# Cepstrum Feature Selection for the Classification of Sleep Apnea-Hypopnea Syndrome based on Heart Rate Variability

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## Abstract

*Cepstrum Coefficients are analyzed in order to study its performance in Sleep Apnea Hypopnea Syndrome (SAHS) screening. A forward feature selection technique is applied in order to know for one thing, what cepstrum parameters can extract better information about the influence of breath sleep disorder on the heart rhythm, and on the other hand, trying to detect apneas based on the RR series obtained from the electrocardiogram (EKG).*

*70 ECG recordings from Computers in Cardiology Challenge 2000 are divided into a learning set and a test set of equal size. Each set consists of 35 recordings, containing a single ECG signal. Each recording includes a set of reference annotations, one for each minute, which indicates the presence or absence of apnea during that minute. These reference annotations were made by human experts on the basis of a complete polysomnography.*

*Statistical classification methods based on Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA) are applied to the classification of sleep apnea epochs. LDA presents a sensitivity of 64.1% and specificity of 90.2% (auc=0.87). QDA presents a sensitivity of 73.7% and specificity of 85.9% (auc=0.89). In both cases, contribution of the 4th coefficient related to Respiratory Sinus Arrhythmia plays an important role in SAHS detection.*

## 1. Introduction

The Sleep Apnea Hypopnea Syndrome (SAHS) is a respiratory disorder characterized by frequent breathing pauses and a collapse of pharynx during sleep. If breathing ceases completely, then the event is called apnea. In case breathing does not cease but there is a reduction in the volume of air entering the lungs, then the event is called hipopnea.

Previous studies have tried to diagnostic SAHS with the RR series obtained from the electrocardiogram (ECG) [1] with good performance, anyway the underlying regulatory mechanisms during apnea are still poorly understood. This fact makes necessary to explore appropriate feature estimation techniques in order to extract as much information as possible.

In previous contribution [2] we have used cepstrum features without taking into consideration any selection criteria. In this paper we apply forward feature selection in order to improve apnea screening performance and find coefficients which describe with more detail the RR pattern in presence of SAHS. We have selected features from a specific cepstrum coefficients set composed by the first 60 elements containing information about periodic structures of the RR series but also about the system modelled by the filter-type elements.

Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA) have been proposed in order to quantify apnea minutes. The system will provide also a global score of the presence of clinically significant apnea based on the minute by minute apnea detection. A subject will be classified globally as SAHS is the percentage of minutes with apnea is at least 16%.

## 2. Database

The database was provided by Prof. Dr. Thomas Penzel for Computers in Cardiology 2000 challenge [3].

The data have been divided divided into a learning set (L set) and a test set (T set) of equal size. Each set consists of 35 recordings, containing a single ECG signal digitized at 100 Hz with 12-bit resolution, continuously for approximately 8 hours. Each recording includes a set of reference annotations, one for each minute, which indicates the presence or absence of apnea during that minute. These reference annotations were made by human experts on the basis of simultaneously recorded respiration signals.

Group A (apnea) contains recordings with at least 100 minutes with apnea. The L set and T set each contain 20 class A recordings. Group B (borderline) contains between 5 and 99 minutes with apnea during the recording. The L set and T set each contain 5 class B recordings. Group C (control) contains fewer than 5 minutes with apnea. The L set and T set each contain 10 class C recordings.

## 3. Apnea and RR series

In some SAHS segments, heart rate tends to decrease during the beginning of an apnea phase and increase once this phase has ended. Figure 1 shows a clear example of this. Every SAHS phase coincides with an arousal and activation of the upper airway muscle permitting the entrance of air in the lungs. A low frequency periodic pattern can be observed from the sample 350.

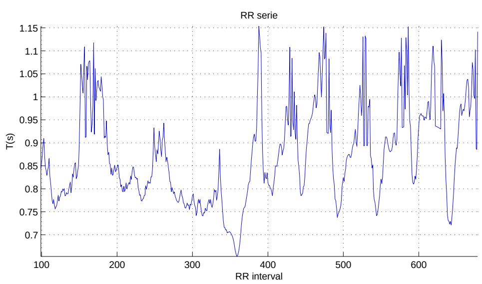


Figure 1. RR series of a SAHS patient

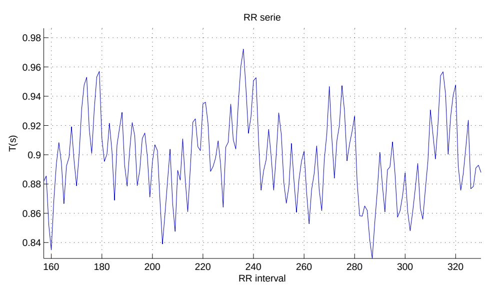


Figure 2. Respiratory sinus arrhythmia

Respiratory sinus arrhythmia (RSA) is a variation in RR series that occurs during a normal breathing cycle. This is another periodicity information taking place around 0.25 cycles/beat as can be seen in figure 2.

