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Application of Support Vector Machines and Gaussian Mixture Models for the Detection of Obstructive Sleep Apnoea based on the RR Series

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Abstract: - In this paper we present the performances of two automatic statistical methods for the classification of the obstructive sleep apnoea syndrome based on the RR series obtained from the Electrocardiogram (ECG). We study the effect of working with Support Vector Machines (SVM) and compare its performance with a reference detector based on Gaussian Mixture Models (GMM). These classifications methods require two previous stages: preprocessing and feature extraction. Firstly, we apply a preprocessing over the ECG for estimating the R instants which is previous to feature extraction. Secondly, a power-ratio-based coefficient (PRC) and a Linear Frequency Cepstral Coefficients (LFCC) parameterization over the RR signal is applied to extract the relevant characteristics. We fix the set of features for both classification methods.

Key-Words: - Sleep apnoea, RR Series, Support Vector Machines, Gaussian Mixture Models.

1 Introduction

Obstructive sleep apnoea is a breathing disorder with major health implications, ranging from excessive daytime drowsiness to serious cardiac arrhythmias.

Apnoea is associated with increased risks of high blood pressure, myocardial infarction, and stroke, and with increased mortality rates [1]. Apnoea produces an alteration of the normal sleep arquitecture with multiple arousals which causes somnolence during the day.

The most widely accepted diagnostic test for the sleep apnoea is overnight polysomnography (PSG). The expensive, time-consuming and disturbing nature of PSG prompts many sleep centers to perform an initial screening test in order to reduce the number of PSG.

A good alternative comes from the RR series obtained from the ECG signals [2]. Such series reflect changes in the airflow. In this paper, we study the application of RR series to apnoea detection. This is related to the necessity of reducing costs and making easier home diagnosis.

Currently, a diagnosis of sleep apnoea is made by counting the number of apnoea and hypopnoea events over a night sleep in an epoch-by-epoch basis (e.g.,[5]). Each one minute epoch is classified as normal or apnoea. After preprocessing the RR series it is necessary to extract features. A variety of techniques are at disposal for use in RR series. We have chosen a power-ratio-based coefficient and Linear Frequency Cepstral Coefficients (LFCC) because of their ability to extract features from the signals and their discrimination capacity.

To carry out the classification task we have preceded with the evaluation of two classification models: Support Vector Machines (SVM) and Gaussian Mixture Models (GMM). In the test phase, the system provides an epoch-by-epoch classification of normal or apnoea.

2 Database

The database was provided by Dr. Thomas Penzel of Philipps-University, Marburg, Germany [1].

The data have been divided divided into a learning set and a test 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 (individual recordings vary in length from slightly less than 7 hours to nearly 10 hours). Each recording includes a set of reference annotations, one for each minute of the recording, which indicates the presence or absence of apnoea during that minute. These reference annotations were made by human experts on the basis of simultaneously recorded respiration signals.

Three classes of recordings have been defined with the criterion proposed during the Computers in Cardiology Challenge 2000 [1]:

• **Group A (Apnoea)**: Recordings in class A contain at least 100 minutes with apnea during the recording. The learning and test sets each contain 20 class A recordings.

• **Group B (Borderline)**: Recordings in class B contain between 5 and 99 minutes with apnea during the recording. The learning and test sets each contain 5 class B recordings.

• **Group C (Control)**: These may be considered normal. Recordings in class C contain fewer than 5 minutes with apnoea during the recording. The learning and test sets each contain 10 class C recordings.

3 Method Overview

Our methods comprise the following steps.

• **Signals segmentation**: To carry out this work we segment our RR series in 5 minutes frames, with 1 minute seconds of displacement between adjacent frames. Thus we have enough time frequency resolution for feature extraction obtaining one feature vector every minute.

• **RR series generation**: Once the ECG signal is segmented, it is band pass filtered between 20 and 35 Hz. Then the signal is full wave rectified and low pass filtered to 12.5 Hz. Finally, a postprocessing is applied to eliminate possible errors with a mean filtering of sixth order followed by a median filter of a fifth order.

• **Feature extraction**: The following features have been applied: Power-ratio-based Coefficient (PRC) obtained by dividing spectral power in the very low frequency band (VLF, 0.01-0.05 cycles/beat) of the RR series by the total spectral power and Linear Frequency Cepstral Coefficients.

