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Detection of Post Apnea Sounds and Apnea Periods from Sleep Sounds

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Abstract—**Obstructive Sleep Apnea Syndrome (OSAS) is defined as a sleep related breathing disorder that causes the body to stop breathing for about 10 seconds and mostly ends with a loud sound due to the opening of the airway. OSAS is traditionally diagnosed using polysomnography, which requires a whole night stay at the sleep laboratory of a hospital, with multiple electrodes attached to the patient's body. Snoring is a symptom which may indicate the presence of OSAS; thus investigation of snoring sounds, which can be recorded in the patient's own sleeping environment, has become popular in recent years to diagnose OSAS. In this study, we aim to develop a new method to detect post-apnea snoring episodes with the goal of diagnosing apnea or creating new criteria similar to apnea / hypopnea index. Emphasis is placed on detecting post apnea episodes, hence the apnea periods. In this method, first segmentation is done to eliminate the silence parts. Then, these episodes are represented by distinctive features; some of these features are available in literature but some of them are novel. Finally, episodes are classified using supervised methods. False alarm rates are reduced by adding additional constraints into the detection algorithm. These methods are applied to snoring sound signals of OSAS patients, recorded in Gulhane Military Medical Academy, to verify the success of our algorithms.**

I. INTRODUCTION

Snoring is the sound that is produced primarily by inspiration as a result of partial collapse of some parts of the upper airways at the back of the mouth or upper throat. This obstruction results in the vibration of the tissues in the airway and the snoring sound [1]. It may be a symptom of many harmful diseases, such as obstructive sleep apnea (OSA) and hypopnea, which are usually confused with sleep disordered breathing. *Hypopnea* is the partial blockage of respiratory airflow due to partial obstruction of the soft tissues in the upper airway and mostly appears as a benign snore except that it causes reduction in the oxygen saturation in the blood [2]. OSA is defined as abnormal pauses in breathing (for more than 10 seconds) or moments of abnormally low breathing during sleep due to obstruction in the upper airway or neurological defects [2], [3]. The frequency of sleep apnea, which is quantified by the apnea index (AI), is a measure of the severity of the disease. AI is defined as the number of apneas in one hour period. In order to find this index, first apnea should be detected.

Apnea and hypopnea are diseases that are not easy to detect because they occur during sleep. The most commonly used technique is keeping the patient in the sleep laboratory of a hospital or a sleep clinic for a whole night, and recording several biological signals with polysomnography (PSG). This technique is expensive, needs professionals to apply and interpret, and also uncomfortable for patients. Due to these drawbacks, alternative diagnosis techniques have been investigated by many researchers. One of the most popular research areas aims to gain information about apnea by using snoring sounds, since the two have been shown to be strongly correlated in recent years.

Snoring mostly bears a low frequency harmonic content. The acoustic characteristic of snoring sounds change due to many factors such as the route of breathing (nasal, oral, both nasal and oral), the source of the snore (palatal snores, tongue based snores, supra-glottic space based snores, or any combination of those), existence of sleep disorders like hypopnea or apnea, body position (supine, left, right), body movements during sleep, sleep stage, age, sex, weight of the patient, the shape of the airway, etc [2], [4]. Tracking the changes in the sound characteristic may supply information about the existence and significance of those factors.

The snore sounds are used to get information on the source of snoring [5], [6] and predict the outcome of surgical outcome [7], [8]. There have been many studies conducted to relate OSA and snoring sounds. Acoustic characteristic of snore sounds tend to carry different characteristic properties for normal snorers and apnea snorers. The apnea patients' snoring episodes are reported to have higher frequency components [9], [10] and less harmonic character compared to normal snorers' [11]. Cavusoglu *et al.* introduced snoring episode duration, snoring episode separation and snoring average power to show the differences between normal snorers and OSA patients [12]. Abeyratne *et al.* defined “intra snore pitch jump probability” to represent the discontinuities in the spectrum of snore sounds of normal snorers and OSA patients [13]. Sola-Soler *et al,* Wakwella *et al.* and Van Brunt *et al.* have made valuable contributions to distinguish simple snorers and OSA patients [14], [15]. Less effort has been spent on investigation or detection of apnea periods of an OSA patient, which could lead to an alternative apnea index that could be extracted from snore sounds only, with the potential application as a pre-screening method for OSA and to determine its severity. Michael *et al.* used periodicity and power spectrum of the snore sounds in order to correlate apnea index and snore sounds [16]. However, their method also uses SpO_2 level, which requires an additional sensor attached to the body. Apart from their

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previous studies, Abeyratne *et al*. used pitch, formant and periodicity information of the snoring sounds and neck circumference to use snoring signals as a pre-signal of OSA [17].

