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# Bayes Classification of snoring subjects with and without Sleep Apnea Hypopnea Syndrome, using a Kernel method

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*Abstract*—**The gold standard for diagnosing Sleep Apnea Hypopnea Syndrome (SAHS) is the Polysomnography (PSG), an expensive, labor-intensive and time-consuming procedure. It would be helpful to have a simple screening method that allowed to early determining the severity of a subject prior to his/her enrolment for a PSG. Several differences have been reported in the acoustic snoring characteristics between simple snorers and SAHS patients. Previous studies usually classify snoring subjects into two groups given a threshold of Apnea-Hypoapnea Index (AHI). Recently, Bayes multi-group classification with Gaussian Probability Density Function (PDF) has been proposed, using snore features in combination with apnea-related information. In this work we show that the Bayes classifier with Kernel PDF estimation outperforms the Gaussian approach and allows the classification of SAHS subjects according to their severity, using only the information obtained from snores. This could be the base of a single channel, snore-based, screening procedure for SAHS.**

*Index Terms*—**Sleep Apnea, Snoring, Bayes Classifier, Kernel PDF estimation.**

## I. Introduction

THE Sleep Apnea Hypopnea Syndrome (SAHS) is a widely spread pathology whose earliest symptom is heavy snoring. The repercussions of snoring range widely in severity from no sleep disruption to continuously disrupted sleep [1]. The gold standard for diagnosing SAHS is the Polisomnograpy (PSG). This is a very expensive, labor-intensive and time-consuming procedure. It would be desirable to have a *screening* method that aids pneumologists to early determine the severity of a subject in order to establish a priority among all candidates to PSG..

Recent studies have shown differences in acoustic snoring characteristics between patients with SAHS and simple snorers [2]-[4]. Those studies usually classify snoring subjects into two groups by means of an Apnea-Hypopnea Index (AHI) threshold. However, no further information about the severity of the subject is provided. A recent work of our group has addressed multigroup analysis of snoring subjects with SAHS [5]. Other authors have used a Bayes classifier with Gaussian PDF assumption [6], but in general the data will not follow a normal distribution. The classifier was fed by snoring information but also with features related to apneas. No automatic method was used for the selection of the independent variables of the classifier.

Our approach is based on a single channel, namely the sound signal. Based exclusively on the information extracted from snores, we investigate the performance of a Bayes classifier with Kernel as compared to Gaussian PDF estimation method. In each case, the best feature set is selected by an automatic sequential variable selection algorithm.

## II. Material and Methods

### A. Signal Acquisition & Subject database

Snoring sounds were noninvasively recorded using a unidirectional electret condenser microphone coupled to the skin surface through a conic air cavity. Snoring sound signals were acquired while full-night polysomnography was performed at the Sleep Disorders laboratory of the *Hospital Universitari Germans Trias i Pujol* in Badalona, Spain. The microphone was placed over the trachea at the level of the cricoid cartilage using an elastic band. The sound signal was amplified and filtered using a second order Butterworth analog 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 snoring episodes were then identified by a previously trained and validated automatic detector developed by our research group [5],[7]. The snoring detector was designed to identify snoring episodes from simple snorers and OSAS patients, and to reject respiratory sounds from regular inspiration and exhalation, cough, voice and other artifacts. All the snores detected during the night were used for subject classification. The characteristics of the 36 subjects database and the total number of detected snores (T=65625 snores) is shown in Table I.

The American Academy of Sleep Medicine proposes a stratification of the severity of SAHS into four levels, according to the thresholds AHI=$5h^{-1}$,$15h^{-1}$ and $30h^{-1}$ [8]. In this work we address the classification of snoring subjects into

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TABLE I
CHARACTERISTICS OF THE DATABASE

| | | G1 | G2 | G3 | $p_{12}$ | $p_{13}$ | $p_{23}$ |
|---|---|---|---|---|---|---|---|
| Subjects (N=36) | M/F | 10/3 | 7/4 | 8/4 | --- | --- | --- |
| Age (yr) | m | 45 | 48 | 52 | 0.706 | 0.096 | 0.460 |
| | s | 11 | 12 | 10 | | | |
| BMI (kg/m²) | m | 27.1 | 28.9 | 32.9 | 0.339 | 0.012 | 0.085 |
| | s | 4.4 | 4.1 | 6.0 | | | |
| AHI (1/h) | m | 1.8 | 8.7 | 44.1 | <0.001 | <0.001 | <0.001 |
| | s | 1.5 | 2.5 | 20.2 | | | |
| Num. Snores | m | 1226 | 2243 | 2084 | 0.068 | 0.044 | 0.580 |
| | s | 1289 | 1177 | 937 | | | |
| | T | 15942 | 24672 | 25011 | | | |