## 4. Method

EKG is segmented in 5 minutes frames, with 1 minute seconds of displacement between adjacent frames. Segments of ECG signals are band pass filtered between 20 and 35 Hz. Then the signal is full wave rectified and low pass filtered to 12.5 Hz.

A postprocessing is applied in the last step to eliminate possible errors with a mean filtering of sixth order followed by a median filter of a fifth order.

Real cepstrum coefficients have been calculated in 5 minutes segments and a forward feature selection technique have been used to try to extract variables related to the influence of breathing sleep disorders on the heart rhythm.

LDA and QDA have been proposed in order to quantify apnea minutes. With this quantification it is possible to report a percentage of apnea minutes with respect to the total number of sleep minutes. A subject will be classified as SAHS if the percentage of apnea minutes is at least 16%. This value represents around 10 apneas per hour.

## 5. Cepstrum analysis

Cepstrum features have been used with great success in the analysis of human speech, for instance, in pitch determination [4]. A cepstrum analysis is the result of taking the inverse Fourier transform of the logarithm of the magnitude of the RR spectrum. In particular, real cepstrum coefficients have been obtained from the original cepstrum. The independent variable in a cepstrum representation is called “quefrency”.

Contributions to the cepstrum due to periodic structures will occur at integer multiples of the fundamental period. In fact, if the signal under analysis is quasi-periodic, the contributions due to periodic structures will occur around the fundamental period.

During apnea episodes, the RR series shows a low frequency periodic structure and in case of normal respiration, a high frequency periodicity can be observed. In other intervals, a mixed periodic-aperiodic behavior may also be found. This fact poses the problem of using an analysis technique that can extract information about periodic structures. In this sense the cepstrum is a well-known technique which can be used for the analysis of RR series in the apnea detection task.

The short-time cepstrum is usually applied to the analysis of signals in a short-term basis and the Fast Fourier Transform (FFT) is used to estimate the spectrum. In this paper, once estimated the cepstral coefficients, we extract the first 60 of them which are expected to carry information about underlying regulatory system.

## 6. Classification

A linear discriminant analysis [5] is used in order to separate apnea and no apnea minutes. This classifier provides a parametric model that maps the feature inputs to the required output classes and has a set of adjustable parameters that are calculated with the learning data.

The models in this study assume that the feature have a class-dependent multivariate Gaussian distribution.

$$f_k(x) = \frac{1}{(2\pi)^{\frac{p}{2}}|\sum_k|^{\frac{1}{2}}} e^{-\frac{1}{2}(x-\mu_k)^T\sum_k{}^{-1}(x-\mu_k)} \tag{1}$$

where $\mu_k$ and $\sum_k$ are the mean vector and covariance matrix of each class k (apnea and no-apnea class).

LDA also makes the simplifying assumption that the class covariances are identical $\sum_k = \sum$ for both classes, and it is possible to define a linear boundary between the classes as:

$$\delta_k(x) = x^T\Sigma^{-1}\mu_k - \frac{1}{2}\,\mu_k^T\Sigma^{-1}\mu_k + log\,\pi_k \tag{2}$$

where $\pi_k$ is the prior probability of class k.

The parameters of the Gaussian distributions will be estimated using the learning data:

$\hat{\pi}_k = N_k/N$ ;

where $N_k$ is the number of class-k observations.

$\hat{\mu}_k = \sum_{g_i=k} x_i/N_k$

$\hat{\Sigma} = \sum_{k=1}^{K}\sum_{g_i=k}(x_i - \hat{\mu}_k)\,(x_i - \hat{\mu}_k)^T/\,(N-K)$

The LDA will classify one minute segment as apnea if

$$x^T\hat{\Sigma}^{-1}(\hat{\mu}_{ap}\text{-}\hat{\mu}_{nap}) > \frac{1}{2}\mu_{ap}^T\,\hat{\Sigma}^{-1}\,\hat{\mu}_{ap} - \frac{1}{2}\mu_{nap}^T\,\hat{\Sigma}^{-1}\,\hat{\mu}_{nap} + \\ + \log(\frac{N_{nap}}{N})\text{-}\log(\frac{N_{ap}}{N}) \tag{3}$$

where $\hat{\mu}_{ap}$ and $\hat{\mu}_{nap}$ are the mean vectors of class apnea and no-apnea respectively and $N_{ap}$ and $N_{nap}$ are the number of apnea and no-apnea observations.

If the $\sum_k$ are not assumed to be the same, we get quadratic discrimimant functions. The boundary region is defined as:

$$\delta_k(x) = -\frac{1}{2}log|\Sigma_k| - \frac{1}{2}(x-\mu_k)^T\Sigma_k^{-1}(x-\mu_k) + log\,\pi_k \tag{4}$$

## 7. Feature selection technique strategy

Repeated random sub-sampling validation is used in order to find what cepstrum parameters can optimize the classification performance, and thus to extract better information about the influence of apnea.

The method randomly splits the 35 recordings learning set (L set) into training and validation data taking into account that features extracted for a patient could not belong, at the same time, to training and validation sets. This process is repeated 50 times and predictive accuracy is assessed using the validation data from the L set.

