Breathing Sounds Spectral and Higher Order Statistics Changes from Wakefulness to Sleep in apneic and non-apneic People

R. Soltanzadeh, *IEEE Student Member*, Z. Moussavi, *IEEE Senior Member*

Abstract— **Breathing sounds analysis conveys valuable information in relation to obstructive sleep apnea (OSA) during both sleep and wakefulness. In this study, we investigated whether the breathings sounds spectral and higher order statistics characteristics (HOS) change from wakefulness to sleep, and more importantly whether this change is associated with severity of OSA. Tracheal breathing sounds of 6 individuals with severe OSA and 6 non-OSA individuals during wakefulness and stage 2 of sleep, both in supine position, were used in this study. The sounds were recorded simultaneously with full overnight polysomnography (PSG) assessment. First, the sounds of 5 noise-free breathing cycles were extracted and sequestered into inspiratory and expiratory phase segments manually for each study subject. After normalizing each sound segment to its energy, spectral and HOS features were calculated. Several features including the median bispectral frequency (MBF), spectral bandwidth (BW) and bispectrum Harmonic Mean (HM) were found to change statistically significantly from wakefulness to sleep mostly in severe OSA group but not as much in non-OSA group. The most prominent and consistent change between the two groups of OSA and non-OSA was observed in MBF; it changed from wakefulness to sleep in the two groups in an opposite manner; this observation is congruent with the hypothesis that the upper airway in OSA population has an increased non-homogeneity.**

1. INTRODUCTION

Breathing sounds analysis provides valuable information about airway structure and respiratory disorders including obstructive sleep apnea (OSA). Analysis of breathing sounds recorded overnight has been used for OSA detection [1-4] with reasonable accuracies compared to that of polysomnography (PSG – the Gold Standard of OSA detection). Recently analysis of breathing sounds recorded for a few minutes (5 breathing cycle) during wakefulness has been used for OSA screening to identify those at high risk of severe OSA with an accuracy of roughly 70-85% [5-7]. The goal of this study is to investigate which breathing sounds feature changes the most from wakefulness to sleep and whether that change is significantly different between the two groups of OSA and non-OSA. The output of the study may help identifying more characteristic sounds features for OSA identification as well as understanding the mechanism of upper airway collapse in OSA individuals.

Imaging studies have shown the upper airway of individuals with severe OSA is narrower than those without OSA [8] and also more collapsible during sleep [9]. Thus, we hypothesize these structural changes of the upper airway must change the breathing sounds that is produced as a result of air turbulence in the upper airway. The more collapsibility of the airway plus its narrowing at some portions of the airway may cause some vortices in the respiratory airflow; these changes will change the breathing sounds characteristics. While, spectral analysis of the sounds is expected to reflect these changes, the effect of plausible vortices would be better seen by higher order statistics, specifically bispectral analysis. Thus, in this study we calculated several bispectral and spectral features of the breathing sounds from both wakefulness and sleep, and investigated their changes within and between two groups of individuals with and without OSA.

2. METHODS AND MATERIALS

The data was adopted from a previous study [5], in which tracheal breathing sounds were recorded from patients undergoing full overnight PSG assessment simultaneously. We selected data from two groups of study subjects: those whose Apnea/Hypopnea index (AHI) was less than 5 (non-OSA Group: 6 individuals, 5 males, 50±15.2y) and those with an AHI> 30 (OSA Group: 6 individuals, 5 males, 55.7±10.3y). In order to reduce variability, tracheal breathing sounds during sleep were extracted from the stage 2 of sleep in supine position (the most common stage and position among patients). Wakefulness data were extracted from their first few minutes, while they were awake and lying in supine position. From each wakefulness and sleep sound dataset, 5 noise-free respiratory cycles of breathing sounds were extracted and sequestered into inspiratory and expiratory segments. After normalizing each segment to its energy, spectral and High Order Spectrum (HOS) features, as described below, were calculated.

