An Approach to the Enhancement of Sleep Apnea Detection by means of Detrended Fluctuation Analysis of RR intervals

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Abstract

In this paper, Detrended Fluctuation Analysis (DFA) of Heart Rate Variability (HRV) is applied in order to study the performance of a classification system of Obstructive Sleep Apnea (OSA), that integrates other variables as cepstrum coefficients and filter banks (FBANK) obtained from HRV

The database contains 70 records, divided into two equal-sized sets: a learning set and a test set. Each recording includes a continuous digitized single channel ECG signal and a set of apnea annotations, where a human expert classifies each minute indicating normal breathing or OSA, on the basis of a complete polysomnography (PSG).

An automatic statistical classification method based on QDA (Quadratic Discriminant Analysis) and Logistic Regression (LR) is applied to the classification of sleep apnea epochs. Particularly QDA presents an accuracy of 82.4% (auc=0.9) when FBANK and cepstrum coefficients are applied. The performance increases to 84.3% (auc=0.91) when DFA is added to the model. Similar improvement with LR when DFA is added can be reached 81.5% (auc=0.88) vs 84.2% (auc=0.91).

1. Introduction

Obstructive Sleep Apnea (OSA) is a sleep respiratory disorder with significant relevance characterized by frequent breathing pauses and a collapse of faringe during sleep.

Currently, the method to diagnose OSA is polysomnography (PSG) [1], however, this technique requires a lot of resources, such as a complex signal collection system and the presence of a specialist for diagnosis.

Detrented Fluctuation Analysis (DFA) has been used previously [2] to avoid spurious detection of correlations in the heartbeat time series in presence of OSA. The main goal of this study is to analyze the improvement of an automatic system using Detrented Fluctuation Analysis (DFA) variable when it is added to filter banks and cepstrum variables, both obtained from heart rate variability (HRV). Filter bank can detect the low frequency components of the heart during apnea episodes and cepstrum variables were extracted due to their usefulness to detect periodicities in the signals [3].

Logistic Regression (LR) and a Quadratic Discriminant Analysis (QDA) have been used as classifiers and two different experiments are realized for both cases. Filter bank and cepstrum analysis for one thing, and DFA variable, filter bank and cepstrum analysis, on the other hand. Thus, it is possible to analyze the contribution of DFA to increase the accuracy of the system.

2. Database

The database used for this research was provided for Dr. Penzel for Computers in Cardiology Challenge 2000. This database is composed of 70 recordings. 35 of these recordings are destined for a learning set and the others 35 for a test set. Each recording includes the electrocardiogram signal (EKG) with their corresponding scoring, which indicates normal breathing or sleep-disordered breathing (SDB) each minute.

After the individual study of each patient, the records are separated into three groups according to the total number of minutes with apnea. Group Apnea is composed of records with 100 or more minutes with respiratory events. There are 40 patients with these conditions (20 for the learning set and 20 for the test set). Group Control consists of the records with 5 or less minutes with respiratory events. There are 20 patients with these conditions (10 for each set). Group Borderline is composed for the rest of the recordings. There are 10 patients in this class (5 for each set).

3. Features obtained from RR series

In this paper, RR series obtained from the electrocardiograms are used for the experiments. An adaptive filtering procedure for automatic artifact removal is applied [4]. Five minutes epochs are used to extract features from RR intervals. Features can be divided into three groups depending on the domain they were extracted.

3.1. Detrented fluctuation analysis

Detrented Fluctuation Analysis allows the detection of long-range correlations embedded in a seemingly non-stationarity time series, and also avoids the spurious detection of apparent long-range correlations that are an artifact of non-stationarity [5]. In this case, DFA was applied to the RR series. The procedure to calculate DFA parameters basically consists of four steps [2]:

- 1. Determine the profile of the RR interval subtracting the mean.

$$Y(i) = \sum_{k=1}^{i} (\tau_k - \bar{\tau}), \quad i = 1,...,N \tag{1}$$

- 2. Divide the profile into $N_t = int(N/t)$ segments of equal length$t$. It is possible that the length N of time series is not multiple of time scale t, so that some samples of the end of the profile could not be included. To solve this, the process of segmenting the series is performed from beginning to end and from the end to the beginning, so that $2Nt$ segments are finally calculated.

