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Acoustic Obstructive sleep apnea detection

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***Abstract*— Obstructive sleep apnea (OSA) is a common respiratory disorder during sleep, in which the airways are collapsed and impair the respiration. Apnea is s cessation of airflow to the lungs which lasts at least for $10s$. The current gold standard method for OSA assessment is full night polysomnography (PSG); however, its high cost, inconvenience for patients and immobility have persuaded researchers to seek simple and portable devices to detect OSA. In this paper, we report on developing a new system for OSA detection and monitoring, which only requires two data channels: tracheal breathing sounds and the blood oxygen saturation level (S_aO_2). A fully automated method was developed that uses the energy of breathing sounds signals to segment the signals into sound and silent segments. Then, the sound segments are classified into breath, snore (if exists) and noise segments. The S_aO_2 signal is analyzed to find the rises and drops in the S_aO_2 signal. Finally, a fuzzy algorithm was developed to use this information and detect apnea and hypopnea events. The method was evaluated on the data of 40 patients simultaneously with full night PSG study, and the results were compared with those of the PSG. The results show high correlation (96%) between our system and PSG. Also, the method has been found to have sensitivity and specificity values of more than 90% in differentiating simple snorers from OSA patients.**

I. INTRODUCTION

Obstructive sleep apnea (OSA) is a common respiratory disorder during sleep, in which the airways are collapsed and impair the respiration. It is diagnosed by detecting periods of cessation of breathing (Apnea) or reduced breathing level (hypopnea) which lasts more than $10s$, and are associated with a minimum of 4% drop in oxygen saturation level in blood (S_aO_2) [1]. Severity of OSA is measured by the number of apnea and hypopnea events per hour (AHI index). About 24% of men and 9% of women aged $30-60$ years were found to have $AHI \geq 5$ [2]. The main consequences of sleep apnea are daytime sleepiness [3], increased risk of cardiovascular disease [4, 5], traffic accidents [6] and impaired quality of life [7].

Full night polysomnography (PSG) is the current gold standard method for OSA diagnosis [8, 9]. However, the high cost of PSG, uncomfort for the patients and the very long waiting lists have persuaded researchers to look for simple and portable monitoring devices that can detect OSA with high accuracy and smaller number of sensors than the conventional PSG [10, 11]. In these devices, nasal pressure [12, 13], S_aO_2 signal [14], respiratory sounds [15, 16] or a combination of 3-4 signals [17-19] are used for estimating the AHI index of the patient. However, nasal pressure flow meters are not only inconvenient for the patient, but also they may fail to give an accurate estimate of breathing flow rate due to the misplacement of the sensor during the night or in case of mouth–breathing. On the other hand, in addition to sleep apnea, there are other factors such as body position variations that can cause drops in the S_aO_2 signal; hence, affecting the accuracy of the methods that are mainly based on the S_aO_2 signal for OSA detection.

Tracheal respiratory sounds convey important information on the pathology and physiology of the airways [20, 21]; hence, respiratory sounds analysis during sleep can reveal useful information about the changes in breathing pattern of the patient. Also, tracheal sounds can be used for respiratory flow estimation [22]. This paper reports on our new ambulatory technology (ASAD) for OSA detection and monitoring. The premise of the system is on the analysis of tracheal respiratory sounds and S_aO_2 signal to estimate the AHI index of the patient. The novelty of the system is its simplicity (using only two data channels) and accuracy compared to that of PSG.

II. METHOD

A. System architecture

Our developed system records two signals: tracheal respiratory sounds and S_aO_2. The sounds are recorded with a small microphone placed on the neck of the patient over the suprasternal notch. The microphone is inserted in a chamber, and attached to the skin with double sided adhesive tape. The microphone and chamber are held in place with a soft neck band that is fastened gently around the patient's neck to ensure comfortability during sleep. The level of S_aO_2 is recorded with a finger probe device, and its analog output (between 0 and 1 corresponding to $0-100\%$ saturation) is fed to the data acquisition module. The sound signals are amplified and lowpass filtered with the cutoff frequency of $5\ kHz$. Finally, the amplified sound signals and S_aO_2 signal are digitized with the sampling rate of $10240\ Hz$.

