

An efficient method for snore/nonsnore classification of sleep sounds

M Cavusoglu¹, M Kamasak^{2,3}, O Eroglu³, T Ciloglu¹, Y Serinagaoglu¹
and T Akcam⁴

¹ Electrical and Electronics Engineering Department, Middle East Technical University, 06530, Ankara, Turkey

² Computer Engineering Department, Istanbul Technical University, 34390, Istanbul, Turkey

³ Gülhane Military Medical Hospital, Biomedical and Clinical Engineering Center, 06018, Ankara, Turkey

⁴ Gülhane Military Medical Hospital, ENT Clinic, 06018, Ankara, Turkey

E-mail: ciltolga@metu.edu.tr

Received 13 March 2007, accepted for publication 24 May 2007

Published 6 July 2007

Online at stacks.iop.org/PM/28/841

Abstract

A new method to detect snoring episodes in sleep sound recordings is proposed. Sleep sound segments (i.e., ‘sound episodes’ or simply ‘episodes’) are classified as snores and nonsnores according to their subband energy distributions. The similarity of inter- and intra-individual spectral energy distributions motivated the representation of the feature vectors in a lower dimensional space. Episodes have been efficiently represented in two dimensions using principal component analysis, and classified as snores or nonsnores. The sound recordings were obtained from individuals who are suspected of OSAS pathology while they were connected to the polysomnography in Gülhane Military Medical Academy Sleep Studies Laboratory (GMMA-SSL), Ankara, Turkey. The data from 30 subjects (18 simple snorers and 12 OSA patients) with different apnoea/hypopnea indices were classified using the proposed algorithm. The system was tested by using the manual annotations of an ENT specialist as a reference. The accuracy for simple snorers was found to be 97.3% when the system was trained using only simple snorers’ data. It drops to 90.2% when the training data contain both simple snorers’ and OSA patients’ data. (Both of these results were obtained by using training and testing sets of different individuals.) In the case of snore episode detection with OSA patients the accuracy is 86.8%. All these results can be considered as acceptable values to use the system for clinical purposes including the diagnosis and treatment of OSAS. The method proposed here has been used to develop a tool for the

ENT clinic of GMMA-SSL that provides information for objective evaluation of sleep sounds.

Keywords: snoring, sound analysis, detection, classification, OSAS

(Some figures in this article are in colour only in the electronic version)

1. Introduction

Tissues of the human body are relaxed during sleep. Relaxation may cause constrictions along the upper airway, and breathing triggers mechanical oscillations of the tissues such as soft palate or tongue around the constriction. Snoring is a result of the oscillatory motion of the tissues. In the last 15 years, the snoring problem has entered the realm of clinical medicine. It is a prevalent symptom, and about 50% of the adult population snore frequently (Lugaresi *et al* 1980, Norton and Dunn 1985). It has been reported as a risk factor for the development of diseases such as ischaemic brain infraction, systemic arterial hypertension, coronary artery disease and sleep disturbance (Wilson *et al* 1999). In recent years, several studies have also shown the relationship between snoring and obstructive sleep apnoea syndrome (OSAS), which is usually associated with loud, heavy snoring (Lucas *et al* 1988, Wilkin 1985). It is a common clinical practice to examine patients' sleep characteristics via whole night polysomnography records, which requires the individual to spend a full night in the facility. On the other hand, investigation of sleep sounds also provides information about breathing abnormalities, OSAS or other pathologies, such as upper airway resistance syndrome, and supports health assessment (Jane *et al* 2003). It is possible to use sleep sound analysis and polysomnography together. However, sleep sounds can easily be recorded in one's own sleeping environment and can be utilized alone as a preliminary source of information before deciding on a polysomnographic study. Reliable diagnosis of the grade and peculiarities of an individual's snore and its possible implications on her/his health requires the analysis of long (possibly whole night) sound recordings. The rate of snores, their regularity, intensity variation and other audio qualities provide information to the clinician. The length of a whole night recording is prohibitive for analysis by listening to and/or visual inspection of signal patterns in audio recordings during sleep. Automatic methods are needed to speed up the analysis task. Furthermore, possible objective measures of snoring characteristics may serve clinicians as a common ground for diagnosis. Therefore, fast automatic snoring signal analysis can be considered as a promising method to identify breathing abnormalities during sleep.

Automatic analysis of snoring sounds can be associated at least with the following three tasks: (i) identification of the source of snoring, e.g. palatal/nonpalatal, (ii) prediction of the outcome of surgical treatment and (iii) simple snoring/OSAS classification (a simple snorer can be defined as an individual having a snoring habit without having any kind of sleep apnoea). Osborne *et al* (1999) and Hill *et al* (1999, 2000) proposed the use of the acoustic crest factor of snoring episodes (the ratio of peak amplitude to root mean square value) to distinguish palatal from nonpalatal snore. Jones *et al* (2005, 2006a, 2006b) used snore duration, snore loudness, snore periodicity and subband energy levels as objective measures to assess the outcome of surgical treatments. Abeyratne *et al* (2005) proposed the measure 'intra-snore-pitch-jump' to diagnose OSAS. Sola-Soler *et al* (2003) studied the differences in spectral envelopes of simple

and OSAS snores and suggested the standard deviation of formant frequencies as a criterion for distinction among simple snores and OSAS snores. McCombe *et al* (1995) introduced a measure of high frequency content (Hawke Index) for screening OSAS.

