Proceedings of the 29th Annual International
Conference of the IEEE EMBS
Cité Internationale, Lyon, France
August 23-26, 2007.

Automatic classification of subjects with and without Sleep Apnea through snoring analysis

Jordi Solà-Soler, Member IEEE, Raimon Jané, Member IEEE, José Antonio Fiz, José Morera

***Abstract*—A new method for indirect identification of Sleep Apnea patients through snoring characteristics is proposed. The method uses a logistic regression model which is fed with several time and frequency parameters from snores and their variability. The information is contained in all the snores automatically detected in nocturnal sound recordings. In the validation of the model, subjects are classified with a sensitivity higher than 93% and a specificity between 73% and 88% when all detected snores are used. The model can also be adjusted to obtain 100% specificity with a corresponding sensitivity between 70% and 87%. This results are better than previous reported methods based on snoring analysis, but with a single channel, and are comparable to the classification scores of several portable apnea monitors when evaluated on a similar number of patients. This technique is a promising tool for the screening of snorers, allowing snorers with a low Apnea-Hypopnea Index (AHI<10) to avoid a full-night polysomnographic study at the hospital.**

I. INTRODUCTION

RECENTLY, several studies concerning to prevalence of snoring and sleep apnea have been published. In Spain, 64% of men and 36% of women are snorers and the probability of Obstructive Sleep Apnea Syndrome (OSAS) is 3.2 times higher in snorers than in non-snorers [1]. The OSAS has important clinical implications, ranging from disruption of sleep with daytime sequelae of excessive sleepiness to suspected cardiovascular consequences in the long term [2].

The nocturnal polysomnography (PSG) and subsequent manual analysis is considered to be the gold standard for the diagnosis of OSAS. The procedure of a PSG, which requires the subject to spend one night at the hospital, is labor intensive and time consuming, and has a limited capacity considering the high prevalence of OSAS. Many alternative methods to assess OSAS have been developed, most of them incorporated in portable devices, that use the traqueal sound as their main signal. The diagnostic accuracy of such methods has been reported to be very low when only one parameter from the tracheal sound was employed. Therefore, most of these methods utilize complementary parameters from other cardiorespiratory signals to detect abnormal breathing events [3]. Type 2 monitors record at least seven channels, including EEG, EOG, submental EMG, ECG or HR, air flow, respiratory effort and SaO_2. Type 3 monitors record at least four channels, including ventilation or airflow, ECG or HR and SaO_2. And Type 4 monitors use at least one respiratory channel, usually either oxygen saturation or airflow [4].

Our main hypothesis is that Sleep Apnea patients, as defined by an AHI≥10, can be detected through the information extracted from the snores of a subject, without the need to detect the Apneas/Hypopneas or to focus on post-apneic snores. A method in this direction has been recently proposed which is based on the pitch of snores. The authors identify Sleep Apnea patients (AHI≥10) through one snoring pitch parameter with a maximum sensitivity of 91% at 67% specificity in a database with 29 patients. To obtain specificity values higher than 85%, their sensitivity always stays below 50% [5]. In this work, we propose and validate a classification model based on logistic regression, which incorporates snore parameters derived from previously developed analysis techniques in time and frequency domains [7-9].

II. MATERIAL AND METHODS

A. Signal Acquisition

Respiratory sound was recorded simultaneously with PSG studies. The sound sensor was a unidirectional electret condenser microphone, coupled to the skin through a conical air cavity, which was placed laterally on the trachea at the level of the cricoid's cartilage using an elastic band. The sound signal was amplified and filtered using a second order Butterworth pass-band filter between 70 and 2000 Hz and then digitized with a sampling frequency of 5000 Hz and a 12 bit A/D converter. The position of the patient was simultaneously captured and digitized through an abdominal sensor.

B. Patient Database and Snore characterization

An automatic snoring detector previously validated was used to identify snoring episodes and to reject cough, voice and other artifacts [6]. The number of detected snores and the patients database is shown in Table I.

Let $s(i)$ be the i'th detected snore and $t_{s(i)}$ its occurrence instant. By means of the time difference $dT_{s(i)} = t_{s(i)} - t_{s(i-1)}$ a subgroup of snores G_1 is defined as follows:

$$G_1 = \{ s(i) \mid dT_{s(i)} < 10\mathrm{s}, dT_{s(i-1)} < 10\mathrm{s} \}$$

Manuscript received on April 13, 2007. This work was supported in part by grants from Ministerio de Educacion y Ciencia and FEDER (TEC2004-05263-C02-01).

