DETECTION OF OBSTRUCTIVE SLEEP APNEA FROM THE FREQUENCY ANALYSIS OF HEART RATE VARIABILITY

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Abstract: This paper presents a new algorithm for the detection of Obstructive Sleep Apnea (OSA) from a single electrocardiogram lead. It is based on the alterations that OSA patients present in the LF and HF bands of the heart rate variability power spectrum. The algorithm calculates the power of the spectrum in two bands that roughly corresponding with the LF and HF bands. Then the ratio between the power of the low band and the power of the high band is obtained. If this ratio is greater than a certain threshold the patient is classified as having OSA, otherwise he/she is classified as not having OSA. Then the algorithm was validated over the test data set of the Apnea-ECG Database, classifying correctly 29 of 30 recordings.

1 INTRODUCTION

Obstructive Sleep Apnea (OSA) is a frequent sleep-breathing disorder characterized by the presence of total and/or partial cessations of respiratory airflow while the patient is sleeping (Köves, 1999). These cessations –called apneas if they are total, and hypopneas if they are partial– are usually caused by a collapse in the upper airway and they produce a disruption of the patient's sleep architecture diminishing the refreshing effects of nocturnal rest. The overall effect is a decrease in the patient's quality of life, and an increase in mortality and morbidity. OSA has a high prevalence –it is estimated to affect 4% of male adults and 2% of female adults – and it is recognized as an important public health issue.

The gold standard for the diagnosis of OSA is based on an analysis of a polysomnogram, a recording of a wide range of physiological parameters obtained while the patient is asleep. These sleep studies are expensive because they require the patient to spend a night in a Hospital Sleep Unit, which must be equipped with sophisticated and expensive electronic systems, as well as a dedicated staff. Hence there is an interest in developing reliable diagnostic techniques based on a smaller number of physiological parameters that do not require dedicated Sleep Units. The 2000 Computers in Cardiology Challenge encouraged the development of such techniques. It consisted of developing an algorithm capable of classifying patients as OSA or non-OSA from the modified lead V2 of the ECG (Penzel et al., 2002). For this purpose, a database of polysomnographic recordings - the Apnea-ECG Database- was made available to the participants of the competition (Penzel et al., 2000).

Several clinical studies have shown that patients with moderate-to-severe sleep apnea present alterations on the heart rate variability (HRV) spectrum (Narkiewicz et al., 1998). OSA patients present increased low frequency (LF) spectral power and decreased high frequency (HF) spectral power. Therefore, it is no surprise that most of the 2000 Challenge participants took advantage of information arising from the spectral analysis of the HRV (Penzel et al., 2002). One of the simplest, but effective, algorithms was the one presented by Drinnan *et al.* (Drinnan et al., 2000). This algorithm calculates the power of the HRV spectrum in two different bands, one between 0.01 and 0.05 Hz, and another between 0.005 and 0.01 Hz. The first one corresponds approximately with the LF band, where patients suffering from OSA present increased activity. The second band serves as a reference level: the algorithm calculates the ratio between the power of the first band and the power of the second one, and it checks if this value is greater than a certain threshold. If so, the patient

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is classified as OSA. This algorithm correctly classified 90% of the training and test recordings of the Apnea-ECG Database. Despite its relative success, Drinnan's algorithm only takes advantage of OSA patients presenting increased activity in the LF band and the band's limits were chosen based on a visual inspection of the recordings' spectrum. Thus, it may be possible to improve these results by tuning the bands' boundaries and by merging information arising from both LF and HF bands.

This paper presents a new algorithm for classifying patients as OSA or non-OSA from a single ECG lead. This algorithm is based on the alterations of the heart rate variability that OSA patients present. Section 2 presents the algorithm which enables patient classification. The results of the algorithm validation over the Apnea-ECG Database are presented in Section 3. Finally, the results obtained are discussed and a series of conclusions on the paper are given.

