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# Relationship of Respiratory Sounds to Alterations in the Upper Airway Resistance

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*Abstract*— **Respiratory sound analysis is a simple and non-invasive way to study the pathophysiology of the upper airway (UA). Recently, it has been used to diagnose partial or complete UA collapse in patients with obstructive sleep apnea (OSA). In this study, we investigated whether fluid accumulation in the neck alters the properties of respiratory sounds in temporal and spectral domains and whether the respiratory sounds analysis can be used to monitor variations in the physiology of the UA, as reflected by UA resistance ($R_{UA}$). We recorded respiratory sounds and $R_{UA}$ from 19 individuals while awake. We applied lower body positive pressure (LBPP) to shift fluid out of the legs and into the neck, which increased $R_{UA}$. We calculated first and second formants and energy of inspiratory sound segments. Our results show that during both control (no LBPP) and LBPP arms of the study, the extracted features were different for the sound segments corresponding to low and high $R_{UA}$. Also, the features were different during control and LBPP arms of the study. With the application of support vector machine (SVM) based classifier, we were able to classify the sound segments into two groups of high/low resistance during control and LBPP arms and into two groups of control/LBPP when including all sound segments. The accuracies of non-linear SVM classifier were $74.5 \pm 19.5\%, 75.0 \pm 15.4\%$ and $77.1 \pm 12.3\%$ for the control arm, LBPP arm and between the arms, respectively. We also showed that during the LBPP arm, the variations in first formant of the sound segments corresponding to low and high $R_{UA}$ was much less than during the control arm. This indicates that with application of LBPP and accumulation of fluid in the neck, there are less variations in the morphology of the UA in response to changes in $R_{UA}$, than during the control arm. These results indicate that acoustic analysis of respiratory sounds can be used to investigate physiology of the UA and how interventions can alter UA properties.**

## I. Introduction

Obstructive sleep apnea (OSA) is a common disorder that increases cardiovascular morbidity and mortality [1, 2]. Although, OSA occurs due to the partial or complete collapse of the upper airway (UA) during sleep, the underlying mechanisms of this collapse are not fully understood. Recently, we proposed a novel paradigm for the pathogenesis of OSA: sedentary living leads to fluid retention in the legs in the daytime and to a shift of some of this fluid into the neck when lying down at night. The rostral fluid shift into the neck causes UA narrowing, induces UA obstruction and predisposes subjects to OSA. Therefore, developing non-invasive techniques to monitor fluid accumulation in the neck may enhance our understanding of the pathophysiology of OSA and to implement treatment targeted at specific causes of OSA in different individuals.

Nocturnal fluid shift from the legs into the neck could cause distension of the neck veins and/or edema of the peripharyngeal soft tissue and facilitate UA obstruction. In previous studies, we applied lower-body positive pressure (LBPP) via inflatable trousers to awake individuals to simulate nocturnal fluid displacement out of the legs. We demonstrated that fluid shift out of the legs to the neck narrowed the UA and increased its resistance to airflow in healthy non-obese subjects [3]. Fluid displacement also increased UA collapsibility in healthy men while awake [4]. We have also shown that during the night, the volume of fluid displaced from the legs strongly related to the degree of overnight increase in neck circumference and severity of OSA in non-obese otherwise healthy men, men with heart failure, end-stage renal disease, and patients with hypertension [5-7].

Respiratory sounds analysis is a simple and non–invasive technique to study the pathophysiology of the UA and has been widely used for investigation of UA obstruction [8-13]. In a previous study, we showed that tracheal sounds analysis can reflect variations in the anatomy of the UA, such as its lengths and diameter [14]. In another study, we applied LBPP to healthy awake individuals and simultaneously recorded upper airway resistance ($R_{UA}$) and respiratory sounds with a microphone in front of the nose. Our results demonstrated that for periods with large differences in $R_{UA}$, the auto regressive (AR) coefficients of the corresponding inspiratory sound segments were different [15].

The goal of this study is to investigate respiratory sound to examine the correlation between changes in $R_{UA}$ and the corresponding variations in the sound features in the temporal and spectral domains. We also aim to validate the accuracy of acoustic methods to predict alterations in the physiology of the UA as assessed by an objective measure of $R_{UA}$.

