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Review of Detection and Classification Methods for Snore Sounds.

Jeslin Renjith E[1]*, and Christy A[2].

[1]Mohamed Sathak College of Arts and Science,bSholinganallur,Chennai-119, Tamil Nadu, India.
[2]Sathyabama University, Jeppiaar Nagar, Chennai-119, Tamil Nadu, India.

ABSTRACT

Obstructive Sleep Apnea (OSA) is a serious chronic disease and a risk factor for cardiovascular diseases. Snoring is a typical symptom of OSA patients. Although awareness of OSA disorders is increasing, limited information is available on whole night detection of snoring. Knowledge of the origin of obstruction and vibration within the upper airways is essential for a targeted surgical approach. The major objective of this review paper is to study the details of several classifiers and feature selection methods which provide a robust, high performance, and sensitive whole-night snore detector based on non-contact technology. The major aim of this survey paper is to systematically compare different acoustic features, and classifiers for their performance in the classification of the excitation location of snore sounds. Here audio-based features extracted from time and spectral domains can accurately discriminate between snore and non-snore acoustic events. This audio analysis approach enables detection and analysis of snoring sounds from a full night in order to produce quantified measures for objective follow-up of patients.

Keywords: Obstructive Sleep Apnea, Snore Sound Classification, Multi-Feature Analysis, Drug-Induced Sleep Endoscopy.

*Corresponding author

INTRODUCTION

Partial or complete collapse of the upper airway during sleep has different effects on the human body, ranging from noisy breathing (simple snoring) to Obstructive Sleep Apnea (OSA), which can lead to considerable cardiovascular morbidity [1]. Snoring is the most common symptom of sleep-disordered breathing. By age 60, snoring adversely affects 60% of men and 40% of women. It is caused by the vibration of soft tissue in the upper airways involving anatomical structures such as the soft palate, uvula, and pharynx. The most common method for evaluating snoring history uses self-report questionnaires. The estimated prevalence of self-reported snoring in the general population extends over a wide range from 16% to 89% [2-3]. This prevalence depends on awareness, age, culture, and partner complaints [4].

Early work has shown a poor correlation between measured loudness of snoring and subjective appreciation by different observers. It was concluded that to a large extent snoring is ‘‘in the ear of the beholder’’ [4]. Thus, reliable snoring reporting cannot be made based solely on a patient’s (or partner’s) history of noisy respiration during sleep [5], or with sleep laboratory technician reports [4]. An additional limitation of questionnaires is that a large portion of the subjects respond that they ‘‘do not know’’ if they snore . To overcome these limitations, some clinicians ask the patient to supply an audio recording of their snoring, for example, prior to snore reduction surgery or to avoid operating on a ‘‘snorer’’ when in fact the problem lies with the bed partner being disturbed by essentially normal nocturnal breathing noise [1].

Polysomnography (PSG) is currently considered the gold standard for sleep evaluation [6]. This method requires a full night laboratory stay and subjects are connected to numerous electrodes and sensors, which are attached on the patient's body. Time series data are aggregated, processed, and visually examined or mathematically transformed in order to reveal insights about sleep-wake states and many aspects of physiology. Moreover, in routine sleep diagnostic procedures, sleep scoring is done manually by applying complex and visual scoring rules simultaneously on multiple signals acquired by applying contact sensors, e.g., electroencephalography (EEG), electrooculography (EOG), electromyography (EMG), electrocardiography (ECG), and respiratory activity [7].