2 MATERIALS AND METHODS

After heartbeat detection, the RR intervals were filtered, in order to eliminate the effects of false positives and false negatives during heartbeat detection. Then they were resampled at 4 Hz. Cubic splines were used for the signal interpolation; a linear interpolation would have produced more distortion –low pass filter effect– than the cubic alternative (Vila et al., 1997). The filtered and resampled RR intervals were stored in ASCII files.

OSA patients have an increased activity in the LF band of the HRV power spectrum, and a decreased activity in the HF band. Thus the ratio between the power of the LF band and the power of the HF band power should be larger for OSA patients than for control patients. This is the idea behind our algorithm. Therefore, we need to find the limits of both bands, and a threshold that allows us to distinguish between OSA and control patients.

A Matlab script that takes as inputs the lower and upper limits of two bands corresponding with the LF and HF regions was created. The script loads the RR distances from the ASCII files and it calculates the spectrum of the complete RR intervals time series corresponding with each of the 10 normal patients. For each patient it calculates the ratio between the power of the LF band and the power of the HF band. The maximum of these values is considered as the boundary between control and OSA patients. Thus, it is used as the threshold for the classification of the 20 OSA patients of the training set. If the ratio between the two spectrum bands of a class A recording is greater than the threshold, the patient is classified as OSA. Otherwise, he/she is normal. After its execution, the script reports the numbers of correctly and incorrectly classified recordings.

Given certain values for the limits of the LF and HF bands, they will be more suitable for our purpose the more class A recordings they classify correctly. A second Matlab script was created to provide the bands to the first script, and to analyze its output. This script starts with two initial bands selected on the basis of a visual inspection of the spectrum of the 30 training set recordings. The initial limits for the low band were set between 0.01 and 0.05 Hz, and for the high band between 0.18 and 0.28 Hz. This script gradually changes the lower and upper limits of the bands by increasing and decreasing their values.

This second script performs an exhaustive search looking for the optimal classification bands. For each band limit modification, it invokes the first script and stores the number of recordings correctly classified, as well as the bands used in this classification. Once it has checked all the preprogrammed bandwidths, it analyzes the results and presents a list of the best bands that have been found. This script ran for two days on a PC with an Intel Core 2 Duo processor at 2.2 GHz and 4 GB of RAM. The results obtained suggested that the best classifications were obtained when the upper limit of the low band was close to or equal to the lower limit of the high band, and they both had a value of approximately 0.08 Hz.

The scripts were modified in order to force the upper limit of the low band to always be equal to the lower limit of the high band. The initial values of the bands were also modified to be close to the values with which the best results were obtained in the first run. Finally, we decreased the magnitude of the increases and decreases that would be applied to the lower and upper limits of each band. This time the initial limits for the low band were set between 0.02 and 0.08 Hz, and for the high band they were set between 0.08 and 0.30 Hz, and the script applied finer modifications to the bands. After running the script for one day, we found that by setting the lower limit of the low bandwidth between 0.021 and 0.048 Hz; the upper limit of the low band (and the lower limit of the high band) between 0.056 and 0.078 Hz; and the upper limit of the high band between 0.232 and 0.276 Hz, all the control recordings and 28 of the 30 OSA recordings were correctly classified.

To select the final frequencies, we looked for the bands which maximize the separability of the class A and the class C test set recordings. To this end, we subtracted the threshold used in the classification; i.e, the maximum of the ratios obtained for the class C recordings, from the LF/HF ratios obtained for each of the class A recordings, and we calculated the sum of all these values. This value can be considered as a measure of the separability of the class of the control patients and the class of the OSA patients: the higher this value is, the greater the average distance from the OSA patients to the control patient which is "closest" to the OSA class is, according to this metric.

The final bands were selected in such a way that they maximize this distance. The low band was set between 0.026 and 0.06 Hz, and the high band between 0.06 and 0.25 Hz. These bands yield a threshold value of 0.42349; i.e., the maximum of the ratios between the power of the low band and the power of the high band for the 10 control patients was 0.42349. This value will be the boundary between classes A and C.