Detection of snoring episodes in a full-night recording of sleep sounds is a fundamental step in all these tasks. Until recently, related studies were based on manual segmentation of snoring episodes; there is a very limited amount of work on automatic detection. Abeyratne *et al* (2005) used the energy and the zero crossing rate as the features in a minimum-probability-of-error approach to identify snoring episodes. Energy and zero-crossing rate are commonly used for audio signal activity detection; however, they are not known as having strong discriminative capabilities in classification. Duckitt *et al* (2006) adopted speech processing techniques for snore detection. Mel-frequency-cepstral coefficients (MFCCs) were used as the features in a hidden Markov model (HMM) based classification framework. Speech is a sequence of phonemes with evolutionary transitions (loose boundaries) from one to another. The characteristics of a speech waveform in a transition segment between two phonemes may deviate considerably more than those observed over the core segments of the neighbouring phonemes. Phonemes are commonly modelled by three state HMMs in order to represent initial, core and final segments distinctively. However, sleep sounds are of dominant discrete nature. Furthermore, snoring sounds remain quite stationary over their intervals of existence. These observations suggest the possibility of using computationally less intensive classification approaches. MFCCs are very widely used in speech signal characterization, much more than they are used with other types of audio signals. Sleep sound recordings contain not only sounds produced by humans but also sounds from other sources. Therefore, sound feature definition and classification methods in automatic snoring episode detection still appear as a ground for exploration.

The motivation of this study was to develop an effective method to detect snoring episodes, which is sufficiently fast to process full-night recordings in a reasonable amount of time. The proposed method is a two-step process. Firstly, sound episodes, which can be defined as the sound activity intervals, were identified and then these episodes were classified as snore or nonsnore based on the characterization of the spectral energy distribution of snoring signals. Spectral characterization involves subband decomposition in the frequency domain. The dimensionality of subband decomposition was investigated via principal component analysis (PCA). It is found that two-dimensional projection of subband decomposition yields a simple classifier design to achieve strongly promising correct detection rates.

The data in this study contain full-night sleep sound recordings of 30 individuals while they were also under polysomnographic recording in Gülhane Military Medical Academy Sleep Studies Laboratory (GMMA-SSL), Ankara, Turkey. The episodes, taken from 30 patients with different apnoea/hypopnea indices (AHI), are classified using the proposed algorithm. In order to validate the system, the results are compared with the manual annotations of an ENT specialist.

2. Materials and methods

2.1. Recording setup

A Sennhiser ME 64 condenser microphone with a 40–20 000 Hz \pm 2.5 dB frequency response was used for recording sounds. This microphone has a cardioid pattern which helps to suppress some of the echoes from the environment. It was placed 15 cm over the patient's head during sleep. The signal was fed via a BNC cable to the Edirol UA-1000 model multi-channel data acquisition system connected to a personal computer via universal serial bus. The computer

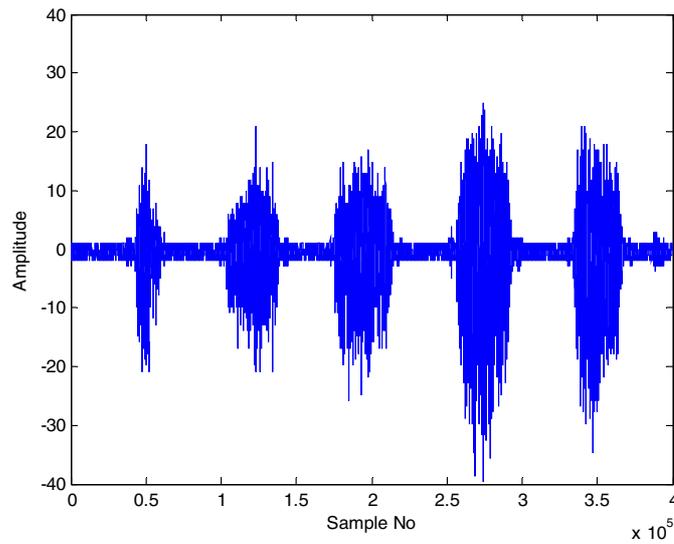


Figure 1. 25 s long snoring signal.

Table 1. Number of individuals, their genders, average ages, AHIs and BMIs in OSA patients and simple snorers. The ranges for age, AHI and BMI are also given.