PSG is time-consuming, tedious, and costly due to complexity and the need for technical expertise. Currently, the biomedical engineering field of sleep disorders evaluation is on a “fast track” towards ambulatory sleep medicine [8]. In recent years, extensive effort has been devoted to seeking alternative simple cost-effective technologies for objective sleep-wake evaluation to increase accessibility in sleep disorders diagnosis. These new technologies are based on reduced channels and sensors, and sophisticated computer-based algorithms [9-10]. Under the assumption that movement is associated with wake phase and lack of movement implies a sleep phase, clinicians and researchers have attempted to measure the binary presence of sleep or wake phases by measuring wrist movements using actigraphy [10]. Field-based activity monitoring devices are increasingly used as simple and cheap accelerometer-based devices [11]. Montgomery-Downs et al [12] recently reported that this new technology has specificity limitations similar to those of a traditional actigraphy device. These devices consistently misidentify wake as sleep and thus overestimate both sleep time and quality. It was long established that central control of ventilation and upper airway patency are strongly affected by transitions from sleep to wake and vice versa [13].

Furthermore, in order to reliably evaluate the severity, ventilation and variability of an individual’s snore, the recording of an entire night is required. Hence, developing an automatic snore detection method to analyze fullnight recordings in a timely and accurate manner would be advantageous. A limited number of studies have addressed this issue of automatic detection and classification of snore signals, and even less is known about snore detection using ambient (non-contact) microphone technology. Several snore/non-snore classification methods have been suggested using different techniques to analyze snore sound events. Some of them are discussed as follows:

It was long established that central control of ventilation and upper airway patency are strongly affected by transitions from sleep to wake and vice versa [13]. During sleep, there is a considerable increase of upper airway resistance due to decreased activity of the pharyngeal dilator muscles [14]. This elevated resistance is reflected by amplification of airpressure oscillations in the upper airways during breathing. These air-pressure oscillations are perceived as breathing sounds during sleep [15]. In contrast, during wakefulness, there is an increase in activity of the upper airway dilating muscles, hence decreased upper airway resistance and airway oscillations. Also demonstrated that the audio signal can be acquired using a non-contact sensor (ambient microphone), which minimizes the interruption of sleep [16]. However, little is known about whether acoustic-breathing parameters can distinguish between sleep-wake patterns.

RELATED WORK

Some of the methods in the literature include pitch and formants, features regarding spectrum modeling such as Mel-Frequency Cepstral Coefficients (MFCC), Linear Predictive Coding (LPC) [17], and standard acoustic measures such as sound intensity [13]. Most of these studies were conducted without separate groups of subjects for their design and validation studies. Duckitt et al [18] recorded sound with an ambient microphone from 6 subjects that was segmented into snoring episodes, breathing, duvet noise, and silence periods using hidden Markov models and spectral-based features.

Cavusoglu et al. [19] proposed a method for snore detection involving 15 subjects for both design and validation study using a linear regression fed by sub-band spectral energy distributions processed by principal component analysis. Karunajeewa et al [20] proposed a method for classifying snores and breathing sounds using the mean and covariance of four features extracted from time and spectral domains. Azarbarzin et al [21] proposed an unsupervised snore sound extractor based on a fuzzy C-means clustering algorithm and achieved higher accuracy using a tracheal microphone, due to a higher signal-to-noise ratio (SNR).

Fewer studies exist on how to determine the location, and form of vibration and obstruction in the upper airway from the acoustic properties of snore sounds. Miyazaki et al [22] adopted fundamental frequency to distinguish SnS generated by soft palate, tonsils/tongue base, combined type such as both palate, and tonsils/tongue base, and the larynx. Based on the examination of 75 adult patients they concluded that, the average value of fundamental frequency was 102.8 Hz, 331.7 Hz, 115.7 Hz and around 250 Hz in the corresponding sites mentioned above, respectively. Hill et al. found the crest factor, the ratio of peak to root mean square value of a time-varying signal, to be significantly higher for palatal snorers (p<0:01, Student-t or Mann-Whitney tests) in 11 patients [23].

Beeton et al proposed a combination of a 2-means clustering method and the statistical dimensionless moment coefficients of skewness and kurtosis to discriminate palatal, and non-palatal SnS collected from 15 patients [24]. They indicated that, the statistical moment coefficients demonstrate a method of measurement of the peakedness and symmetry of the impulse.