## II. Method

### A. Data

Data of this study were recorded from 18 subjects (14 men, 4 women) aged $55.6 \pm 10.2$, with a mean body mass index (BMI) of $32.2 \pm 8.7$, and mean number of apneas and hypopneas per hour of sleep (apnea-hypopnea index, AHI)

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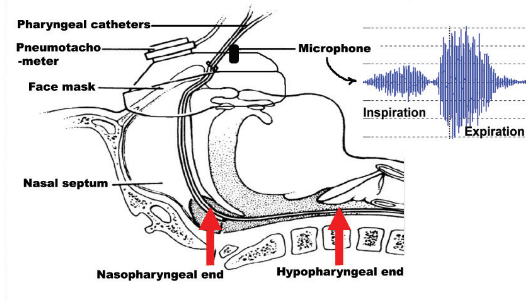


Fig. 1. Schematic of the setup for recording respiratory sounds and transpharyngeal pressure, along with samples of the recorded sound [15].

of $36.73 \pm 20.80$. Subjects were recruited by advertisement with no restriction on sex, age or BMI. With subjects awake and lying supine, respiratory sounds were recorded with a microphone (MX185, Shure) which was embedded in a full face mask and positioned in front of the subject's nose. Respiratory sounds were bandpass filtered in the frequency range of $[20-10,000]Hz$ and digitized with a sampling rate of $22kHz$. The sound signals were later lowpass filtered with the cutoff frequency of $4kHz$, which includes the main frequency components of respiratory sounds, and down-sampled to the sampling rate of $10kHz$.

Transpharyngeal pressure was measured as the difference between nasopharyngeal and hypopharyngeal pressure which were recorded by two catheters as shown in Fig. 1. Airflow was measured simultaneously by a pneumotachometer attached to the outlet of the mask. $R_{UA}$ was measured by dividing the transpharyngeal pressure by airflow. This study was approved by Research Ethics Board of Toronto Rehabilitation Institute.

### B. Lower Body Positive Pressure

To simulate overnight rostral fluid displacement out of the legs, LBPP was applied to both legs with an inflatable vinyl trousers connected to an air pump and manometer. The trousers were fitted around the subjects legs from the ankles to the hips in the deflated state. The subjects were randomly assigned to either a control arm, during which trousers were left deflated, or to a LBPP arm, during which the trousers were inflated to 40 mmHg. After a 15 minute of washout period, subjects were crossed over to the opposite arm. Respiratory sounds, transpharyngeal pressure and flow were recorded continuously during both arms.

### C. Feature Extraction and Investigation

Research personnel detected periods of inspiratory sounds void of snoring and wheezing noises by listening to the sounds and observing the signals in both time and frequency domains. Inspiratory sound segments were extracted during both control and LBPP arms of the study, and the corresponding $R_{UA}$ were also measured. For every sound segment, linear predictive coding (LPC) was used to find the formant frequencies which represent resonance in the UA [16]. Since the duration of the inspiratory segments can be as long as two seconds, the sounds are not stationary in the whole segment. Therefore, in every segment, sound signals were windowed with a Hamming window of $50ms$ with 75% overlap. In each window, the signal was estimated by an AR model. The optimum order of the AR model for formant estimation has a strong correlation with the sound sampling rate [17]. It was found that for sampling rates of $Fs \in [6-18]kHz$, the optimum order of the AR model would be $M = Fs(kHz) + \gamma$ where $\gamma = 4, 5$. In this study, we down–sampled the sound signals to the sampling rate of $10kHz$. Therefore, an AR model of order 14 was used to estimate formant frequencies. The roots of the AR model were calculated and angles of the complex roots with positive real values were estimated to find the first two formant frequencies (F1, F2).

In order to investigate how formant frequencies change with variations in $R_{UA}$, we used the average of the recorded $R_{UA}$ during control and LBPP arms as a threshold to define sound segments with high and low $R_{UA}$. For every subject, the average of formants ($F_i$) for sound segments with high and low $R_{UA}$ were calculated and the difference $\Delta F_i = F_i(R_{UA}(High)) - F_i(R_{UA}(Low))$ was estimated for control and LBPP arms. We estimated the probability density function (pdf) of $\Delta F_i$ ($pdf(\Delta F_i)$) among all subjects and investigated its variations in each arm of the study as a measure of the local variations in the morphology of the UA due to variations in $R_{UA}$.

On the other hand, UA narrowing increases turbulence of airflow which consequently increases respiratory sounds intensity. Therefore, we investigate the average of sound intensity in every inspiratory segment as the third feature to monitor variations in $R_{UA}$ due to the increase in fluid accumulation in the neck.

### D. Sounds Segments Classification

In this study, our aim was to investigate whether respiratory sound analysis can reflect variations in the physiology of the UA as assessed by increases in the $R_{UA}$ or application of LBPP. To achieve this goal, we took two approaches: first, a linear regression model was applied to the sound features including formant frequencies (F1,F2) and sound intensity. Performance of the regression model was validated in terms of the statistical significance of the model outputs (p-values of less than 0.05). In the second approach, we used both linear and nonlinear Support Vector Machine (SVM) classifier to group the inspiratory sound segments into two clusters.