J. Solà-Soler and R. Jané are with the Centre de Recerca en Enginyeria Biomedica, Universitat Politècnica de Catalunya, Pau Gargallo, 5. 08028 Barcelona, Spain (phone:34-934017158; fax:34-934017045;
e-mails: jordi.sola@upc.edu; raimon.jane@upc.edu)
J.A. Fiz and J.Morera are with Hospital Universitari Germans Trias i Pujol, Badalona, Spain.
e-mails: jafiz@msn.com; josepmorera.germanstrias@gencat.net

In this subgroup, the first and second snores after an apnea (post-apneic snores) are excluded. The snores in group G_1 will also be called *regular snores*.

Several techniques in time and frequency domains have been developed in our previous studies for the analysis and characterization of snores. In the time domain, snores are characterized by the period of the sound vibrations or pitch [7]. The pitch waveform of a snore is parameterized by its mean value (*Pm*), standard deviation (*Ps*) and interquartile range (*Piqr*); the pitch density (*Pdens*), defined as the fraction of time with pitch over the total duration of a snore; and the number of intervals with pitch into a snore (*Pints*).

TABLE I
CHARACTERISTICS OF THE SNORER SUBJECTS ANALYZED

Subjects	N		Age	BMI	AHI	NS	NSG1
Snorers AHI<10	12/5	M	46	27.1	3.8	1484	1137
		SD	12	4.1	3.1	1227	1097
		R	27-69	18.9-35.5	0.0-8.9	117-3277	27-2788
OSAS AHI≥10	13/6	M	51	32.3	40.3	2202	1641
		SD	10	5.4	21.7	1093	1050
		R	31-66	26.5-47.6	10.7-90.8	166-4197	71-3905

N: Number of subjects (Male/Female). M: Mean. SD: Standard Deviation. R: Range. BMI: Body Mass Index, AHI: Apnea-Hipoapnea Index, , NS: Total number of snores, NSG1: Number of snores in group G1.

The frequency content of a snore is calculated by its Power Spectral Density (PSD). The shape of the PSD is characterized by a set of parameters [8]: the mean, median, peak and maximum frequencies (F_{mean}, F_{med}, F_{peak}, F_{max}); the standard deviation of frequency (*StdDev*); and the symmetry and flatness coefficients (*Csymm, CFlatn*). The power distribution of the PSD is measured by energy ratios in three frequency bands of interest: $B=(0,500)Hz$, $B=(100,500)Hz$ and $B=(0,800)Hz$. The energy in each band B is computed over the total energy (RW_B) and over the energy out of that band ($Rout_B$).

The oral and nasal cavities introduce resonances into the snoring sound. These can be measured through the peaks of the AR spectral envelope (also called formants). The formants of snores acquired at the traquea were found to be located in five frequency bands B_1-B_5 [8]. Each formant was characterized by its frequency F_i, its amplitude with respect to the maximum (M_i) and its depth (L_i), $i=1:5$.

In previous works [8] it has been found that the variability of snoring features over the night is significantly higher in OSAS patients (AHI≥10) than in snorers with a low Apnea-Hypopnea Index, and that the differences are much more significant when this variability is measured in a snore by snore basis [8,9]. For a given parameter P of snore $s(j)$, $P_{s(j)}$, the first difference $dP_{s(j)} = P_{s(j)} - P_{s(j-1)}$ is calculated. The time series dP oscillates around zero and its amplitude is measured by the standard deviation (*SdP*) and the interquartile range (*IQdP*). The difference dP is also computed over the time difference dT ($dtP \equiv dP/dT$) between the instants of consecutive snores. The amplitude of several snore parameters'first difference was found to be correlated with the AHI [8].

C. Classification model

A logistic regression model is used for the classification of patients. This technique has the advantage over other classification techniques, such as discriminant analysis, that it does not require a normal hypothesis over the data and that the model can be adjusted for a desired sensitivity or specifity. A dichotomic variable Y is defined that assumes the value $Y=0$ in snorers with a low Apnea-Hypopnea Index and $Y=1$ in Sleep Apnea patients (AHI≥10). The probability that $Y=1$ is calculated by the logistic model

$$p_i = p(Y=1|x_{i1},\ldots,x_{iK}) = 1/\left(1+\exp\left(\beta_0+\beta_1 x_{i1}+\ldots+\beta_K x_{iK}\right)\right)$$

where the model parameters β_j, $j=0:K$, are estimated by the maximum likelihood method from the N_{obs} available observations (x_{i1}, ..., x_{iK}), $i=1:N_{obs}$, of the variables X_j, $j=1:K$. For a good estimation of the model parameters, the number of observations and variables should satisfy

$$N_{obs} \geq 10\cdot(K+1) \qquad (1)$$

The independent variables X_j are selected among all the snore parameters derived from the sound intensity, the PSD, the AR spectral envelope, and the Pitch (see section II.B). In a previous study, only variability parameters from the PSD were considered [8]. Here, for every parameter P, six independent variables X_j are obtained performing the measures described in Table II. The average values are calculated over a number of $N=500$ snores. This way, several observations are available for the classification of every patient, and a greater number of variables can be included in the model according to (1) because the total number of observations N_{obs} is now greater than the number of patients N_{pac} ($N_{obs}=85\text{-}143$, $N_{pac}=36$; Table III).