Power Spectrum (PSD) was calculated using Welch method as [10]:

$$PS = \sum_{f=Fl}^{Fu} P(f)\Delta f, \qquad (1)$$

where *f* is the frequency, *P (.)* is the power of the signal, and *Fl=100 Hz, Fu=2500 Hz* were chosen as the lower and upper frequency ranges, respectively. The PSD was estimated over windows with the length of 80ms and 50% overlap [4].

Resrach supported by National Science and Engineering Research Council (NSERC) of Canada Foundation.

R.Soltanzadeh is PhD student of Biomedical Engineering, University of Manitoba (e-mail: soltanzr@myumanitoba.ca).

Z.Moussavi. Director of Biomedical Engineering Program, University of Manitoba (Phone: 204-474-7023; e-mail: Zahra.Moussavi@umanitoba.ca).

978-1-4244-7929-0/14/$26.00 ©2014 Crown

Spectral Centroid (SC) is the weighted average frequency of the area under the PSD for the aforementioned frequency band and was calculated as [11]:

$$SC = \frac{\sum_{Fl}^{Fu} f\, P(f)\Delta f}{\sum_{Fl}^{Fu} P(f)\Delta f} \ . \qquad (2)$$

Spectral Bandwidth (BW) presents the weighted average of the squared distance between different frequency components and spectral centroid [12]:

$$BW = \frac{\sum_{Fl}^{Fu} (f - SC)^2\, P(f)\Delta f}{\sum_{Fl}^{Fu} P(f)\Delta f} \ , \qquad (3)$$

where *SC* is Spectral Bandwidth.

Bispectrum (BS) is the third-order frequency-domain measurement [13], and is estimated as

$$B_3^x(\omega_1, \omega_2) = \sum_{\tau_1=-\infty}^{\infty} \sum_{\tau_2=-\infty}^{\infty} c_3^x(\tau_1, \tau_2) \exp\{-j(\tau_1\omega_1 + \tau_2\omega_2)\}, \qquad (4)$$

where $c_3^x(.)$ is the third-order cumulant, which is calculated as

$$c_3^x(\tau_1, \tau_2) = E\{X(k)X(k+\tau_1)X(k+\tau_2)\}, \qquad (5)$$

and E {.} is the statistical expectation of the signal X (.), which has been shifted by τ_1, τ_2 in time.

Median Bi-Frequency (MBF) is the frequency, at which the areas of bispectrum at each side of MBF are equal [13].

Mean-Absolute and Mean-Angle of Bispectrum Coefficients: The bispectrum coefficients are complex values. Thus, they have amplitude and angle. The mean of these parameters were extracted as two features.

Harmonic Mean of Bispectrum Coefficients: The bispectrum is a complex-valued squared matrix. The size of this matrix is 2M × 2M, which is symmetric diagonally. Therefore, for decreasing calculation we should reduce this matrix to a real-valued feature without losing much information [6]. For this purpose, many methods have been provided in [6, 7, 14-18]. One of these methods is called *Harmonic Mean (HM)* calculated as [14].

$$HM = M\left(\sum_{i=1}^{M}(M-i+1)\left(\sum_{j=i}^{M}|B(i,j)|^{-1}\right)^{-1}\right)^{-1}, \qquad (6)$$

where B(.) is the estimated bispectrum coefficients.

