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Bispectral Analysis of Tracheal Breath Sounds for Obstructive Sleep Apnea*

Ehsan Shams, *Student Member, IEEE*, Davood Karimi and Zahra Moussavi, *Senior Member, IEEE*

Abstract—**Obstructive Sleep Apnea (OSA) is a respiratory disorder with serious consequences that is characterized by repetitive cessation of breathing for more than 10s often associated with a drop of more than 4% in the blood's Oxygen saturation level. The gold standard for OSA diagnosis is full-night Polysomnography (PSG), which is a time-consuming, inconvenient, and costly assessment. On the other hand, our team has showed that the analysis of tracheal respiratory sounds recorded during wakefulness holds promises to be used as a simple and effective tool for screening moderate and severe OSA. In this paper, we examine the nonlinear characteristics of tracheal breath sounds and the possibility to extract features from Higher Order Spectra (HOS) for OSA screening. The data used in this study were recorded during wakefulness in two body positions, supine and upright, and during mouth and nose breathing. We estimated the bispectrum of the sounds in each respiratory cycle, calculated the median bifrequencies and the energy of the bispectrum, and investigated any statistically significant differences between the extracted features in two groups of non-OSA and severe OSA data. The differences in the features between body positions and nose/mouth breathing were also looked at. One-way ANOVA revealed significant differences in the features between non-OSA individuals and those with severe OSA. The results encourage the use of these features in future studies for OSA screening.**

I. Introduction

Obstructive Sleep Apnea (OSA) is a respiratory disorder with serious health consequences including cardiovascular complications, hypertension, and stroke [1]. Recent research has also raised the possibility of a causal relationship between OSA and type II diabetes [2]. People with OSA usually experience fatigue and are unable to maintain efficiency throughout the day [3]. Polysomnography (PSG) is currently the standard method to diagnose OSA [4]. It is resource-intensive and costly. Furthermore, it might not be available in urgencies. This has motivated researchers to seek non-invasive, portable and less costly methods to diagnose OSA.

Analysis of tracheal breath sounds has been used for OSA diagnosis with a comparable accuracy with that of PSG when recorded over night [5]. Our team has recently shown promising results on the use of spectral features of tracheal breath sounds recorded during wakefulness for screening moderate and severe OSA from non-OSA individuals [6].

Spectral features fail to account for the nonlinear behavior of tracheal breath sounds resulting from the turbulence of air in the trachea. These features also provide no information on the phase-related characteristics of the signals [7]. Higher Order Spectra (HOS) analysis reveals and quantifies information related not only to the amplitude of the signal, but also to its phase. For example, phase coupling, which occurs as a result of nonlinear interactions between harmonic components, can only be captured using HOS features such as the bispectrum [7]. The bispectrum, defined as the Fourier transform of the third-order cumulant of a process, is a HOS feature which is nonzero for nonlinear processes. As with other HOS, the bispectrum contains information pertaining to interactions of correlated harmonics and is a useful feature to capture and study the nonlinearities that arise when the process deviates from a purely Gaussian model [7]. Another advantage of using HOS is that cumulants in this domain are blind to additive Gaussian noise that is recorded along with a non-Gaussian signal [7].

Bispectral analysis has been applied to snoring sounds in recent studies [8, 9]; however, it has not yet been used on tracheal breath sounds for OSA screening. Since tracheal breath sounds can be recorded during wakefulness with minimum disruption to a person's daily routine, screening methods based on these sound signals will be less intrusive and more accessible than methods based on night-time signals such as snoring. As a pilot study, in this paper, we have examined the hypothesis that the nonlinear HOS features of tracheal breath sounds are significantly different between severe OSA and non-OSA individuals.

II. Methods

A. Data

Tracheal breath sounds used in this study were recorded at the Sleep Disorders Clinic at Misericordia Hospital in Winnipeg, Canada. Participants were referred for overnight PSG, and participated in our study prior to PSG assessment. The AHI value for each participant was scored by sleep technicians following the PSG. The study was approved by the Biomedical Ethics Board of the University of Manitoba and also that of Misericordia Hospital. Tracheal breath sounds were recorded by a small microphone (Sony ECM-77B) embedded in a plastic chamber placed over the suprasternal notch, and held in place by a double-sided adhesive disc. The sounds were digitized at 10240 Hz (14 bits resolution).