A LabView based software was developed to record and save the digitized signals on a laptop computer. To synchronize our recording device with the PSG system, the clock of our laptop and the PSG were synchronized, and the start time on our recording system was automatically saved in a text file; this information was later used to retrieve the exact time of different events and associate them with the PSG–based

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Fig. 1. ASAD recording hardware.

TABLE I
PATIENTS' DEMOGRAPHIC INFORMATION.

Parameter	Age ($\mu \pm \sigma$)	BMI ($\mu \pm \sigma$)	AHI ($\mu \pm \sigma$)
Average	52.6 ± 12.2	32.3 ± 5.3	31.4 ± 36.0
Range	$[25 - 87]$	$[22.5 - 47.9]$	$[0.8 - 125.7]$

information. Figure 1 shows the view of our recording device at its research stage. Later, we developed a prototype which is much smaller in size, and also has a microprocessor inside; hence, it is independent of the computer for recording. The developed system is capable of acquiring and recording data during the entire night.

B. Data recording

Forty patients going through full–night PSG study at the Health Sciences Center Sleep Disorders Clinic (Winnipeg, Canada) consented to participate in this study. Subjects were recruited randomly with no limitations in terms of age, gender or BMI. The study was approved the Ethics board of University of Manitoba prior to experiments. The patients' demographic detailed information is shown in Table I. The sounds were recorded with a Sony (ECM-77B) microphone, and were amplified and lowpass filtered using Biopac (DA100C) amplifiers. The filtered breath sound and S_aO_2 signals were digitized by National Instruments data acquisition module ($NI9217$) and saved in a file every 3 minute (resulting approximately 140 files for every night of recording).

C. Signal Analysis

1) Automatic sound segmentation: The recorded sounds were first highpass filtered with a Butterworth filter of order 5 and cutoff frequency of $200Hz$ to remove low frequency noises including motion artifacts and heart sounds. The filtered sounds were segmented into windows of $20ms$ in duration with 75% overlap between the adjacent windows. In each window, the logarithm of the variance of the signal, $LogVar$, was calculated. The median of the $LogVar$ values of all windows was used as a threshold to classify the windows into sound or silent windows.

2) Apnea-Hypopnea detection: The cessation or reduction of breathing level are counted as an event if they are associated with a minimum drop of 4% in the S_aO_2 signal. Given that S_aO_2 signal is a low frequency signal, it is much faster and more efficient to analyze this signal and determine its drops and rises than analyzing the breath sounds. Therefore, in the first step, the S_aO_2 signal was analyzed, and all the drops (more than 4%) and rises of the signal were marked. Then, the tracheal sounds within the periods between a drop and the following rise in the S_aO_2 were found, and analyzed for apnea/hypopnea event detection.

We have shown that energy of the tracheal sounds in log scale is linearly related to the amount of respiratory flow [22]. Hence, by analyzing the breath sound signal we can have a good estimate of the reduction of the flow (hypopnea) or lack of flow (apnea). Therefore, in each period of S_aO_2 drop, the energy of the sound segments and their duration were compared with those of the normal breathing of the subject in the wake period. Note that a few minutes of breath sounds of the subject at the beginning of each recording when he/she was awake, was used to derive the energy level and duration of the normal respiratory cycle of the subject as a reference.

An apnea event is defined as the cessation of breathing for at least $10s$. It is easily detected by finding the periods, in which the sounds energy is below 90% of the reference value, and its duration is more than $10s$. However, detecting hypopnea events is more complicated; they can be either in terms of very shallow breathing, short durations of normal breathings with periods of no–breathing in between or combinations of shallow breathing and snoring which indicates partial obstruction in the airways. All of these conditions may result in a deficiency in the breathing level and a drop in the S_aO_2 signal. Furthermore, these conditions are different for each subject, and they even change during the night for the same subject.