Patient information	OSA patients	Simple snorers
Number of patients	12	18
Age	53.26 (44.87–61.65)	46.92 (40.21–53.63)
Gender	12 males, no females	16 males, 2 females
AHI (apnoea h ⁻¹)	39.21 (22.17–56.25)	4.29 (3.03–5.55)
BMI (kg m ⁻²)	32.76 (27.47–38.05)	27.66 (23.41–31.91)

was placed outside the sleeping room to avoid its noise in the recording. The acquired signal was digitized at a sampling frequency of 16 kHz with 16 bit resolution. The data were stored in the computer together with the patient information. Figure 1 shows a 25 s long snoring signal.

2.2. Snoring database

The database contains whole night sound recordings of 30 individuals taken in GMMA-SSL. These individuals were also under polysomnographic recording during their whole night sleep in order to determine their AHIs. Each recording has a duration of approximately 6 h. Among the 30 individuals, 18 of them were simple snorers and 12 of them were diagnosed with OSAS. The average values and ranges of the ages, AHIs and body mass indices (BMI) of these individuals are given in table 1. The sound episodes were manually annotated by an ENT (ear-nose-throat) specialist as snore or nonsnore to create the testing and training datasets for the classification problem. The data were presented to the specialist before automatic segmentation. The compositions of training and testing datasets are described in section 3.

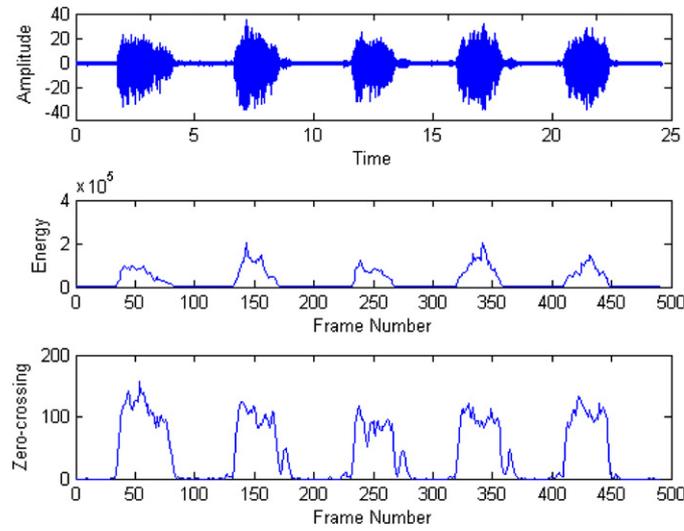


Figure 2. A signal sample (top), its energy pattern (middle) and its ZCR pattern (bottom).

2.3. Segmentation subsystem

The first step in snoring detection is to identify the intervals of sound activity. Energy and zero crossing rate (ZCR), which are conventional measures for determining boundaries of sound activity, were used to determine the boundaries of sound segments. Energies and ZCRs of signal frames of length 100 ms, with 50 ms overlaps, are calculated. The energy, E_k , in the k th frame of the signal is computed as

$$E_k = \sum_{i=0}^{N-1} s_k^2[i] \quad (1)$$

where $s_k[i]$ is the signal in the k th frame of length N samples. Figure 2 shows a sample recording and the corresponding energy and ZCR patterns.

Sound activity episodes were determined in three steps. First, those frames for which the energy and the ZCR values are above certain thresholds simultaneously were marked as activity frames. Then, the starting and ending points of episodes were found by searching for continuities of activity frames. Finally, those episodes separated by less than a certain duration were merged.

The energy threshold, T_E , was determined as

$$T_E = \min(I_1, I_2) \quad (2)$$

where

$$I_1 = a \times [\max(E_k) - \min(E_k)] + \min(E_k)$$

$$I_2 = b \times \min(E_k).$$

The ZCR threshold, T_Z , was determined as

$$T_Z = c \times \overline{ZC} \quad (3)$$

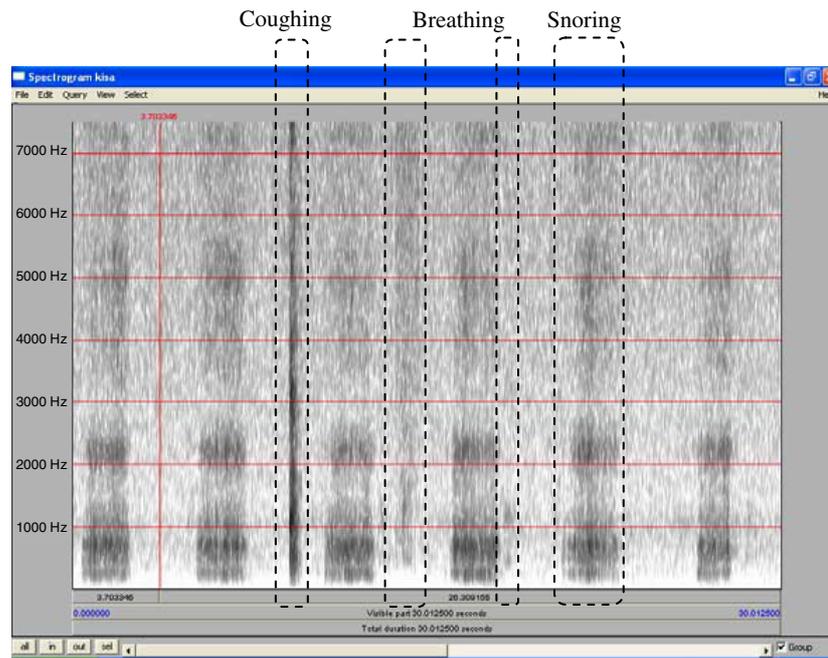


Figure 3. Spectrogram of a sample recording.

where \overline{ZC} is the average ZCR of snoring episodes in the training dataset. The values of constants a , b and c were set experimentally ($a = 0.02$, $b = 3$, $c = 0.3$).