In the recent some of the additional features such as CP, CC, and CI (collectively named “periodicity features”; see Methods) are strongly influenced by breathing properties, such as rate and consistency. It was well established that changes in vigilance states strongly affect breathing rate and regularity in humans and animals [25-26]. The snore-characteristics features are designed to find the probability of a given epoch to contain snores. The basic idea is that the probability of detecting snoring events is increased during sleep. Snoring is caused by the vibration of soft tissue in the upper airways due to elevated upper airway resistance during sleep.

Recently, it was shown that snore analysis may carry valuable information about sleep conditions [27-28]. In order to calculate these snore characteristics features used our high performance (>98% detection accuracy rate) snore detector module. By using all these (eight) features as a multi-dimensional input to our sleepwake classifier, the performances were superior to using each feature separately . AdaBoost [29] algorithm is used to classify epochs as sleep or wake. The main advantage of this algorithm is its ability to discriminate multi-dimensional complex-patterns using a nonparametric, non-linear boundary threshold [29]. The use of this kind of classifier was supported by an earlier study [30], which claimed that sleep and wake activity (using wrist-actigraph) should be discriminated using non-linear classifiers. In addition, other studies have shown that there is a strong correlation between the labels (sleep/wake) of adjacent (30 sec) epochs [31]. Therefore configured AdaBoost classifier as a time-series model, in which the prediction of each epoch state is influenced by the adjacent epochs, i.e., it is unlikely (though it's possible) to find a fragmented sequence of [wake-sleep-wake] and vice versa

Most studies [32–33] have defined snores as acoustic events with sound intensity exceeding a certain amplitude value. Other studies have defined them as acoustic events that contain an oscillatory component

[32] and even as any sound perceived as such by the observer holding the microphone. Moreover, some studies have explored only selected snores (usually loud events) and did not analyze the whole sleep [34]. Since there is no unified approach to exactly define a snore, and it is more ‘‘in the ear of the beholder’’ included every noisy inhalation sound made during sleep that was .20 dB, i.e., the minimum sensitivity of the recording device.

Recently, this process was found to be beneficial in cases where the speech signal was contaminated with loud background noise. Lee et al [34] removed estimated background noise from an entire audio signal using a fixed filter. Their estimation was based on the spectrum from the initial ten minutes of the recording (empty room). This approach was better than most fixed noise reduction techniques (such as linear time invariant filter), but it did not follow the background noise properly through the night. To overcome the SNR challenge, some studies used a contact microphone, e.g., the tracheal microphone [35]; however, data were easily affected by a variety of noises such as cardiac and respiratory sounds and movements.

INFERENCE FROM THE SURVEY

In the recent work thin tube with multiple pressure sensors is introduced into the upper airway. The pattern of pressure changes during breathing of the different sensors allows a determination of the obstruction location during an apnoeic or hypopnoeic event. An advantage of this method is that, it can be used in natural sleep. However, the tube within the upper airway is not tolerated by every patient.

Acoustic analysis could be an alternative to determine the vibration mechanisms within the upper airway, which is easier for doctors and patients. Fewer studies exist on how to determine the location, and form of vibration and obstruction in the upper airway from the acoustic properties of snore sounds

The studies mentioned above are focused on evaluating certain well-selected acoustic features for their sensitivity to the anatomical mechanisms of snoring sound generation or upper airway obstruction. The comparisons and results are based on statistical analysis, and basic signal observation. The application of multi-feature analysis have better solution for this application and however, advanced signal processing methods, and machine learning models have been used for this purpose to increase higher accuracy.

CONCLUSION AND FUTURE WORK

This survey paper aimed to study and discuss the details of many snore detection classifiers using a noncontact technology. These classifiers are performed based on the signal enhancement and features extracted from different domains as they have complementary information about snore/non-snore discrimination. It also concludes that the new simple classifiers and detection methods are needed in order to improve patient accessibility to sleep diagnosis; this in turn will reduce the cost of management and treatment and improve quality of life and health to solve the issues of the existing methods. Moreover, this survey also includes comprehensive review of many classifiers and feature selection methods, the major issues of the existing work also discussed in this survey work. The comparisons and results of various methods are based on statistical analysis, and basic signal observation. The application of multi-feature analysis have better solution for this application and advanced signal processing methods, and machine learning models have been used for this purpose to increase higher accuracy is considered as scope of the future work.

