Sleep Apnoea Detection
in Single Channel ECGs by Analyzing Heart Rate Dynamics

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Abstract-**Sleep apnoea is often cause of/or associated with hypertension and of risk factors like "seconds sleep" during the day. Sleep disorders are typically investigated by means of polysomnographic recordings. We have analyzed 70 eight-hour single-channel ECG recordings to find out to which extent sleep apnoeas may be detected from the ECG alone. From the 70 data sets 35 were annotated by experts for phases of regular sleep and phases with sleep apnoea. Our analysis is 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 were applied using spectral components and other variables derived from the records. Classification was made for patient records as a whole and for the minutes in each of the recordings. Classification of cases was based on three variables. For the Learning Set a sensitivity for apnoea of 95.0% at a specificity of 100% was achieved. For the minutes allocation a sensitivity of 90.8% at a specificity of 92.7% was obtained.**

Keywords - **Sleep apnoea, ECG Analysis, HR-Variability**

1. INTRODUCTION

Detection of *Obstructive Sleep Apnoea* (OSA) from heart rate variability has gained increasing interest during the past years. A major advantage is the non-invasive data acquisition procedure since the signal to be analyzed 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 points of heart rate variability from normals of different age groups and for patients with coronary artery disease. 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 channel or single channel ECGs respiration could be derived. In 1999 Penzel reported on "Sleep Stage Dependent Heart Rate Variability in Patients with Obstructive Sleep Apnoea" [4]. This paper (as well as the fact that sleep disorders have a significant impact on public care, since prevalence of sleep apnoea was estimated as high as 9% for women and 25% for man (New England Journal of Medicine 1993 [5])) has stimulated international research for detection of obstructive sleep apnoea in ECG recordings taken during night time.

In 2000 a database of 70 cases with and without sleep apnoea has been made publicly available from T. Penzel, Marburg University, through the Harvard-M.I.T. PhysioNet [6]. All of the eight-hour ECG recordings have been annotated for phases with sleep apnoea and sleep with regular respiration. The annotations have been based on polysomnographic recordings with respiration measurements, ECG, EOG, EMG and blood oxygen saturation measurements.

1.1 Heart Rate Variability - Sleep Apnoea

Obstructive Sleep Apnoea is characterized by repetitive cessations of respiratory flow during sleep. The cessations of respiratory flow occur due to a collapse of the upper airway at the level of the oropharynx. There is an imbalance between the neural activation of the diaphragm and the upper airway muscles in patients with obstructive apnoea. The collapse in the upper airway results in a reduced airflow and as a consequence a lack of oxygen and an increase of CO_2 which causes a central nervous activation called *Arousal*. In most patients a drop of heart rate is also observed during each apnoea followed by an increase of heart rate near the end of the apnoea. This increase peaks during the few breaths after the apnoea. The cyclic behavior of heart rate has been called Cyclical Variation of Heart Rate and is considered as being specific for sleep apnoea [6,7,8].
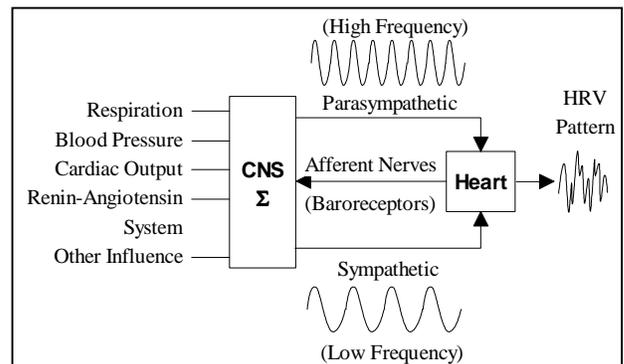

Figure 1. The interaction between the heart and the Central Nervous System (CNS).

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 sympathetic- and the parasympathetic nervous system.

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Abstract

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If the autonomous nervous system reacts, it is possible to detect some of these effects on the HR (e.g. OSA) through different analyzing methods of HR.

Different methods have been applied to investigate characteristic properties of HRV by means of autoregressive modeling (e.g. Cerutti) [9], by non-linear dynamics (e.g. Unbehaun) [10]. Our work focussed on spectral analysis methods.

2.0 MATERIAL AND METHODS

2.1 Material

A data set of 70 ECGs with a recording duration between 401 and 578 min were used from the PhysioNet database [6] for the study. 35 of the 70 were provided with annotation based upon polysomnographic analysis. All ECGs had a digital resolution of 100 Hz sampling frequency with an amplitude quantization of 12 bit and 5µV/LSB. The annotated 35 cases could be used as Learning Set.

The subjects of these recordings are men and women between 27 and 60 years of age, with weights between 53 and 135 kg. The Learning Set consists of: 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 apnoea annotations for each minute of recording, made by human experts. Eight of the recordings are provided with three respiration signals.