2.4. Classification of the episodes

Classification as snore or nonsnore of the sound episodes identified by the segmentation subsystem was carried out in two steps. In the first step, spectral features are computed and the feature space is reduced. In the second step, episodes are classified by finding a linear boundary between the two classes. The developments of these steps are described in the following two subsections.

2.4.1. Feature extraction. When the spectrograms of snoring sound waveforms and those of other sound waveforms (cough, breath, sounds of vehicles/doors/animals, and sounds due to the motion of the subject, etc) are examined, it is observed that the energy distributions differ over the frequency spectrum. In particular, the spectra of snoring sounds have been observed to exhibit a significant coherence while displaying discriminative characteristics relative to other sounds' spectral patterns. The spectrogram of a sequence of snoring and some other sound episodes is shown in figure 3. The regularity of snoring episodes and their distinction from some other sound patterns can be observed in this figure. The disparity of spectral energy distributions among snoring and other sounds suggests the use of spectral features in order to distinguish among snoring sounds and other waveforms.

The spectral features in this study have been obtained by dividing the 0–7500 Hz frequency range into 500 Hz subbands and calculating the average normalized energy in each subband for each episode. To cope with inter- and intra-patient variation of sound intensity the energy

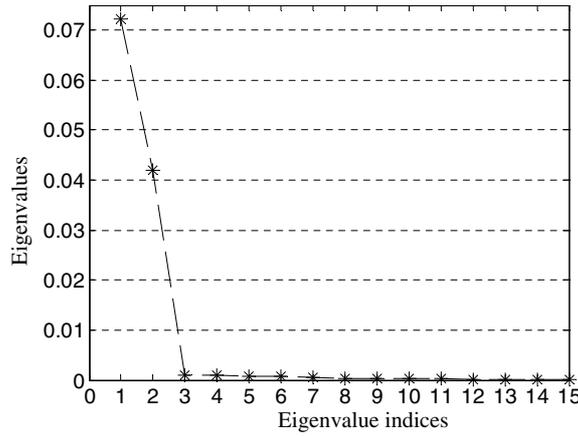


Figure 4. The eigenvalues of the covariance matrix sorted in descending order.

of each 500 Hz subband was normalized by the total energy of the episode. For the k th episode consisting of N_k subframes (with each subframe containing 1600 samples), the i th element, ξ_i^k , of its feature vector, ξ^k , is computed as

$$\xi_i^k = \frac{\sum_{j=1}^{N_k} \sum_{f=500(i-1)}^{500i} |y(j, f)|^2}{\sum_{j=1}^{N_k} \sum_{f=0}^{7500} |y(j, f)|^2} \quad i = 1, 2, \dots, 15 \quad (4)$$

where $y(j, f)$ is the short time Fourier transform (using the Hanning window) of the j th frame of the episode.

The dimensionality of snoring sound feature vectors was studied via principal component analysis. The principal components are found by first computing the covariance matrix, \mathbf{C} , of all snoring sound feature vectors, ξ^k , in the training database,

$$\mathbf{C} = \frac{1}{K} \sum_k (\xi^k - \bar{\xi})(\xi^k - \bar{\xi})^T, \quad (5)$$

where $\bar{\xi}$ is the mean of snoring feature vectors obtained from the training data set and K is the total number of snoring feature vectors. The eigenvectors corresponding to the largest eigenvalues of the covariance matrix are the basis vectors of the subspace. These eigenvectors span the new classification space. By examining the eigenvalues of the covariance matrix (see figure 4), it is seen that the largest two eigenvalues are much higher than the others. This implies that two-dimensional classification subspace is sufficient for this problem.

New features can be computed by projecting the feature vectors onto this subspace. These projection vectors are computed as

$$\hat{\xi}^k = \begin{bmatrix} x_k \\ y_k \end{bmatrix} = \mathbf{W}^T \xi^k \quad (6)$$

where the columns of \mathbf{W} are the two eigenvectors corresponding to the largest two eigenvalues of the covariance matrix. Figure 5 shows a typical distribution of two-dimensional projection vectors of simple snorers. The figure includes all sound events (a total of 3978) of a whole night recording from one subject. Two useful observations can be made. First, the projection vectors obtained from snoring and other sound episodes are distributed almost in a completely separable manner. Second, the projection vectors of snoring episodes are confined to an almost linear strip.

