



## The Effects of Anthropometric Parameters on the Breathing Sound Features while Screening Obstructive Sleep Apnea during Wakefulness

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### Abstract

Anthropometric characteristics, such as gender, body mass index (BMI), age, etc. are considered as risk factors for obstructive sleep apnea (OSA). These information are used for screening OSA during wakefulness, but they provide a poor specificity compared to our screening method using tracheal breathing sound analysis. Despite that, one of the main challenges of using breathing sounds analysis for classification of OSA during wakefulness is the effect of confounding variables. Breathing sounds are not only affected by OSA, but also by the anthropometric factors. In this work, we investigated which sound features show the least correlation to anthropometric factors. Tracheal breathing sounds of 114 individuals (66 subjects with apnea/hypopnea index (AHI) < 15 and 48 with AHI > 15) were recorded during wakefulness in supine position. Spectra and bi-spectra of the signals of the two AHI groups were analyzed to extract the most significant features. Our results suggest it is possible to find the best features with high sensitivity to AHI and least sensitivity to confounding variables.

### Introduction

Obstructive sleep apnea (OSA) disorder is a common syndrome characterized by repetitive episodes of complete (apnea) or partial (hypopnea) pharyngeal collapse during sleep [1]. It can cause a severe effect on the quality of life of the affected people. OSA has various consequences including increasing the risk of developing heart disease, hypertension, stroke, depression, diabetes, and headaches, as well as traffic accidents (due to daytime sleepiness) [2]. Furthermore, OSA may lead to a preoperative morbidity and/or an after-surgery mortality [3]. Thus, diagnosing a subject with OSA, prior to conducting a surgery

requiring a full anesthesia, would reduce the mentioned risks [3].

Sleep apnea severity is measured by apnea/hypopnea events index (AHI) per hour. The gold standard for OSA diagnosis is Polysomnography (PSG). However, the availability of equipment, sleeping rooms, and skilled sleep technicians pose some challenges. As a result, PSG assessment has usually a long waiting list [4].

The long waiting list associated with PSG obstructs patients from conducting an objective OSA diagnosis quickly, which is crucial to know for patients prior to a major surgery. Therefore, physicians use one of the available subjective OSA diagnosis/screening tools such as STOP-BANG questionnaire [5].

Subjective tools, such as questionnaires, are easy to implement, fast, and inexpensive, but they have a very poor specificity (~10%) [5]. Consequently, they are not the most reliable and prompt choice. Accordingly, the need for a better solution to diagnose and screen subjects for OSA has massively increased. Such a solution will help in reducing the PSG waiting list and decreasing the possible harm consequences from conducting an operation.

Several research groups around the globe are working on finding objective alternative tests using sound analysis to screen for OSA during wakefulness [6]-[9]. In our previous work, we showed that tracheal breathing sounds analysis could be used for screening OSA during wakefulness. It showed a high testing classification accuracy of 84% with a comparable specificity and sensitivity between non-OSA (AHI ≤ 5) and OSA (AHI ≥ 10) groups [10].

While our previous work [10] has shown a significant superiority of using tracheal breathing sound features during wakefulness over the use of the anthropometric information for screening OSA, the effect of anthropometric

parameters on the breathing sound features was not investigated. Anthropometric characteristics, such as gender, body mass index (BMI) and age are risk factors for developing OSA [11]. They have shown their impact on the morphology of the upper airway structure [12], [13]. Thus, it is expected that anthropometric parameters have an impact on the tracheal breathing sounds.

In this work, our main objective was to investigate which sound features show the highest receiver operating characteristics (ROC), high testing classification accuracy, high correlation to AHI on supine position, and the least dependence on anthropometric parameters.

## Methodology

### Data

Using a microphone placed over the suprasternal notch of the trachea, we recorded 5 full deep breathing cycles through nose with mouth closed, followed by 5 deep breaths through mouth while wearing a nose clip for each subject. Data of this study were adopted from previous study [10], in which breathing sounds of 186 individuals were recorded during wakefulness in supine position.

Since wakefulness data were recorded in supine position, in this study, we excluded data of subjects who had not an AHI in supine position. Thus, data of 114 subjects were selected for the analysis. The signals of the dataset were divided into two groups: a non-OSA group ( $n=66$ ,  $AHI < 15$ ) and an OSA group ( $n=48$ ,  $AHI > 15$ ). The anthropometric parameters of the analyzed subjects are presented in Table 1.

