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Apnea Detection by Acoustical Means

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Abstract— **In this paper a new non-invasive method for apnea detection is proposed. Eight healthy subjects participated in this study. They were instructed to breathe very shallow with different periods of breath hold to simulate sleep apnea. Following our previous study in successful use of entropy for flow estimation, in this study the Otsu threshold was used to classify the calculated entropy into two classes of breathing and apnea. The results show that the method is capable of detecting the apnea periods even when the subjects breathe at very shallow flow rates. The overall lag and duration errors between the estimated and actual apnea periods were found to be 0.207 ± 0.062 and 0.289 ± 0.258 s, respectively. The results are encouraging for the use of the proposed method as a fast, easy and promising tool for apnea detection.**

I. Introduction

SLEEP apnea syndrome (SAS) is a common respiratory disorder. By definition, apnea is the cessation of airflow to the lungs (usually during sleep) which lasts for at least 10 seconds [1]. Polysomnography (PSG) during the entire night is currently the only reliable diagnostic method of sleep apnea. The standard PSG consists of recording various physiological parameters including EEG, ECG, EMG of chins and legs, nasal airflow, electro-oculogram (EOG), abdominal and thoracic movements, and blood oxygen saturation (SaO2) [2]. However, the high cost of the system, discomfort of the electrodes connecting to the body and the high amount of information required to be analyzed are the main disadvantages of this method [3].

Several researchers have tried to detect apnea using smaller number of features such as airflow, SaO2 and respiratory effort [3-5]. Also, in a recent study [6] an acoustical method based on lung sounds power at different frequency ranges was proposed for apnea and snore detection with a sensitivity of about 77% at best situation. In the other studies airflow was measured using either face masks or nasal cannulae and its cessation was detected as the main sign of apnea [3-5]. However, face mask results in unavoidable changes in breathing pattern [7] and also its application is a challenge when studying children with neurological impairments [8]. On the other hand, usage of nasal cannulae is highly questionable due to the leakage of airflow and possibility of breathing through the mouth.

In this study an acoustical method for apnea detection is proposed. In our previous study it was shown that tracheal sound entropy is a promising feature for airflow estimation at different flow rates [9]. The proposed method in this study uses tracheal sound entropy to detect apnea occurrence during breathing.

II. Method

A. Data

Eight healthy subjects (3 males) aged 33.1 ± 6.6 years with body mass index of 23.3 ± 3.5 participated in this study. Tracheal sound was recorded using Siemens accelerometer (EMT25C) placed over suprasternal notch using double adhesive tapes. Respiratory flow signal was measured by a mouth piece pneumotachograph (Fleisch No.3) connected to a differential pressure transducer (Validyne, Northridge, CA). The subjects were instructed to breathe at very shallow flow rates with different periods of breath hold (2, 4, 6 sec) to simulate apnea. Tracheal sound and flow signals were recorded and digitized simultaneously at a 10240 Hz sampling rate.

B. Feature Extraction

Among several features of tracheal sound such as the sound's mean amplitude, average power and entropy used for flow estimation, entropy has been shown to be the best feature following flow variation [9]. Therefore, in this study tracheal sounds entropy was used to detect apnea (breath hold in the experiments of this study) without the use of the measured flow signal. However, the recorded flow signal was used for validation of the acoustically detected apnea.

Tracheal sound signal was band-pass filtered in the range of [75-600] Hz, and then segmented into 50ms (512 samples) windows with 50% overlap between the adjacent windows. In each window the tracheal sound probability density function (pdf) was estimated based on kernel methods. Then, using the method described in [9, 10] Shannon entropy was calculated in each window that represents the changes in the signal's pdf. The effect of heart sounds which is most evident in the frequency range below 200 Hz was removed by the method introduced in [9, 10].

Fig. 1 shows the calculated entropy and its corresponding flow signal for a typical subject. By comparing the signals depicted in Fig. 1(a) and Fig. 1(c) (solid line), it is evident that the values of entropy in the breath hold segments are smaller than those during breathing.

It should be noted that when localizing the segments including heart sounds, it is nearly impossible to find out the exact boundaries of heart sounds segments. Therefore, there is always a tradeoff between the amount of heart sounds interference in respiratory sounds and the amount of respiratory sounds information missing during heart sounds cancellation. The high peaks in the calculated entropy (Fig. 1-a) are related to the heart sounds components remained in the tracheal sound.