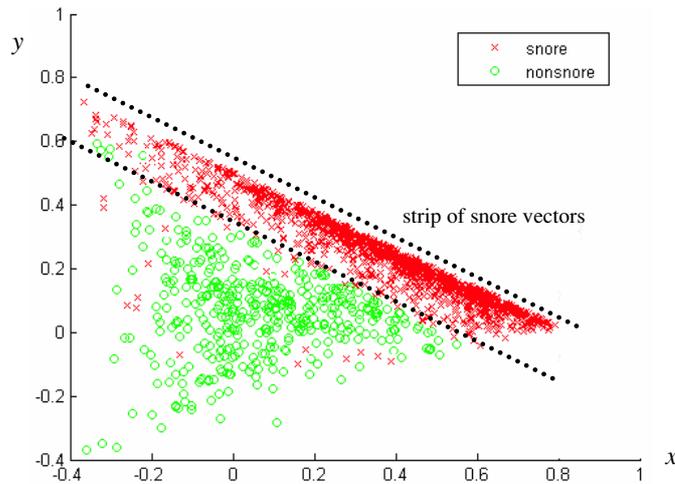


Figure 5. Typical distribution of two-dimensional projection vectors of simple snorers.

2.4.2. *Finding the classification boundary by robust linear regression.* The idea behind the classification method is to identify the boundary separating the strip where snore vectors are mainly clustered from the region where nonsnore vectors are distributed. The simplest way would be to fit a straight line aligned with the strip and to define a range around this line. However, the existence of outliers (sparsely distributed red crosses among green circles) complicates the identification of this straight line. To overcome this difficulty robust linear regression (RLR) was used (Holland and Welsch 1977). RLR attempts to minimize the effects of outliers by a weighted least square formulation in which those samples yielding large errors are weighted less.

Let $\hat{\xi}^k = [x_k \ y_k]^T$, $k = 1, 2, \dots, K$, be the projection vectors obtained from the training set. The problem is to find the coefficients a and b in the equation $y_k = a x_k + b$ such that

$$w_1 [y_1 - (ax_1 + b)]^2 + w_2 [y_2 - (ax_2 + b)]^2 + \dots + w_N [y_N - (ax_N + b)]^2 \quad (7)$$

is minimized. In this problem, the weight, w_p , values depend on the coefficients a and b so they are not known in advance. They have to be found together with the coefficients iteratively. In general, to suppress the effect of outliers, a weight value w_p decreases as $|y_p - (ax_p + b)|$ increases. There are a number of weighting functions proposed for iterative solution in the literature (Street *et al* 1988, Baryamureeba 2000). In this study, we used 'bisquare function' (Street *et al* 1988, Baryamureeba 2001) according to which w_p at the k th iteration is defined as

$$w_{p,k} = |r_{p,k-1}|(1 - r_{p,k-1}^2)^2 \quad (8)$$

where $r_{p,k}$ is

$$r_{p,k} = \frac{\text{pth residual in the } k\text{th iteration}}{\text{tune} \times s \times \sqrt{1 - h_{p,k}}} \quad (9)$$

where $h_{p,k}$ is the leverage value from the least squares fit for the p th weight, s is an estimate of the standard deviation of the error term and the constant 'tune' is used to adjust the sensitivity to the distance between data points and the regression line in the computation of weight values (tune = 4.685).

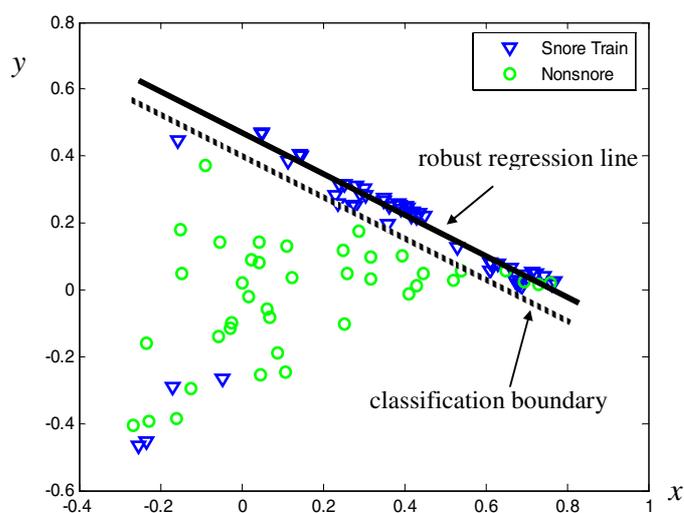


Figure 6. The distribution of snore and nonsnore data, the illustration showing line fit according to robust linear regression and the classification boundary line.

After fitting a line to the snore train data, a parallel line at some distance below is determined empirically and is used as the classification boundary between snore and nonsnore episodes. Figure 6 shows the distribution of snore and nonsnore data, the line fit according to robust linear regression and the classification boundary line.