Harmonic Mean of Real-Bispectrum Coefficients (RHM) is calculated by applying equation (6) to the real part of bispectrum coefficients [14]:

$$RHM = M\left(\sum_{i=1}^{M}(M-i+1)\left(\sum_{j=i}^{M}\mathrm{Real}(|B(i,j)|)^{-1}\right)^{-1}\right)^{-1}. \ (7)$$

Arithmetic Mean of Bispectrum Coefficients (AM) is also used to reduce the size of bispectrum coefficient matrix [10-14]:

$$AM = \frac{1}{M}\left(\sum_{i=1}^{M}\frac{1}{(M-i+1)}\left(\sum_{j=i}^{M}|B(i,j)|\right)\right). \qquad (8)$$

Arithmetic Mean of Real-Bispectrum Coefficients (AMR) is calculated similar to AM feature but for real parts of bispectrum coefficients [14]:

$$AM = \frac{1}{M}\left(\sum_{i=1}^{M}\frac{1}{(M-i+1)}\left(\sum_{j=i}^{M} Real(B(i,j))\right)\right). \qquad (9)$$

The above features were calculated from each respiratory phase, and their change from wakefulness and sleep were investigated within and between the two groups of OSA and non-OSA subjects.

3. Results

All of the features showed changes from wakefulness to sleep in both OSA and non-OSA groups but not necessarily consistently. The most significant and consistent changes from wakefulness to sleep in both groups were observed by MBF, HM and BW features. Figures 1 and 2 show the MBF feature (averaged over the 5 breathing cycles for each subject) during sleep and wakefulness for OSA and non-OSA groups, respectively.

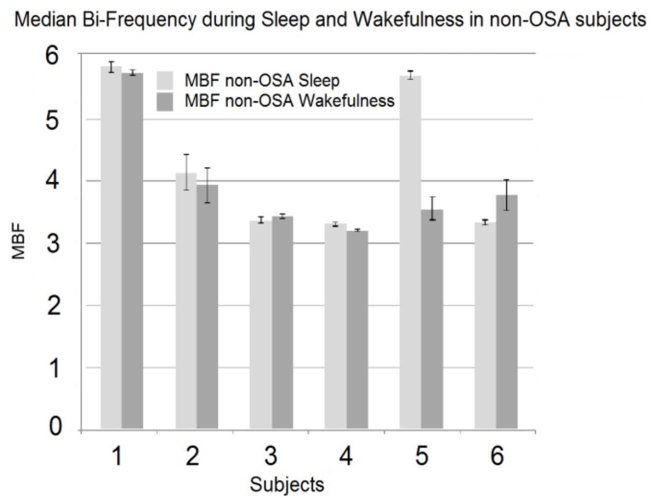

Fig. 1. Mean and standard error of MBF value of breathing sounds (averaged over the 5 breathing cycles) of 6 non-OSA subjects during sleep and wakefulness

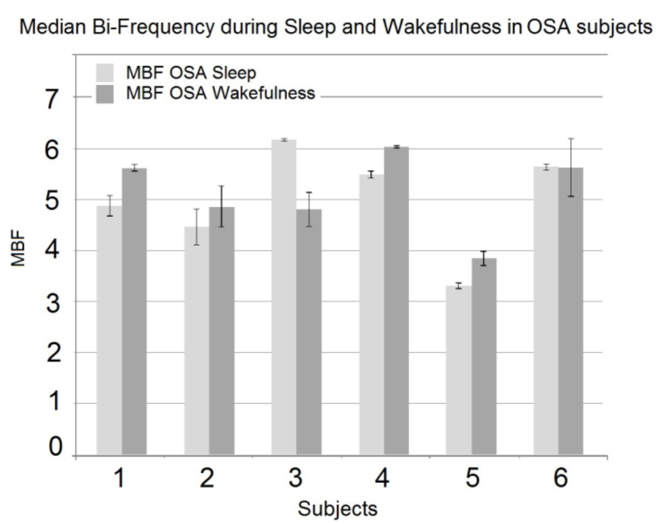

Fig. 2. Mean and standard error of MBF value of breathing sounds (averaged over the 5 breathing cycles) of 6 OSA subjects during sleep and wakefulness

As can be seen, the MBF values decreased during sleep compared to that during wakefulness in all individuals of OSA group except one (subjects 3, Fig. 2); this relationship was reversed for majority of non-OSA group (Fig. 1). This reversed relationship can be better seen in the scatter plot in Fig. 3.

