Detection of Sleep Apnea in Single Channel ECGs from the PhysioNet Data Base

M Schrader, C Zywietz, V von Einem, B Widiger, G Joseph

Biosignalprocessing, Medical School, Hannover, Germany

Abstract

We have analyzed single channel ECGs from the Marburg Sleep Laboratory downloaded from Physionet. 35 Data sets with sleep apnea annotation (Learning Set) and 35 testing cases without annotation were available. Our Analysis and annotations are based on spectral components of heart rate variability. Frequency analysis was performed using Fourier and Wavelet Transformation with appropriate application of the Hilbert Transform. Classification is based on four frequency bands. We defined: ULF band (0-0.013 Hz) VLF band (0.013-0.0375 Hz) LF band (0.0375-0.06 Hz) and the HF band 0.17-0.28 Hz).

For classification linear discriminant functions using spectral components and other variables derived from the records have been used. Classification of cases by means of three variables resulted for the Learning Set in a sensitivity for apnea of 95,0% at a specificity of 100.0% and for the minutes annotation a sensitivity was 90.8% and specificity 92.7%. Allocation per minute based on a discriminant function using 30 variables.

1. Introduction

Detection of *Obstructive Sleep Apnea* (OSA) from heart rate variability has gained increasing interest during the past years. A major advantage is the non invasive data aquisition procedure since the signal to be analysed might be taken from a Holter ECG recorded even outside the hospital.

Akselrod published in 1981 a paper on Power Spectrum Analysis of Heart Rate Fluctuation: A quantitative prove of beat to beat cardiovascular control [1]. The major attraction of this result was that measurements for the activity of the sympathetic and parasympathetic autonomous cardiovascular control could be derived and investigated on normals and specifically on patients with heart disease. In 1999 Otzuka [2] published Circadian reference values for different end point of heart rate variability from normals of different age groups and for patients with coronary artery diseases. Moody et al [3] reported 1985 on the Derivation of Respiratory Signals from multi lead ECGs.

In this investigation they focused on Vectorial Changes of the ECG but postulated already that also from two or single channel ECGs respiration could be derived. In 1999 Penzel reported on "Sleep Stage Dependent Heart Rate Variability in Patients with Obstructive Sleep Apnea" [4]. This paper as well as the fact that sleep disorders have a significant impact on public care since prevalence of sleep apnea was estimated as high as 9% for women and 25% for man (New England Journal of Medicine 1993 [5]) have stimulated the organizers of the Computers in Cardiology 2000 Conference to open a contest for detection of sleep apnea from single channel ECGs.

1.1. Heart rate variability – sleep apnea

The *Heart Rate Variability* (HRV) represents the net effect of the parasympathetic nerves, which slow down HR, and the sympathetic nerves, which accelerate it. For transfer of breathing disorders there are afferent impulses from the baroreceptors. Then the vasomotor centers modulate the sympathetic- and the parasympathetic nervous system.

So if the autonomous nervous system reacts, it should be able to detect some of its effects on the HR (e.g. OSA) through different analyzing methods of HR.

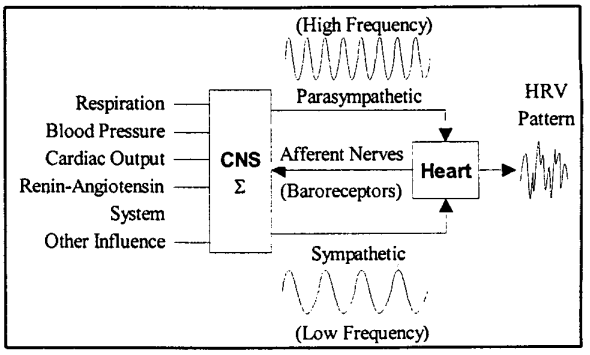

Figure 1. The interaction between the heart and the Central Nervous System (CNS).

Different methods have been applied to investigate characteristic properties of HRV by means of

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Computers in Cardiology 2000;27:263-266.

autoregresive modeling (e.g. Cerutti) [6], by nonlinear dynamics (e.g. Unbehaun) [7]. Our work focussed on spectral analysis methods.

2. Materials and methods

2.1. Materials

The analysing methods are based on a Learning Set to classify a Test Set downloaded from the Physionet Database. Each set consists of 35 ECG recordings digitized at 100 Hz with 12-bit resolution (5μV/LSB), continuously for approximately 8 hours.

The subjects of these recordings are men and women between 27 and 60 years of age old, with weights between 53 and 135 kg. The Learning Set consists: 20 ECGs with OSA > 100 minutes (Class A), 10 with OSA < 5 minutes (Class C) and 5 with OSA > 5 and < 100 minutes (Class B). For each ECG from the Learning Set there exist reference annotations, one for each minute of recording, made by human experts. Eight recordings include three respiration signals.