3. Experiments and results

Figures 7 and 8 depict the detection of snoring episodes of two simple snorers. Figure 9 shows the detection of snoring episodes of an OSA patient. Sound activity segments identified by the system are shown in rectangular pulses. Then, those which are classified as snore episodes are marked by a second rectangular pulse above the first one. In these figures, we show parts of recordings where there are no false negatives (i.e., missed snore episodes) and no false positives (i.e., nonsnore episodes marked as snore).

Three different experiments were performed:

- (1) *Snore detection tests for only simple snorers (Exp-1)*. The individuals in the training and testing datasets are different. The training dataset contains 300 randomly selected snoring episodes from each of 12 simple snorers (a total of 3600 snoring episodes). The testing dataset was composed of 6 simple snorers. For each of these subjects a randomly selected recording interval containing 300 snoring episodes was included in the testing dataset. Random selection of episodes means that they have been chosen by the observer with no specified rule.
- (2) *Snore detection tests for both simple snorers and OSA patients (Exp-2A)*. The individuals in the training and testing datasets are the same; however, the recording intervals in each of these datasets are different. The first half of the recordings (first 3 h) was used to compose the training dataset and the second half (the last 3 h) to compose the testing dataset. The training dataset contains 150 randomly selected snoring episodes from each of the 30 subjects. The testing dataset contains a randomly selected recording interval that includes 150 snoring episodes from each of the 30 subjects.

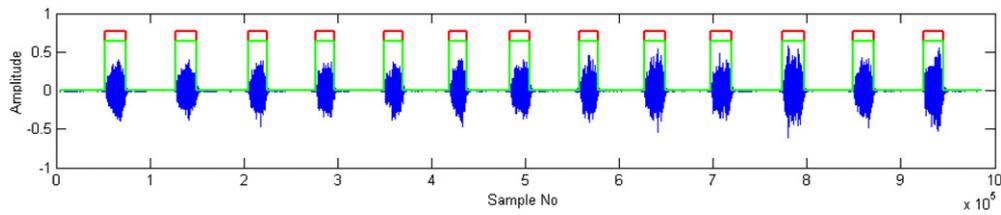


Figure 7. Detection of snoring episodes that belong to a simple snorer. Sound activity segments identified by the system are shown in rectangular pulses. Those which are classified as snore episodes are marked by a second rectangular pulse above the first one.

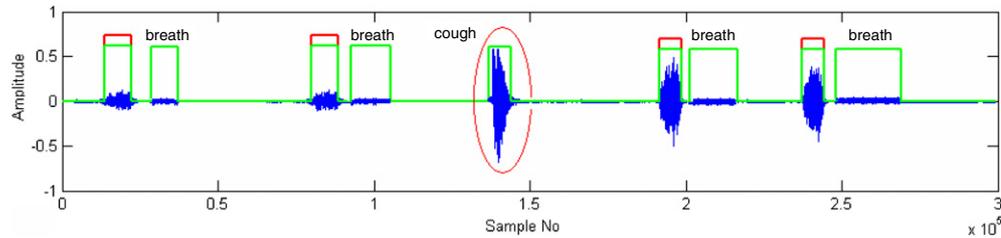


Figure 8. Output of the detection system to a cough episode. Sound activity segments identified by the system are shown in rectangular pulses. Those which are classified as snore episodes are marked by a second rectangular pulse above the first one.

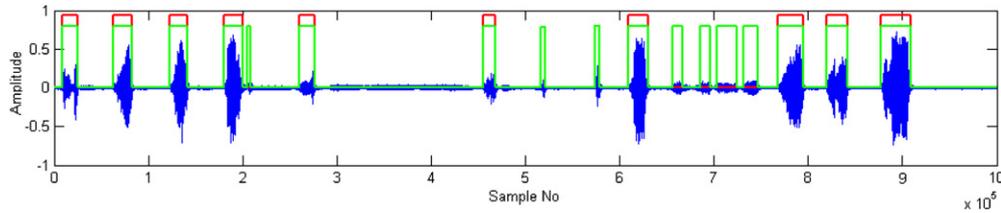


Figure 9. Detection of snoring episodes taken from an OSA patient. Sound activity segments identified by the system are shown in rectangular pulses. Those which are classified as snore episodes are marked by a second rectangular pulse above the first one.

- (3) *Snore detection tests for both simple snorers and OSA patients (Exp-2B).* The individuals in the training and testing datasets are different. Each dataset involves 9 simple snorers and 6 OSA patients (two disjoint datasets of 15 subjects). The training dataset contains 300 randomly selected snoring episodes from each of 15 training subjects (a total of 4500 snoring episodes). For each of the 15 subjects in the testing dataset, a randomly selected recording interval containing 300 snoring episodes was included in the testing dataset.

Table 2 summarizes the compositions of the testing and training datasets in these experiments.

The results of Exp-1, Exp-2A and Exp-2B are shown in tables 3–5, respectively. The numbers of true positive (TP), false negative (FN), true negative (TN) and false positive (FP) detections are given in these tables. Detection performance was evaluated in terms of accuracy, which is defined as $100 \times TP / (TP + FN)$, and the positive predictive value (PPV), which is

Table 2. Compositions of testing and training datasets in the experiments.