A forward feature selection technique is used in each iteration and misclassification error rate can be calculated with the validation data. The final criteria to choose features, consists of taking the cepstrum coefficients which appear with more frequency in the order that are extracted.

In a second step (with the features selected in the order they were chosen in the previous task), the misclassification error is calculated for the validation data, chosen as another 50 repeated random sub-sampling validation set. It is possible to plot the averaged misclassification error in function of the number of features selected (figures 3 and 4).

Finally, the performance of the classifier is evaluated for the independent 35 recordings (T set) with the features selected via the L set.

## 8. Experiments and results

Forward cepstrum selection technique based on LDA and QDA have been proposed to the apnea quantification task. Only Group A and C training recordings have been used during the learning phase leaving out group B. Group A, B and C test recordings were taken into account in order to evaluate the success rates.

60 first cepstrum coefficients have been selected to extract information from the periodic and non periodic structures of the RR series.

Features are selected with a forward selection process where cepstrum coefficients are chosen in function of the frequency in which features are chosen for each iteration and order position.

Figure 3 shows the misclassification error obtained for the L set for LDA. For one thing, the graphic shows the evaluation of the error for training data in function of the number of variables selected. On the other hand, the evaluation of the error for the 50 times repeated random sub-sampling validation is also shown. Figure 4 shows the same process for QDA.

The number of features finally selected will depend on the capacity to obtain better performance for the validation data. In figure 3 for example, 56 features obtain the best results.

Table 1 summarizes the results of evaluating the independent T set with the features selected previously.

The rate obtained with LDA method for the T set is 80.3% (auc=0.87) for the classification of 1 minute segments, with 64.1% as sensitivity and 90.2% as specificity.

Global classification for LDA is 83.33%, taking into account a percentage greater than 16% of the minutes classified with apnea to decide if a recording belongs to a

SAHS patient or not.

QDA classifier improves the performance of the LDA detector for the T set with a classification rate of 81.3% (auc=0.89) with 73.7% as sensitivity, 85.9% as specificity and 93.33% as global classification.

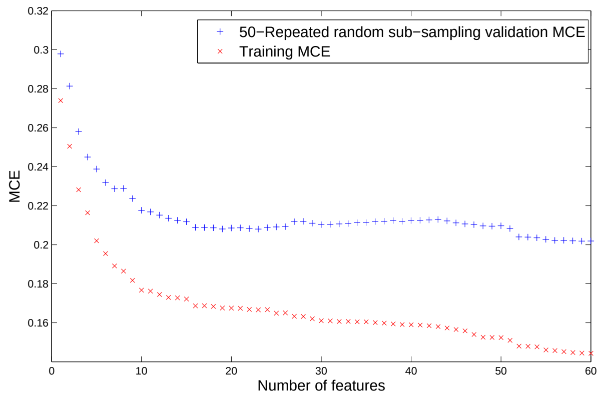


Figure 3. Evaluation of the misclassification error for L set and LDA

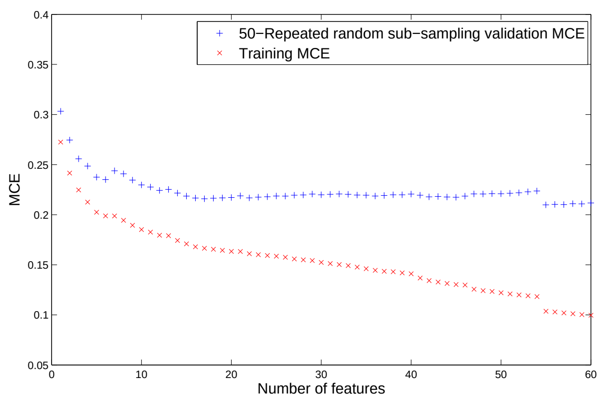


Figure 4. Evaluation of the misclassification error for L set and QDA

Concerning the relevance of the feature chosen, we must say that the misclassification rate maintains stable from 16 features are selected. The contribution of the variable situated in the quefrency 4, related to the RSA component (0.25 cycles/beat), is especially important. This feature was chosen more than 47 times from 50 iterations in LDA and also in QDA. Cepstrum coefficient in quefrency 15 is also selected as one of the most significant variables and it is related to the low frequency fluctuation in breathing sleep pauses.

Table 1. Success Rate for the T set

| CLASSIFIER | CLASS. RATE(%) | SENSITIVITY (%) | SPECFICITY (%) | GLOBAL CLASS.(%) | AUC |
|---|---|---|---|---|---|
| LDA | 80.3 | 64.1 | 90.2 | 83.33 | 0.87 |
| QDA | 81.3 | 73.7 | 85.9 | 93.33 | 0.89 |

# 9. Discussion

The use of cepstrum coefficients has been tested and its contribution extracting parameters usually related to the presence of periodicities, presents good results in the apnea classification task.

It can be concluded, that cepstrum coefficients, specially $4^{th}$ and $15^{th}$ coefficient, show good statistical information about the presence or not of breathing pauses during sleep. As a result, the use of cepstral coefficients could help to improve the performance of screening devices based on ECG and other biosignals.

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