C. Apnea Detection

In order to smooth the calculated entropy, it was segmented into windows of 200ms with 50% overlap between adjacent windows. Each window was then presented by its median value which is not sensitive to jerky fluctuation of the signal.

Next, the smoothed entropy signal was classified into two groups of breathing and apnea using a nonparametric and unsupervised method for automatic threshold selection [11]. This method has been proposed for image processing purposes and its main objective is to select an adequate threshold of gray level to extract objects from their background. Assume the pixels of a given picture are represented in L gray levels $[1,2,\cdots,L]$. The number of pixels in level i is defined by n_i and the total number of pixels is N. Thus, the probability of each gray level i is given by:

$$p_i = \frac{n_i}{N}, \qquad \sum_{i=1}^{L} p_i = 1. \tag{1}$$

The goal is to find a threshold k to divide the gray levels into two classes of $C_1 = [1,2,\cdots,k]$ and $C_2 = [k+1,\cdots,L]$. In this case the probability and mean values of the classes are defined as [11]:

$$w_0 = \sum_{i=1}^{k} p_i = w(k), \tag{2}$$

$$w_1 = \sum_{i=k+1}^{L} p_i = 1 - w(k), \tag{3}$$

$$\mu_0 = \sum_{i=1}^{k} ip_i / w_0, \tag{4}$$

$$\mu_1 = \sum_{i=k+1}^{L} ip_i / w_1. \tag{5}$$

where w_0, μ_0 are the probability and mean values of the class C_0, respectively and w_1, μ_1 are the probability and mean values of the class C_1, respectively.

The total mean (μ_T) and variance (σ_T) of the original picture are defined as [11]:

$$\mu_T = \sum_{i=1}^{L} ip_i, \tag{6}$$

$$\sigma_T^2 = \sum_{i=1}^{L} (i - \mu_T)^2 p_i, \tag{7}$$

where it can be easily shown that:

$$w_0\mu_0 + w_1\mu_1 = \mu_T. \tag{8}$$

In this method the discriminant criterion for choosing the optimal threshold is to maximize the separability of the resultant classes. Otsu defined the between-class variance as [11]:

$$\sigma_B^2 = w_0(\mu_0 - \mu_T)^2 + w_1(\mu_1 - \mu_T)^2, \tag{9}$$

and the optimum threshold k^* is selected so as:

$$\sigma_B^2(k^*) = \max_{1 \le k < L} \sigma_B^2(k). \tag{10}$$

The value of:

$$\eta = \sigma_B^2(k^*) / \sigma_T^2, \tag{11}$$

is defined as a measure to evaluate the separability of the classes. This measure is invariant under any shift and dilation transforms and it is in the range of $0 \le \eta < 1$.

Investigating the data of different subjects, it was found that when the subjects breathe at very shallow flow rates, the separability ratio decreases and the Otsu threshold shifts toward greater values. Since the values of tracheal sound entropy during breathing are smaller than those during breath hold periods, the average of entropy values is another statistical measure that can be used to detect apnea segments. In this study both the Otsu and the average value of entropy were used to define the classification threshold as:

$$Thr = \min\{k^*, m\}, \tag{12}$$

where k^* is the Otsu threshold and m is the average of the entropy values.

In order to evaluate the results, the actual apnea segments were also manually by examining the acquired flow signal and listening to the tracheal sound records. For each subject the lag between the estimated and the actual apnea period (lag error) were calculated. Also, the difference between the duration of the actual and estimated apnea periods (duration error) were calculated. These errors (ε) represent the overall performance of the method for detecting apnea acoustically.