2.2 ECG preprocessing

The single channel ECGs were off-line re-digitized at a sampling frequency of 500 Hz after a cubic spline interpolation to construct RR-tachograms with our own HES LKG (Holter) ECG algorithm. For the RR-interval analysis the signal was refined from spikes and extrasystoles. The RR Interval series was interpolated linearly and resampled at frequencies between 1 Hz...4Hz for various frequency transformations.

2.3 Fourier Transformation (FT)

The mean spectral diagram, that is calculated from the power spectrum of the all ECGs of the learning set, shows different frequency bands due to the RR-interval fluctuations (Figure 2). Four major components can be identified: the Ultra Low Frequency band ULF (0-0.013 Hz), the Very Low Frequency band VLF (0.013-0.0375 Hz), the Low Frequency band LF(0.0375-0.06 Hz) and the High Frequency band HF (0.17-0.28 Hz).

The HF range reflects the fast changes in the RR-variability 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.
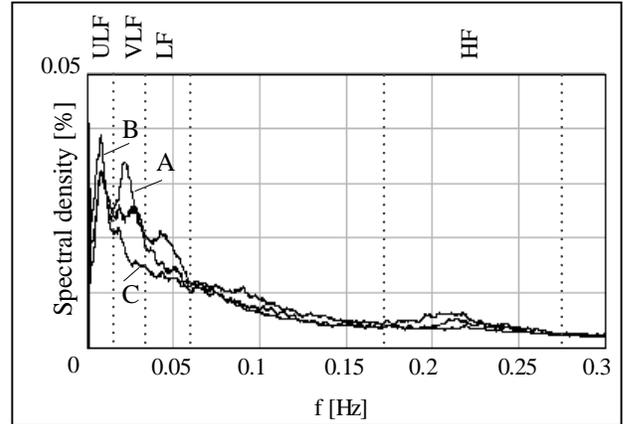

Figure 2. Mean spectral density of the RR-intervals from Learning Set

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 data intervals up to the full record length ~ 500 min and 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.

The occurrence of the VLF frequency can also be seen with graphical display of *Discrete Fourier Transformation* (DFT) results. Using a base interval of 30 minutes shows, that this band is only present if there is Obstructive Sleep Abnoea (Figure 3).
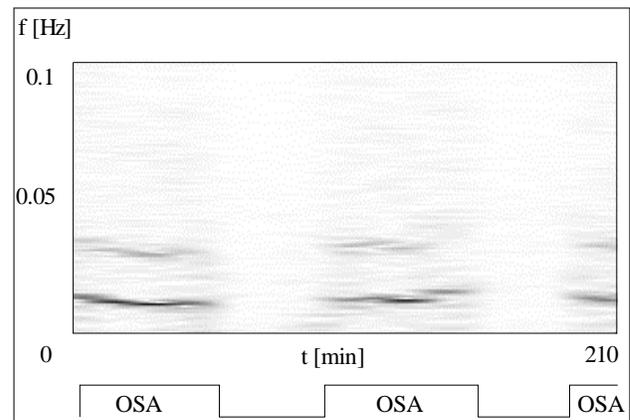

Figure 3. DFT from RR-intervals, window width 30 minutes, step with 0.5 minutes

2.3 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 separates a signal into multiresolution components. Like Fourier analysis, wavelet analysis features a fast algorithm for decom-

posing a signal into its fundamental component elements. The localization property of wavelets allows to efficiently portray signals and images which are non-stationary in the frequency components.

2.3.1 Discrete Wavelet Analysis (DWT)

The disadvantage of the CWT is that the provided information is highly redundant as far as the reconstruction of the signal is concerned. It requires high computational effort. We used the DWT. The DWT is applied to a multiplication of the data vector with the matrix. The matrix is applied in a hierarchical algorithm, often 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 (Figure 4). Within the stop band the phase shift is almost zero and the decay at the cut off frequency reaches 400 dB / decade (see fig.4).
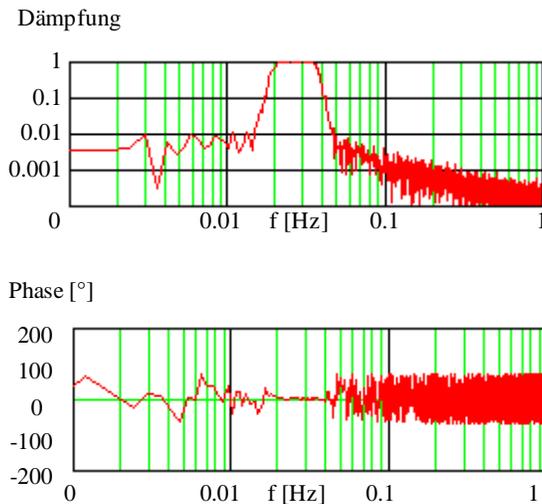
Dämpfung

Phase [°]

