DETECTION AND SCREENING OF SLEEP APNEA USING SPECTRAL AND TIME DOMAIN ANALYSIS OF HEART RATE VARIABILITY

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Abstract

Sleep apnea syndrome (SAS) is one of the most common breathing related sleep disorder. Sleep apnea (SA) may be of particular concern in chronic heart failure patients due to its high levels of cardiovascular morbidity and mortality. The aim of this work was to assess the diagnostic potential of SA using spectral analysis of nocturnal heart rate, and to introduce new simple time domain heart rate variability (HRV) measures for screening SA. Data subjects supplied by the Physionet database [1] were analyzed. The preliminary results established the effectiveness of the spectral algorithm as a potential detection tool for SA with $p<0.0001$, and demonstrated the usefulness of the new proposed time domain parameters.

I. INTRODUCTION

Sleep apnea (SA) is a breathing disorder characterized by brief interruptions of breathing (more than 10 seconds) during sleep. It owes its name to a Greek word " *apnea*" meaning, " want of breath". There are two types of sleep apnea:

- Central Sleep Apnea (CSA).
- Obstructive Sleep Apnea (OSA).

Central sleep apnea, which is less common, occurs when the brain fails to send the appropriate signals to the breathing muscles to initiate respiration. Thus there is a loss of inspiratory airflow that occurs because of a loss of phasic diaphragmatic activity. Obstructive sleep apnea is far more common and occurs when air cannot flow into or out of the person's nose or mouth although efforts to breathe continue.

Sleep apnea also can occur in obese people when an excess amount of tissue in the airway causes it to be narrowed. With a narrowed airway, the person continues his or her efforts to breathe, but air cannot easily flow into or out of the nose or mouth. Unknown to the person, this results in heavy snoring, periods of no breathing, and frequent arousals (causing abrupt changes from deep sleep to light sleep). In a given night, the number of involuntary breathing pauses or " apneic events" may be as high as 20 to 30 or more per hour. These breathing pauses are almost always accompanied by snoring between apnea episodes, although not everyone who snores has this condition. Sleep apnea can also be characterized by choking sensations. The frequent interruptions of sleep, restorative sleep often lead to early morning headaches and excessive daytime sleepiness.

Early recognition and treatment of sleep apnea is very important. The consequences of sleep apnea range from annoying to life threatening. They include depression, irritability, sexual dysfunction, learning and memory difficulties, and falling asleep while at work, on the phone, or while driving [2]. High blood pressure, heart attack, and stroke may also increase in those with sleep apnea. In addition, sleep apnea is sometimes implicated in sudden infant death syndrome. It is worth mentioning that the gold standard for a definitive diagnosis of SA is polysomnography (PSG). PSG is expensive, time consuming, and inconvenient, resulting in a reduced likelihood of the test being performed.

Sleep related breathing disorders have a high prevalence in the adult population. Epidemiological studies indicate a high prevalence of 4% in males and 2% in females in the general population [2]. Furthermore, OSA is regarded as the most common of the different types of sleep-related breathing disorders. Throughout this work, we don't distinguish between the two different types of SA.

The variations in heart rate (HR) reflect the variations in autonomic nerve traffic responsible for its control. Heart rate variability (HRV) analysis has found a wide variety of applications as a non-invasive probe of autonomic function.
HRV processing is usually carried out in the spectral domain, to allow identification of the various components of the signal by frequency. HRV spectra are traditionally analyzed in terms of the power contained within fixed frequency bands. Various spectral methods [3, 4, 5] have been applied since the late 1960s.

In 1984 Guilleminault et al [6], was the first to show that the presence of cyclical variation of heart rate (CVHR) can identify patients with sleep apnea. Despite the potential of using CVHR to screen for sleep apnea on routine Holter recordings, Guilleminault's findings were not applied. This lack of enthusiasm may have resulted from the technical difficulties associated with generating the requisite R-R interval plots, or possibly because the prevalence and clinical significance of sleep apnea were yet not fully appreciated.

In similar lines with Guilleminault's observations many other researchers [7] had confirmed the fact that sleep-disordered breathing can be achieved by making use of several distinctive features of heart rate oscillation associated with sleep apnea. These features include:

- Periodicity (i.e., repetition rate of each apnea-arousal episode).
- Amplitude changes (peak-to-peak > 10 bpm).
- Morphology of the oscillations.

Aligned with these facts, this work was aimed to:

- Assess the diagnostic potential of SA using spectral analysis of nocturnal heart rate. We hypothesize that the distinct oscillations in heart rate associated with SA manifest themselves in spectral peaks lying in certain frequency bands corresponding to their recurrence.
- Introduce a new simple time domain HRV measures for screening SA.

The rest of this paper is structured as follows. Section II, presents the subject data that were used in evaluating the performance analysis of this study. Section III describes the spectral analysis algorithm in details. The time domain HRV parameters are presented in Section IV. Finally, conclusions are drawn in section V.