M=Males, F=Females, m=mean, s=standard deviation, BMI=Body Mass Index, AHI=Apnea Hypopnea Index, T=Total number of snores, Gx=Group x, G1=AHI<5, G2=5≤AHI<30, G3=AHI≥30, $p_{xy}$=Statistical Significance of the Mann-Whitney U test between groups x and y.

three groups of SAHS severity given by thresholds AHI=5h$^{-1}$ and AHI=30h$^{-1}$. In this way, each group will have a comparable size according to the subjects available in our database. The groups are G1 (no SAHS, AHI<5h$^{-1}$), G2 (mild to moderate SAHS, 5h$^{-1}$≤AHI<30h$^{-1}$) and G3 (severe SAHS, AHI≥30h$^{-1}$). All patients were snorers (total number of snores range from 117 to 4214).

### B. *Snore characterization*

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. The pitch waveform of a snore is parameterized by its mean value ($P_m$), standard deviation ($P_s$) and interquartile range ($P_{iqr}$); the pitch density ($P_{dens}$), 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 ($P_{ints}$) [9].

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 [10]: 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 Spectral Envelope (also called formants). Each formant is characterized by its frequency $F_i$, its amplitude with respect to the maximum $M_i$ and its attenuation $L_i$ [11].

The independent variables $X_j$ of the classification model are selected among all the snore parameters derived from the sound intensity, the PSD, the Spectral Envelope, and the Pitch. The number of independent variables has been limited to 10.

### C. *Naive Bayes Classifier*

The Bayes rule provides a direct way of multigroup subject classification. The independent variables $X_j$ are assumed to be independent (Naive Bayes assumption) so that their joint Probability Density Function (PDF) can be factored into the product of the individual PDF's. In order to avoid managing products of extremely low quantities, the logarithm of the PDF's can be used instead of the PDF's themselves. Thus, in a model with $K$ independent variables $X_1,\ldots, X_K$ an observation $(x_{i1}, \ldots, x_{iK})$ would be classified into the group $G_{class}$ given by:

$$\begin{aligned} G_{class} &= \underset{i=1:3}{\operatorname{argmax}}\left\{P(G_i)\cdot p_{X_1,\ldots,X_K}\left(x_{j1},\ldots,x_{jK}\middle|G_i\right)\right\} \approx \\ &\approx \underset{i=1:3}{\operatorname{argmax}}\left\{\hat{P}(G_i)\cdot\prod_{i=1}^{K}\hat{p}_{X_i}\left(x_{ji}\middle|G_i\right)\right\} = \\ &= \underset{i=1:3}{\operatorname{argmax}}\left\{\log\left(\hat{P}(G_i)\right)+\sum_{i=1}^{K}\log\left(\hat{p}_{X_i}\left(x_{ji}\middle|G_i\right)\right)\right\} \end{aligned} \quad (1)$$

The Naive approximation has been reported to give good results in most scenarios [12]. The probability $P(G_i)$ of pertaining to each class is estimated by the number of subjects in that class over the total number of subjects. Previous studies have used the Gaussian assumption for the conditional PDF $p_{Xi}(X_i|G_j)$ of the independent variables [5]. However, in general the available data is not normally distributed, so it's better to use a Kernel based PDF estimation. Given a symmetric Kernel function $K(\cdot)$ and a set of $N$ observations $(x_{1i}, \ldots, x_{Ni})^T$ of the variable $X_i$, the estimated PDF is given by

$$\hat{p}_{X_i}(x) = \frac{1}{N}\sum_{j=1}^{N}K\left(\frac{x-x_{ji}}{h}\right) \quad (3)$$

where $h$ is the kernel bandwidth [12]. The Kernel PDF estimation will be compared with the Gaussian one. In both cases, the optimum independent variables are automatically selected with the Sequential Floating Forward Selection (SFFS) algorithm described in Fig.1. At each step, variables are elected to enter or leave the model depending on a performance measure $J(\cdot)$ to be optimized. Consider the confusion matrix C given by

$$C = \begin{pmatrix} G1_{G1} & G2_{G1} & G3_{G1} \\ G1_{G2} & G2_{G2} & G3_{G2} \\ G1_{G3} & G2_{G3} & G3_{G3} \end{pmatrix} \quad (3)$$

where $Gi_{Gj}$ is the number of subjects of group Gj that have been classified into group Gi. We define three performance

