Obstructive Sleep Apnea Detection Based on Electrocardiogram Analysis

Z Shinar, A Baharav, S Akselrod

Abramson Centre for Medical Physics, Tel-Aviv University
Sleep and Fatigue Institute, Sheba Medical Centre, Israel

Abstract

Obstructive Sleep Apnea is a frequent disorder with detrimental health, performance and safety effects. The diagnosis of the disorder is cumbersome and expensive. New methods for screening and diagnosis are needed. The method we describe in this work is based on detection of respiratory disturbance during sleep from continuously monitored ECG during the night. The detection is based on QRS complex changes caused by apneas and spectral abnormalities in the Heart Rate Variability which are related to recurrent respiratory events. An automatic step-by-step approach, based on these two already described phenomena, was developed, validated and then applied on data supplied by Physionet for the CinC Challenge 2000. The methods yield results in excellent agreement with the manually scored standard sleep studies, and achieved 14788/17262 correct classifications on minute-by-minute bases.

1. Introduction

Obstructive Sleep Apnea (OSA) represents a major, yet mostly unrecognised night-time disease which adversely affects daytime health, performance and wellbeing. This widespread disorder has both individual and public implications. The main drawback in diagnosis, besides insufficient awareness, is the cost of the standard diagnostic polysomnographic studies and the lack of reliable screening methods of detection.

The surface Electrocardiogram (ECG) is a robust, easy to acquire physiological signal, which contains concealed information on central autonomic control of cardiovascular function, respiration, and the electric activity of the heart itself.

Slight anatomical shifts and/or rotations that occur with the respiratory excursion or with a change in body position can be now detected in the ECG. The necessary assumption is that respiratory abnormalities might be uncovered by detection of subtle changes in the electrocardiogram.

The objective of the present study was to develop a method of detection of OSA based on ECG **only**.

2. Methods

We first developed a general design aimed to detect respiratory disturbances as they are reflected in the ECG. Then we validated this step-by-step apnea detection algorithm on a training set data supplied by Physionet database for CinC challenge 2000 [1]. Finally we applied the algorithm on a test set of data that included night-time recordings from 35 subjects. This time we were blinded on the diagnosis and degree of sleep related breathing disorder of the patients. The data included only the ECG traces (sampled at 100Hz) of the whole night sleep study.

The automated algorithm consisted of the following steps:

1. Prepare RR interval (RRI) data for spectral analysis and pattern searching, by dividing the records into segments containing data collected from a single body position and excluding awakenings.
   1.1. Scan ECG for peak detection, and correct artefacts to obtain two RRI series:
      1.1.1. A first one (type I) for R Wave Duration (RWD) calculations, according to the algorithm described in [3]. In this series only normal QRS were kept and abnormal beats ignored. Less than 1% of beats were discarded during this process.
      1.1.2. A second series (type II), for spectral analysis, included abnormal beats and interpolations in case of premature or missing beats.
   1.2. Use RWD series to dissect the RR signal into segments according to subject's body position [3](see fig 1). We chose 200 seconds as minimal segment length, considering multiple body position changes during such a period as one position change.
      1.2.1. Upsample ECG data and calculate RWD, for each QRS, from RRI series type I, thus obtaining a RWD series (fig 1b).
      1.2.2. Use a 4th order Butterworth low pass filter (LPF) on RWD signal to enhance the difference between RWD levels (body positions – see fig 1c).

1.2.3. Use a moving threshold to identify a step change in filtered RWD. First determine the cross point of the threshold and the RWD signal, then detect a step change wherever RWD signal is below/above the threshold for at least 200 seconds before the cross point and above/below the threshold for at least 200 seconds after the cross point. The dashed lines in figure 1 indicate the step changes found by the algorithm.

1.3. Identify awakenings by filtering the RRI series type II with a low pass filter (LPF) with cutoff frequency of 0.01Hz, and marking the components under 0.85 of averaged value as wake periods (fig 2). This method is based upon 3 characteristics of night-time awakenings that were defined from unpublished sleep studies data which included EEG. The characteristics are:
   a. HR accelerates during awakening,
   b. Trace duration above 30 seconds,
   c. Awakenings do not oscillate with periods shorter than 100 sec, if at all. This is of high importance since apnea (especially severe apnea) often does oscillate with periods within 25-100 seconds long.
1.4. Score all minutes that include awakenings as wake.
1.5. Further fragmentation, of the segments in stage 1.2.3, by elimination of intervening awakenings.
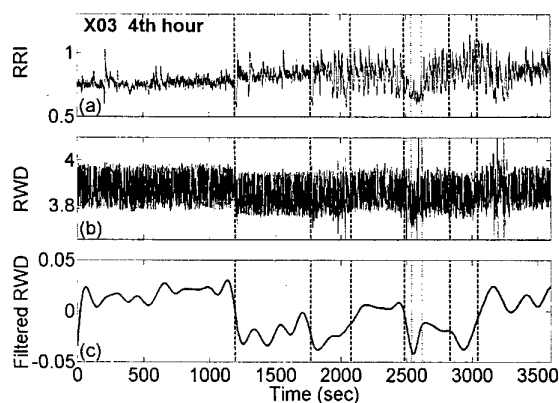

Figure 1. The process of dividing data records into one-position segments. (a) RRI signal as a function of time, in the 4th hour recording of subject x03. (b) RWD signal extracted from the QRS of every heartbeat during the hour. (c) RWD signal after LPF as described in the text. The dashed vertical lines indicate the step changes found by the automatic algorithm. Note the different characteristics of the (RWD divided) segments in the RRI series.