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Ehsan Shams (Phone: (204) 999-2429, shamse@cc.umanitoba.ca), Davood Karimi (d_karimi@umanitoba.ca) and Zahra Moussavi (Zahra_Moussavi@umanitoba.ca) are with the Department of Electrical and Computer Engineering, University of Manitoba, Winnipeg, Manitoba, Canada.

For this study, data of participants whose AHI was either below 5 (non-OSA) or above 30 (severe OSA) were considered. Breath sounds were recorded in two body positions of sitting upright and supine. Participants were instructed to breathe normally and then deeply for each breathing position, and to breathe through the nose and then the mouth. At least five breaths were recorded for each breathing maneuver. In this paper, we only examined sound signals of deep breathing. Table 1 shows the anthropometric information of the participants in the study.

TABLE I. ANTHROPOMETRIC INFORMATION OF PARTICIPANTS

Group	***Participant Information***			
	Number	***AHI***	***Age***	***BMI***
Non-OSA	79 (34 female)	1.6±1.5	58.6±7.6	30.2±7.3
Severe OSA	29 (8 female)	72.1±33.6	57.6±12.7	36.8±7.0

B. Onset Detection

The signals were filtered by a bandpass filter over 100-2600 Hz. We used the method outlined in [6] to separate the inspiratory and expiratory phases. Selecting the deep breathing sound signals from the two breathing maneuvers (mouth/nose) in the two postures (supine/upright), and then separating inspiratory/expiratory phases resulted in 8 signals for each participant. We then calculated the bispectrum of each of the 8 signals as described in the following sections.

C. Calculation of Bispectrum

The bispectrum is defined as the Fourier transform of the third-order cumulant of a process as follows [7]:

$$C_3(f_1,f_2)=\sum_{\tau1=-\infty}^{+\infty}\sum_{\tau2=-\infty}^{+\infty}c_3(\tau_1,\tau_2)\exp\{-2\pi j(f_1\tau_1+f_2\tau_2)\},\qquad(1)$$

where $c_3(\tau_1,\tau_2)$ is the third-order moment or cumulant, and is defined by:

$$c_3(\tau_1,\tau_2)=m_3(\tau_1,\tau_2)=E\{X(K)X(K+\tau_1)X(K+\tau_2)\}.\qquad(2)$$

We used the conventional direct method of bispectrum estimation, which is an approximation of bispectrum for the time series with limited available samples [7]. Since the bispectrum is symmetric across multiple axes due to the symmetric nature of the cumulant, we only considered the nonredundant region otherwise known as the principle domain [7]. Furthermore, we limited our analysis of the bispectrum to the frequencies ranging from 100-2600 Hz in every dimension of the bispectrum with a frequency resolution of 5Hz. Fig. 1 shows the bispectrum over positive values of f_1 and f_2 for individuals with AHI values of 0 and 30, respectively, for the mouth/supine/inspiration signal.

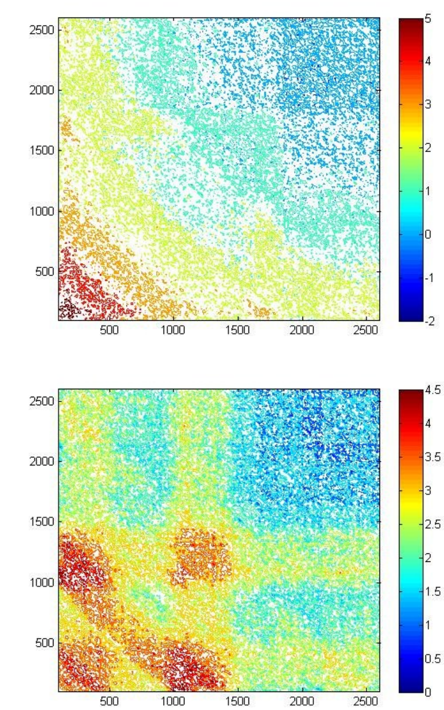

Figure 1. The Bispectrum of tracheal breath sound signals for mouth/supine/inspiration of individuals with AHI values of zero (top) and 30 (bottom) (drawn on the logarithmic scale)