2.2. ECG preprocessing

The single channel ECGs were off-line digitized after 2nd degree cubic spline interpolation to a sampling frequency of 500 Hz to allocate the RR-tachograms with our own HES LKG (Holter) ECG algorithm. For a better RR-interval analysis the signal was refined of spikes and extrasystoles. To get equidistant time series, the signal was digitized to 4 Hz with a linear interpolation and analyzed using the Discrete Fourier Transformation.

2.3. Fourier transformation (FT)

The mean spectral diagram, that is calculated from the power spectrum of the complete ECGs, shows different frequency bands based on the RR-interval fluctuations from the Learning Set (Figure 2). Four major components ca be identified: ULF band (0-0.013 Hz), VLF band (0.013-0.0375 Hz), LF band (0.0375-0.06 Hz) and the HF band (0.17-0.28 Hz).

The HF range reflects the fast changes in the beat-to-beat variability which are due to parasympathetic or vagal stimulation, whereas the VLF is thought to reflect mostly sympathetic stimulation. The LF region represents a mixture of both sympathetic and parasympathetic stimulation of the heart.

The highest differences between pathologic and non pathologic RR-interval spectra are in the VLF band.

It should be kept in mind that the resampling frequency of the RR-intervals determines the upper frequency limit detectable while the resolution in the lower frequency band depends on the length of the data section transformed. We have experimented with sampling rates of 1..4 Hz for the RR-series. The best match with the significant VLF band in the Learning Set was 2.4Hz.

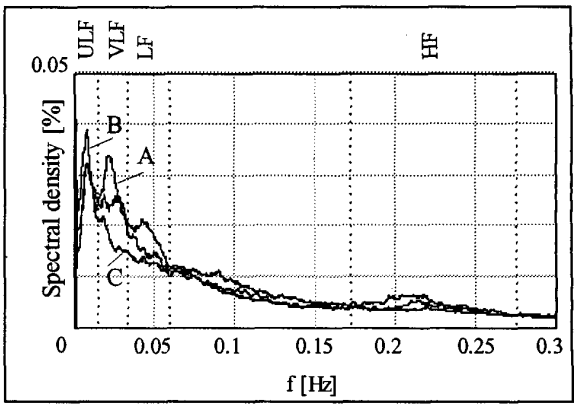

Figure 2. Mean spectral density of the RR-intervals from Learning Set

The occurance of the VLF frequency can also be seen with graphically visualization of *the Discrete Fourier Transformation* (DFT). Using a base interval of 30 minutes shows, that this band is only present if there is OSA in the ECG (Figure 3).

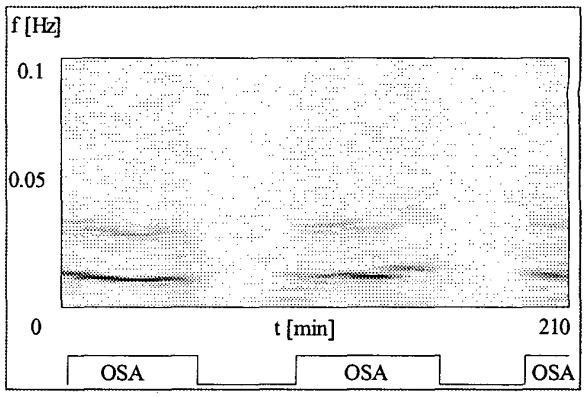

Figure 3. DFT from RR-intervals, window width 30 minutes, step 0.5 minutes

2.4. Wavelet analysis

The *Continuous Wavelet Transformation* (CWT) uses linear combinations of wavelet functions to represent a signal f(t). In contrast to the infinite-duration sinusoids of Fourier analysis, a *wavelet* is localized in time, and separate a signal into multiresolution components. Like Fourier analysis, wavelet analysis features a fast algorithm for decomposing a signal into its simpler

component elements. The localization property of wavelets allows them to efficiently portray signals and images with discontinuities.

2.4.1. Discrete wavelet analysis (DWT)

The disadvantage of the CWT is the fact that the information it provides is highly redundant as far as the reconstruction of the signal is concerned and it requires high computational effort. So we used the DWT. The DWT is applied to a multiplication of the data vector with the matrix. The matrix is applied in a hierarchial algorithm, sometimes called *pyramidal algorithm.*

The matrix is first applied to the original, full-length vector. Then the vector is smoothed and decimated by half and the matrix is applied again. This process continues until a desired base level (lower frequency band) is reached. Therefore the number of data points from the signal must be a 2^L value (L=number of levels).

We used the Battle-Lemarie wavelet. It shows very good filter characteristics. Within the stop band the phase shift is almost zero and the decay at the cut off frequency reaches 400 dB / decade.

The following picture shows the original signal (OS), the hilbert transformation (HT), the level 6 of wavelet transformation (DWT) and the OSA annotation based on the functions described before.