SVM is commonly used to classify data vectors $\mathbf{x}_i$ ($\mathbf{x}$ is a vector of F1, F2 and intensity) into two classes of $c_i = \pm 1$. The optimal separating hyperplane, is defined for which the margin between the most similar samples in each class, which are called support vectors (SVs), is the largest. When boundaries between the two classes are more complex, a set of non-linear functions $\phi(\mathbf{x})$ is defined to transform the data vectors into a higher dimension; for which the transformed vectors can be separated by a hyperplane (Non-linear SVM). For non-linear SVM, the classification problem reduces to maximizing the function $L(\alpha)$ with respect to $\alpha$ [18]:

$$L(\alpha)=\sum_{i=1}^{n}\alpha_i-\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\alpha_i\alpha_j c_i c_j K(x_i x_j), \quad (1)$$

satisfying the conditions that $\sum_{i=1}^{n}\alpha_i c_i=0$ and $\alpha_i\geq 0, i=1,\cdots,n$. In this study, we investigated the classification performance for linear SVM and non-linear SVM with two different kernels:

$$\text{Quadratic Kernel :}\quad K(\mathbf{x}_i,\mathbf{x}_j)=(\mathbf{x}_i.\mathbf{x}_j)^2,$$

$$\text{RBF Kernel :}\quad K(\mathbf{x}_i,\mathbf{x}_j)=exp(-\frac{\|\mathbf{x}_i-\mathbf{x}_j\|^2}{2\sigma^2}).$$

We investigated the performance of a linear regression model and SVM classifiers in three different scenarios. The goal of the first and second scenarios was to classify the sound segments into high and low $R_{UA}$. In the first scenario, sound segments were selected from each subject during the control arm. For each SVM classifier, cross validation was used to select 70% of sound segments as a training data-set and the rest as a validation data-set and then to estimate the accuracy of the classifier. This routine was repeated 50 times and the accuracy values were averaged among all trials to remove sensitivities to the choice of training and validation data-sets.

The second scenario is similar to the first one, except that sound segments were extracted during LBPP period. For the third scenario, we used the sound segments recorded during both control and LBPP arms of the study. The aim of the third scenario was to investigate how accurately the regression model and SVM classifiers can distinguish between the sound segments recorded during different arms of the study, regardless of the variations in the $R_{UA}$ within each arm.

## III. Results and Discussion

In order to determine how features of respiratory sound segments change within different scenarios, formants data of a typical subject are shown in Figure 2. In Fig. 2a the sound segments were extracted during the control arm of the study and the two clusters show the feature vectors corresponding to low and high values of the $R_{UA}$. Similarly, Fig. 2b shows the scatter plot of the features during LBPP period. Comparing the results of Fig. 2a and b, it is clear that although for this subject linear SVM can classify the feature vectors during the LBPP arm, its performance would be poor for the control arm, and non-linear SVM would perform better. For this subject, the accuracy of linear SVM classifiers were 66.7% and 83.3% for control and LBPP arms, respectively, while the RBF SVM classifier performed better for the control and LBPP arms with the accuracies of 93.8% and 100%, respectively.

On the other hand, the scatter plot of feature vectors shows that during the control arm, first formant frequencies were expanded over a larger range of frequencies ($[195-700]Hz$), while during LBPP arm, the range of variations in $F1$ are smaller ($[200-313]Hz$). This is more evident in Fig 2c which shows the scatter plot of all sound segments during control and LBPP arms of the study. Furthermore, the difference between the average of $F1$ for the sound segments with low and high $R_{UA}$ (Fig 2a and b) is smaller during LBPP arm.

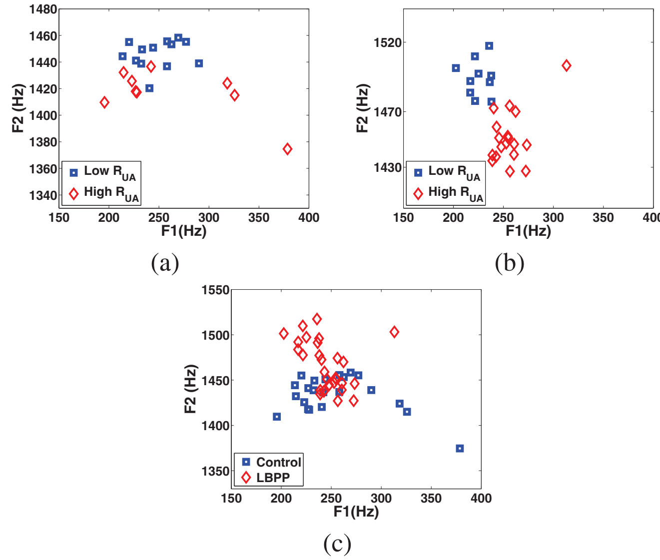


Fig. 2. Scatter plots of the first and second formants extracted from inspiratory sound segments of a typical subject during: a) control arm, b) LBPP arm, and c) both arms.