- 3. Subtract the local trend for each segment. Local trend is calculated using a least-square fit of the data. Then, determine the variance of each segment $\nu, \nu = 1, \dots, N_t$.

$$F_t^2(\nu) = \frac{1}{t} \sum_{t=1}^{t} [Y((\nu-1)t + i) - p_\nu(i)]^2 \tag{2}$$

- 4. Fluctuation function is calculated averaging over all segments and then taking the square root.

$$F(t) = \sqrt{\frac{1}{2N_t} \sum_{\nu=1}^{2N_t} F_t^2(\nu)} \tag{3}$$

Steps 2 to 4 must be repeated for different time scales t.

If the data are long-range power-law correlated, increases, for large values of t, as a power-law

$$F(t) \sim t^{\alpha} \tag{4}$$

where the scaling exponent is an indicator of correlations. Values of $\alpha = 0.5$ indicate non-correlations in the time series.

In order to measure the long-range correlations, time scales t between 10 and 40 beats were applied. A second-order polynomial was fitted to the data (DFA2).

3.2. Filter bank

For the experiments, the study in the frequency domain was performed using the periodogram that gives an estimation of the power spectral density of the signal

$$S(k) = \frac{1}{N} \left| X_N(k) \right|^2 \tag{5}$$

where $X_N(k)$ is the discrete Fourier transform (DFT).

Once periodogram has been estimated, the signal is passed through a filter bank (FBANK). A bank of 34 filters equally spaced was used to analyze the spectrum.

3.3. Cepstrum coefficients

A cepstrum analysis was recently used to detect periodicities during apnea episodes [2] with good yield. This is due to the existence of periodic structures during these events in RR series. Specifically, a low frequency component during SDB can be observed, while a high frequency component during normal breathing may be found.

A cepstrum analysis is the result of taking the inverse Fourier transform of the logarithm of the magnitude of the RR spectrum.

For the experiments, 20 real cepstrum coefficients are obtained from RR intervals, since the information of interest is located in the lower part of the spectrum.

4. Classifiers

4.1. Logistic regression

Classification of apnea epochs was realized using Logistic Regression (LR). In this case, probability of apnea class is defined by p_{ap}. The expression of this probability is:

$$p_{ap} = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_{i1} + \dots + \beta_p X_{ip})}} \tag{6}$$

where $\beta_{0,\dots,p}$ are the coefficientes that fit the model.

4.2. Quadratic discriminant analysis

Quadratic Discriminant Analysis (QDA) has been also proposed in order to discuss the contribution of the

variables.

QDA assumes that the features have a class-dependent multivariate Gaussian distribution.

$$f_k(x) = \frac{1}{(2\pi)^{\frac{p}{2}}|\sum_k|^{\frac{1}{2}}} e^{-\frac{1}{2}(x-\mu_k)^T\sum_k{}^{-1}(x-\mu_k)} \quad (7)$$

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

The boundary region is defined as:

$$\delta_k(x) = -\frac{1}{2}log|\sum_k| - \frac{1}{2}(x-\mu_k)^T\sum_k^{-1}(x-\mu_k) + log\,\pi_k \quad (8)$$

where π_k is the prior probability of class k.

5. Feature selection technique

Once the features have been obtained, it is important to analyze those variables that provide more information about the respiratory events.

A repeated random sub-sampling validation, which splits the training set (35 recordings) into training and validation sets, is used in the experiments. These data sets are divided so that they do not have feature vectors of the same patient in both groups. The predictive accuracy is quantified using the validation set obtained from the original training set. This procedure is repeated for 50 iterations.

For different iterations, a forward feature selection is used, creating a new feature vector based on the number of times that they were extracted in each position, according to the technique that is used.

In the next step, the misclassification error is calculated using this new feature vector. The process is also repeated 50 times. Now, it is already reasonable to check the averaged misclassification error in function of the number of features.

6. Experiments and results

LR and QDA have been used for the experiments. For both classifiers, two studies have been performed, one using only FBANK and cepstrum variables (Table 1) and the other one, adding DFA (Table 2). After the feature extraction, the data set is normalized in order to minimize the dynamic range. In figures 1-4, misclassification error in function of number of features is shown. For example, in figure 4 (QDA using DFA), 5 features obtain the best results being selected DFA in first position.

The rates for both classifiers are similar, having a clear improvement when DFA is incorporated into the experiments.

For LR, the quantification rate is 81.5% (auc=0.88). The sensitivity obtained is 67.9% and specificity is 90% when only FBANK and cepstrum variables are used. In the study case with DFA variables, the rate improves up to 84.2% (auc=0.91) with 73.1% as sensitivity and 91.1% as specificity.