1.6. Fragments shorter than 200 sec are not suited for Discrete Fourier Transform (DFT) and they were dealt with according to stage 3. Fragments longer than 200 seconds containing one body position (stage 1.2) and no awakenings (stage 1.5) were directed to stage 2.

2. DFT of the above fragments from RRI series type II.
   2.1. Calculate the power of the signal in the frequency 'apnea range' 0.01-0.04Hz (25-100 seconds). High power in this range is characteristic of recurrent apnoeas cycle, and is indicative of the presence respiratory disturbance events along the entire segment.
   2.2. Calculate the total power of the signal up to 0.5Hz. This should contain most of signals power.
   2.3. Scoring every minute in the fragment as apnea if the power over the 'apnea range' is greater than 50% of total power. Passing the un-scored fragments to stage 3.
3. Search for an apnea specific 'U' shaped pattern in the RRI type II series. We found a good correlation between apnea and this 'U' pattern (unpublished data and data from the learning set in the CinC Challenge 2000 data), which consisted of a decrease followed by a rapid increase in RRI. Note that this stage was applied only on short fragments (derived in step 1.6) or fragments that did not seem to contain multiple apneas (as derived from step 2.3).
   3.1. Detect transient decreases in RR below a given threshold and score the relevant minute as apnea. Otherwise score as normal.
4. All fragments, scored as wake, were considered as normal for the purpose of the automatic scorer of the CinC2000 challenge.

3.   Results

We present first results from different subjects in order to emphasize the step-by-step algorithm developed and its applicability in patients with a variety of disorders, arrhythmia included.

Figure 1 shows a typical result of stage 1.2. The segmentation of RRI was performed according to the RWD signal., Note that different segments usually present different characteristics of the RRI series as well. That was more apparent with apnea segments.

In figure 2 two examples of the awakening identification (step 1.3) are presented..

The upper frame shows a decrease in RRI at a time between seconds 1000-1200. This segment was scored wake. It was followed by a periodic pattern, with large RRI fluctuations, which was later scored as apnea,. The LPF (solid curved line) diminished the periodic pattern, it only smoothed the first decrease.
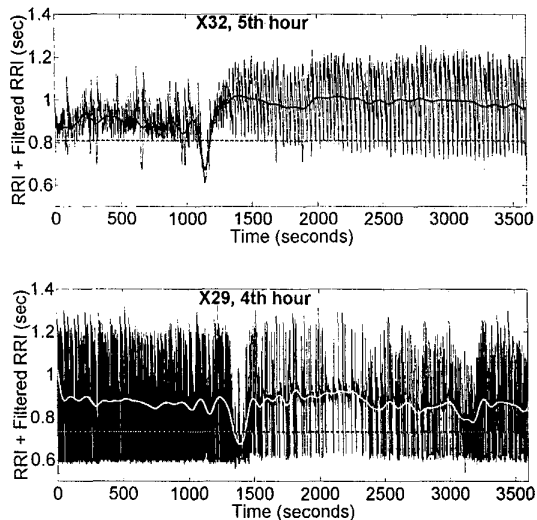
Figure 2. Identifying awakenings from RRI series. The 'noisy' background is the RRI series, the solid curved line is the low-pass-filtered RRI with cutoff frequency of 0.01Hz, and the horizontal dashed line is the threshold at 85% of averaged RRI. Periods bellow threshold were scored wake. (a) RRI signal during the 5th hour of subject x32 recording. (b) RRI signal during the 4th hour of subject x29 recording. This subject had arrhythmia, and a very variable RRI.

The lower frame is an example of the successful application of the designed LPF on a RRI series in apatient with frequent premature beats.

The power spectrum of three adjacent fragments of RRI, can be seen in figure 3. The first spectrum (fig 3b), corresponds to the first segment of RRI series (fig 3a) and contains energy in the respiratory range (slightly below 0.3Hz). The ratio AR/TP was below 0.5, thus this segment was sent to further analysis (step 3). The next spectrum (fig 3c), corresponds with the main central segment from the RRI series (fig 3a); more than half of its power content is located in the AR. Each minute within this segment was scored as apnea containing with no need to be further analyzed. The third spectrum (fig 3d), was calculated for last short RRI segment right to the main central segment, has most of its energy below 'apnea range', thus it was sent to stage 3 analysis.

The results of our algorithm received the score of 14788 correct minute-by-minute classifications, out of 17268 minutes (~85%) during the 35 recordings. This result is of the same order of the commonly cited inter-observer variability in the sleep diagnosis field.