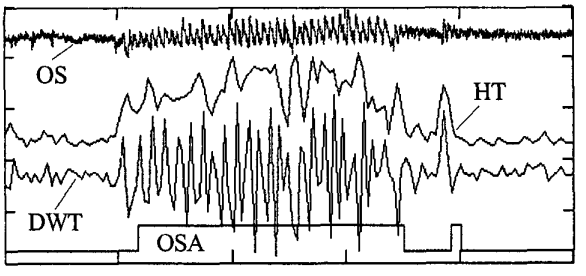

Figure 4. Original signal transformations and annotation

2.4.2. Multi resolution analysis (MRA)

Multiresolution Analysis was formulated based on the study of orthonormal, compactly supported wavelet bases. The MRA allows multiresolution information extraction from geometrical information along with the associated textures.

Figure 5 illustrates the original signal (OS), MRA level 5 (MRA5), MRA level 3 (MRA3) and the OSA annotation. MRA level 3 shows the respiration signal (breathing) and while OSA, the frequency in MRA level 5 is higher than without OSA.

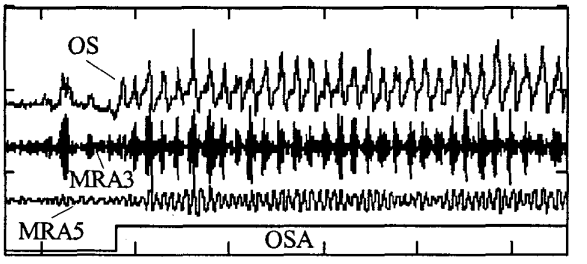

Figure 5. Multiresolution Analysis of the RR-interval

2.5. Discriminant function analysis

The main use of *Linear Discriminant Analysis* (LDA) is to predict group membership from a set of predictors (variables). LDA consists of finding a transform which gives the maximum ratio of difference between a pair of group multivariate means to the multivariate variance within the groups.

In a first step a step wise multivariate analysis of variance was performed. Based upon F-statistics and correlation the best variables were kept and discriminant functions were computed.

The variables for case and minutes allocation based on about 25 subgroups of frequency and statistic signal analysis. For case allocation we got three and for minutes allocation we got 30 significant variables.

3. Results

3.1. Case allocation (screening)

The results for case A and C, based on LDA and cross validation, with three variables shows an accuracy of 96.7% (Learning Set) and 93.3% (Test Set). The values for sensitivity, specificity, the negative praedictive value and the positive praedictive value from the Learning Set are calculated.

Performance measures for Normal/Apnoe cases

Sens	95.0 %	Spez	100.0 %
Neg Prae	90.9 %	Pos Prae	100.0 %

X1	X2	X3	X4	X5	X6	X7
X8	X9	X10	X11	X12	X13	X14
X15	X16	X17	X18	X19	X20	X21
X22	X23	X24	X25	X26	X27	X28
X29	X30	X31	X32	X33	X34	X35

Table 1. Case classification A (gray) and C (white) with three variables

3.2. Minute allocation (quantification)

The results, based on LDA and cross validation, with thirty variables shows an accuracy of 92.0% (Learning Set) and 88.31% (Test Set). The values for sensitivity, specificity, the negative praedictive value and the positive praedictive value from the Learning Set are calculated.

These numbers give the following performance measures for the minutes allocation

Sens	90.8 %	Spez	92.7 %
Neg Prae	94.2 %	Pos Prae	88.6 %

Table 2 shows the case classification with 30 variables based on apnea minutes allocation. An index (Table 3) was calculated (Apnea minutes/ECG recording minutes). If the Index is greater than 8% it is classified as case A.

X1	X2	X3	X4	X5	X6	X7
X8	X9	X10	X11	X12	X13	X14
X15	X16	X17	X18	X19	X20	X21
X22	X23	X24	X25	X26	X27	X28
X29	X30	X31	X32	X33	X34	X35

Table 2. Case classification A (gray) and C (white) based on apnea minutes allocation

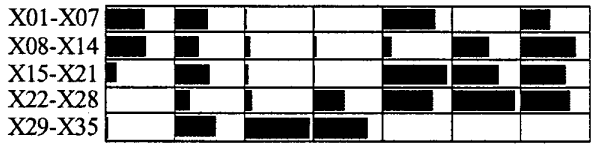

Table 3. Index (Apnea minutes/ECG recording time) based on 30 variables

4. Summary and conclusion

ECG Data for this type of study should sampled at least with 500 S/s to make sure that measurement errors are at least one order of magnitude smaller than the variable to be investigated. More than one lead should be recorded to identify more reliable extrasystoles and eventually ischemia effects.

We achieved on the Learning Set a sensitivity of 90.8% and a specificity of 92.7% (OSA minutes allocation). This is a promising result for further work to detect OSA non invasive by means of the ECG. Our analyses was only focused on spectral components. It is well possible that stratification of data sets, autoregressive modeling and use of non linear dynamics the OSA minutes detection rate could be improved.

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Address for correspondence
M. Schrader, Chr. Zywietz
Biosignalprocessing –8440-
Medical School MHH
Carl-Neuberg-Str. 1
30625 Hannover, Germany
e-mail: Schrader.Mark@MH-Hannover.de