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Acoustical Flow Estimation in Patients with Obstructive Sleep Apnea during Sleep

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***Abstract*— Tracheal respiratory sound analysis is a simple and non-invasive way to study the pathophysiology of the upper airways; it has recently been used for acoustical flow estimation and sleep apnea diagnosis. However in none of the previous studies, the accuracy of acoustical flow estimation was investigated neither during sleep nor in people with obstructive sleep apnea (OSA). In this study, we recorded tracheal sound, flow rate and head position from 11 individuals with OSA during sleep and wakefulness. We investigated two approaches for calibrating the parameters of acoustical flow estimation model based on the known data recorded during wakefulness and sleep. The results show that the acoustical flow estimation parameters change from wakefulness to sleep. Therefore, if the model is calibrated based on the data recorded during wakefulness, although the estimated flow follows the relative variations of the recorded flow, the quantitative flow estimation error would be high during sleep. On the other hand, when the calibration parameters are extracted from tracheal sound and flow recordings during sleep, the flow estimation error is less than 5%. These results confirm the reliability of acoustical methods for estimating breathing flow during sleep and detecting the partial or complete obstructions of the upper airways during sleep.**

I. Introduction

Tracheal respiratory sounds analysis is a simple and non–invasive technique to study the pathophysiology of upper airways. It has been used for respiratory flow estimation [1, 2], investigation of the upper airways abnormalities such as wheezes, tracheal stenosis, and airway obstructions [3-6]. One of the main applications of acoustical flow estimation is to detect the upper airway abnormalities and examine obstructions in the upper airways during sleep, specially in patients at risk of obstructive sleep apnea (OSA). However, all the previous studies that investigated the flow–sound relationship and acoustical estimation of respiratory flow were focused on data of non-OSA individuals during wakefulness [1, 2, 7-11].

OSA is highly prevalent in the general population, approaching about 24% of men and 9% of women aged $30-60$ years old [12]. The main consequences of sleep apnea are daytime sleepiness, increased risk of cardiovascular and cerebrovascular disease, traffic accidents, and impaired quality of life [13-16]. OSA is defined as periods of airflow cessation (apnea) or reduced airflow by more than 30% (hypopnea) associated with a minimum of 4% drop in blood's oxygen saturation level [17]. The severity of sleep apnea is usually measured by apnea–hypopnea index (AHI) which shows the number of apnea and hypopnea events per hour.

Full night polysomnography (PSG) is considered as the gold standard method for sleep apnea diagnosis [17, 18]. However, the high cost of PSG and the high prevalence of OSA in the general population have persuaded researchers to look for portable monitoring devices, such as acoustic techniques, for sleep apnea monitoring [5, 6, 19-22]. However, the previous studies on flow–sound relationship were all focused on data of awake non–OSA individuals. It is important to note that the relationship between tracheal sound and flow may change from wakefulness to sleep and it might also be different between OSA and non-OSA individuals. Therefore, in order to implement acoustic flow estimation algorithms for sleep studies, it is important to investigate the accuracy of the methods during sleep and in individuals with OSA.

In a previous study, we developed a robust acoustic method for flow estimation. The method's performance was verified on data of 93 healthy individuals during wakefulness, and its accuracy was found to be greater than 90% [11]. In this study, we investigated acoustic flow estimation in individuals with OSA during sleep. The goal of this study was to investigate how the model parameters were changing from wakefulness to sleep, and to quantitatively validate the flow estimation accuracy during sleep.

II. Method

A. Data

Data of this study were recorded from 11 (2 women) individuals who were referred to the Misericordia Hospital Sleep Disorders Center for full night sleep study. The study was approved by the Biomedical Research Ethics board of the University of Manitoba as well as the Miserecordia Hospital prior to the clinical trial. Subjects were recruited randomly with no strict limitations in terms of age, sex or body mass index (BMI). The subjects' detailed information are shown in Table I. Tracheal sound was recorded by a Sony microphone (ECM-77B) embedded in a chamber (diameter of $6mm$) and placed over the suprasternal notch of the

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TABLE I

ANTHROPOMETRIC INFORMATION OF THE SUBJECTS, BMI IS THE BODY MASS INDEX, AND AHI IS THE APNEA/HYPOPNEA INDEX.