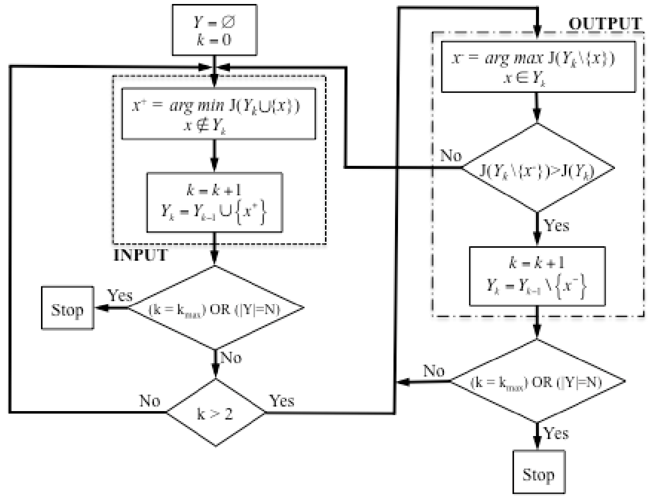


Fig. 1. Sequential Floating Forward Selection (SFFS) algorithm used in the Bayes Classifier. The cost functions *J(.)* studied are $NPV_{G1}$, ACC and TFN. After the end of the algorithm, the optimum model is $Y_{opt}$ = arg max{J($Y_k$)}.

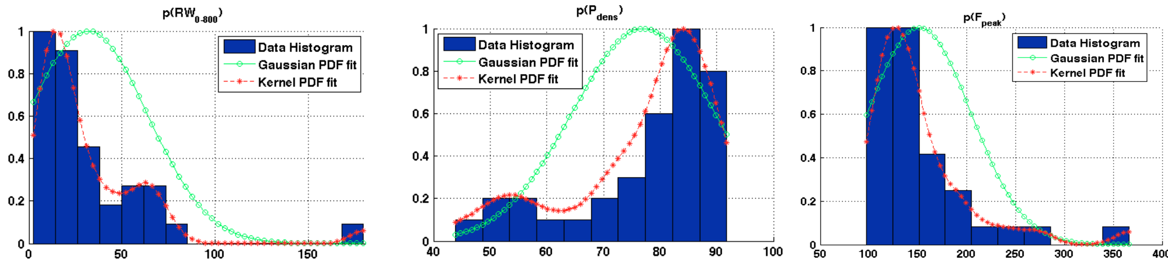


Fig. 2. Data Histogram, Gaussian PDF Fit (circles) and Kernel PDF estimation (asterisks) for snore parameters $RW_{0\text{-}800}$, $P_{dens}$ and $F_{peak}$.

measures of interest: the Negative Predictive Value (NPV) of the group of healthy subjects ($G_1$, AHI<$5h^{-1}$) given by

$$NPV_{G1} \equiv G1_{G1} / (G1_{G1} + G2_{G1} + G3_{G1}) \tag{4}$$

The Total False Negatives (TFN), i.e. the number subjects classified into a group with severity lower than it should:

$$TFN \equiv G1_{G2} + G1_{G3} + G2_{G3} \tag{5}$$

And the Accuracy (ACC), defined as

$$ACC \equiv \frac{tr(C)}{sum(C)} \tag{6}$$

where *sum(C)* is the sum of all the elements and *tr(C)* is the trace of the confusion matrix C. The SFFS algorithm involves a single (main) performance measure *J(·)*. If, in a given iteration, the maximum or minimum of *J(·)* is reached for several variable sets, a secondary measure *J2(·)* is used to select the best set. We have studied the performance of the SFSS algorithm with the 6 possible combinations of *J(·)* and *J2(·)* using the performance measures (4)-(6).

After selection of the optimum set of independent variables by the SFFS algorithm, the optimum models are validated by means of the leave-one-out crossover procedure.

## III. Results

Fig. 2 shows a comparison of the two PDF estimation methods in three snore parameters. We can see that in general the data does not follow a Normal distribution. In some cases it even has a bimodal distribution, which is well approximated by the Kernel PDF estimation.

The evolution of the SFFS algorithm for the different combinations of the cost functions *J(·)* and *J2(·)* using the performance measures (4)-(6) is shown in Fig.3 for the Kernel PDF estimation. The best performance was obtained for J=ACC (Fig.3a) and J=$NPV_{G1}$ (Fig.3b). In these cases, the results were independent of the choice of the secondary measure *J2(·)*, so only one of them is shown.