Therefore, a smart function was developed which uses the sound segments energy, duration and the relationship between the energy values of the adjacent segments to classify tracheal signal segments into silence, breathing, snoring and noise (clicks, body movements, blanket noise) segments (Fig. 2). To consider different situations that can cause apnea or hypopnea event in a period with a drop in S_aO_2 signal, four parameters of sound segments were investigated. The first parameter is the total energy of the breath sound segments which shows the breathing level and will distinguish an apnea event or a hypopnea event due to shallow breathing. The second parameter is the duration percentage of the breathing sound segments, which is correlated to the first parameter and improves its performance. Since, snore sounds are common during hypopnea events, the third parameter is the duration percentage of snore sound segments in each period of S_aO_2 drop. The last parameter is the amount of drop in S_aO_2 signal which is used to represent the severity of the event. Then, each parameter is fuzzified with a sigmoid function and the fuzzy output of the four fuzzy functions are added together; if it is less than 0.5, the period is considered as an apnea/hypopnea event.

For each subject, the apnea and hypopnea events were estimated with the above mentioned method, the AHI index was calculated (AHI_{ASAD}), and was compared with that

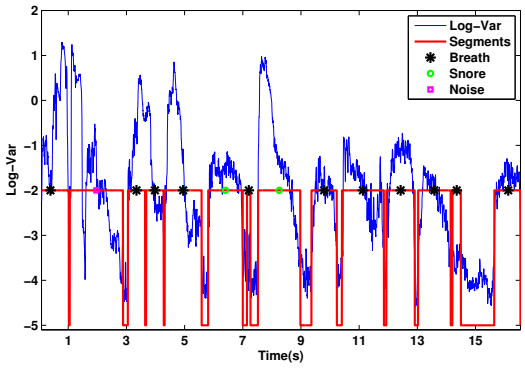

Fig. 2. A typical 16 period with the sound segmentation and classification results.

of the PSG study (AHI_{PSG}) that were manually calculated by the sleep lab technicians. The two AHI indeces were compared in terms of linear correlation and Bland-Altman measures among the subjects [23]. Bland-Altman measure is widely used in analyzing biomedical data, and is designed to measure the agreement between two methods that investigate the same property. Finally, the estimated AHI_{ASAD} values were used to classify the subjects into two groups of simple snorers and OSA patients. However, there is no specific threshold of AHI as the gold standard value to differentiate simple snorers from OSA patients. Therefore, four different values of AHI_{PSG} were used as the thresholds to find the true classification of subjects. For each threshold, the AHI_{ASAD} values were used to classify the subjects, and the receiver operating curve (ROC) and the area under the ROC curve (AUC) were estimated to evaluate the performance of the classifier.

III. Results and Discussion

Due to the huge amount of the processed data, it was impossible to verify the results of sound segments classification into sound, silent and noise in detail. However, for some random periods the results of sound segments classification were examined manually, and the results were found to be promising (more than 95% accuracy).

The results of sound segments classification and amount of drop in the S_aO_2 signal were used to determine the occurrence of an apnea or hypopnea event and the AHI index was calculated for each subject. The patients' AHI indeces calculated by our proposed automated acoustic method were compared with those of the PSG study. It should be noted that ASAD and PSG scoring were performed completely independent from each other, and the PSG information was only used to verify the results. Figure 3 shows the scatter plot of the AHI_{ASAD} and AHI_{PSG} values.

The correlation ratio between the AHI_{ASAD} and AHI_{PSG} values was found to be 0.96, indicating a very high correlation between the performance of the two systems. In addition, Bland-Altman test was performed, and the average and standard deviation values were 0.92 and 6.15, respectively; only 3 subjects were outside the 95% confidence

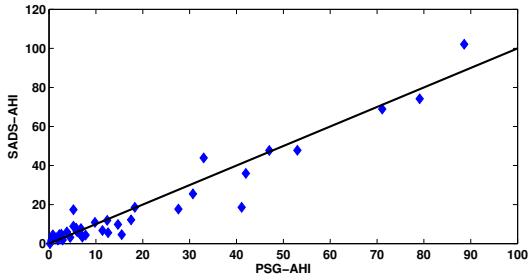

Fig. 3. Scatter plot of the AHI_{ASAD} and AHI_{PSG} values.

