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Gender dependant snore sound based multi feature obstructive sleep apnea screening method

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Abstract - **Obstructive Sleep Apnea (OSA) is a serious sleep disorder that occurs due to collapsing upper airways (UA). More than 80% of OSA sufferers remain undiagnosed and the situation demands simplified, convenient technology for community screening. Almost all OSA patients snore and snoring is the earliest nocturnal symptom of OSA. Snore signals (SS) are produced due to vibration of soft tissues in the narrowed parts of the UA. It is known that the UA properties are gender specific. In this paper, we work under the hypothesis that gender specific analysis of snore sounds should lead to a higher OSA detection performance. We propose a snore based multi-parametric OSA screening technique, which incorporates the gender differences in the algorithm. The multi feature vector was modeled using logistic regression based algorithms to classify subjects into OSA/non-OSA classes. The performance of the proposed method was evaluated by carrying out K-fold cross validation. This procedure was applied to male (n=51) and female (n=36) data sets recorded in a clinical sleep laboratory. Each data set consisted of sound recordings of 6-8 hr. duration. The performance of the method was evaluated against the standard laboratory method of diagnosis known as polysomongraphy. Our gender-specific technique resulted in a sensitivity of 93±9% with specificity 89±7% for females and sensitivity of 91±8% with specificity 89±12% for males. These results establish the possibility of developing cheap, convenient, non-contact and an unattended OSA screening technique.**

I. Introduction

Obstructive Sleep Apnea (OSA) syndrome is a serious sleep disorder characterized by the repeated closure of the upper airway (UA) during sleep. Full closure of airways is termed *Apnea* and a partial closure is known as *Hypopnea*. OSA severity is measured by Apnea-Hypopnea Index (AHI) which is calculated by averaging the number of apnea/hypopnea events per hour of sleep.

OSA is highly prevalent among males compared to females; and it affects around 20% of US adult population and approximately 90% remain undiagnosed [1]. Male gender increases the risk of OSA by a factor of 2~3 [2] and obesity by 2.33 times [3]. However, recently clinicians start focusing more on neck circumference (NC) [3] in clinical observation. NC indirectly indicates the geometrical properties of the UA.

OSA, by definition, is closely coupled with UA patency in sleep. The existence of gender specific functional differences in UA was highlighted by [4].

Loud/disruptive snoring is the most common nocturnal symptom of OSA [5,6]. Excessive daytime sleepiness, fatigue and tiredness are the associated diurnal symptoms. Extent of severity in symptoms found to be different in men and women who are having the same degree of sleep disordered breathing problems [7].

Almost all OSA patients snore and snoring is a complex acoustical phenomenon [8]. Snoring occurs due to vibrations of soft tissues in airway that caused by airflow and airway wall compliance imbalance. These acoustic waves are spectrally modified by the UA anatomical structures (at constrictions) to generate distinctive snore sounds (SS) [9].

Despite its huge potential, at present, SS are not being analyzed in clinical OSA diagnosis. Researchers have previously proposed [6,9-12,15,17-18] snore-sound based OSA diagnosis techniques. None of these work, however, considered the gender-specific information within snoring sounds.

It is a well known fact that there exists gender specific differences in vocal tract dimensions, elastic properties of tissues and prephonatory glottal shapes that involves in speech sound generation [13]. Considering the analogy of human speech and snore generation mechanisms, it is highly likely that acoustic properties of SS may be influenced by gender and gender specific information should be embedded in the acoustic properties of SS.

In this paper we address this issue and develop gender-specific models for OSA diagnosis based on snore analysis. We consider features of snore sounds represent structural and functional properties of upper airways. We also implemented gender dependant logistic regression based classification algorithm for OSA/non-OSA grouping and also cross validated our results. Easily available NC was also augmented to the snore vector to investigate the impact of this clinical variable on our proposed algorithm.

II. Method

Figure 1 shows the overall method followed in this paper.

A. Subject database

Our subject database consists of 51 male and 36 female subjects who were referred to the sleep clinic, Princess Alexandra hospital, Brisbane, Australia for the diagnosis of suspected OSA. Table I shows subject database characteristics.

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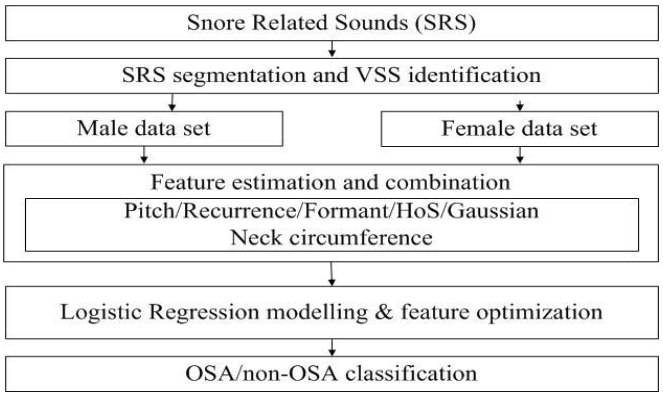

Fig1. Method consists of Voice Snoring Segment (VSS) identification, feature estimation and OSA/non-OSA classification using logistic regression analysis technique.