Figure 3 shows $pdf(\Delta F1)$ for all subjects. It is clear that $pdf(\Delta F1)$ is wider during the control arm than during the LBPP arm, where it is congregated around zero. Based on these results, it can be shown easily that the entropy of variations in the first formant of inspiratory sound segments is smaller during LBPP than during the control arm. Similar to speech signals, variations in the area and shape of the UA change the formant frequencies [19]. Therefore, wider variations in $\Delta F1$ in response to variations in its resistance indicate that during control arm the shape of the UA probably changed more than it did during LBPP. One interpretation could be that by applying LBPP, part of the fluid which is moved out of the legs accumulates in the internal jugular vein which is located adjacent to the UA. The extra fluid around the UA not only narrows the size of UA, but it may reduce the available space between UA and internal jugular vein and may limit the possible range of variations in the shape and size of the UA. This hypothesis can only be verified by imaging the neck and UA before and after the application of LBPP. It should be noted that $pdf(\Delta F_2)$ was similar for both arms of the study (data not shown due to the lack of space).

The results of linear regression models for separating the sound segments into two groups of low/high resistance (during control or LBPP arms) or control/LBPP arms (for all sound segments) are shown in Table I. The results show that during control and LBPP arms, the linear regression model was significant only for 47% and 37% of subjects, while for the between arm scenario, the model was significant for 74% of subjects. Figure 4 shows the average and standard deviation of accuracy of different SVM classifiers for differ-

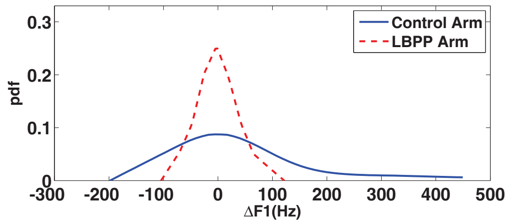


Fig. 3. Pdf($\Delta F_1$) for the sound segments with low and high $R_{UA}$ during control (solid line) and LBPP (dashed line) arms of the study.

TABLE I
THE NUMBER OF SUBJECTS WITH SIGNIFICANT RESULTS OF THE LINEAR REGRESSION MODEL IN MAPPING SOUND FEATURES INTO TWO GROUPS.

| | Scenarios | | |
|---|---|---|---|
| Number (%) of Subjects | Control Arm | LBPP Arm | Between Arms |
| | 9 (47%) | 7 (37%) | 14 (74%) |

ent selection of sound segments. In general, RBF classifier performs better than the other classifiers and the detailed results are presented in Table II.

The results of this study confirm that the first two formants and energy of inspiratory sound segments can represent variations in the morphology of the UA due to the accumulation of fluid in the neck as assessed by changes in $R_{UA}$. These results may pave the way to develop acoustic methods for investigating the variations in the UA properties due to fluid accumulation in the neck or other factors that may change UA shape and predispose to OSA. Furthermore, this information might be useful in assessing the site of UA obstruction, how treatments of OSA affect the UA properties and which types of treatment may achieve better outcomes in different populations of patients with OSA.

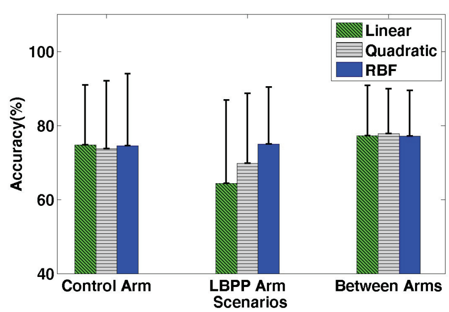


Fig. 4. Average and standard deviation of accuracy of different SVM classifiers for different selections of sound segments.

TABLE II
ACCURACY OF RBF BASED CLASSIFIER FOR DIFFERENT SELECTION OF SOUND SEGMENTS.

| | Control Arm | LBPP Arm | Between Arms |
|---|---|---|---|
| Sensitivity (%) | $79.3 \pm 27.6$ | $81.2 \pm 14.5$ | $79.8 \pm 13.7$ |
| Specificity (%) | $70.2 \pm 34.5$ | $62.7 \pm 31.0$ | $75.5 \pm 15.2$ |
| Accuracy (%) | $74.5 \pm 19.5$ | $75.0 \pm 15.4$ | $77.1 \pm 12.3$ |


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