• **Training and Classification**: A Support Vector Machines has been proposed and its performance has been compared to a GMM–based model classification with a supervised training technique to estimate the models. We try to determinate the epochs with apnoea. Thus we try to identify the number of apnoea minutes presented during the night.

3 RR series and apnoea

Heart rate tends to decrease during the beginning of an apnoea phase and increase once this phase has ended. It can be seen an example of this in figure 1.

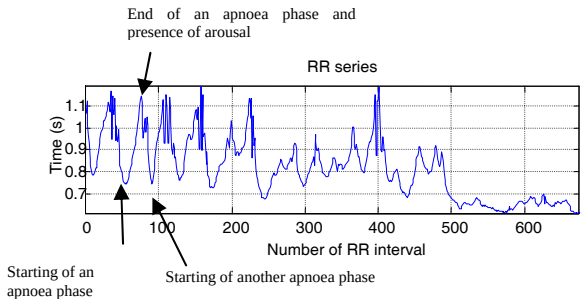

Fig. 1. Example of RR series in a patient with apnoea.

Every phase coincides with an arousal and activation of the upper airway muscle permitting the entrance of air in the lungs. Some authors [2] take into account the information that is present in the VLF band of the RR series. The mayor differences between pathological and non pathological RR series are centred in the VLF band and therefore, this consideration must be taken into account [4]. Frequency resolution in the VLF band is determined by the data length of the frames. The segmentation proposed allows a good frequency resolution in the VLF band and a proper feature extraction is possible.

In figure 2, we can appreciate an apnoea representation process of the patient with apnoea a03. In figure 2.a, a manual apnoea scoring is presented where the presence or absence of apnoea can be visualized. In figure 2.b, RR variations in the first 169 sleep minutes can be observed. Finally in figure 2.c, a RR series spectrogram for our 169 minutes sleep segment is analyzed. For this visualization we have chosen 256 beats length (about 5 minutes) and 205 overlapped beats. Thus it will be considered spectral information each 1 minute segment.

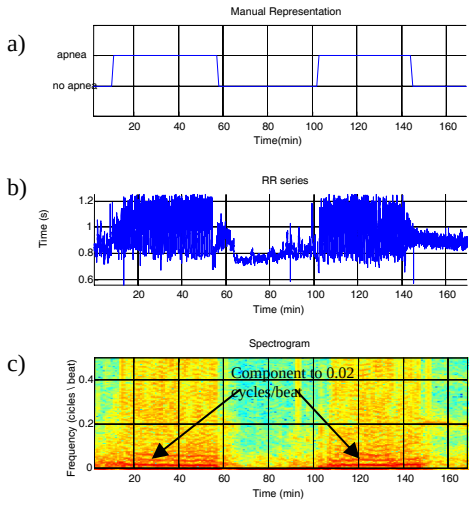

Fig. 2. Patient with apnoea a03. a) Manual representation, b) RR series, c) First 169 sleep minutes spectrogram.

4 Feature Extraction

The features that were considered are:

Power-ratio-based coefficient (PRC). The very low frequency band of the RR series reflects the existence of apnoea events [4]. We use a quotient between the power in the VLF band and the total power.

Linear Frequency Cepstral Coefficients (LFCC).

We have stated that the presence of apnoea has a clear consequence in the VLF band of the RR series energy. However, we must note that it exists RR series segments where these patterns are not so clearly visible [3]. This situation allows us to suggest an analysis with filter banks (Fbank) that covers the whole frequency band instead of a portion. A FFT-based bank of equally spaced filters is applied to obtain the power at each band. To avoid dependencies with signal dynamics, we normalise each filter output with the total signal power. A logarithm operation is applied to the power values in order to reduce the dynamic range thus keeping the whole frequency information. The number of filters used in our work has been 35.

Discrete Cosine Transform (DCT) has the property of decorrelating power values and reducing the dimensionality of the feature vectors while preserving the relevant information [4]. Thus, a matrix transformation is applied to the Fbank vectors where matrix coefficients are obtained with the DCT obtaining finally a 34 dimension vector.