TABLE I. Subject characteristics

		#	AHI	NC	Age	BMI
AHI < 15	Female	19	6.2±4.8	32.9±3.6	49.7±9.9	27.0±8.9
	Male	12	8.7±4.0	42.0±5.2	47.3±12.	33.1±6.7
AHI >15	Female	16	41.7±27.	39.5±4.7	52.2±13.	35.7±10.
	Male	39	45.5±24.	44.8±3.4	53.5±13.	33.0±5.3
AHI < 30	Female	22	9.7±6.7	37.5±3.6	48.4±11.	29.9±8.5
	Male	23	14.1±7	42.9±4.9	48.5±13.	31.9±6.2
AHI >30	Female	13	51.8±27.	41.6±3.9	49.6±12.	40.6±9.1
	Male	28	55.5±22.	45.2±3.4	55±13.6	34.0±4.9

(# : number of subjects, AHI : Aponea Hypopnea Index, NC: Neck circumference, BMI : Body Mass Index)

B. PSG and snore data acquisition

The PSG data was collected using Compumedics sleep acquisition system and recording montage included EEG, EOG, EMG, ECG, Leg movements, nasal air flow, nasal pressure, respiratory movements, blood oxygen saturation, the body position and breathing sounds.

A high fidelity, CD-quality computerized data acquisition system was used for Snore related sound (SRS) acquisition. SRS were captured using two matched low noise microphones having a Hypercardiod beam pattern (Model NT3, RODE®, Sydney, Australia). Two microphones with equal gain were placed 50cm away from each other behind the patients head. The nominal distance from the microphone to the mouth of the patient was 50cm, but could vary from 40cm to 70cm due to patient movements. A/D converter unit (Model Mobile-Pre USB, M-Audio®, California, USA) and a low-end, professional quality pre-amplifier were used for SRS acquisition. The SRS collection process involved capturing SRS data: the amplification, filtering and A/D conversion is done within the M-Audio system. The sampling rate was kept at 44.1 k samples/s to obtain the best sound quality. However, the proposed method did not rely upon on the sound intensity and the results were independent of the mouth-to-microphone distance.

C. Snore Related Sound segmentation and Voiced Snore Segment identification

We adopted a pattern recognition algorithm developed by our research group [14,15] to categorize SRS into snore, breathing and silence. Based on the pitch period presence, snore episodes were further scrutinized to recognize voiced snoring segments (VSS). (Please refer to appendix for VSS definition).

D. OSA diagnostic feature vector

We perceive that speech and snore share many commonalities in the mechanism of their generation. Inspired by these similarities, we adapt speech processing techniques to SS analysis. In below paragraphs, we introduce OSA diagnostic features in detail.

a) *Pitch variation based features*: We estimated pitch values and then calculated mean, standard deviation, skewness and kurtosis values for all VSS. Subsequently, we computed the mean and standard deviation of the above variables respectively. Those features were augmented with weight group pitch variation probability (WGPV) feature which was developed in our previous work explained in [15] in detail. WGPV captures, quantifies the pitch variations of VSS and discounts the effects introduced due to VSS length variation.

b) *Recurrence based features:* Spatio-temporal information of SS was obtained by adopting a feature commonly used in speech disorders analysis [16] named as normalized recurrence time probability density entropy (NRTPDE). We computed NRTPDE for VSS and then estimated mean, standard deviation, skewness and kurtosis. We also adopted another feature developed in [15] and named as quantified recurrence probability density entropy which quantifies the extent of deterministic structure presence in VSS.

c) Formant based features: We recognize that UA physical dimension changes may embedded in SS properties which get constrained during apnea events. First formant frequency (F1) is a resonance frequency of the UA. We estimated mean and standard deviation of F1 for all VSS and computation details are explained in [15]. Next, we computed mean, standard deviation, skewness, kurtosis of *mean F1*. We also estimated the ratio of VSS that are having values below 400Hz (*b400*), between 400 and 800 (*bet4800*) and above 800Hz (*a800*) to total number of VSS.