The results of our algorithm received the score of 14788 correct minute-by-minute classifications, out of

17268 minutes (~85%) during the 35 recordings. This result is of the same order of the commonly cited inter-observer agreement in the sleep diagnosis field.

4. Discussion

The real need of inexpensive means of diagnosis of sleep related breathing disorders, specifically obstructive sleep apnea, was the reason for the present CinC challenge. The algorithm we developed for this purpose was designed to detect multiple apnea events by means power spectral analysis of the RR interval, and identification of sporadic apnea events by tracing a characteristic 'U' shape in the RRI series.

Using such an algorithm may give rise to certain problems. RRI power spectral analysis, for example, may be misleading if applied to periods containing both apneic and normal segments. 'U' pattern search may give erroneous results, as this shape also characterizes other events that involve arousals. We specifically addressed those problems by the preparation stages described in the methods section. Since apnea is often position related the algorithm divided the entire data record into segments each containing a single body position. By doing so we tried to avoid analysis of mixed apneic and non-apneic periods. The algorithm avoids the confusion between wake and apnea event by removing awakening periods before the main analysis, using the method described here and based on sleep studies containing EEG [4] (the gold standard in determining a wake state).

As can be seen in figure 1, RWD signal could after using LPF to discriminate different body positions. We had to use a large windowed LPF since the originally slow sample rate of the data made the differences in RWD values at different body positions very small.

Figure 2 emphasizes the robustness of the method for identifying awakenings. The method worked well with data containing apnea events, as well as with data containing arrhythmias.

Some of the problems yet remaining unresolved include: 1. discriminating between short arousals, which may accompany various processes during sleep, and apnea events, although we removed awakening periods from RRI data; 2. as mentioned before, a higher sampling rate may improve considerably the detection of body position changes, and the correct segmentation of data.

A comparison of the automated results with manual scanning of the RRI series, shows that our 'U' pattern search algorithm is not yet optimized, and probably is responsible for many false detections of apnea.

Our algorithm is one of several different approaches presented during the CinC Challenge, all achieving surprisingly good results. Thus, we believe ECG based analysis for sleep apnea screening, detection and diagnosis is feasible.
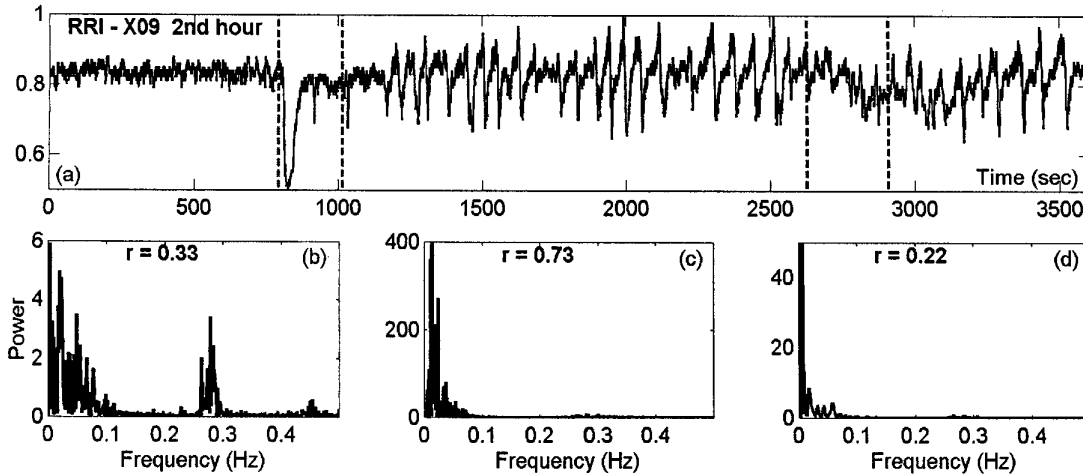
Figure 3. Power spectrum of predefined segments. (a) The segmented RRI series. Second segment (800-1050 sec) was pre-scored as wake and was not spectrally analyzed. (b) Power spectrum of the left most segment (0-800 sec). (c) Power spectrum of the main central segment (1050-2620 sec), and (d) Power spectrum of the segment (2620-2910 sec). The ratio of the power in 'apnea range' and total power is indicated with the variable r.

References

[1] http://www.physionet.org//cinc-challenge-2000.html
[2] Shiomi T, Guilleminault C, Sasanabe R, Hirota I, Maekawa M, Kobayashi T. Augmented very low frequency component of heart rate variability during obstructive sleep apnea. Sleep 1996;19:370-7.
[3] Shinar Z, Baharav A, Akselrod S. R Wave duration as a measure of body position changes during sleep. Computers in Cardiology 1999;26:49-52.
[4] Shinar Z, Baharav A, Sivan Y, Ezra R, Akselrod A. Identification of arousals using heart beat-to-beat variability. Sleep 1998;21S:294.

Address for correspondence.

Zvika Shinar.
Physics Department, Tel-Aviv University, Tel-Aviv.
zvikas@vishnu.tau.ac.il