\hat{B}(f_1,f_2)$ over all bifrequencies in D. In fact, the procedure looks like:

1. Calculate the summation of $|\hat{B}(f_1,f_2)|$ at all bifrequencies in D.
$$B_T = \sum_{f_1}\sum_{f_2}|\hat{B}(f_1,f_2)|\ , \qquad f_1,f_2 \in D, \quad (5)$$
2. Set $f_1 = 0$.
3. For all bifrequencies (f_1,f_2) satisfying the condition $\{0 < f_2 \leq f_1,\ 2f_1 + f_2 \leq f_s\}$ calculate:
$$SB(f_1,f_2) = \sum_{f_1}\sum_{f_2}\left|\hat{B}(f_1,f_2)\right|, \qquad (6)$$
4. Check if $SB(f_1,f_2) \geq \frac{1}{2}B_T$

   If **YES,** end the algorithm and $\left(f_1^{mp},f_2^{mp}\right) = (f_1,f_2)$

   If **NO,** increase f_1 and go to step 3. (Note that: $f_1^{max} = \frac{f_s}{2}$.)

   Once the MBF is computed, the PMBF, f^p, can be determined by the projection of $\left(f_1^{mp},f_2^{mp}\right)$ onto the identity line $\{f_2 = f_1, \quad f_1,f_2 \in D\}$ corresponding to the diagonal slice of the bispectrum.

2) *Skewness and Kurtosis*

Let $s(n)$ be a zero-mean random process. Skewness (γ_1) and kurtosis (γ_2) are defined as:

$$\gamma_1 = \frac{c_3(0,0)}{\sigma_s^3}, \gamma_2 = \frac{c_4(0,0,0)}{\sigma_s^4}, \qquad (7)$$

where σ_s is the standard deviation of $s(n)$ and $c_3(0,0)$ and $c_4(0,0,0)$ are its zero-lag 3[rd] and 4[th] order cumulants respectively [24].

3) *Calculation of features*

As mentioned in the section II.A, the number of SS segments is different for each patient. Let us denote i^{th} SS segment of patient X by $s_i^X,\ i = 1,\dots,I^X$. First, $(f^p)_i^X$,

$(\gamma_1)_i^X$, and $(\gamma_2)_i^X$ for all segment were calculated resulting in a finite number of observations for each feature. Then, the sample median of each feature set was estimated.

The reason we used median instead of mean is the insensitivity of median to outliers. It is also known that when the data is not symmetrically distributed, the median outperforms the mean in measuring the middle range of data [25]. Our extracted feature sets were not symmetrically distributed.

D. Statistical Analysis

To investigate the effect of anthropometric parameters such as age, gender, height, BMI, and AHI on the extracted HOS features, we ran statistical tests assuming the significance level as $p = 0.05$. First, these parameters were categorized into different groups. Since the distribution of the features deviated from normal distribution, the one-way KWAV was used to test the equality of the median of the extracted HOS features among different groups. This test is the non-parametric counterpart of one-way analysis of variance (ANOVA) that assumes normal distribution of the variables [26, 27]. Table II shows how the patients were grouped based on their anthropometric parameters.

TABLE II
THE BOUNDARIES OF GROUPING FOR HEIGHT (H), AGE, APNEA/HYPOPNEA INDEX (AHI), AND BODY MASS INDEX (BMI).

Group	H(#)	BMI(#)	Age	AHI
0	≤170(11)	≤29.9(12)	≤45(11)	≤5(8)
1	170-180(20)	30-34.9(14)	45-60(26)	>5(32)
2	>180(9)	>=35(14)	>60(3)	

III. RESULTS

As shown in Table III, four out of five anthropometric parameters significantly affected the HOS features of the SS segments. The height of individuals was observed to be a significant factor influencing the value of f^p ($p < 0.05$). There was a negative relationship between height and f^p. The taller the individuals, the lower frequency components were in their snoring bispectrum.