TABLE II
INDEPENDENT VARIABLES DERIVED FROM EACH SNORE PARAMETER

Name	Description
P	Mean value of the parameter
SP	Standard Deviation of the parameter
SdP	Standard Deviation of the parameter's first difference
IQdP	Interquartile Range of the parameter's first difference
SdtP	Standard Deviation of the parameter's first difference over time
IQdtP	Interquartile Range of the parameter's first difference over time

P stands for any of the snore parameters defined in section II.B. The same symbol *P* is used for the parameter and its mean value. The averages are performed over groups of 500 snores.

The optimum independent variables are selected by a forward stepwise algorithm included in the SPSS packet. In each step of the algorithm, the variable with the higher score statistic is selected to enter the model. A variable can also be removed according to the significance of its conditional likelihood ratio statistic. This algorithm allows all the available variables to be eligible for entering the model. Then, the algorithm selects the best variables among all these, and thus an optimum model is obtained.

Using the optimum model parameters, each observation $(x_{i0}, x_{i1}, \ldots, x_{iK})$ is classified in one of the two groups through the estimated probabilities p_i using a threshold $c \in (0,1)$. The i'th observation is classified as $Y=1$ if $p_i \geq c$, and as $Y=0$ otherwise. A snorer is classified as a sleep-apnea patient if his/her number of observations (groups of 500 snores) classified as $Y=1$ is equal or greater than his/her number of observations classified as $Y=0$. In this work, the threshold c is optimized to obtain the maximum specificity with 100% sensitivity in the classification of patients.

Three different models are estimated from the available database: model A, using all the detected snores; model B, using only snores in group G_1; and model C, using the detected snores in supine position. The performance of the optimum models is evaluated by their sensitivity and specificity. Each model is validated by the live-one-out procedure. The probabilities p_i from all patients are used to generate a Receiver Operating Curve (ROC) of each model, and the area under this curve (AUC) is estimated.

III. Results

The performance of the optimum estimated models for patient classification is shown in Table III. Models A and B include a combination of eight parameters derived from the PSD, the AR spectral envelope and the Pitch of snores. At least four of these parameters quantify the snoring variability. Model B (group 1 snores) obtains a better specificity than model A, but the sensitivity and the AUC become much lower in the validation. Model C includes snore parameters from the PSD alone, and all of them quantify the snoring variability. This model has the same sensitivity and a better specificity than model A. But it has a reduced AUC, which indicates a poorer performance for other working points. The performance of the validated models for probability thresholds different from the optimum one can be observed in the ROC (Figure 1).

IV. Discussion

We have shown that it is possible to identify Sleep Apnea patients using a logistic model that contains only three to eight independent variables derived from snoring. Most of the automatically selected parameters measure the snoring variability in a snore by snore basis. In previous studies we had observed a significantly higher variability of snoring spectral parameters in consecutive snores in OSAS patients [7,8]. The snoring variability also seems to be a key to classify snorers with or without Sleep Apnea.

Good classification results are also obtained using only G_1 snores (Table III). This fact confirms that Sleep Apnea patients are detectable with the information extracted from regular snores, without the contribution of the first and second snores after an apnea. However, in order to conduct a screening test aimed at allowing snorers with a low Apnea-Hypopnea Index (AHI<10) to avoid a full-night PSG study, the sensitivity of the classification model needs to be as high as possible. In our validation process the highest sensitivity (94.1%) was obtained with the models that use all snores available (Table III). When the model is estimated only from snores generated in supine position the same sensitivity and a better specificity is obtained. Therefore, it seems that these snores contain the relevant information for the detection of Sleep Apnea patients. However, it would not be wise to base a screening test on the information contained in the snores generated in a particular position, because it is possible for a person not to snore in this position at all during the night.

Only one alternative method for the classification of patients through snoring information has been published to the date [5]. The method uses a model based on the snoring pitch, and a sensitivity of 91% at a specificity of 67% is obtained in the detection of Sleep Apnea patients (AHI≥10).