III. Results and Discussion

Fig. 1(b) presents the results of applying the nonlinear

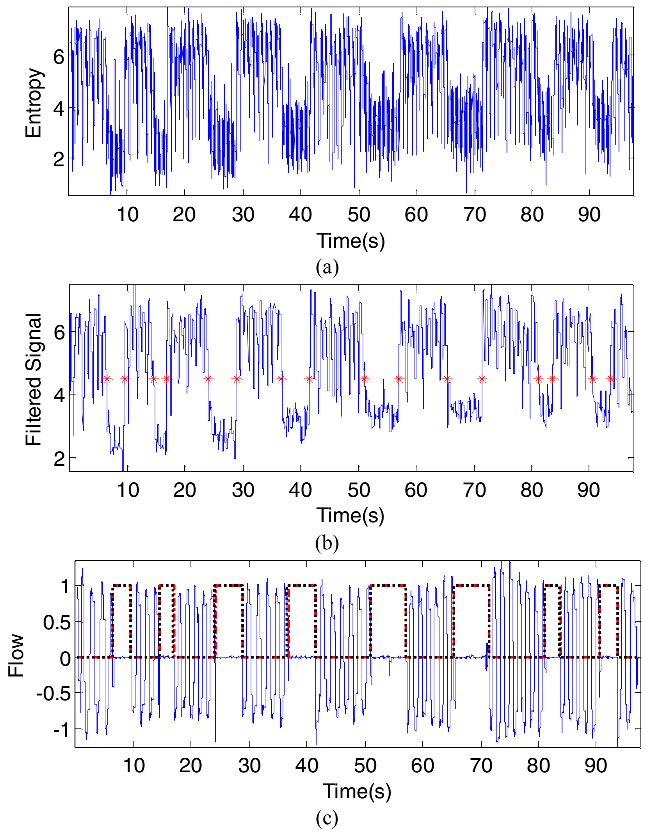

Fig. 1. a)Tracheal sound entropy, (b) entropy after applying nonlinear median filter (star marks represents the estimated apnea segments) and c) flow signal (solid line) along with the estimated (dotted line) and real (dashed line) apnea segments for a typical subject.

median filter for removing the peaks of the calculated entropy and smoothing the signal. Comparing the results depicted in Fig. 1(a) and Fig. 1(b), the effect of applying median filter is evident. The star marks in Fig. 1(b) show the estimated apnea segments. Fig. 1(c) shows the acquired flow signal along with the estimated (dotted line) and the actual (dashed line) apnea segments. It is clear that the proposed method detects all the apnea segments and classifies them correctly from the breath segments.

Fig. 2 shows the overall performance of the method for apnea detection. The results indicate that for almost all the subjects (except subject 8) the lag between the detected boundaries of apnea and the actual ones were about 200ms. Subject 8 had little control on her breathing pattern; it can be seen in her flow signal shown in Fig. 3(c). Comparing Fig. 1(c) and Fig. 3(c), it is evident that this subject was unable to stop breathing completely and there existed flow leakage during breath hold periods.

Furthermore, subject 8 breathed at very shallow flow rate, which was the main source of error. By comparing the calculated entropy data (Fig. 3(a)) during breathing and breath hold periods, it can be seen that the values of entropy are very similar; this makes finding a suitable threshold for detecting apnea challenging.

The key factor in detecting apnea by acoustical means is the difference between the average power of the respiratory

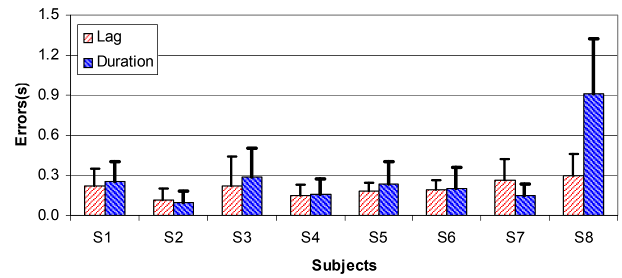

Fig. 2. Mean and standard deviation values of errors in estimating apnea periods for different subjects.

sounds during breathing and breath hold periods, which in turn affects the entropy values. Hence for further investigation, the breath hold segments of each subject were manually extracted and the difference between the average power of the breathing and breath hold periods were calculated (P_d).

Fig. 4(a) shows the relationship between P_d and both the lag and duration errors. It can be seen that with increasing the power difference, P_d, the errors decrease. The power difference for subject 8 was 0.89 dB which was smaller than those of the other subjects. This result is congruent with her high apnea detection errors.

Both errors were averaged among the subjects and mean and standard deviation values were calculated. The overall lag and duration errors were fount to be 0.207 ± 0.062 and 0.289 ± 0.258 s, respectively. It should be noted that the median filter was applied in the windows of 200 ms duration which imposes a resolution of 200 ms.

Fig. 4(b) illustrates the relationship between power difference and the Otsu separation parameter (η). As it can be seen, increasing the power difference increases the separability between breathing and breath hold periods; hence, improving the performance of the method.

IV. Conclusion

In this study a new acoustical method for apnea detection is proposed which is based on tracheal sound entropy. The subjects were asked to breathe at shallow flow rate that was likely less than the subjects' normal flow rate during sleep. The results indicate that the method is capable of detecting apnea segments with an overall error of about 200ms lag. Also, in cases that flow was not ceased completely but reduced to very small values –the so called hypopnea [4]- the method could still detect the apnea segments.