REFERENCES

[1] Greenberg-Dotan S, Reuveni H, Simon-Tuval T, Oksenberg A, Tarasiuk A (2007) Gender differences in morbidity and health care utilization among adult obstructive sleep apnea patients. Sleep 30: 1173–1180.
[2] Marin JM, Gascon JM, Carrizo S, Gispert J (1997) Prevalence of sleep apnoea syndrome in the Spanish adult population. Int J Epidemiol 26: 381–386.
[3] Sands M, Loucks EB, Lu B, Carskadon MA, Sharkey K, et al. (2013) Self- Reported Snoring and Risk of Cardiovascular Disease Among Postmenopausal Women (from the Women’s Health Initiative). Am J Cardiol 111: 540–546.

[4] Reuveni H, Tarasiuk A, Wainstock T, Ziv A, Elhayany A, et al. (2004) Awareness level of obstructive sleep apnea syndrome during routine unstructured interviews of a standardized patient by primary care physicians. Sleep 27: 1518–1525

[5] Stoohs RA, Blum HC, Haselhorst M, Duchna HW, Guilleminault C, et al. (1998) Normative data on snoring: a comparison between younger and older adults. Eur Respir J 11: 451–457.

[6] Iber C, Ancoli-Israel S, Chesson A, Quan SF (2007) The AASM Manual for the Scoring of Sleep and Associated Events: Rules, Terminology, and Tech-nical Specifications; 1, editor. Westchester, IL: The American Academy of Sleep Medicine.

[7] Collop N, Anderson WM, Boehlecke B, Claman D, Goldberg R, et al. (2007) Clinical guidelines for the use of unattended portable monitors in the diagnosis of obstructive sleep apnea in adult patients. J Clin Sleep Med 3: 737–747

[8] Hedner J, Pillar G, Pittman SD, Zou D, Grote L, et al. (2004) A novel adaptive wrist actigraphy algorithm for sleep-wake assessment in sleep apnea patients. Sleep 27: 1560–1566.

[9] Sommermeyer D, Schwaibold M, Schöller B, Grote L, Hedner J, et al. (2010) Detection of sleep disorders by a modified Matching Pursuit algorithm. Springer. pp. 1271–1274.

[10] Choi JH, Kim EJ, Kim YS, Choi J, Kim TH, et al. (2010) Validation study of portable device for the diagnosis of obstructive sleep apnea according to the new AASM scoring criteria: Watch-PAT 100. Acta oto-laryngologica 130: 838–843.

[11] Appelboom G, Camacho E, Abraham ME, Bruce SS, Dumont EL, et al. (2014) Smart wearable body sensors for patient self-assessment and monitoring. Archives of Public Health 72: 28.

[12] Montgomery-Downs HE, Insana SP, Bond JA (2012) Movement toward a novel activity monitoring device. Sleep and Breathing 16: 913–917

[13] Malik V, Smith D (2012) Respiratory Physiology During Sleep. Sleep Medicine Clinics 7: 497–505.

[14] Edwards BA, White DP (2011) Control of the pharyngeal musculature during wakefulness and sleep: implications in normal controls and sleep apnea. Head & neck 33: S37–S45.

[15] Dafna E, Tarasiuk A, Zigel Y (2013) Automatic Detection of Whole Night Snoring Events Using Non-Contact Microphone. PLoS One 8: e84139.

[16] Ben-Israel N, Tarasiuk A, Zigel Y (2012) Obstructive apnea hypopnea index estimation by analysis of nocturnal snoring signals in adults. Sleep 35: 1299–1305C.