d) *Higher order statistics (HoS) based features:* We presume that SS can be model as a convolution of source signal that represents acoustical energy and Total Airway Response (TAR) which captures acoustical signature of the UA [17]. We quantified the TAR by estimating bispectrum of TAR for all VSS and obtaining diagonal slice of principal domain triangle. We computed the center frequency, standard deviation of frequency, symmetry coefficient, ratio of total band amplitude for a given frequency band (500,800,1000Hz) ratio of total band amplitude for a given frequency band to a total amplitude outside that band (500,800,1000Hz), mean and variance of TAR. (Please refer [17] for TAR estimation details)

e) *Non-Gaussianity based feature:* Non-gaussianity of VSS was considered in characterizing OSA. We estimated Non-Gaussianity Score (NGS) which is a quantitative measure of the deviation from Gaussianity of a data segment using a method centered on the normal probability plot which is a qualitative tool in visualizing the "Gaussianity" of a given set of data. We computed mean (*gm)*, standard deviation *(gsd)* and skewness(*gsk)* of NGS for each VSS. We derived three OSA diagnostic parameters by calculating overall mean of *gm, gsd* and *gsk*. We further 6 parameters were derived by estimating the ratio of total number of VSS to, 1. The number

of VSS having *gm* > mean (*gm*), 2. The number of VSS having *gm* values in between mean (*gm*) ± standard deviation (*gm*), 3. The number of VSS having *gsd* > mean (*gsd*), 4. The number of VSS having *gsd* values in between mean (*gsd*) ± standard deviation (*gsd*), 5. The number of VSS having *gsk* > mean (*gsk*), 6 number of VSS having *gsk* values in between mean (*gsk*) ± standard deviation (*gsk*). (NGS calculation is illustrated in detail in [18]).

f) *Neck circumference:* Obesity is one of the few controllable risk factors associated with OSA. But it is observed that fat deposition distribution in the body varies depending on gender and pharyngeal airway size reduction can be better predicted with NC. NC is a common clinical variable measured prior to PSG test by sleep technologist on the subject before going to bed and the data are readily available.

E. OSA/non-OSA classification model

For the work of this paper, we adopted Logistic regression (LR) based method to classify subjects into OSA/non-OSA due its robust nature for this application. The dependent variable Z is assumed to be equal to "zero" (Z=0) for non-OSA subjects and "one" (Z=1) for OSA subjects. A model is derived using LR to estimate the outcome variable probability Z=1 for a set of *n* predictor independent variables as follows;

$$P_n(Z=1|x_1,x_2,...x_n)=\frac{\exp(\beta_0+\beta_1x_1+....+\beta_nx_n)}{1+\exp(\beta_0+\beta_1x_1+....+\beta_nx_n)}$$

where β_m (m=0,1,2....n) is the model parameters estimated by the maximum likelihood method.

F. Model parameter estimation

Subject databases were divided into two parts termed as training and testing data set. 70% of subjects were randomly chosen for the training set and the remaining were allocated for testing purposes. We developed 15 such classification data sets by randomly picking subjects. It must be noted that training and testing sets were independent and mutually exclusive from each one another.

The training data set was used to derive the model parameters (β_m : m=0,..,n) and final model was determined by removing the non-contributory parameters based on *p* value from the model. Final model parameters were used to estimate the probability (P_n) and then classification was achieved comparing it with a probability threshold P_{thre}.

G. OSA classification model performance evaluation

We considered the clinical diagnosis was positive for OSA at that particular decision threshold, if the PSG derived AHI > $AHI_{THRESHOLD}$ ($AHI_{THRESHOLD}$ = 15,30), otherwise regarded as negative. For the work of this paper, the clinical diagnosis obtained using PSG based diagnosis was considered as the absolute truth. The LR analysis based classification (OSA/non-OSA) of the subject was compared to the 'absolute truth', and the class of the decision was recorded as one among in true positives, true negatives, false positives or false negatives. We found the optimal P_{thre} value by capitalizing on the most widely used Receiver Operating Characteristics curve techniques. Sensitivity/specificity values were computed for testing data sets for different AHI decision threshold values. We K-fold cross validated our results by repeating the above process for different classification sets.

III. RESULTS

The compliance between the reference standard PSG and our proposed method results were compared. Next, we calculated sensitivity/specificity values for fifteen different classification sets for two AHI decision thresholds (15 and 30) and results are summarized below for the corresponding feature vectors.

TABLE II. OSA detection performance for 15 testing data sets when considered only snore derived features (pitch, HoS recurrence, formants, non-gaussianity features) (for $AHI_{decision\ threshold}$ = 15)

	Female	Male	Male and Female
AUC	0.97±0.02	0.94±0.04	0.81±0.02
Sensitivity	93.3 ±9.7	91.5±8.9	77.4±1.98
Specificity	89.6±9.75	89.4±12.8	86.6±3.52
PPV	0.93±0.09	0.91±0.08	0.77±0.01
NPV	0.89±0.09	0.89±0.12	0.86±0.03

AUC : Area Under Curve, PPV:Positive Predictive Value, NPV:Negative Predictive Value, HoS :Higher order Statistics