By calculating the difference between the average power of tracheal sound during breathing and breath hold periods, it was found that the errors increase when the difference is smaller than 1dB. On the other hand, a linear relationship between the average power difference and the Otsu separability parameter was found. Hence, an increase in the average power difference results in smaller error.

Overall, the results of the proposed method are

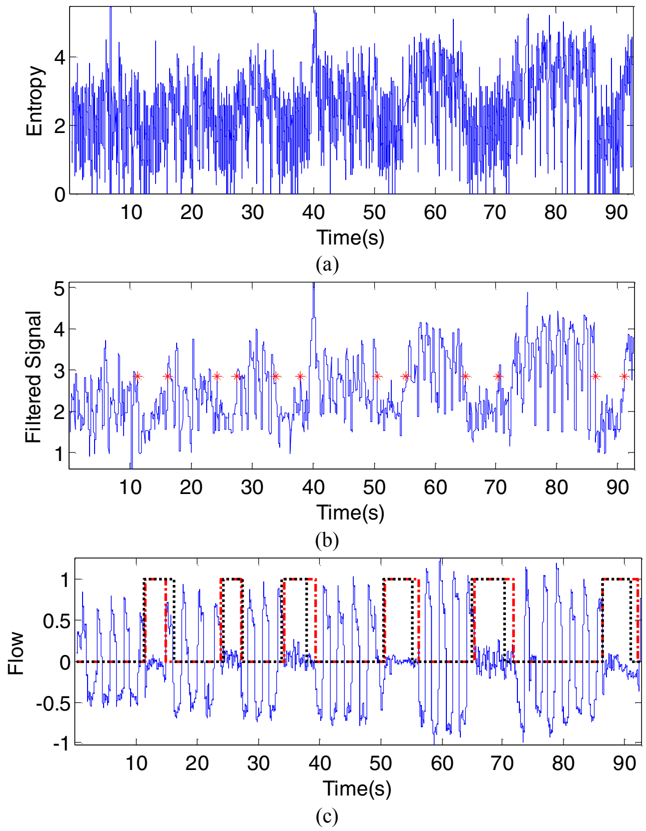

Fig. 3. a) Tracheal sound entropy, (b) entropy after applying nonlinear median filter (star marks represents the estimated apnea segments) and c) flow signal (solid line) along with the estimated (dotted line) and real (dashed line) apnea segments for subject 8.

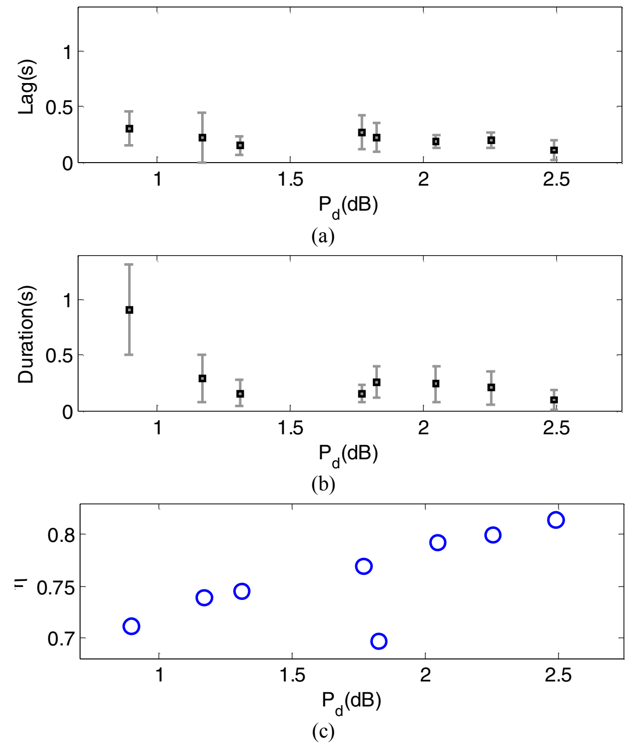

Fig. 4. Relationship between the power difference and a) lag error, b) duration error, c) separability ratio, averaged between the subjects.

encouraging to continue investigation on the possibility of apnea detection by acoustical means with practical applications. The proposed method is also fast and easy to be implemented, which makes it a promising tool for on-line applications.

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