Using QDA, quantification rate is 82.4% (auc=0.9) with a sensitivity of 69.4% and specificity of 90.5% when FBANK and cepstrum variables are extracted from test set. The study using DFA improves the results. The quantification rate is 84.3% (auc=0.91) with 74.7% as sensitivity and 90.2% as specificity.

Table 1. Success Rate without DFA.

CLASSIFIER	CLASS. RATE (%)	SENSITIVITY (%)	SPECIFICITY (%)	AUC
LR	81.5	67.9	90	0.88
QDA	82.4	69.4	90.5	0.9

Table 2. Success Rate with DFA.

CLASSIFIER	CLASS. RATE (%)	SENSITIVITY (%)	SPECIFICITY (%)	AUC
LR	84.2	73.1	91.1	0.91
QDA	84.3	74.7	90.2	0.91

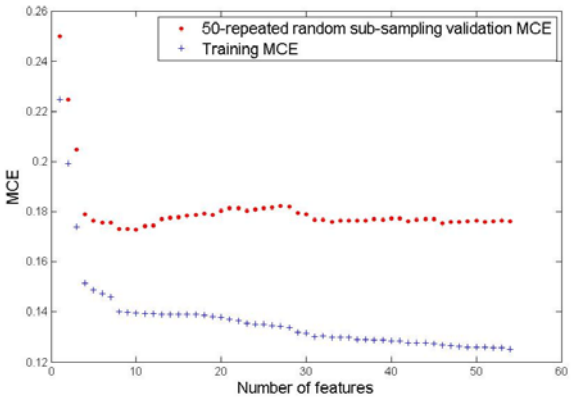

Figure 1. Evaluation of misclassification error for LR without DFA.

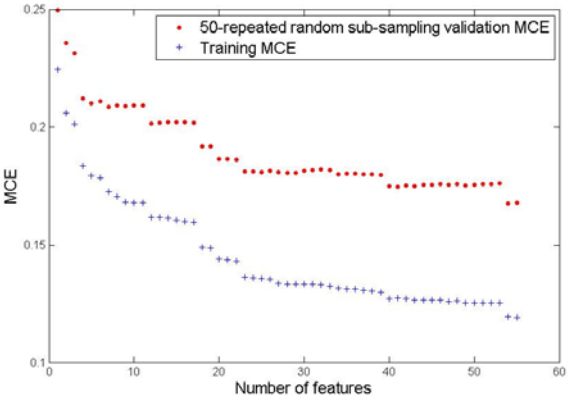

Figure 2. Evaluation of misclassification error for LR with DFA.

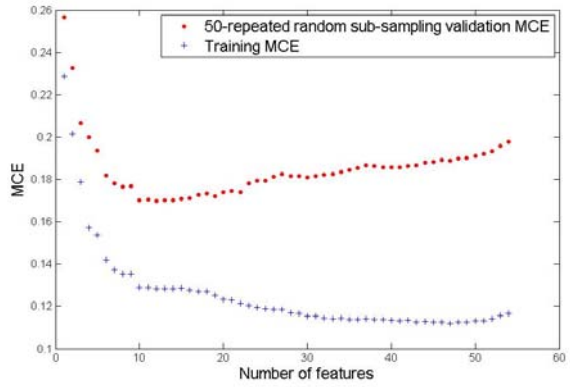

Figure 3. Evaluation of misclassification error for QDA without DFA.

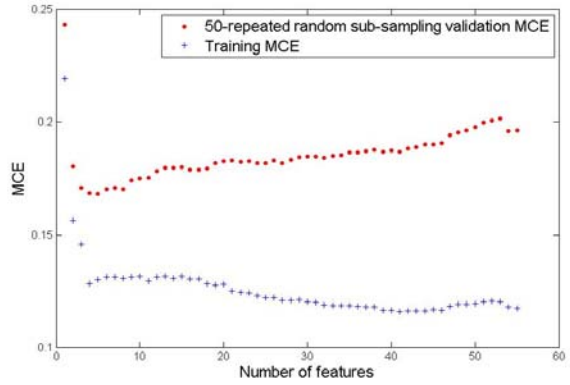

Figure 4. Evaluation of misclassification error for QDA with DFA.

7. Discussion

The use of Detrended Fluctuation Analysis has been tested. Both classifiers performed best using information derived by DFA.

It is especially important the contribution of slope of the fluctuation function (time scales t between 10 and 40 beats) which is selected in first position for QDA. Moreover, combination of these features with oximetry variables could improve the performance of the classifier.

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