TABLE III. OSA detection performance for 15 testing data sets when snore derived features augmented with NC (for $AHI_{decision\ threshold}$ = 15)

	Female	Male	Male and Female
AUC	0.99±0.01	0.96±0.03	0.83±0.05
Sensitivity	94.6 ±9.1	92.9±9.09	83.7±5.94
Specificity	94.6±9.1	91.9±7.31	82.7±1.77
PPV	0.94±0.09	0.92±0.09	0.83±0.05
NPV	0.94±0.09	0.91±0.07	0.82±0.01

AUC : Area Under Curve, PPV:Positive Predictive Value, NPV:Negative Predictive Value, HoS :Higher order Statistics

Table II shows that male female separation allows us to obtain increment in sensitivity in the range from 14.1~15.9% while at the same time increment of 2.8~3% in specificity. Table II and III illustrates that augmentation of neck circumference to our feature vector resulted 1.3~1.4% and 2.5~5% increments in sensitivity and specificity respectively.

TABLE IV. OSA detection performance for 15 testing data sets when considered only snore derived features (pitch, recurrence, formants, HoS, non-gaussianity features) (for $AHI_{decision\ threshold}$ = 30)

	Female	Male	Male and Female
AUC	0.98±0.02	0.88±0.04	0.83±0.05
Sensitivity	91.2±10.24	88.3±3.22	83.7±5.94
Specificity	92.5±10	87.4±5.02	82.7±1.77
PPV	0.91±0.1	0.88±0.03	0.83±0.05
NPV	0.92±0.1	0.87±0.05	0.82±0.01

AUC : Area Under Curve, PPV:Positive Predictive Value, NPV:Negative Predictive Value, HoS :Higher order Statistics

Similarly for $AHI_{THRESHOLD}$=30, table IV shows that, adaptation of gender dependant algorithm lead us to obtain sensitivity (specificity) increments of 4.6~7.5% (4.7~9.8%). Table IV and V illustrates that augmentation of NC to our feature vector resulted 2.3~2.5% (1.2~3.6%) increments in sensitivity (specificity).

NC is a one-time measurement done on the subject before going to bed, and not a continuous overnight measurement can be acquired with an insignificant cost of time and effort.

TABLE V. OSA detection performance for 15 testing data sets when snore derived features augmented with NC (for AHI $_{\text{decision threshold}}$ = 30)

	Female	Male	Male and Female
AUC	0.98±0.01	0.96±0.03	0.87±0.04
Sensitivity	93.7 ±9.57	90.6±5.59	84.4±9.20
Specificity	93.7±9.57	91.0±7.14	82.9±1.83
PPV	0.93±0.09	0.90±0.05	0.84±0.09
NPV	0.93±0.09	0.91±0.07	0.82±0.01

AUC : Area Under Curve, PPV:Positive Predictive Value, NPV:Negative Predictive Value, HoS :Higher order Statistics

We have not calculated sensitivity/specificity for $AHI_{THRESHOLD}$=5 due to lack of subjects below the threshold in our database.

IV. Discussion and Conclusion

Although almost all OSA patients snore, snoring itself is not a marker of the disease. Development of proper diagnostic features by applying advanced digital signal processing techniques enabled us to obtain above results which are superior to previous reported results of [10,11 and 12] and also comprehensive. These results established the feasibility of developing snore sound based OSA screening device. It has also shown that the adaptation of gender based algorithm improves the detection sensitivity/specificity. Pitch based features contributed evenly in both male and female methods. Apart from that, recurrence and higher order statistics based features have shown more discriminative power in females while first formant and non-gaussianity based features were dominant in males. NC can be acquired with no extra cost or effort, improves the classification sensitivity/specificity.

The proposed method is fully automated and free of subjective analysis. It does not require a dedicated sleep laboratory or the attendance of a sleep technologist. The low cost of implementation together with the unprecedented diagnostic performance makes it an ideal candidate for population screening of OSA.

However, it is essential to assess our methods using a larger database and also evaluate the performance of the methods at AHI decision threshold=5 as well. It should be noted that these results have been obtained using data recorded in a relatively calm hospital environment. These methods need to be further verified using recordings acquired at ambulatory home environment before implementation.

Appendix

Objective definition for Snoring Episodes (SE),

(a) We define a term '*Breath Record*' as the snore related sound data originated from the patient from the start of an inspiration to the corresponding end of expiration.

(b) We define a term '*Snoring Episode*' (SE) as a *Breath Record* with at least one portion of it containing sound with a detectable pitch. The part with detectable pitch is termed as '*Voiced snoring segment (VSS)'*. The rest of the SE containing sound without pitch is classified as 'Unvoiced snoring segment (UVSS)'.

(c) A Breath Record that is not a Snoring Episode is called a '*Pure-Breath Record'*.

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