### Signal analysis and feature extraction

From each breathing sounds, we estimated the power spectrum density (PSD) using the Welch method [14], the bispectrum using the indirect class of conventional bispectrum estimator [15], Katz and Higuchi fractal dimensions [16], [17], and Hurst exponent. Our interested frequency band for tracheal sounds was 100–2500 Hz [18]. Several features (i.e., mean, standard deviation, spectral entropy, skewness and kurtosis, spectral centroid, etc.) were extracted from the non-overlapping area between the

average spectra/bispectra and their 95% confidence intervals. The rest of the features were evaluated by analyzing Katz and Higuchi fractal dimensions and Hurst exponent.

### Feature reduction

For each extracted feature, p-value, using unpaired t-test, and area under the curve of ROC between the two groups were computed. Out of the initially extracted 412 features, 89 features were selected for further analyses based on the following criterion: 1) p-value between the two groups for the feature is  $\leq 0.05$ , 2) any two features with an in-between correlation coefficient  $0.95 > r > 0.8$  and p-value  $> 0.05$ , the feature with the lower area under ROC curve was rejected, and 3) any two features with an in-between correlation coefficient  $\geq 0.95$ , the feature with the lower area under ROC curve was rejected.

Then, the selected 89 features went through a restricted reduction procedure to find the set of features characterized by the highest areas under ROC curves. In this process, the first 10 features with the highest area under ROC curve were selected for next stage of analysis. The p-value between the two groups for these 10 features was evaluated using t-test, in addition, the correlation between each feature and  $AHI_{\text{Supine}}$  was computed. Furthermore, using SVM classifier with a linear kernel, testing classification accuracy using leave-one-out technique was calculated for each feature.

### Features and Anthropometric parameters

For each feature of the selected 10 features, the area under ROC curve, the p-value between the two groups, the correlation with  $AHI_{\text{Supine}}$ , and the testing accuracy were evaluated for different subsets of the data based on anthropometric parameters, one at a time. For example, they were evaluated for two groups of male vs female,  $BMI \leq 30$  vs  $BMI > 30$ , etc.

Among the different subsets, the coefficient of variation (CV) of the area under ROC curves and the testing accuracies was computed for each feature, separately. Furthermore, features with a  $CV \leq 0.08$  and a variation less than 0.2 were selected as the least dependent (to the anthropometric) parameters.

Table 1: Study subjects' anthropometric parameters. NC is neck circumference, and MS is mallampati score

	AHI <sub>Supine</sub>	Age	Gender	BMI	NC	Height	Weight	MS
<b>Non-OSA (AHI&lt;15, n=66)</b>	3.92 ± 4.5	47.23 ± 12.86	28 M, 38 F	30.29 ± 6.55	38.52 ± 3.77	167.35 ± 10.6	84.62 ± 19.58	34 'I', 16 'II', 9 'III' and 7 'IV'
<b>OSA (AHI&gt;15, n=48)</b>	57.133 ± 34.27	49.64 ± 12.7	40 M, 8 F	34.29 ± 7.45	44.11 ± 3.48	170.45 ± 10.45	100.15 ± 21.22	17 'I', 16 'II', 9 'III' and 6 'IV'

## Results

Anthropometric parameters' statistics of the two groups are reported in Table 1. Table 2 shows the details of the feature reduction results on the best 10 features.

Table 2: Results of the selected 10 features in a descending order based on the area under ROC curve; using the total dataset

Feat-ure num-ber	Subj-ects with AHI <15	Subj-ects with AHI >15	RO C-cur-ve	P value	Corre-latin coefficient	Testing accurac-y
1	58	39	0.83	4E-08	-0.62	0.79
2	58	39	0.82	0.0004	-0.34	0.62
3	64	46	0.86	0.0072	0.21	0.76
4	64	46	0.80	3E-08	0.50	0.73
5	58	39	0.79	1E-06	-0.55	0.77
6	59	40	0.77	1E-05	-0.55	0.68
7	59	40	0.76	1E-05	-0.47	0.72
8	64	46	0.76	4E-05	0.45	0.72
9	63	45	0.76	6E-07	0.53	0.76
10	63	47	0.75	6E-07	0.54	0.67

Figure 1 shows the area under ROC curve of each single feature for different subsets that divided of the confounding variables. Figure 2 shows the CVs for the area under ROC curve, the testing accuracy and the average value of for each feature. Figure 3 shows the CV of the two measures for each feature. As can be seen from these figures, features 1, 4 and 9 show a low CV ( $\leq 0.08$ ) and variation ( $< 0.2$ ) values. These features are defined below:

$$Feature1 = \frac{\sum_{f=150}^{f=250} P_{InsM}(f)}{\sum_{f=150}^{f=250} P_{InsM}(f) + \sum_{f=1200}^{f=1500} P_{InsM}(f)}$$

$$Feature4 = \frac{f=1400}{f=1250} A_{mean}(P_{InsM}(f) \text{ in dB})$$

Feature9 = Fundamental frequency estimation using zero-crossing technique with a cut off frequency of 1600 Hz for InsM

where, InsM is mouth inspiration breathing phase; Amean is arithmetic mean.