Parameter	Range	Average $\pm$ Std
Age	$[33-59]$	46.5 ± 7.5
Height	$[164-188]$	175.4 ± 7.9
BMI	$[25.8-43.5]$	32.3 ± 4.8
AHI	$[6.8-116.9]$	31.6 ± 29.9

TABLE II

AVERAGE AND STANDARD DEVIATION OF DATA(IN SECONDS) THAT WERE EXTRACTED FROM THE SUBJECTS AT DIFFERENT POSITIONS.

Position	Wakefulness (s)	Sleep (s)
Supine (s)	66.1 ± 83.3	152.1 ± 133.5
Left (s)	30.8 ± 17.0	95.5 ± 45.4
Right (s)	32.7 ± 17.7	255.5 ± 457.1

subject's neck with a double sided adhesive tape. Respiratory flow was measured simultaneously by a full face mask pneumotachograph (Fleisch No.3) connected to a differential pressure transducer (Biopac, TSD127). An accelerometer was taped on the patient's forehead to monitor the head position during sleep.

Full PSG study was running simultaneously with our recording. We used the EEG recordings to monitor the subject's sleep stage. Since, sleep stage may change sound properties, we extracted data during second stage of non-REM sleep which was common among all of our subject. In order to compare variation in the model parameters from wakefulness to sleep, respiratory sounds and flow were recorded from the subjects at different positions, while they were awake. The sound signals were monitored manually, and the periods void of noise and snore sounds were selected. Table II shows average and standard deviation of the data duration (in seconds) that were extracted from the subjects at different positions during sleep and wakefulness.

B. Acoustical Flow Estimation

Different sources contribute to the generation of tracheal sounds. In previous studies, it was shown that flow-sound relationship in trachea follows a power law [1, 7, 8]; this implies that tracheal sound's energy and flow follow a linear relationship in the logarithmic scale. This linear relationship can be used to estimate flow from tracheal sound as:

$$\log F_{est} = \acute{a} \log E_s + \acute{b}, \qquad (1)$$

where F_{est} is the estimated flow and E_s is the tracheal sound's variance which represents the sound's average power [5]. Tracheal sounds were bandpass filtered in the frequency range of $[100-1000]Hz$ to remove the low- and high–frequency noises, while keeping the main frequency components of tracheal sounds. Tracheal sound's variance was calculated in windows of $50ms$ with 75% overlap between the adjacent windows. Respiratory sounds are non-stationary signals in general. To overcome this problem, in every inspiratory/expiratory breath cycle, the sound segments for which the corresponding flow rate was more than 60% of the peak flow within that breath cycle were considered for investigation.

For every subject, the model parameters $\acute{a}$ and $\acute{b}$ (Eq. 1) must be derived through a calibration process. Furthermore, it was shown that the rate of increase in sound's average power is not similar at different flow rates [10]; hence, using the same model for all flow rates will cause over/under estimation at the lower/higher flow rates than the flow rate used for calibrating the model [23, 24]. Therefore, the model was modified as:

$$\begin{aligned} \log F_{est} &= \bar{E}_s/\bar{E}_{base} \times \acute{a} \times \log(E_s) + \acute{b} \\ &= \bar{E}_s \times \left[\acute{a}/\bar{E}_{base}\right] \times \log(E_s) + \acute{b}, \end{aligned} \qquad (2)$$

where $\bar{E}$ is the average function, E_s is the sound's variance in the overlapping windows of current breath cycle, and E_{base} is the sound's variance in the breath cycle used for calibrating the model.