Figures 4 and 5 depict the BW features calculated from during wakefulness and sleep of OSA and non-OSA subjects, respectively. This feature showed statistically significant changes between wakefulness and sleep among OSA subjects but not among non-OSA subjects (Table 1). However, as it is clear from the bar graphs, the change was not consistent among the subjects; thus, one cannot conclude any consistent physiological changes associated with OSA from this feature.

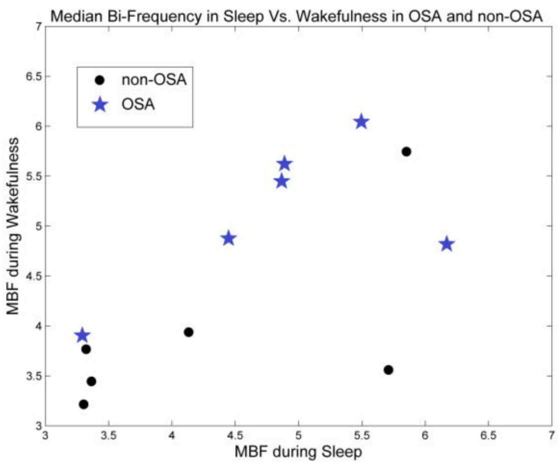

Fig. 3. Scatter plot of MBF values (averaged over 5 breathing cycles) during sleep and wakefulness of OSA and non-OSA subjects.

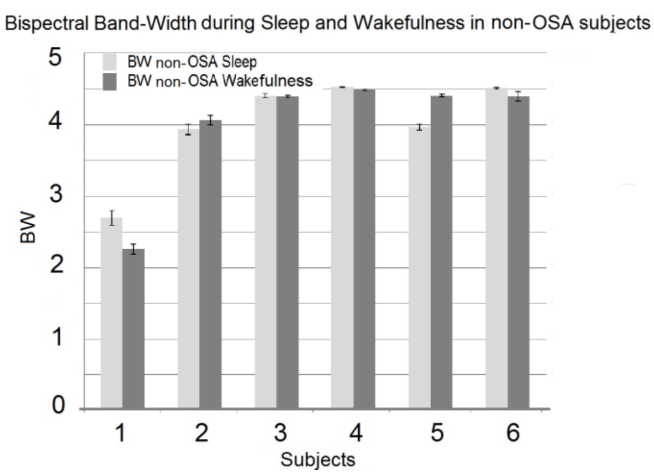

Fig. 4. Mean and standard error of BW value of breathing sounds (averaged over the 5 breathing cycles) of 6 non-OSA subjects during sleep and wakefulness

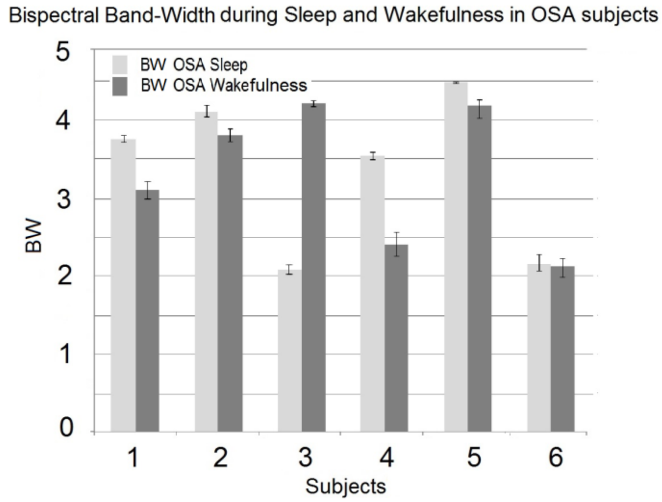

Fig. 5. Mean and standard error of BW value of breathing sounds (averaged over the 5 breathing cycles) of 6 OSA subjects during sleep and wakefulness

Since the data did not pass the normality test, instead of *t*-test, the Mann-Whitney U-test was used to investigate whether there was any significant difference in the features values between wakefulness and sleep within each of the two groups of OSA and non-OSA; the results are shown in Table 1. As can be seen, the changes of the first 4 listed features from wakefulness to sleep were found to be noticeably different in the two groups of OSA and non-OSA.