D. Feature Extraction

The median bifrequencies were calculated along each frequency dimension of the nonredundant region of the bispectrum for each breath phase, using the following method:

1) The sum of all values of the bispectrum for all bifrequencies over the non-redundant region was calculated.
2) The value of f_1 was set at the smallest value in the nonredundant region and a temporary variable tSum was initialized to 0.
3) The values of the bispectrum for all possible bifrequencies (f_1, f_2) in the non-redundant region were added to tSum.
4) If the value of tSum was greater than or equal to half of the sum calculated in step 1, then the value of f_1 was taken as the median frequency for the first dimension. Otherwise, f_1 was incremented 5Hz (the resolution of the bispectrum) and steps 3 and 4 were repeated.

To estimate f_2, a similar algorithm was used, with the only difference that the value of f_2 was incremented at each step. Finally, the values obtained were averaged for each dataset for each individual to yield one pair of median bifrequencies for each signal.

As for a second feature, we calculated the energy of the bispectrum over equal and non-overlapping subbands in the nonredundant region. Specifically, the frequency band of 100-2600 Hz in each of the f_1 and f_2 frequency axes was divided into 10 equal non-overlapping subbands, each extending 250 Hz in frequency. We calculated the bispectral energy matrix for each breath phase and took the average bispectral energy matrix as the second feature.

E. Statistical Analysis

For each of the features, a one way analysis of variance (ANOVA) was employed to test whether the extracted features were significantly different between the two groups of severe OSA and non-OSA datasets. The ANOVA test was also performed for the difference in feature values between nose and mouth breathing (value for mouth breathing subtracted from the value for nose breathing) and the difference between breathing in the supine and upright positions. In all statistical tests, a *p*-value of less than 5% was considered as significant.

III. RESULTS

The bispectrum was non-zero for all datasets for all individuals. This shows that there are nonlinear properties resulting from phase relations of the harmonic components of the signals that can be captured using HOS [7].

The ANOVA test results for the median bifrequencies rejected the null hypothesis (that the median bifrequency for a certain breathing maneuver for OSA and healthy individuals belong to the same population) for a considerable number of datasets. Out of the 4 datasets of mouth breathing, the null hypothesis was rejected for one dataset for median frequency f1 and for three datasets for f2 (Table II). The ANOVA test results for the difference in median frequencies between nose and mouth breathing rejected the null hypothesis in all datasets for f1 and in three out of the four datasets for f2 (Table III). For the difference in median bifrequencies between the supine and upright positions, the null hypothesis was rejected only for the nose/inspiration dataset.

As for the energy of the bispectrum between the non-OSA and sever OSA groups, the most notable differences existed for the mouth/supine/inspiration dataset. Table IV shows the number of times the null hypothesis was rejected for each subband across all datasets.

The ANOVA test on the difference in the energy between nose and mouth breathing showed significant differences (Table V). In all tables pertaining to the energy of bispectrum matrices, the number 1 to 10 represent frequency bands with a width of 250 Hz from 100Hz to 2600Hz.

TABLE I. P-VALUE DERIVED FROM THE ANOVA TEST ON THE MEDIAN BIFREQUENCIES BETWEEN NON-OSA AND SEVERE OSA GROUPS

	Mouth Breathing			
	Supine		***Upright***	
	Inspiration	Expiration	Inspiration	Expiration
f_1	0.014	0.125	0.230	0.089
f_2	0.010	0.002	0.239	0.012

Datasets for which the null hypothesis was rejected are shown with a shade of grey.

TABLE II. P-VALUE DERIVED FROM THE ANOVA TEST ON THE DIFFERENCE BETWEEN MEDIAN FREQUENCY F_1 BETWEEN NOSE AND MOUTH BREATHING AMONG NON-OSA AND SEVERE OSA GROUPS

	Difference between Nose and Mouth Breathing			
	Supine		***Upright***	
	Inspiration	Expiration	Inspiration	Expiration
f_1	0.010	0.047	0.007	0.019
f_2	0.068	0.001	0.019	0.024

Datasets for which the null hypothesis was rejected are shown with a shade of grey.