The confusion matrix (3) of the optimum selected models is shown in Table II for Gaussian PDF estimation and in Table IV for Kernel PDF estimation. We can see that the Kernel method outperforms the Gaussian approach in almost all cases. In the model with J=$NPV_{G1}$, no patient with SAHS (G2 or G3) is classified as healthy (G1), and all healthy subjects are correctly classified (Table II-d, Table IV-c,d). The model with J=ACC obtains a better TFN, but some patients with SAHS are classified into the healthy group (Table IV-b).

The corresponding confusion matrixes of the crossover validation are shown in Tables III and V for Gaussian and Kernel PDF estimation, respectively. Under validation, the

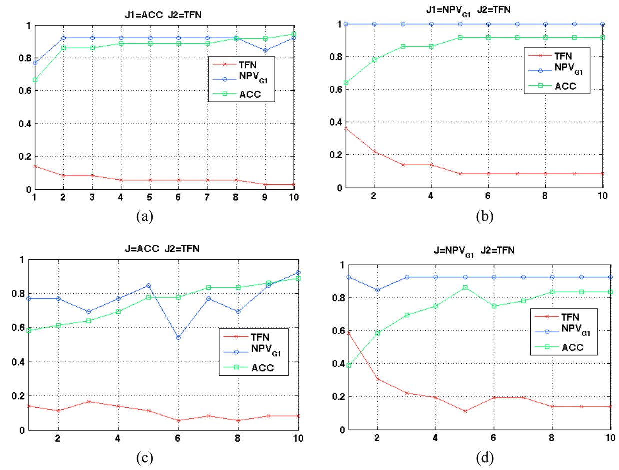


Fig. 3. Evolution of the SFFS algorithm for the different combinations of the performance measures *J(·)* and *J2(·)* using the Kernel (a,b) or the Gaussian (c,d) PDF estimation method. The horizontal axis is the iteration number, which coincides with the number of variables in the model.

model with Kernel PDF using J=ACC provides the best balance of low TFN and high $NPV_{G1}$ (Table V-a,b).

## IV. Discussion and Conclusions

Previous studies used to classify snoring subjects into two groups based on a single AHI threshold [2]-[4], or analyzed parameters of three groups of subjects, without classification methods [5]. The multi-group classifier proposed recently by Ben-Israel *et al.* [6] uses Bayes method with snoring information but also with two features related to apneas, which require synchronizing the acoustic signal to the PSG signals. This additional complexity permits the use of a sub-optimum Gaussian PDF estimation.

Our method provides a way of classifying snoring subjects according to their SAHS severity, based exclusively on snore features obtained from a single channel system. The method could be the basis of an early screening process. The $NPV_{G1}$ should be as high as possible, as every healthy subject that is wrongly sent to a second stage (PSG) supposes a big cost to the Public Health Care System. The TFN should also be kept to a minimum, in order not to mistake any SAHS patient (G2 or G3) by a healthy subject.

Performance measures could alternatively be stated in terms of Total True Positives (TTP). The low validation rates obtained may be due to overfitting of the optimum classification model. We are currently improving the method to achieve better validation results. The method also needs to be validated over a greater database.

TABLE II

Confusion Matrix of the **Optimum** Classification Models (**Gaussian** PDF estimation)

| | J=ACC, J2=TFN<br>NPV$_{G1}$=92.3%<br>TFN=8.3% | | | J=ACC, J2= NPV$_{G1}$<br>NPV$_{G1}$=76.9%<br>TFN = 5.5% | | | J= NPV$_{G1}$, J2=ACC<br>NPV$_{G1}$=92.3%<br>TFN = 13.9% | | | J= NPV$_{G1}$, J2=TFN<br>NPV$_{G1}$=100%<br>TFN = 13.9% | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Classified Group (%) | | | Classified Group (%) | | | Classified Group (%) | | | Classified Group (%) | | |
| Original Group (%) | G1 | G2 | G3 | G1 | G2 | G3 | G1 | G2 | G3 | G1 | G2 | G3 |
| G1 | *92.3* | 0 | 7.7 | *76.9* | 7.7 | 15.4 | *92.3* | 0 | 7.7 | *100* | 0 | 0 |
| G2 | 27.3 | 72.7 | 0 | 9.1 | 90.9 | 0 | 9.1 | 90.9 | 0 | 0 | 100 | 0 |
| G3 | 0 | 0 | 100 | 0 | 8.3 | 91.7 | 8.3 | 25 | 66.7 | 0 | 25 | 75 |
| | (a) | | | (b) | | | (c) | | | (d) | | |