[17] Duckitt WD, Tuomi SK, Niesler TR (2006) Automatic detection, segmentation and assessment of snoring from ambient acoustic data. Physiol Meas 27: 1047– 1056.

[18] Cavusoglu M, Kamasak M, Erogul O, Ciloglu T, Serinagaoglu Y, et al. (2007) An efficient method for snore/nonsnore classification of sleep sounds. Physiol Meas 28: 841–853.

[19] Karunajeewa AS, Abeyratne UR, Hukins C (2008) Silence-breathing-snore classification from snore-related sounds. Physiol Meas 29: 227–243.

[20] Azarbarzin A, Moussavi ZM (2011) Automatic and unsupervised snore sound extraction from respiratory sound signals. IEEE Trans Biomed Eng 58: 1156– 1162.

[21] Azarbarzin A, Moussavi Z (2012) Snoring sounds variability as a signature of obstructive sleep apnea. Med Eng Phys.

[22] S. Miyazaki, Y. Itasaka, K. Ishikawa, and K. Togawa, “Acoustic analysis of snoring and the site of airway obstruction in sleep related respiratory disorders,” Acta OtoLaryngologica, vol. 118, no. 537, pp. 47–51, 1998.

[23] P. Hill, B. Lee, J. Osborne, and E. Osman, “Palatal snoring identified by acoustic crest factor analysis,” Physiological Measurement, vol. 20, no. 2, pp. 167–174, 1999.

[24] R. J. Beeton, I. Wells, P. Ebden, H. Whittet, and J. Clarke, “Snore site discrimination using statistical moments of free field snoring sounds recorded during sleep nasendoscopy,” Physiological Measurement, vol. 28, no. 10, pp. 1225–1236, 2007.

[25] Smith L, Schwartz AR (2012) Effect of end-expiratory lung volume on upper airway. J Appl Physiol 113: 691–699.

[26] Rostig S, Kantelhardt JW, Penzel T, Cassel W, Peter JH, et al. (2005) Nonrandom variability of respiration during sleep in healthy humans. Sleep 28: 411

[27] Ben-Israel N, Tarasiuk A, Zigel Y (2012) Obstructive apnea hypopnea index estimation by analysis of nocturnal snoring signals in adults. Sleep 35: 1299–1305C.

[28] Akhter S, Abeyratne UR, Swarnkar V (2013) Variations of snoring properties with macro sleep stages in a population of Obstructive Sleep Apnea patients. Conf Proc IEEE Eng Med Biol Soc 2013: 1318–1321

[29] Freund YS, Schapire RE (1997) A decision-theoretic generalization of on-line learning and an application to boosting. Journal of Computer and System Sciences 55: 119–139.

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[30] Tilmanne J, Urbain J, Kothare MV, Wouwer AV, Kothare SV (2009) Algorithms for sleep–wake identification using actigraphy: a comparative study and new results. Journal of sleep research 18: 85–98.
[31] Robinson P, Phillips A, Fulcher B, Puckeridge M, Roberts J (2011) Quantitative modelling of sleep dynamics. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences 369: 3840–3854.
[32] Issa FG, Morrison D, Hadjuk E, Iyer A, Feroah T, et al. (1993) Digital monitoring of sleep-disordered breathing using snoring sound and arterial oxygen saturation. Am Rev Respir Dis 148: 1023–1029
[33] Series F, Marc I, Atton L (1993) Comparison of snoring measured at home and during polysomnographic studies. Chest 103: 1769–1773
[34] Lee LA, Yu JF, Lo YL, Chen YS, Wang DL, et al. (2012) Energy types of snoring sounds in patients with obstructive sleep apnea syndrome: a preliminary observation. PLoS One 7: e53481
[35] Lee H-K, Lee J, Kim H, Ha J-Y, Lee K-J (2013) Snoring detection using a piezo snoring sensor based on hidden Markov models. Physiological measurement 34: N41.