	EXP-1		EXP-2A		EXP-2B	
	Training	Testing	Training	Testing	Training	Testing
Simple snorers	12 subjects 3600 snoring episodes	6 subjects 1800 snoring episodes	18 subjects 2700 snoring episodes	18 subjects 2700 snoring episodes	9 subjects 2700 snoring episodes	9 subjects 2700 snoring episodes
OSA patients	–	–	12 subjects 1800 snoring episodes	12 subjects 1800 snoring episodes	6 subjects 1800 snoring episodes	6 subjects 1800 snoring episodes

Table 3. Results of Exp-1.

	TP	FN	TN	FP	Accuracy	PPV
Simple snorers	1752	48	1917	6	97.3%	99.6%

Table 4. Results of Exp-2A.

	TP	FN	TN	FP	Accuracy	PPV
Simple snorers	2505	195	2743	19	92.8%	99.2%
OSA patients	1607	193	1855	87	89.2%	94.8%

Table 5. Results of Exp-2B.

	TP	FN	TN	FP	Accuracy	PPV
Simple snorers	2438	262	2636	32	90.2%	98.7%
OSA patients	1564	236	1859	103	86.8%	93.8%

defined as $100 \times TP / (TP + FP)$. All performance figures were computed with reference to the manual annotations.

The following observations can be made in the detection of snores of simple snorers. The best detection performance was achieved in Exp-1 where both the training and the testing datasets contain only simple snorers. Accuracy dropped by 4.6% (from 97.3% to 92.8%) in Exp-2A where snores of OSA patients were included in the training dataset, even though the testing and training datasets are obtained from the same individuals. Accuracy dropped by 7.3% in Exp-2B (from 97.3% to 90.2%). On the other hand, PPV values are in general higher than, and do not decrease as much as, the accuracy values in this sequence of experiments.

In the detection of snores of OSA patients, accuracy and PPV values are less than those of the simple snorers. However, the accuracy values in Exp-2A and Exp-2B are still high enough (89.2% and 86.8%, respectively) to be considered for clinical applications.

In these experiments, it has been found that the average snore episode duration is about 1.7 s for both simple snorers and OSA sufferers. The average of absolute values of snore duration errors (automatically found duration – manually found duration) is 0.05 s (3.32%) for simple snorers; this figure is 0.07 s (4.3%) for OSA cases. Both of these errors are significantly small compared to the average duration of snoring episodes, especially in the context of the targeted use of the results (such as snore intensity variation, ratio of total snore time to total sleep time).

4. Discussion and conclusion

In this study, we proposed a new algorithm to detect snoring episodes from the sleep sound recordings. The algorithm classifies sleep sound segments as snores and nonsnores according to their subband energy distributions. It was observed that inter- and intra-individual spectral energy distributions of snore sounds show significant similarities. This observation motivated the representation of the feature vectors in a lower dimensional space which was achieved using principal component analysis. Sleep sounds have been efficiently represented and classified as snore or nonsnore in a two-dimensional space. The proposed system was tested by using the manual annotations of an ENT specialist as a reference. The accuracy for simple snorers was found to be 97.3% when the system was trained using only simple snorers' data. It dropped to 90.2% when the training data contain both simple snorers' and OSA patients' data. (Both of these results were obtained by using training and testing sets of different individuals.) This suggests that, in a practical setting, the individual can first be roughly identified as a simple snorer or OSA patient using a composite training dataset and then the results can be refined by using a system trained with the specific type of data. In the case of snore episode detection with OSA patients, the accuracy was 86.8%. All these results can be considered as acceptable values to use the system for clinical purposes including the diagnosis and treatment of OSAS.

The tests were carried out on a dataset formed by the 6 h recordings of 30 individuals (18 simple snorers and 12 OSA patients). The size of this dataset can be assumed to be sufficient for the reliability of the results of the particular binary classification problem.

The information, such as total snoring time, snore-to-sleep ratio, variation of snoring rate and regularity of snoring episodes in time and in amplitude, may be useful for the diagnosis of sleep disorders. These kinds of information can be obtained by detecting snore episodes. This fact and the need for a reasonable processing time of night-long recordings justify a binary classification scheme as snore or nonsnore. It takes 6 min to process 6 h of data (whole night sleep recording) sampled at 16 kHz. This can be considered as a reasonable processing time for night-long recordings.

The classification boundary in this work was found heuristically. It may be possible to improve the performance by using boundaries generated in a more systematic and optimal manner via large margin classification methods such as support vector machines (Bartlett *et al* 2000).

It has been found that the first three subbands dominate the formation of the two-dimensional feature vectors obtained by PCA. Therefore, it may be possible to perform the classification task with similar performance by using only the first three subbands without projection operation and provide computational saving.