TABLE III

Confusion Matrix of the **Crossover Validation** of the Classification Models (**Gaussian** PDF estimation)

| | J=ACC, J2=TFN<br>NPV$_{G1}$=46.1%<br>TFN = 36.1% | | | J=ACC, J2= NPV$_{G1}$<br>NPV$_{G1}$=46.1%<br>TFN = 25.0% | | | J= NPV$_{G1}$, J2=ACC<br>NPV$_{G1}$=61.5%<br>TFN = 33.3% | | | J= NPV$_{G1}$, J2=TFN<br>NPV$_{G1}$=61.5%<br>TFN = 33.3% | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Classified Group (%) | | | Classified Group (%) | | | Classified Group (%) | | | Classified Group (%) | | |
| Original Group (%) | G1 | G2 | G3 | G1 | G2 | G3 | G1 | G2 | G3 | G1 | G2 | G3 |
| G1 | *46.1* | 23.1 | 30.8 | *46.1* | 23.1 | 30.8 | *61.5* | 15.4 | 30.8 | *61.5* | 15.4 | 30.8 |
| G2 | 36.4 | 18.2 | 45.4 | 45.4 | 27.3 | 27.3 | 45.4 | 36.4 | 18.2 | 45.4 | 36.4 | 18.2 |
| G3 | 25.0 | 50.0 | 25.0 | 8.3 | 25.0 | 66.7 | 25.0 | 33.3 | 41.7 | 25.0 | 33.3 | 41.7 |
| | (a) | | | (b) | | | (c) | | | (d) | | |

TABLE IV

Confusion Matrix of the **Optimum** Classification Models (**Kernel** PDF estimation)

| | J=ACC, J2=TFN<br>NPV$_{G1}$=92.3%<br>TFN = 2.8% | | | J=ACC, J2= NPV$_{G1}$<br>NPV$_{G1}$=92.3%<br>TFN = 2.8% | | | J=NPV$_{G1}$, J2=ACC<br>NPV$_{G1}$=100%<br>TFN = 8.3% | | | J=NPV$_{G1}$, J2=TFN<br>NPV$_{G1}$=100%<br>TFN = 8.3% | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Classified Group (%) | | | Classified Group (%) | | | Classified Group (%) | | | Classified Group (%) | | |
| Original Group (%) | G1 | G2 | G3 | G1 | G2 | G3 | G1 | G2 | G3 | G1 | G2 | G3 |
| G1 | *92.3* | 0 | 7.7 | *92.3* | 0 | 7.7 | *100* | 0 | 0 | *100* | 0 | 0 |
| G2 | 9.1 | 90.9 | 0 | 9.1 | 90.9 | 0 | 0 | 100 | 0 | 0 | 100 | 0 |
| G3 | 0 | 0 | 100 | 0 | 0 | 100 | 0 | 25 | 75 | 0 | 25 | 75 |
| | (a) | | | (b) | | | (c) | | | (d) | | |

TABLE V

Confusion Matrix of the **Crossover Validation** of the Classification Models (**Kernel** PDF estimation)

| | J=ACC, J2=TFN<br>NPV$_{G1}$=53.8%<br>TFN = 30.6% | | | J=ACC, J2= NPV$_{G1}$<br>NPV$_{G1}$=53.8%<br>TFN = 30.6% | | | J=NPV$_{G1}$, J2=ACC<br>NPV$_{G1}$=53.8%<br>TFN = 41.7% | | | J=NPV$_{G1}$, J2=TFN<br>NPV$_{G1}$=53.8%<br>TFN = 41.7% | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Classified Group (%) | | | Classified Group (%) | | | Classified Group (%) | | | Classified Group (%) | | |
| Original Group (%) | G1 | G2 | G3 | G1 | G2 | G3 | G1 | G2 | G3 | G1 | G2 | G3 |
| G1 | *53.8* | 15.4 | 30.8 | *53.8* | 15.4 | 30.8 | *53.8* | 15.4 | 30.8 | *53.8* | 15.4 | 30.8 |
| G2 | 36.4 | 36.4 | 27.2 | 36.4 | 36.4 | 27.2 | 27.3 | 63.6 | 9.1 | 27.3 | 63.6 | 9.1 |
| G3 | 16.7 | 41.7 | 41.7 | 16.7 | 41.7 | 41.7 | 33.3 | 33.3 | 33.4 | 33.3 | 33.3 | 33.4 |
| | (a) | | | (b) | | | (c) | | | (d) | | |

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