Figure 4. Wavelet Amplitude- and Phasecharacteristics

The following figure shows the original (RR-interval) signal (OS), the Hilbert transformation (HT), the level 6 of wavelet transformation (WT) and the OSA annotation based on the functions described before.
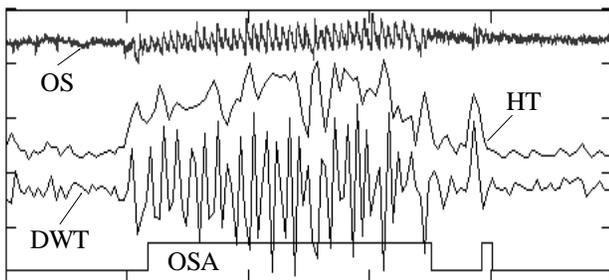

Figure 5. Original signal, transformations and annotation

2.3.2 Multi Resolution Analysis (MRA)

Multiresolution Analysis was 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). During obstructive sleep apnoea (OSA ="high") MRA levels 3 and 5 show the higher "frequency content", the frequency in MRA level 5 is higher than without OSA.
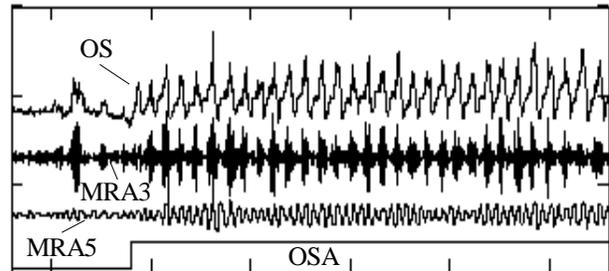

Figure 6. Multiresolution Analysis of the RR-interval

2.4 Discriminant Function Analysis

Signal parameters of patients, respectively of ECGs, are typically characterized by statistical properties, e.g., mean value x and standard deviation s. These values may differ in different classes of patients/ECGs, e.g., during sleep at regular respiration and during apnoea phases. Those parameters may be used to allocate a measurement to one of these classes. However, typically the measurements show overlap of their distributions between the groups. This results in misclassifications if these variables are used for group allocation. The group separation may be improved if several variables are used for this purpose. If there is a set of n-variables available, for statistical reasons, a subset of m-variables may be used for classification. This subset can be found by linear discriminant function analysis. Applying analysis of variance to the total set of variables, the most discriminant variables are selected based on their contribution to a statistical distance measure between the groups. A linear combination of variables is calculated where selection of variables and their weight is calculated after a transformation which maximizes the between group distance and minimizes the within group distance of cases. In this study two types of allocations were performed:

a. separation of cases with and without sleep apnoea
b. identification of minutes with sleep apnoea against minutes without sleep apnoea.

Discriminant functions are rather robust if the number of variables used is much smaller than the number of cases. To determine these variables, with input from the amplitude time signal as well as from the transformed signals the set of 35 annotated ECG records has been subdivided into a sub-learning set of 18 cases and a sub-testing set of 17 cases.

Three variables have been finally selected for separation of cases.

For allocation of minutes several thousands of minutes with and without sleep apnoea have been available from the same Learning Set and therefore thirty variables from the amplitude time signals and from the transformed signals have been selected.

3.0 RESULTS

3.1 Case allocation (Screening)

The results for case A and C classification, based on LDA and cross validation, using three variables, shows an accuracy of 96.7% (Learning Set) and 93.3% (Test Set). The values for sensitivity, specificity, the negative predictive value and the positive predictive value from the full Learning Set (35 cases) are:

Performance measures for Normal/Apnoea cases

| Sens. | 95.0 % | Spec. | 100.0 % |
| Pos. Pre. | 100.0 % | Neg. Pre. | 90.9 % |

The following table shows the case allocation of the Test Set where the annotation was unknown.

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

From the PhysioNet Center this classification was evaluated as 28 out of 30 clear-cut cases (class A and class C) correct. This gives a performance of 93.3 %.

3.2 Minutes allocation (Quantification)

The results, based on LDA and cross validation, with thirty variables shows an accuracy of 92.0% on the Learning Set. The values for sensitivity, specificity, the negative predictive value and the positive predictive value are shown on the following table:

Performance measures for Normal/Apnoea min

| Sens. | 90.8 % | Spec. | 92.7 % |
| Pos. Pre. | 88.6 % | Neg. Pre. | 94.2 % |

4. SUMMARY AND CONCLUSIONS

ECG Data for this type of study should be sampled at 500 S/s to reduce ECG complex localization uncertainty. Also more than on lead should be available for better identification of exrasystoles. The results we achieved are promising for further work to detect OSA non invasively by means of the ECG. Our analyses were only focused on spectral components. It is well possible that stratification of data sets, autoregressive modeling and use of non-linear dynamics could improve our detection rates.

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