The method proposed here has been used to develop a tool for the ENT clinic of GMMA-SSL. It provides information for objective evaluation of sleep sounds (Cavusoglu *et al* 2007). The tool can be used to support clinicians in the following tasks:

- identification of sleep disorders such as simple snoring or OSAS;
- evaluation of the treatment effectiveness of sleep disorders by comparison of snore statistics obtained before and after treatment;
- studying the relationship between the nightlong recordings of physiological signals (polysomnography) and corresponding snoring profiles, e.g., the relationship between sleep stages and snore characteristics.

Future work includes identification of the physiological sources, such as palatal/nonpalatal, of snoring to guide the treatment strategy. Currently, data collection is being carried out for this purpose.

Acknowledgments

We thank the staff of Gülhane Military Medical Academy Sleep Studies Laboratory where the sound recordings and polysomnography results were taken.

References

- Abeyratne U R, Wakwella A S and Hukins C 2005 Pitch jump probability measures for the analysis of snoring sounds in apnea *Physiol. Meas.* **26** 779–98
- Bartlett P J, Schölkopf B, Schuurmans D and Smola A J 2000 *Advances in Large-Margin Classifiers* (Cambridge, MA: MIT Press)
- Baryamureeba V 2000 Solution of robust linear regression problems by pre-conditioned conjugate gradient type methods *Technical Report No: 187* Department of Informatics, University of Bergen, 5020 Bergen, Norway, 22 March
- Baryamureeba V 2001 The impact of equal-weight of both low-confidence and high confidence observations on robust linear regression computation *BIT* **41** 847–55
- Cavusoglu M, Kamasak M, Erogul O, Ciloglu T, Akcam T and Serinagaoglu Y 2007 A Matlab based graphical user interface for sleep and snoring analysis *Proc. Int. Symp. on Health Informatics and Bioinformatics (30 April–2 May, Antalya, Turkey)*
- Duckitt W D, Tuomi S K and Niesler T R 2006 Automatic detection, segmentation and assesment of snoring from ambient acoustic data *Physiol. Meas.* **27** 1047–56
- Hill P D, Lee B W V, Osborne J E and Osman E Z 1999 Palatal snoring identified by acoustic crest factor analysis *Physiol. Meas.* **20** 167–74
- Hill P D, Osman E Z, Osborne J E and Lee B W V 2000 Changes in snoring during natural sleep identified by acoustic crest factor analysis at different times of night *Clin. Otolaryngol.* **25** 507–10
- Holland P W and Welsch R E 1977 Robust regression using iteratively reweighted least-squares *Commun. Stat.—Theory Methods A* **6** 813–27
- Jane R, Fiz J A, Sola-Soler J, Blanch S, Artis P and Morera J 2003 Automatic snoring signal analysis in sleep studies *Proc. 25th Int. Conf. of the IEEE EMBS*
- Jones T M, Ho M-S, Earis J E and Swift A C 2006a Acoustic parameters of snoring sound to assess the effectiveness of sleep nasendoscopy in predicting surgical outcome *Otolaryngol. Head Neck Surg.* **135** 269–75
- Jones T M, Swift A C, Calverley P M A, Ho M S and Earis J E 2005 Acoustic analysis of snoring before and after palatal surgery *Eur. Respir. J.* **25** 1044–49
- Jones T M, Walker P, Ho M-S, Earis J E, Swift A C and Charters P 2006b Acoustic parameters of snoring sound to assess the effectiveness of the Müller Manoeuvre in predicting surgical outcome *Auris Nasus Larynx* **33** 409–16
- Lucas J, Golish J, Sleeper G and O’Ryan J A 1988 *Home Respiratory Care* (Englewood Cliffs, NJ: Prentice-Hall) chapter 6, pp 132–6
- Lugaresi E, Cirignotta F, Coccagna C and Piana C 1980 Some epidemiological data on snoring and cardiorespiratory disturbances *Sleep* **3** 221–4
- McCombe A W, Kwok V and Hawke W M 1995 An acoustic screening test for obstructive sleep apnoea *Clin. Otolaryngol. Allied Sci.* **20** 348–51
- Norton P G and Dunn E V 1985 Snoring as a risk factor for disease: an epidemiological survey *Br. Med. J.* **291** 630–2
- Osborne J E, Osman E Z, Hill P D, Lee B W V and Sparkes C 1999 Acoustic method of differentiating palatal from non-palatal snoring *Clin. Otolaryngol.* **24** 130–3
- Sola-Soler J, Jane R, Fiz J A and Morera J 2003 Spectral envelope analysis in snoring signals from simple snorers and patients with obstructive sleep apnea *Proc. 25th Int. Conf. of the IEEE EMBS*
- Street J O, Carroll R J and Ruppert D 1988 A note on computing robust regression estimates via iteratively reweighted least squares *Am. Stat.* **42** 152–4
- Wilkin R L 1985 *Clinical Assessment in Respiratory Care* (St Louis, MO: Mosby) pp 268–72
- Wilson K, Stoohs R A, Mulrooney T F, Johnson L J, Guilleminault C and Huang Z 1999 The snoring spectrum: acoustic assesment of snoring sound intensity in 1,139 individuals undergoing polysomnography *Chest* **115** 762–70