Two approaches were applied to calibrate the model and to estimate the model parameters. In the first approach, we investigated the possibility of using the subject's data during wakefulness to calibrate the model and estimate flow during sleep. In this approach, the model was calibrated using one breath cycle with known flow recorded during the wake time at a similar head position. In the second approach, one breath cycle with known flow during sleep was used to calibrate the model and estimate parameters $\acute{a}$ and $\acute{b}$. Analysis of variance (ANOVA) was used to find the statistical significance (p-value <0.05) of variations in the model parameters from wakefulness to sleep. Also, for every calibration scheme, the total flow estimation error was estimated for each individual during sleep:

$$Error = \frac{mean(F - F_{est})^2}{mean(F^2)} \times 100, \qquad (3)$$

where, F and F_{est} represent real and estimated values of flow, respectively. The values of error were averaged among all subjects for inspiratory and expiratory phases.

III. RESULTS

Although, we used data of every individual to calibrate the flow estimation model parameters, the parameters were different during wakefulness and sleep. However, the results of statistical analysis showed that the changes in model parameters were not significant except for $\acute{b}$ during expiration (Table III). Figure 1 shows the average and standard deviation of the model parameters (Eq. 2) among all subjects during wakefulness and sleep, which comply with the results presented in Table III.

Figure 2a shows samples of the recorded flow from a subject during sleep and at left position. The results of flow estimation based on the first and the second calibration schemes are shown in Fig. 2b and 2c, respectively. From these results, it is clear that when the model parameters were calibrated based on wakefulness data at the similar

TABLE III

THE RESULTS OF ANOVA ANALYSIS (P–VALUES) FOR CHANGES IN THE FLOW ESTIMATION MODEL PARAMETERS FROM WAKEFULNESS TO SLEEP (* INDICATES SIGNIFICANT RESULTS).

Parameter	Inspiration	Expiration
$\acute{a}$	0.49	0.71
$\acute{b}$	0.32	0.03*

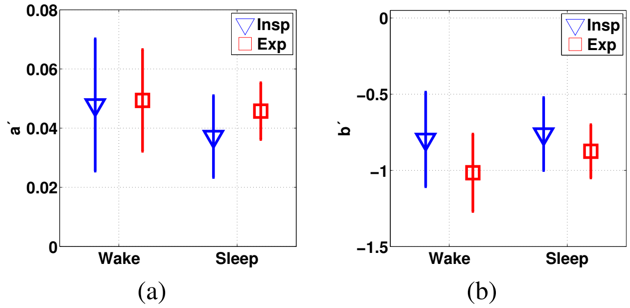

Fig. 1. Average and standard deviation of model parameters (Eq. 2) among all subjects during wakefulness and sleep, a) $\acute{a}$ and b) $\acute{b}$.

position (first approach), the estimated flow can only follow the relative variations in the actual flow; while by calibrating the model based on the sleep data (second approach), the estimated flow follows the actual flow quantitatively.

Figure 3 shows the average and standard deviation of the quantitative flow estimation errors among all subjects for different calibration approaches. For subjects with data in more than one body position, the errors at different positions were averaged. As expected, the results show that the flow estimation error is significantly higher for the first calibration approach than the second one. Total flow estimation errors were averaged among all individuals (Table IV); for the second approach they were found to be $2.3\pm3.2\%$ and $3.5\pm4.6\%$ during inspiration and expiration phases, respectively.

IV. DISCUSSION

Tracheal sounds analysis is a practical and non–invasive tool for investigating the pathophysiology of the upper airways and acoustical flow estimation [1, 2, 25, 26]. One of the main applications of tracheal sounds analysis is acoustical flow estimation to determine the cessations or reductions of breathing flow during sleep, and detect apnea and hypopnea events during sleep. For sleep apnea monitoring, it is not necessary to have a quantitative estimation of flow rate.

TABLE IV

AVERAGE AND STANDARD DEVIATION OF FLOW ESTIMATION ERRORS AMONG ALL SUBJECTS FOR DIFFERENT CALIBRATION SCHEMES.