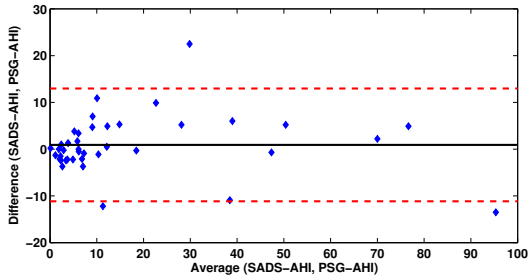

Fig. 4. Bland-Altman plots between the AHI_{ASAD} and AHI_{PSG}, the solid line shows the average difference and the dashed lines present the mean $\pm$ 1.96 of standard deviation of the difference.

interval (Fig. 4). The statistical results of the propsed system was found to be similar or better than the results of the previously proposed portable monitoring devices [12-19]. However, since we are recording breathing and snore sounds with high quality, our system can also provide information about the breathing pattern and airway condition of the patient during different events.

Finally, AHI_{ASAD} values were used as a threshold to classify the subjects into simple snores (SS) and OSA patients, and the ROC curve and AUC values were estimated to investigate the performance of the classifier. The experiment was repeated for four different thresholds of AHI_{PSG} values $(5, 10, 15, 20)$ corresponding to different severity levels of OSA as the reference in finding the true classes of the subjects (Fig. 5). The values of AUC for different thresholds of AHI_{PSG} values are shown in Table II. The higher the values of AUC, the better the performance of the classifier. For each threshold of AHI_{PSG} the best sensitivity and specificity values with the corresponding threshold of AHI_{ASAD} are shown (Table II). It can be seen that the proposed method has high specificity and sensitivity in differentiating between simple snorers and OSA patients. Overall, the calculated AHI_{ASAD} indeces by the proposed method are close to those of the PSG study but slightly under–estimated in severe cases; this has also been the case in previous studies.

IV. Conclusion

In this study a new fully automatic acoustic method was developed to detect apnea and hypopnea events with no need for respiratory flow measurement. The method uses only tracheal respiratory sounds and S_aO_2 signals to find the

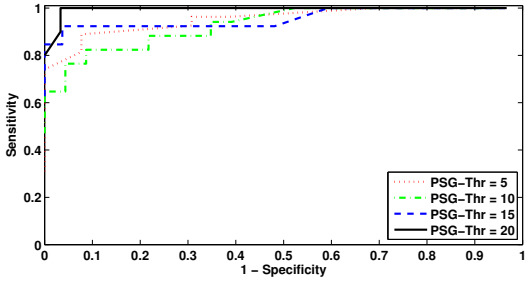

Fig. 5. ROC curves of the classifier for different thresholds of AHI_{PSG}.

TABLE II

AREA UNDER THE CURVE (AUC) OF THE CLASSIFIER FOR DIFFERENT THRESHOLDS OF AHI_{PSG}.

AHI_{PSG} Threshold	5	10	15	20
AUC	0.856	0.884	0.915	0.962
Sensitivity	88.9	82.4	92.3	100.0
Specificity	92.3	91.3	96.3	96.7
AHI_{ASAD}	5	9	12	18

events. Tracheal respiratory sounds were segmented automatically to sound and silent segments, and the sound segments were classified into breathing, snore and noise segments. The AHI indeces of the proposed method (AHI_{ASAD}) was compared with those of the PSG analysis, and the correlation between the outcomes of the two systems were found to be very high (0.96). Also, the results of Bland-Altman test revealed that only 3 out of 40 subjects were out of 95% confidence interval, idicating a high accuracy of the proposed system. Furthermore, the classification results of the subjects into simple snorer and OSA patients shows sensitivity and specificity of more than 90%. Overall, the results of the proposed method were found to be similar or superior to those of the previous proposed amulatory devices. However, in this method, respiratory breath and snore sounds are recorded with high quality which can be used to extract further information regarding the physiolgy of upper airways and breathing pattern of the patient.

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