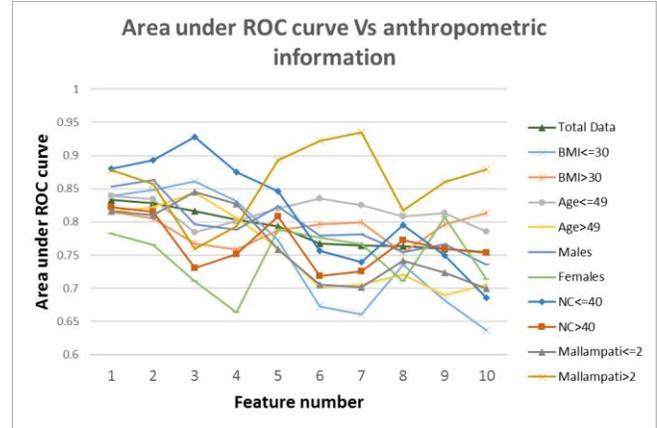


Figure 1: Area under ROC curve using the selected 10 features within different subsets based on the anthropometric parameters

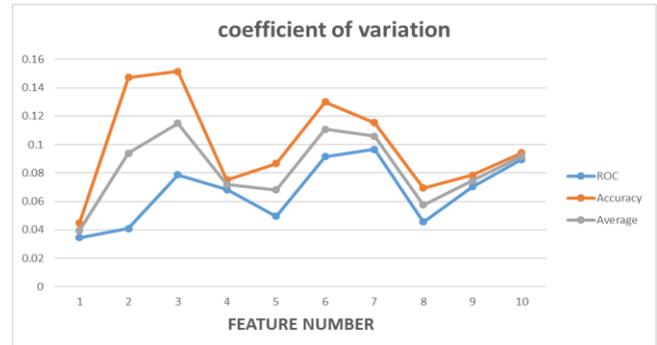


Figure 2: Coefficient of variation of the area under ROC curve and testing accuracy of the 10 features among different anthropometric parameters

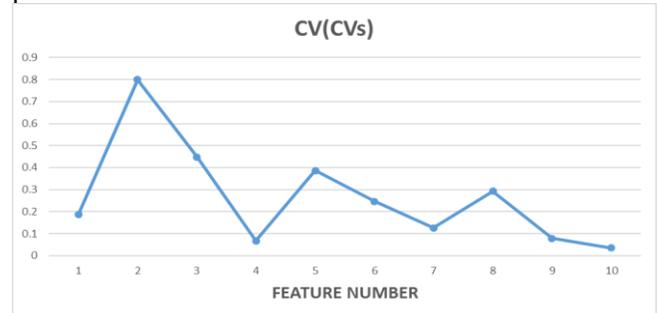


Figure 3: Coefficient of variation between the CV of the area under ROC curve and the CV of testing accuracy of the 10 features

### Discussion

The results of this study show that the anthropometric parameters affect the breathing sound features. However, it is possible to find the sound features with the least effect of confounding variables using the proposed methodology based on ROC and variation measures.

ROC value provides an explicit intuition about the specificity and sensitivity of a classification system. Thus, the selected features were ranked based on their areas under ROC curve. The 10 features giving the highest values were selected for further analysis. The number 10 was arbitrary selected to reduce computational cost of analysis.

Interestingly, the selected 10 features were all extracted from signals recorded through mouth breathing during inspiration phase. Although using a different analysis, this result is congruent with those of our previous study [10]. Three features (1, 4 and 9 on Fig. 2) showed the least dependence on the confounding variables.

Overall, this study has shown that anthropometric parameters have an effect on the sound features, but it is possible to find sound features that are least affected. The least dependent features on the confounding variables are probably better representatives of the OSA severity. However, having a reasonably large balanced groups of subjects for each subgroup between the two OSA groups is a serious limitation in our study that need to be addressed and resolved in future studies.

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