TABLE III. NUMBER OF TIMES THE NULL HYPOTHESIS WAS REJECTED BY THE ANOVA TEST ON THE ENERGY OF BISPECTRUM MATRIX FOR ALL DATASETS BETWEEN NON-OSA AND SEVERE OSA GROUPS

		F1 frequency bands (Hz)									
F2 frequency bands (Hz)		100-350 (1)	350-600 (2)	600-850 (3)	850-1100 (4)	1100-1350 (5)	1350-1600 (6)	1600-1850 (7)	1850-2100 (8)	2100-2350 (9)	2350-2600 (10)
	(1)	2	0	0	4	3	0	0	2	0	0
	(2)		3	5	3	1	1	0	1	0	0
	(3)			0	1	1	0	0	0	0	0
	(4)				1	4	1	1	0	0	0
	(5)					2	1	1	1	1	0
	(6)						1	0	1	0	0
	(7)							0	0	0	0
	(8)								1	1	0
	(9)									0	0
	(10)										0

TABLE IV. P-VALUE DERIVED FROM THE ANOVA TEST ON THE DIFFERENCE IN THE ENERGY OF BISPECTRUM MATRIX BETWEE NOSE AND MOUTH BREATHING FOR THE SUPINE/INSPIRATION DATASETS BETWEEN NON-OSA AND SEVERE OSA GROUPS

		F1 frequency bands									
F2 frequency bands		1	2	3	4	5	6	7	8	9	10
	1	0.03	0.34	0.45	0.03	0.02	0.16	0.29	0.15	0.43	0.76
	2		0.11	0.01	0.01	0.00	0.05	0.61	0.57	0.48	0.54
	3			0.04	0.03	0.02	0.32	0.11	0.90	0.18	0.30
	4				0.03	0.04	0.03	0.07	0.61	0.29	0.43
	5					0.00	0.03	0.07	0.51	0.38	0.51
	6						0.06	0.12	0.70	0.70	0.29
	7							0.29	0.75	0.82	0.41
	8								0.19	0.06	0.46
	9									0.06	0.73
	10										0.39

Cells for which the null hypothesis was rejected are shown with a shade of grey.

IV. DISCUSSION

The results of this study indicate that HOS features of the tracheal breath sounds recorded during wakefulness have the potential to be used for OSA screening. Even though previous studies have established a strong connection between HOS features of snore sounds and OSA [9, 10], there has been very little effort to find a similar connection for breath sounds. One study has found that kurtosis of breath sounds is a useful feature for OSA screening [6], but no previous study has investigated the bispectral features; that was investigated in this study. The results of the statistical analysis of variance clearly show that HOS features capture further differences between non-OSA and severe OSA groups. The difference observed in HOS features might be due to the narrowing of the airway which has been shown to be important in the pathogenesis of OSA [11]. We believe that as the airway narrows, the nonhomogeneity of the airway walls and tissues becomes more apparent; thus, the flow of air in the upper airway can no longer be assumed to be laminar. Furthermore, this heterogeneity may result in vortices with more than one source of oscillation which spectral analysis cannot reveal.

It is worth noting that the fact that the estimated bispectrum is non-zero does not necessarily mean that the breath sounds are non-linear signals. To establish non-linearity of breath sounds requires rigorous statistical tests such as the one proposed in [12]. However, the complex pathophysiology of OSA, along with the results presented in this paper, are good reasons to suspect the linearity of tracheal breath sounds and warrant further research on the usefulness of HOS features for OSA diagnosis.

The results of the one-way test of ANOVA reveal that features are indeed different between non-OSA and severe OSA groups. These differences may be due to the nonlinearity of tracheal breath sounds and reflect phase relationships between correlated harmonics. The most promising results for median bifrequencies were obtained from the differences in the nose and mouth breathing. In healthy subjects, the upper airway resistance has been found to be similar between the mouth and nose breathing during wakefulness; however, during sleep in supine position, the upper airway resistance was much higher while breathing through the mouth [13]. The observed differences between the nasal and oral breathing sounds were significantly different between the non-OSA and severe OSA groups, implying that upper airway resistance in the two groups must be different depending on the breathing route during wakefulness. This observation is congruent with the results in [14] who found 50% of their OSA population associated with the upper airway resistance syndrome.