4. Discussion AND Conclusion

In this pilot study, we investigated how the spectral and higher order statistical characteristics of the breathing sounds may change from wakefulness to sleep, and whether this change might be different between two groups of OSA and non-OSA groups.

Almost all of the spectral and bispectral features showed some changes from wakefulness to sleep; overall, those changes were more significant in OSA group (Table 1). Comparisons of the spectral and bispectral features indicate that changes in breathing sounds between wakefulness and sleep in relation OSA are better represented by the bispectral features (MBF); they show more consistent changes within and between the two groups of OSA and non-OSA. This was expected: it is known that the upper airway of individuals with OSA is more collapsible [19], and that changes the airway structure; thus, expectedly the flow of air in a more collapsible airway may cause turbulence and perhaps vortices even during normal breathing. Breathing sounds are due to the flow of air in trachea; thus, the turbulence and/or vortices of airflow in trachea would be reflected more noticeably in the breathing sounds bispectrum because if there is a phase coupling in the two sources of air oscillation it will not be shown in power spectrum but only be reflected in higher order statistics, i.e. bispectrum of the sounds signals.

The feature that showed the most significant and consistent changes within and between the two groups of OSA and non-OSA was Median Bi-Frequency, MBF. As can be seen in Fig. 3, for most of the subjects in both groups the change of MBF from wakefulness to sleep was small. However, the important observation here is that the changes of this feature from wakefulness to sleep in the two groups were almost opposite: overall for non-OSA group, it increased during sleep, while in OSA group it decreased. This indicates a structural change of upper airway in the OSA group compared, and is supportive of the results of a recent study of our research team [20], in which it was shown the flow-sound relationship changes substantially during sleep in OSA group. Figure 5 shows this reversed relationship during sleep and wakefulness of the two groups. On the other hand, Fig. 5 also shows the more variability among the non-OSA group. Given the very small population of this study, it is difficult to draw a general conclusion. However, one should not forget that even the non-OSA group were referred patients for PSG; they were also snorers although we analyzed sounds segments free of snoring sounds. Furthermore, anthropometric factors such as smoking history in particular would affect the airway structure and thus, the breathing sounds. To address such variability we definitely need data from a large population.

Overall, the results of this study are encouraging to continue and investigate the observed patterns in a larger population.

Table 1. The score of each extracted feature during sleep and wakefulness

Feature	p-value between sleep and wakefulness	
	OSA	**Non-OSA**
Spectral Centroid	0.0766	0.4765
Spectral Bandwidth	**0.0035**	**0.1124**
Median bifrequency	**0.0823**	**0.1260**
Harmonic Mean of bispectrum coefficients	**0.0865**	**0.2002**
Arithmetic Mean of bispectrum coefficients	0.1016	0.2129
Harmonic Mean of real-bispectrum coefficients	0.4113	0.5433
Arithmetic Mean of real-bispectrum coefficients	0.4373	0.2450

REFERENCES

[1] Sharma, S. K., Kumpawat, S., Banga, A., Goel, A. "Prevalence and risk factors of obstructive sleep apnea syndrome in a population of Delhi, India," *CHEST*, 130.1 (2006)

[2] Flemons, W. W., Douglas, N. J., Kuna, S. T., Rodenstein, D. O., Wheatley, J. "Access to diagnosis and treatment of patients with suspected sleep apnea," *American journal of respiratory and critical care medicine,* 169.6 (2004)