5 Classification

The classification system we use is as follows:

5.1 Gaussian Mixture Models

A Gaussian Mixture Model (GMM) has been proposed as a classification method. The statistical distribution of the feature vectors for a given class (normal or apnoea) is represented by means of gaussian mixture with M Gaussian density functions in the mixture as follows [8]:

$$p(x \mid \Theta) = \sum_{i=1}^{M} \alpha_i p_i(x \mid \theta_i) \qquad (1)$$

where α_i is the weight of the i=th mixture and $p_i(x/\Theta_i)$ is a gaussian density for which the parameters $\Theta_i = \{\mu_i, \Sigma_i\}$ are μ_i the mean vector and Σ_i its covariance matrix, and M is the number of densities.

For the training phase we proceed with the application of the Expectation Maximization (EM) algorithm. For the election of the optimal number of gaussians M, we take into account the Bayes Information Criterion to try to solve the compromise between complexity and performance. With this criterion that number has been set to 7 in all experiments.

5.2 Support Vector Machines

In a binary classification task, a SVM provides the optimum hyperplane that maximize the separation margin among classes.

This procedure consists of a SVM training phase and a classification phase. Under certain condition (Mercer Condition), the scalar product in the output space can be written through a certain kernel K(x,y). [9].

$$(\phi(x_1) \cdot \phi(x_2)) = K(x_1, x_2) \qquad (2)$$

In these conditions, it is only necessary to know the kernel K(xi, xj), and not the transformation function $\phi(x_i)$.

The SVM output can be written as:

$$f(x) = sign\left(\sum_n \alpha_n y_n K(x, x_n) + b\right) \qquad (3)$$

where x_n are the training patterns, y_n the desired outputs and α_n the Lagrange multipliers. Vector associated to none zero multipliers are called “support vectors”, and fix the decision hiperplane.

In this work we have employed the following gaussian kernel:

$$K(x_i, x_j) = \exp\left(-(x_i - x_j)^2 * gamma\right) \quad (4)$$

The code used for the implementation of our application is the SVM Light [10].

6 Experiments and Results

The number of filters used for the experiments has been 35. On the other hand 34 coefficients is the output dimension of our DCT features. In addition, we insert the PRC as a first element of the feature vector leading to 35 elements feature vectors. These features are fixed and try to evaluate the classification methods proposed.

We have developed a comparative among SVM and GMM. We only have used Group A and C training recordings leaving out group B during the learning phase. However Group A, B and C test recordings were taken into account in order to

evaluate the success rates.

GMM procedure requires assuming some considerations [3]. For one thing, it has been considered a probability density function based on a sum of gaussian probability distributions. On the other hand, the optimum number of gaussian distributions has been elected according to a Bayes Information Criteria (BIC). Thus 7 is the number of gaussians elected. The rate obtained with this method is 81.7% for the global classification, 83.7% as sensibility and 80.5% as specificity.

It has been analyzed a SVM with gaussian Kernel through the SVM Light. In order to obtain the best results with SVM, it has been selected different gamma values. We have proceeded varying this parameter around the quantity which is obtained as "1/ the dimension of the feature vector". Gamma election must be a compromise among good learning performance from the training test and good classification rate with the probe database.

We have 35 coefficients in our feature vector, thus we can start with a gamma close to 0.03. According to the probe database the best results are observed for a gamma equal to 0.006 reaching a classification rate of 84.21%. The sensibility and specificity rates have been 79.2% and 87.3% respectively. From the sensibility and specificity point of view, it could be concluded that SVM detect better apnoea events than no apnoea ones.

In table 1 we can see a comparative of the procedures used in this work. (SVM vs GMM).

7 Conclusion

In this work we have probed procedures that present good results in the apnoea classification task.

It can be concluded, for the same database and features, a better performance of SVM versus GMM in the classification task. However we must take into account a better performance of GMM in the sensibility task. On the other hand SVM presents better specificity. In some applications as in ambulatory cases, it is desirable an automatic detection system with good sensibility.

Obstructive apnoea can be detected with good performance through the use of our procedures applied to a simple ECG signal and more concretely to a RR series derived from the ECG.

Our work confirms that a classification method using frequency domain features is a good election following the obtained results.

The algorithm can offer results which are similar to the ones obtained by an expert in a manual way, with the total set of apnoea signals.

Finally, our system results a simple and practical method of solving the obstructive sleep apnoea classification task.

TABLE I
SVM AND GMM SUCCES RATE FOR THE PROBE DATABASE

CLASSIFICATION METHOD	CLASSIFICATION RATE %	SENSIBILITY %	SPECIFICITY %
GMM	81.7	83.7	80.5
SVM	84.2	79.2	87.3

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