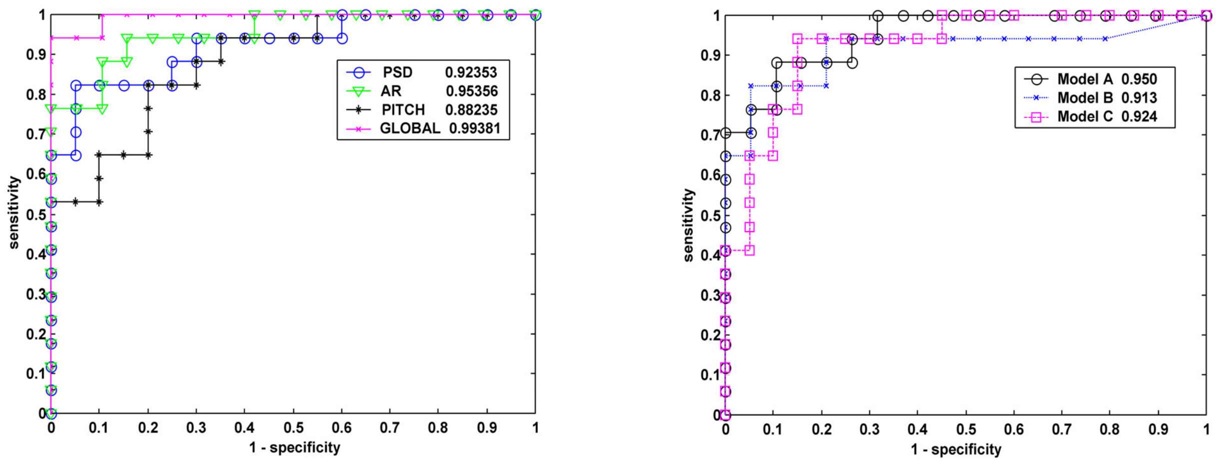
In the preliminary attempts of our study, using only information derived from the snoring pitch, the models obtained a reduced specificity (45%) at 100% sensitivity. When the PSD and AR spectral envelope parameters were included into the model, the specificity increased to 89% (Fig.1a). We believe that pitch-based classification models have poorer performance because pitch only contains information about the frequency of the oscillating structures that originate snores. The PSD and the AR spectral envelope contain additional and valuable information about the filtering and the acoustic resonances that take place in the upper airway. Our models also have good behavior when adjusted to maximize specificity. For example, model A obtains 70% sensitivity at a specificity of 100% (Fig.1b). In pitch-based classification methods the sensitivity is under 50% for specificities above 83% [5].

The performance of several portable apnea monitors is shown in Table IV. In most cases, the detected apneas and hypoapneas are manually revised by a technician before giving a definite value of the AHI. Using just one channel - the tracheal sound- the classification models proposed in this work allow an indirect detection of Sleep Apnea patients through the characteristics of snores and their variability. Their performance is comparable to that of type 2 and type 3 portable apnea monitors when evaluated on a similar number of patients [4].

TABLE III
THE OPTIMUM MODELS AND THEIR PERFORMANCE IN THE VALIDATION

Model	Optimum Model Performance						Leave-one-out Validation Results						N_{pac}	N_{obs}	c_{opt}
	TP	FN	TN	FP	Sens (Spec)	AUC	TP	FN	TN	FP	Sens (Spec)	AUC			
A	17	0	17	2	100 (89.5)	0.994	16	1	14	5	94.1 (73.7)	0.950	19+17	63+80	0.45
B	17	0	18	1	100 (94.7)	0.994	14	3	17	2	82.3 (89.5)	0.913	19+17	51+63	0.50
C	17	0	18	1	100 (94.7)	0.997	16	1	15	4	94.1 (78.9)	0.924	19+17	33+52	0.50

TP: True Positives. FN: False Negatives. TN: True Negatives. FP: False Positives. Sens: Sensitivity (=TP/(TP+FN)). Spec: Specificity (=TN/(TN+FP)). N_{pac}: Number of patients. N_{obs}: Number of observations (groups of 500 snores). c_{opt}: optimum probability threshold.



(a) (b)

Fig.1: Receiver Operating Curves (ROC) of the analyzed models. (a) Performance of the optimum model estimated individually with snore parameters from the pitch, the PSD and the AR envelope, and with all of them altogether. (b) Validation performance of the models using all snore parameters.