Error (%)	Calibration based on data from	
	Wakefulness	Sleep
Inspiration	10.53 ± 21.06	2.26 ± 3.17
Expiration	23.96 ± 17.38	3.46 ± 4.56

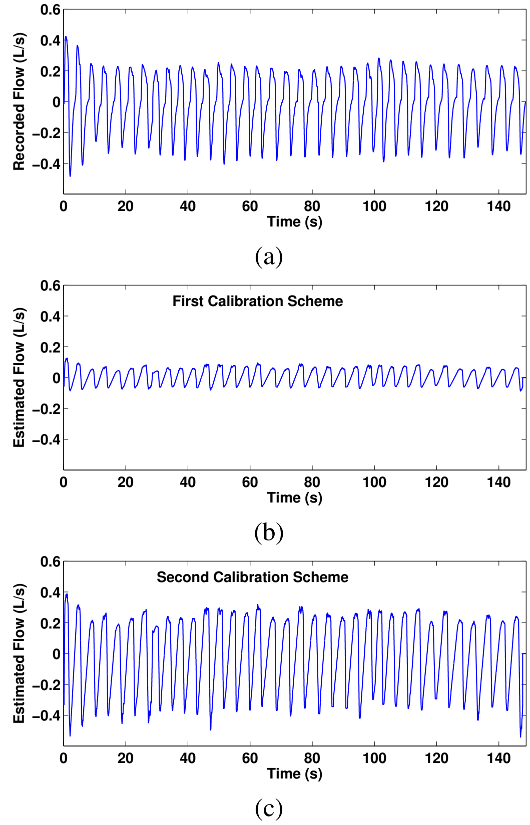

Fig. 2. Examples of flow estimation results during sleep from data of subject $S11$ at left position. A) recorded flow, and estimated flow based on b) first calibration approach, and c) second calibration approach.

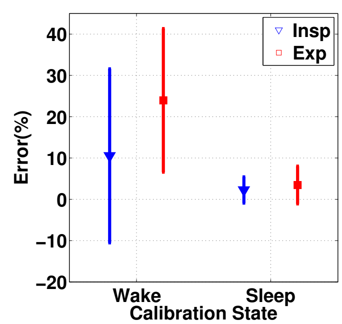

Fig. 3. Average and standard deviation of the flow estimation error for different calibration approaches during inspiration and expiration phases.

For these applications, the relative values of flow would be enough to detect apnea and hypopnea events.

Having said that, it is still of interest to examine the accuracy of flow estimation algorithm during sleep, as it will be an indicator of the reliability of relative flow estimation results. More importantly, it would be helpful to verify the possibility of calibrating the model at wakefulness and apply it to the sleep data. Therefore, we used two approaches to calibrate the flow–sound model and calculate the model parameters. In the first approach the goal was to study the possibility of using the recorded data during wakefulness to calibrate the model and estimate flow during sleep. If successful, this method would have greatly simplified the flow estimation algorithm. In the second approach, we used sleep data to calibrate the model parameters and estimate flow during sleep. The results showed that regardless of the head position, the model parameters change from wakefulness to sleep.

When the model was calibrated using the wakefulness data, the estimated flow during sleep was following the relative variations in the real flow rate (Fig. 2–a). However, due to differences in the model variables during wakefulness and sleep, the first approach for calibrating the model variables can not give an accurate estimation of the quantitative flow rate (Fig. 2–a) and the estimation errors were high (Fig. 3 and Table IV). On the other hand, by using the second calibration method, the model followed the variation of flow signal with small errors of less than 5% during both respiratory phases (Fig. 3 and Table IV). This confirms the reliability of acoustical flow estimation for investigating flow variations during sleep. However, it still needs calibration with one known breath during sleep.

Our study had a few limitations which were mainly imposed by recording flow with a full face mask. Because of the difficulties of breathing through the mask, we considered patients with BMI of less than 40 and younger than 60 years old, who would have less difficulty to breathe with the mask. We had no control on the sex or AHI of the recruited patients. Data was recorded in the hospital with no control on the environmental noises and conditions. Furthermore, the use of face mask made it difficult for patients to fall asleep, and consequently increased patients' movements. Theses factors increase the noise level of the recorded signal, and deteriorate the signal to noise ratio. Despite the experimental apparatus limitations, the results of this study are very encouraging as for the first time, it verifies the accuracy of acoustical flow estimation during sleep in individuals with OSA.

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