During apnea period, as the breathing stops, no snoring sound is detected. Almost after every apnea, the silence period ends with a relatively louder snoring noise due to the opening of the airway. Those noises are indicators of apnea moments. Some of the peculiar features of these sounds are given in literature [4]. These studies inspired us to use post-apnea sounds in order to detect OSA. Based on the prior knowledge of power spectrum differences between post apnea episodes and normal snore episodes, we studied methods for detecting and discriminating post apnea episodes. As for our goal, we first carried out a feasibility study on the classification of sleeping sounds to detect post apnea episodes. The background on post apnea episodes has been used to develop an apnea period detection method.

II. RECORDING SETUP AND SLEEP SOUND DATABASE

All the experiments for this study have been conducted with the snoring data recorded from eight OSA patients, who were undergoing a polysomnography test at Gulhane Military Medical Academy (GMMA). The data is digitized with 16000 Hz sampling rate and 16 bit resolution. All of the patients are male and over the age of 50 with average apnea index of twenty-five. The sleep sound recordings were first time-synchronized with the PSG recordings and then annotated by an ear-nose-throat specialist; the episodes in the recordings are grouped into five subcategories with the guidance of the information gathered from the PSG. These subcategories are: normal snoring episodes, hypopnea period snoring sounds, post hypopnea snoring sounds that occur at the end of the hypopnea period, post apnea snoring sounds and the unexpected sounds occurring during apnea period. Also an additional class is created which includes external noises such as door slam, blanket noise, bed noise, etc.

III. METHOD

Fig. 1 shows the flowchart of the algorithm that we use in detecting the post apnea sounds, and detecting related apnea episodes. We briefly explain each step of the algorithm in this section.

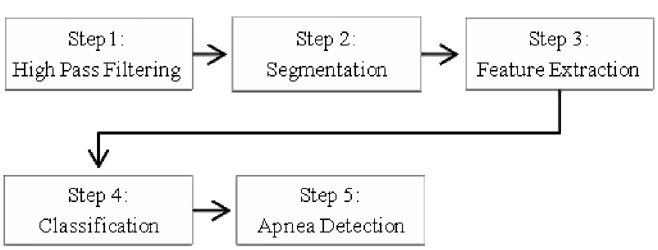

Fig. 1. Flow of the algorithm

A. *High Pass Filtering*

In order to cancel low frequency noise, FIR filters are implemented. The stop band edge is defined as 60 Hz, the transition edge is defined between 60 Hz and 100 Hz, and the band from 100 Hz, to Nyquist frequency (8 kHz) is defined as the pass-band. The length of the filter is ~0.03 seconds (500 samples).

B. *Segmentation*

In the scope of this study, snore episodes or other sleeping sound episodes are the parts we focus on. However, silent parts in the recordings take almost half of the recording time, and classification of complete recordings increases computational load and causes unnecessary classes. We applied a segmentation method to eliminate the silent parts between the episodes and to obtain the beginning and end points of the sound episodes. We used short time energy, which is an indicator of the strength of the signal, and spectral flux, which is a measure of the rate of change of spectrum in time, to differentiate the silence and the sound active parts. To determine the thresholds, we used the dynamic thresholding method proposed by Giannakopoulos *et al* [18]. In order to find the dynamic thresholds, first the normalized histograms of the features are computed, and then the two local maxima of these histograms are found (M_1 *and* M_2). Thresholds are weighted averages of those maxima:

$$T = \frac{W * M_1 + M_2}{W + 1} \qquad (1)$$

The weights are defined by the user heuristically.