II. SUBJECT DATA

The two part of this study were evaluated on data set that was downloaded from the Computers in Cardiology 2000 Challenge, available from the Physionet web site [1]. This data set consists of overnight, single channel ECG recordings digitized at 100 Hz (12-bit resolution), with period varied from just less than 7 hours to more than 10 hours. Each ECG recording includes a set of reference minute-by-minute annotations, that indicate the presence or absence of apnea. These reference annotations were made by human experts on the basis of simultaneously recorded respiration signals. It worth noting, that this database does not contain episodes of pure central apnea or of Cheyne-Stokes respiration, all apneas in these recording are either obstructive or mixed. For our study, we randomly picked subjects from two groups of this data set:

- Group (1), we called Class A (n= 9), at least 100 min with apnea.
- Group (2), we called Class B (n= 8), 5 min or less with apnea.

III. SPECTRAL ANALYSIS

The proposed algorithm targets the unique heart rate rhythm associated with sleep apnea. In particular, it examines the energy distribution in the frequency bands lying between 0.01 and 0.05 Hz (which are corresponding to the repetition rate of 20 to 100 sec, this frequency band was based on visual inspection which was consistent with previous reported bands [3]). It assesses the diagnostic potential of spectral analysis of heart rate variability using the Discrete Fourier Transform (DFT).

The most salient part of this algorithm that differentiates it from previously reported algorithm is the conversion from RR intervals to instantaneous HR using a special tachometer that was proposed by Berger et al [8]. This tachometer translates RR intervals (sec) into instantaneous HR (beats/minute) evenly sampled in time; this is done by constructing a continuous and piecewise constant signal whose value during any RR interval is 60/RR. This continuous signal is anti-alias filtered using a rectangular ("boxcar") window of width twice the interval between samples, and then re-sampled at 4 Hz, producing the output. This step was specifically intended for translating RR intervals into a signal with "nice" properties for further spectral analysis. The idea here is to assume that we are given an input stream consisting of time intervals in the first column and RR interval values in the second. We want to make an evenly sampled output that represents what we would get if we assumed that the true analog signal is a series of steps. Each step has duration corresponding to the time interval, and amplitude corresponding to the value. In order to produce the evenly sampled signal, we want to apply an anti-aliasing filter to the hypothetical analog signal. We do this by integrating the analog signal over a boxcar window.

Figure 1 illustrates the basic elements of this algorithm.

Each subject's data were first filtered and converted to a sequence of RR-interval by taking the time difference between consecutive beats. Data were then re-sampled at 4 Hz, by constructing a continuous and piecewise constant signal that was anti-alias filtered using a boxcar window of width twice the interval between samples. This step was specifically intended for translating RR intervals into a signal with "nice" properties for further Spectral Analysis. Then the output was segmented into 5-min non-overlapped windows, and analyzed in the frequency domain using the Discrete Fourier Transform (DFT). Subjects were automatically classified based on power distribution threshold, calculated in different frequency bands.

A. Results

The energy distribution in different frequency bands was evaluated (by integrating the PSD in the defined frequency bands). The total mean value of all the energies of each 5-min widow was calculated for each patient. Oscillations in heart rate associated with sleep apnea resulted in a spectral peak lying between 0.01 and 0.05 Hz (corresponding to repetition rate of 20 to 100 sec), for visual illustration see figures 2 and 3. We then applied the T-test to the calculated mean energies of the two classes in the frequency band {0.01 – 0.05 Hz}. The T-test showed statistically significant difference with $p < 0.0001$ (see table 1, due to space limitation we only show the overall mean energy of the two population).

These results demonstrated that an algorithm based on information (observed in clinical studies, which usually done by visual inspection) on the apnea repetition frequency can give a reasonably high detection accuracy. This technique might also provide a simple visual method of manual classification.

However, it worth noting two limitations of the proposed approach:

- It cannot classify the severity of SA.
- With the lack of previous information about the repetition frequency of the SA, defining the most appropriate spectral band to "capture" the SA, is usually not an easy task.