TABLE IV
PERFORMANCE OF OTHER SLEEP APNEA DETECTION METHODS REPORTED WITH A SIMILAR NUMBER OF PATIENTS

Detection Method	Subject Scoring	Sens (Spec) [%]	N_{pac}	Ref.
AM–T2	Manual	80 (90)	20	[4]
AM–T3	Manual	100 (66)	34	[4]
AM–T3	Automatic	100 (100)	29	[4]
AM–T3	Manual	100 (64)	30	[4]
AM–T3	Manual	95 (100)	25	[4]
Snoring Pitch	Automatic	91 (67)	29	[5]

AM: Apnea Monitor Ref.: Reference. Sens: Sensitivity. Spec: Specificity. N_{pac}: Number of patients analyzed. T2: Type 2, T3: Type 3 apnea monitors.

Another method for the detection of Sleep Apnea patients based on the transient fluctuations of a logarithmic average of the respiratory sound intensity was recently validated [3]. Subjects were classified with sensitivity (specificity) of 93% (67%) for a Sleep Apnea threshold of AHI≥5, and 99% (46%) for AHI≥15. For AHI≥10, intermediate scores would be expected. Our method has a similar sensitivity and a higher specificity, but the number of subjects analyzed is much lower, so this comparison must be taken with caution until a validation on a greater database is available.

V. CONCLUSION

A new method for indirect detection of Sleep Apnea patients through snoring characteristics is proposed. The method uses a logistic regression model which is fed with several time and frequency snore parameters and their variability. The information is contained in all the snores automatically detected in nocturnal sound recordings. In the model validation, subjects are classified with sensitivity higher than 94% and specificity between 73% and 89% when all detected snores are used. The models can also be adjusted to obtain 100% specificity with a corresponding sensitivity between 70% and 87%. These results are better than previous reported methods based on snoring analysis, and are comparable to the classification scores of several portable apnea monitors when evaluated on a similar number of patients, but using only one signal channel. The method could be complemented with a respiratory disturbance index obtained from any auxiliary signal. This technique is a promising tool for the screening of snorers, allowing snorers with a low Apnea-Hypopnea Index (AHI<10) to avoid a full-night polysomnographic study at the hospital. A validation on a greater database remains to be done in order to further evaluate the performance of the method.

ACKNOWLEDGMENT

The authors would like to thank SIBEL S.A. for its collaboration in the medical intrumentation.

REFERENCES

[1] J. Durán, S. Esnaola, R. Rubio, A. Iztueta, "Obstructive Sleep Apnea-hypopnea and related clinical features in a population-based sample of subjects aged 30 to 70 yr," *Am J Respir Crit Care Med*, vol. 63, pp. 685-689, 2001.

[2] K. Banno, M. H. Kryger, "Sleep Apnea: Clinical investigations in humans, " *Sleep Med*, vol. 8, pp. 400-426, 2007.

[3] H. Nakano, M. Hayashi, E. Ohshima, N. Nishikata, T. Shinohara, "Validation of a new system of tracheal sound analysis for the diagnosis of sleep apnea-hypopnea syndrome,", *Sleep*, vol. 27, pp. 951-957, 2004.

[4] W. W. Flemons, M. R. Littner, J. A. Rowley, P. Gay, W. M. Anderson, D. W. Hudgel, R. D. McEvoy, D. I. Loube, "Home diagnosis of sleep apnea: a systematic review of the literature," *Chest*, vol. 124, pp. 1543-1579, 2003.

[5] U. R. Abeyratne, A. S. Wakwella, C. Hukins, "Pitch jump probability measures for the analysis of snoring sounds in apnea," *Physiol Meas*, vol. 26, pp. 779-798, 2005.

[6] R. Jané, J. A. Fiz, J. Solà-Soler, S. Blanch, P. Artís, J. Morera, "Automatic snoring signal analysis in sleep studies," *Proc of the 25th Intl Conf of the IEEE EMBS*, vol. 3, pp. 2527-2530, 17-21 Sept. 2003.

[7] J. Solà-Soler, R. Jané, J. A. Fiz, J. Morera, "Pitch analysis in snoring signals from simple snorers and patients with Obstructive Sleep Apnea," *Proc of the 24th Intl Conf of the IEEE EMBS*, vol. 2, pp. 1527-1528, 23-26 Oct. 2002.

[8] J. Solà-Soler, R. Jané, J. A. Fiz, J. Morera, "Variability of snore parameters in time and frequency domains in snoring subjects with and without Obstructive Sleep Apnea," *Proc of the 26th Intl Conf of the IEEE EMBS*, pp. 2583-2586, 17-21 Sept. 2005.

[9] J. Solà-Soler, R. Jané, J. A. Fiz, J. Morera, "Spectral envelope analysis in snoring signals from simple snorers and patients with Obstructive Sleep Apnea," *Proc of the 25th Intl Conf of the IEEE EMBS*, vol. 3, pp. 2527-2530, 17-21 Sept. 2003.