C. *Acoustic Features*

Feature selection plays the most important role in classification because inappropriate choice of features may result in overlapping clusters or incorrect classification results. Thus, in order to successfully discriminate sleep sounds, we took into account the fact that the post apnea sounds are more broad-band white noise, with more power at higher frequencies [4], [19]. We also considered the acoustic differences of normal snore episodes, environmental sounds, hypopnea sounds, etc. Zero-crossing rate gives the total number of times that the waveform passes the zero-line within a time-frame. Spectral roll-off frequency and spectral flux are used to characterize the spectral characteristic of the sound episodes. Spectral entropy is a measure of spectral energy irregularity. Energy entropy is a less frequently used feature in acoustic studies; it characterizes the complexity of the audio signal with the changes in time domain. In abrupt changes, this feature behaves significantly differently. In the post apnea sounds we expect sudden changes in energy due to opening of the airway, thus energy entropy is expected to be a useful feature in detecting those sudden changes, and hence the post apnea sounds. In addition to these well known acoustic features, we used new features, via linear prediction (LP) analysis, obtained by the change in prediction error as a function of the model order (Fig. 2). This curve is an exponential-like decaying curve, which represents the decrease in the prediction error with increasing order. Initial value, final value and decay rate (time constant of the decaying curve) of LP error curve provide information about the periodicity/harmonicity of the signal.

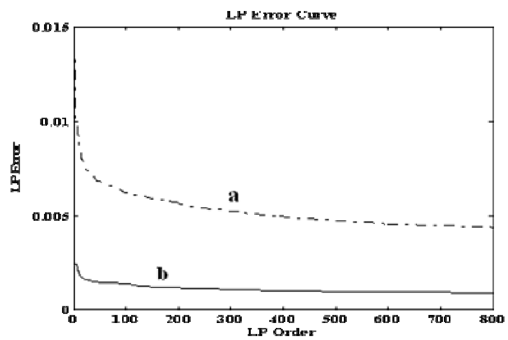

Fig. 2. LP error vs prediction order curve for two frames taken from a) post apnea sound, b) normal snoring sound

A feature vector including all of the features is extracted for 50 ms. non-overlapping frames in each sound episode. Each episode has length of 0.5-4 s. meaning there are 10-80 frames in each episode. Thus, to represent each episode by a single feature vector, mean, standard deviation and coefficient of variation (the ratio of the standard deviation over mean) are used.

D. Classification

Classification is the arrangement of a given data set into *n* disjoint subsets according to similarities of the values and/or features. Our aim in this study is to classify the sleep sound episodes into previously defined categories. For this purpose, we used the well known classification method based on Gaussian Mixture Models (GMM) [20].

E. Apnea Detection

At the end of the classification step, all the episodes were grouped into six categories, and labeled according to the training database of the classifier. However, when we compared these labels with the annotations by the specialist, we observed that some of the episodes labeled as post apnea sounds are in fact false positives (false alarms). To reduce the effect of miss-classification, we added one more step to our method; we know that the apnea period is expected to contain a relatively longer silence period. Besides that silence period, there may be some obstruction sounds like choking or whistling during apnea. Considering these properties, our program checks for a silence period or existence of those sounds in order to determine whether a sound flagged as a post apnea sound is really a post apnea sound and whether the period is really an apnea period.

IV. RESULTS

We evaluated our classification algorithm on randomly selected fifteen minute - segments from whole night sleep sound recordings of three different patients. These fifteen minute segments compose our test data. To test different scenarios, four different training sets are generated, and the test data are classified according to these four training sets:

CASE - 1: The test and training data come from the same patient; sound episodes randomly chosen outside of the test data range in the same patient's recording compose the training set.

CASE - 2: The test and training data come from different patients. The training set includes two patients’ recordings with clearly detectable post apnea snoring episodes that have very similar characteristics as the test data episodes.

CASE - 3: The training set contains sound episodes from all eight of the available data in hand, including episodes from the tested patient’s snoring episodes. However, the episodes of the tested audio parts are excluded from the training set.

CASE - 4: Data from one of the patients are reserved for testing, and all the remaining patients’ recordings form the training set.