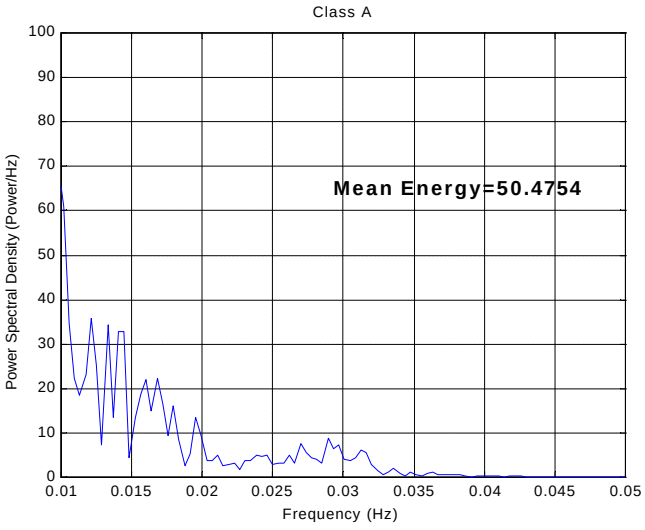

Figure 2. *Illustrative example*: *Class A: Patient with SA.*

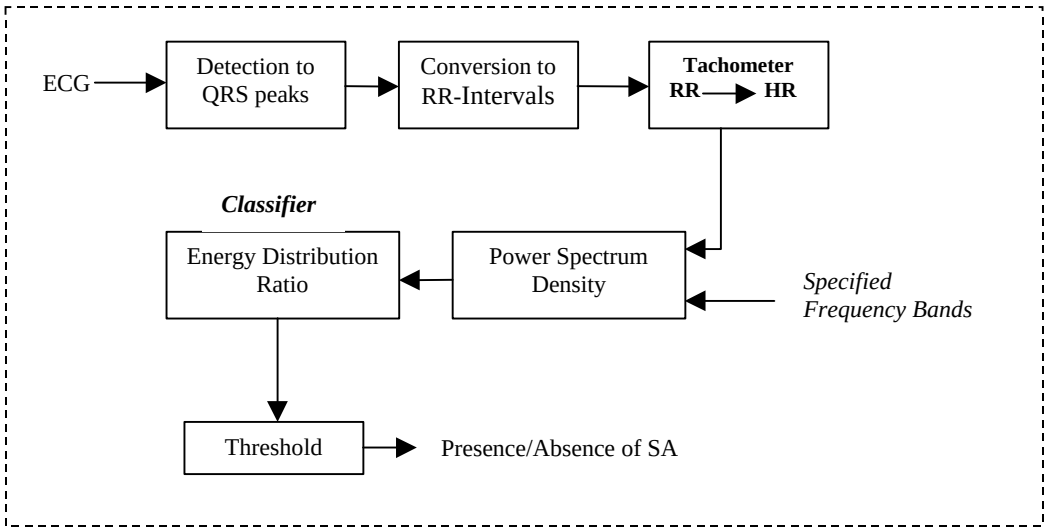

Figure 1. *Block Diagram of the basic elements of the Spectral algorithm.*

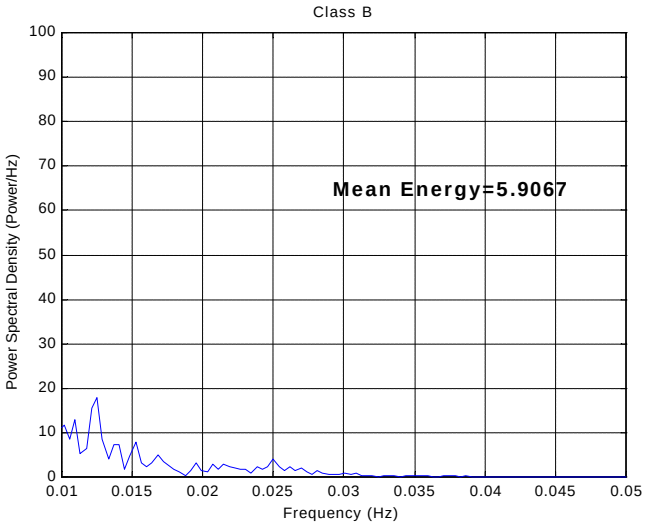

Figure 3. *Illustrative example: Class B: Patient with control SA.*

Class A (n=9) **Mean** of Energy ± **SD**	**Class B** (n=8) **Mean** of Energy ± **SD**
40.24 ± 12.74	**13.53 ± 2.79**

Table 1. *Overall calculated mean energies of two classes in the frequency band 0.01 – 0.05 Hz.*

IV. TIME DOMAIN ANALYSIS

As we mentioned earlier, variations in heart rate may be evaluated by a number of methods. Perhaps the simplest to perform are the time domain measures.

Frederic et al [9], showed that time-domain analysis of heart rate variability (HRV) can represent an accurate and inexpensive screening tool in clinically suspected SA patients. In this study, time-domain HRV variables (such as, SDNN, SDNN-Index, r-MSSD, SDANN, see [10] for more details) were calculated for daytime and nighttime periods, as well as the differences between daytime and nighttime values $\Delta[D/N]$). Effective screening of sleep apnea requires the use of both day and night values of those variables. The night value alone were not enough for accurate screening. This approach is therefore difficult to implement simply because most of the commercially available diagnosis systems (e.g., associating snoring, arterial oxyhemoglobin saturation, and HR monitoring) are limited in their recordings to nighttime.