[3] Azarbarzin A. and Moussavi Z. "Snoring Sounds Variability as a Signature of Obstructive Sleep Apnea," *J Med Eng Phys,* 35(4):479-85, (2013)

[4] Yadollahi A., Giannouli E. and Moussavi Z. "Sleep Apnea Monitoring and Diagnosis based on Pulse Oximetry and Tracheal Sound Signals," *J. Med. Biol. Eng. Comput.,* 48(11):1087-97, (2010)

[5] Karimi D. and Moussavi Z. "Obstructive Sleep Apnea Severity estimation during wakefulness based on tracheal breath sounds analysis," *Proc Sleep Conf*, June (2013)

[6] Montazeri A., Giannouli E. and Moussavi Z. "Assessment of Obstructive Sleep Apnea by Respiratory Sound Analysis during Wakefulness," *J. Annals on Biomed. Eng.,* 4(4):916-924, (2012)

[7] Karimi D. "Spectral and Bispectral Analysis of Awake Breathing Sounds for Obstructive Sleep Apnea Diagnosis," Diss. University of Manitoba, (2012)

[8] Schwab, R. J., Gefter, W. B., Hoffman, E. A., Gupta, K. B., Pack, A. I. "Dynamic upper airway imaging during awake respiration in normal subjects and patients with sleep disordered breathing." *American Review of Respiratory Disease*, 148(5): 1385-1400, (1993)

[9] Schwab, R. J., Gupta, K. B., Gefter, W. B., Metzger, L. J., Hoffman, E. A., Pack, A. I. "Upper airway and soft tissue anatomy in normal subjects and patients with sleep-disordered breathing Significance of the lateral pharyngeal walls." *American Journal of Respiratory and Critical Care Medicine*, 152(5):1673-1689, (1995)

[10] Oppenheim A.V., Willsky A.S., Hamid S., *Signals and Systems,* 2nd Edition, Prentice Hall, (1996)

[11] D. FitzGerald and J Paulus "Unpitched Percussion Transcription," *Signal Processing Methods for Music Transcription*, 1st Edition, Springer, (2006)

[12] Rauscher C. "*Fundamentals of Spectrum Analysis,"* 1st Edition, Rohde & Schwarz, (2001)

[13] Nikias, C. L. and M. R. Raghuveer "Bispectrum Estimation: A Digital Signal Processing Framework," *Proceedings IEEE*, 75(7):86S-891, July (1987)

[14] Orosco, E. C., Lopez, N. M., di Sciascio, F. "Bispectrum-based features classification for myoelectric control," *Biomedical Signal Processing and Control*, 8(2):153-168, (2013)

[15] Nikias, C. L., Mendel, J. M. "Signal processing with higher-order spectra," *IEEE Signal processing magazine* 10(3):10-37, (1993)

[16] Kaplanis, P. A., Pattichis, C. S., Hadjileontiadis, L. J., Roberts, V. C. "Surface EMG analysis on normal subjects based on isometric voluntary contraction," *J Electromyography and Kinesiology,* 19(1):157-171, (2009)

[17] Chen, X., Zhu, X., Zhang, D. "A discriminant bispectrum feature for surface electromyogram signal classification," *J Medical engineering & physics*, 32(2):126-135, (2010)

[18] Hussain, M. S., Reaz, M. B. I., Mohd-Yasin, F., Ibrahimy, M. I. "Electromyography signal analysis using wavelet transform and higher order statistics to determine muscle contraction," *J Expert Systems,* 26(1):35-48, (2009)

[19] Younes M., "Role of respiratory control mechanisms in the pathogenesis of obstructive sleep disorders," *J Applied Physiology*, 105(5):1389-1405, (2008)

[20] Yadollahi A., Azarbarzin A., Montazeri A and Moussavi, Z., "Respiratory flow-sound relationship during both wakefulness and sleep and its variation in relation to sleep apnea," *J. Ann Biomed Eng.,* 41(3):537-546, (2013)