The training sets contain post-apnea sounds, post-hypopnea sounds, normal snore sounds, hypopnea period snore sounds, apnea period sounds and environmental sounds.

To assess the classification results, we first count true positives (TP), false positives (FP), false negatives (FN) and true negatives (TN). Then we obtain the following measures: *Sensitivity* (TP/(TP+FN))*, Specificity* (TN/(FP+TN))*, False Positive Ratio* (FN/(FN+TP))*, False Negative Ratio* (FP/(FP+TN))*,* and *Accuracy* (TP/(TP + FP)). We expect high sensitivity, specificity, and accuracy values and low false negative and false positive values for successful classification.

We classified three different test data with the four different training sets described in Cases 1 to 4. Fig. 3 shows the five quantitative measures for these experiments; horizontal-axis represents each tested case, and for each case, three color-coded bars specify each test data. The average values of the statistical measures over three test data for each case are presented in Table I.

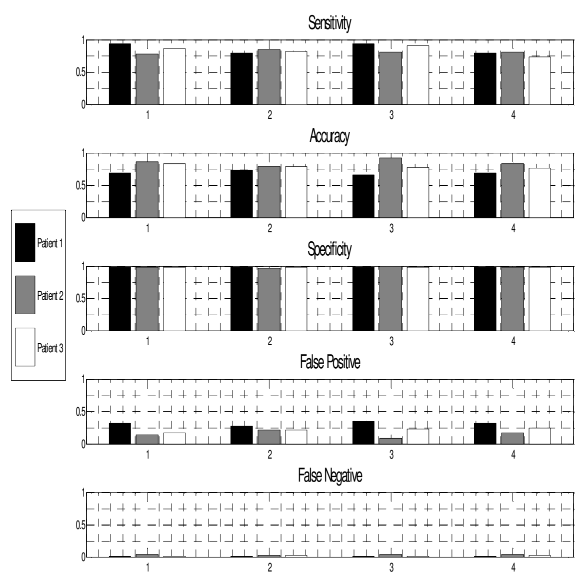

Fig. 3. Classification performances

TABLE I
MEAN VALUES OF THE STATISTICAL RATIOS FOR EACH CASE

	Case 1	Case 2	Case 3	Case 4
Sensitivity	**0.86**	**0.81**	**0.88**	**0.77**
Accuracy	**0.79**	**0.77**	**0.78**	**0.76**
Specificity	**0.98**	**0.97**	**0.98**	**0.98**
False Positive Ratio	**0.21**	**0.23**	**0.22**	**0.24**
False Negative Ratio	**0.02**	**0.01**	**0.02**	**0.02**

The performance of the algorithm is examined by obtaining the statistical ratios defined previously. The detected number of post apnea episodes did not change a lot among different cases.

The accuracy values are not so high and the false positive values seem to be quite high; during apnea period, normally a total silence is expected. But due to obstruction some voices like chocking or whistles occur sometimes while the patient breaths. The definition of those sounds should be made very carefully as occurrence of those sounds is one of the basic constraints in our false alarm reduction algorithm. Unfortunately, there is a lack of information for those sounds in the literature. Also, medical doctors could not guide us a lot about those sounds. Despite these, we could not exclude those apnea period sounds from our training sets in order to avoid missing apnea periods. The high values of false positive ratios are mainly because of this reason. Additional information should be gathered about those sounds, so that acoustic features can be selected in order to differentiate those sounds and to obtain more accurate solutions.

One other problem is that there are many external sounds in the recordings. Also the variety of those sounds is more than expected compared to an average sleeping environment. The recording room was not in an isolated place and also the room was not sealed well against that much noise. We tried to include some of those noises in the training set and proper audio feature are used to distinguish them, but high variety and high quantity of those noises caused incorrect classification results, especially false alarms.

V. CONCLUSION

In this study we have shown that post apnea sounds can be used to detect apnea periods. We introduced new features that were extracted from the LPC error curve, and presented a different property, high energy variation of post apnea sounds through the use of the entropy of energy variation. Although all the apnea periods do not end with a "post apnea sound," the ones that end with such sounds may be used to quantify the severity of the OSAS, which could facilitate the development of algorithms to diagnose apnea from only snoring sound recordings in the future.

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