After determining the RR-intervals of the ECG recording downloaded from the Physionet database, we evaluated the above statistical variables, using the same two groups: Class A (n=9), and Class B (n=8) that we used in the previous algorithm, to see if these statistical variables can provide us with a potential screening tool for SA. Due to space limitation, those results are not provided here. We found that none of those variables can provide us with a good screening tool for SA (T-test p>0.05), when they applied to night recording only. Thus we decided to further investigate alternative statistical measures. After applying the same tachometer [8] that we used in the previous algorithm, and in similar lines to the standard HRV variables, we define the following new measures:

- **SDAHR**: Standard deviation of the averages of Instantaneous HR beats in all 5-min segments of the entire recording. Gives an estimate of the long-term components of HRV.

- **RMSSD_HR**: The square root of the mean of the sum of the squares of differences between adjacent Instantaneous HR beats. Gives an estimate of the short-term components of HRV.
- **SD_HR-Index**: Mean of the standard deviations of all Instantaneous HR beats for all 5-min segments of the entire recording.
- **PHR50**: The fraction of consecutive instantaneous HR beats that differ by more than 50 msec.

Also we introduce another two new statistical measures:

- **HR-Index**.
- **HRD**.

The formulas for calculating the HR-Index, and DHR are given by equations 1, and 2 respectively.

$$HR-Index(n) = \sqrt{HR(n) \cdot \left|HR(n) - HR(n-1)\right|} \quad (1)$$

$$HRD(n) = \left|HR(n) - HR(n-1)\right| \quad (2)$$

Again, we evaluated the above statistical variables, using the same two groups: Class A (n=9), and Class B (n=8) that we used in the previous algorithm (Physionet database), to see if these statistical variables can provide us with a potential screening tool for sleep apnea. Results of this evaluation and applying the T-test are summarized in tables 2 and 3.

As we can see from the results, some variables (the bolded ones in tables 2 and 3) showed statistically significant difference with $p < 0.05$ (the P values of those variables are bolded in the tables) between the two classes. Those HRV variables could thus represent an efficient screening tool in SA diagnosis.

V. CONCLUSIONS

This study assesses the diagnostic potential of SA using spectral analysis of nocturnal heart rate, and introduces new simple time domain heart rate variability (HRV) measures for screening SA. Although this study sampled only a small number of patients, our preliminary results established the effectiveness of the spectral algorithm as a potential detection tool for SA, and demonstrated the usefulness of the new proposed time domain parameters.

VI. REFERENCES

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Class Type	SDAHR	**SD_HR-Index**	RMSSD_HR	**PHR50**
A1	3.9603	8.5795	0.9477	0.4353
A2	9.2187	8.7669	2.6704	0.4071
A3	6.526	6.769	0.5458	0.3791
A4	5.3242	5.1919	0.4637	0.3978
A5	3.354	6.0684	1.2534	0.3358
A6	5.0795	8.9641	1.1843	0.4154
A7	6.3705	5.3749	0.8504	0.3388
A8	5.4239	9.332	3.1199	0.3716
A9	9.7163	6.8	1.4246	0.3789
B1	6.9512	4.7561	0.734	0.3372
B2	3.8028	5.1735	0.8457	0.3754
B3	3.7536	3.9492	0.91	0.3959
B4	8.9492	4.0225	0.5945	0.2817
B5	8.7347	4.2461	0.6234	0.282
B6	8.5506	4.7559	0.6594	0.3535
B7	3.9463	3.3197	0.8151	0.2902
B8	2.2366	4.3515	0.89	0.3024
P	0.8429	**0.0003**	0.0764	**0.0111**

Table 2.

Class Type	**HR-Index (Mean)**	**HR-Index (Std)**	**HRD (Mean)**	HRD (Std)
A1	2.8163	4.0239	0.3727	0.8714
A2	3.2725	6.3488	0.5769	2.6074
A3	2.2478	3.2432	0.2407	0.4898
A4	2.1086	2.9256	0.2027	0.417
A5	1.9628	3.7146	0.2604	1.2261
A6	3.2352	4.8205	0.4433	1.0982
A7	2.2052	3.6312	0.2572	0.8106
A8	3.3963	7.4152	0.7661	3.0244
A9	2.3063	4.141	0.3371	1.3842
B1	1.9053	3.2481	0.2297	0.6971
B2	2.2545	3.5328	0.3223	0.7819
B3	2.6537	3.9769	0.3706	0.8312
B4	1.5233	2.7913	0.1681	0.5702
B5	1.5265	2.8126	0.1695	0.6
B6	2.2896	3.561	0.2372	0.6152
B7	1.5905	2.9571	0.1636	0.7985
B8	1.5903	3.2137	0.1862	0.8703
P	**0.0115**	**0.0430**	**0.0443**	0.0815

Table 3.