The results of the KWAV test on BMI groups shows that BMI significantly affects the value of f^p ($p < 0.05$). We observed that the higher the BMI, the lower were the f^p values. However, as shown in Table III, none of the features were significantly different among age groups. It was also found that AHI and gender were significant parameters affecting the frequency features of the SS segments. The individuals with higher AHI had lower frequency-based features (f^p) ($p < 0.05$). It was also found that the female snorers of this study had higher frequency-based features (f^p) ($p<0.05$) than the male snorers.

IV. DISCUSSION

In this study, the relationship between anthropometric parameters of 40 snorers and the 3rd and 4th order statistical features derived from the SS segments were investigated.

The height has been shown to affect the tracheal sound spectral features [28]. It was reported that the tracheal sounds in children had higher frequency components than in healthy adults. In another study [29], it is shown that the anatomy of the trachea determines the characteristic features of tracheal sounds. However, there was no study confirming the change in the features of SS segments due to the height. Based on our findings, the PMBF feature of extracted SS segments (f^p) is negatively related to the height of individuals. Assuming that taller individuals have taller neck, this result implies that the characteristics of SS segments reflect resonances (existing in SS) that depend on the upper airway's length.

TABLE III
KRUSKAL-WALLIS TEST RESULTS FOR FIVE ANTHROPOMETRIC PARAMETERS. THE HIGHLIGHTED VALUES ARE THE SIGNIFICANT FACTORS

Features	H		BMI	
	Chi-sq	P	Chi-sq	P
γ_1	0.97	0.62	2.84	0.24
γ_2	1.53	0.46	3.64	0.16
f^p	**7.56**	**0.023**	**9.31**	**0.009**

Features	Age		AHI		Gender	
	Chi-sq	P	Chi-sq	P	Chi-sq	P
γ_1	0.45	0.8	2.2	0.137	0.71	0.4
γ_2	3.87	0.14	0.16	0.69	0.55	0.46
f^p	3.87	0.14	**6.14**	**0.013**	**4.05**	**0.04**

As known, obesity is a factor strongly associated with the presence of OSA [30]. Obese individuals with sleep apnea have been shown [31] to have more (about 42%) fat in their cervical region than normal subjects as well as non-obese individuals with OSA; hence, resulting in pharyngeal area narrowing. It is also known [32] that higher BMI is associated with increased level of leptin (a hormone produced by the adipose tissue and has also actions on the respiratory centre control). Therefore, our observed changes in the acoustical properties of the SS segments due to BMI can be explained by both anatomical and hormonal changes of the upper airway.

We observed that the SS segments of women consisted of higher frequency components than men. This difference was significant. Although there was no study investigating the gender effect on the snoring sounds, this observation is congruent with findings reported in [33, 34] focused on breath and lung sounds. According to those studies, breath and lung sounds in healthy women contain higher frequency components than in men. It has also been shown that men have higher pharyngeal and supraglottic resistances than women [35]. Hence, given that the size and mechanical properties of pharynx are significantly different between men and women [36], the snoring sounds of women and men can be expected to be significantly different as the results of our study indicates. Moreover, these might be also a reason for greater incidence of OSA in men [35, 36].

The f^p feature of SS segments was found to be significantly different in snorers with different AHI. This result is congruent with previous studies. In people with OSA, usually the lateral pharyngeal muscular wall is narrower [37]. Therefore, minimum area of the airway has been shown to be significantly smaller in apneic individuals than non-OSA people. The size of airway plays a major role in the frequency components of the sound produced by the flow turbulence in the airway. This explains the change in the frequency based HOS feature of the SS segments between OSA patients and simple snorers. One important point is that these frequency changes due to small changes in the airway size may not always be detectable by spectral analysis of the sounds. However, as known, HOS techniques complement the information obtained from 2nd order statistical techniques, i.e. spectral analysis. Hence, we propose the use of HOS techniques for snoring sound analysis as a better tool to increase the diagnosis accuracy of OSA.

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