The results of this study are encouraging, and if verified in a larger population may shed light on the physiopathology of the OSA and also help in OSA diagnosis during wakefulness. Nevertheless, since anthropometric parameters such as gender, age, height and weight significantly affect the tracheal breath sounds [15], we need to have a larger dataset including individuals with matched anthropometric parameters to re-evaluate the observed differences.

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References

[1] F. Lopez-Jimenez, F. H. Sert Kuniyoshi, A. Gami and V. K. Somers, "Obstructive Sleep Apnea, Implications for Cardiac and Vascular Disease," *Chest,* vol. 133, no. 3, pp. 793-804, 2008.

[2] E. Tasali, B. Mokhlesi and E. Van Cauter, "Obstructive Sleep Apnea and Type 2 diabetes," *Chest,* vol. 133, no. 2, pp. 496-506, 2008.

[3] M. W. Johns, "Daytime sleepiness, snoring, and obstructive sleep apnea:," *Chest,* vol. 103, no. 1, pp. 30-36, 1993.

[4] B. Jafari and V. Mohsenin, "Polysomnography," *Clinics in Chest Medicine,* vol. 31, no. 2, pp. 287-297, 2010.

[5] A. Yadollahi, E. Giannouli and Z. Moussavi, "Sleep apnea monitoring and diagnosis based on pulse oximetery and tracheal sound signals," *Medical & Biological Engineering & Computing,* vol. 48, no. 11, p. 1087–1097, 2010.

[6] A. Montazeri, E. Giannouli and Z. Moussavi, "Assessment of Obstructive Sleep Apnea and its Severity during Wakefulness," *Annals of biomedical engineering,* vol. 40, no. 4, p. 916, 2012.

[7] C. Nikias and M. Raghuveer, "Bispectrum estimation: A digital signal processing framework," *Proc. IEEE,* vol. 75, no. 7, pp. 869-91, 1987.

[8] A. Azarbarzin and Z. Moussavi, "Nonlinear properties of snoring sounds," in *Acoustics, Speech and Signal Processing (ICASSP), 2011 IEEE International Conference on*, 2011.

[9] A. Ng, T. Koh, U. Abeyratne and K. Puvanendran, "Investigation of Obstructive Sleep Apnea Using Nonlinear Mode Interactions in Nonstationary Snore Signals," *Annals of Biomedical Engineering,* pp. 1796-1806, 2009.

[10] A. Ng, K. Wong, C. Tan and T. Koh, "Bispectral analysis of snore signals for obstructive sleep," in *Engineering in Medicine and Biology Society, 2007. 29th Annual International Conference of the IEEE*, 2007.

[11] P. Suratt, P. Dee, R. Atkinson, P. Armstrong and S. Wilhoit, "Fluoroscopic and computed tomographic features of the pharyngeal airway in obstructive sleep apnea," *The American Review of Respiratory Disease,* vol. 127, no. 4, pp. 487-492, 1983.

[12] M. Hinich, "Testing for Gaussianity and linearity of a stationary signal," *Journal of Time Series Analysis,* vol. 3, no. 3, pp. 169-176, 1982.

[13] M. Fitzpatrick, H. Mclean, A. Urton, A. Tan, D. O'Donnel and H. Driver, "Effect of nasal or oral breathing route on upper airway resistance during sleep.," *European Respiratory Journal,* vol. 22, no. 5, pp. 827-832, 2003.

[14] M. Epstein, S. Chicoine and R. Choudary Hanumara, "Detection of Upper Airway Resistance Syndrome Using a Nasal Cannula/Pressure Transducer," *Chest,* vol. 117, no. 4, pp. 1073-1077, 2000.

[15] A. Azarbarzin and Z. Moussavi, "Do anthropometric parameters change the characteristics of snoring sound?," in *Engineering in Medicine and Biology Society,EMBC, 2011 Annual International Conference of the IEEE* , 011.