The optimal classification bands we have found differ significantly from the values traditionally associated with the LF and HF bands. We tried to classify the recordings using bands as close as possible to the traditional LF and HF bands (between 0.04 and 0.14 Hz, and between 0.14 and 0.4 Hz, respectively). To this end, we launched our training script with these initial values for the bands' boundaries and we allowed only small changes to be made. In the best case obtained, 6 training set and 8 testing set recordings were misclassified. These results suggest that the bands in which patients suffering from OSA present HRV alterations do not exactly match the traditional definitions of the LF and HF bands.

3 RESULTS

Using the bands selected in the training phase, we validated our algorithm using the test set recordings of the Apnea-ECG Database. Before applying the algorithm, the threshold value was rounded to 0.43. This change did not affect the classification results obtained for the training set recordings. All patients in the control test set were correctly classified as non OSA. Of these recordings, the one which provided the bigger LF/HF ratio value, i.e, the one which was "closest" to the OSA class, was 17c, which yielded a value of 0.41. Among the patients who suffered OSA, only one was classified as healthy (the 15a); all others were correctly classified.

Tables 1 and 2 summarize the results obtained over the training and test sets, respectively. These tables also show the classification results for the five Class B recordings of the training and test sets. Given that these recordings correspond to patients who are on the borderline between normality and suffering from the disorder, it is not possible to use them to judge the quality of the results of a binary classifier as the one proposed here.

Table 1: Training set recordings classification results.

Class	Classification	
	OSA	non-OSA
Class A	18	2
Class B	3	2
Class C	0	10

Table 2: Test set recordings classification results.

Class	Classification	
	OSA	non-OSA
Class A	19	1
Class B	2	3
Class C	0	10

4 DISCUSSION

Our algorithm correctly classifies 95% of the 60 OSA and control recordings of the Apnea-ECG Database, compared to 90% of the Drinnan *et al.* algorithm that inspired ours. This has been achieved by taking advantage of the altered HRV that OSA patients present both in the LF band and in the HF band and by including a semi–automatic training stage to fine tune the bands' boundaries. All the classification errors committed by our algorithm, and by the Drinnan *et al.* algorithm, correspond to OSA patients who are misclassified as normal. From the viewpoint of the construction of a diagnostic or a screening test, the classification of a patient who suffers from OSA as healthy is less desirable than the classification of a healthy patient as having OSA. Therefore, we might prefer an algorithm that, even though it incorrectly classifies a higher number of patients, it classifies less OSA patients as healthy.

To achieve this in the training set, we would have had to set the threshold used by our algorithm to 0.32. In the case of the test set, the threshold would have had to have been set to 0.35014. In the first case, this would lead to the classification of 6 of the 10 control patients as having OSA; in the latter 5 control patients would have been misclassified. An algorithm that classifies half or more of the healthy patients as having OSA does not seem a good compromise.

A visual inspection of the 3 incorrectly classified recordings shows that they do not present altered HRV in the LF or HF bands. Visual inspection also reveals that some recordings only present alterations in one of the two bands. In these cases, our algorithm is still able to make the correct classification thanks to the merging of information arising from both bands. In the case of the Drinnan *et al.* algorithm, the patient must present altered activity in the only band the algorithm considers –LF.

The fact that neither the Drinnan *et al.* algorithm nor ours classified any of the control patients as having OSA suggests that both algorithms have a rather high specificity. This specificity may have its root in the fact that healthy patients do not usually show altered HRV activity in any of the two bands, although some OSA patients do not present the typical altered activity, despite their disorder.

The scientific literature states that patients suffering from OSA have decreased activity in the LF band and increased activity in the HF band. However, the best classification bands found by our scripts for the Apnea-ECG Database recordings differ from the traditional LF and HF bands. Our high band –between 0.06 and 0.25 Hz– incorporates a fragment of the LF band (between 0.06 and 0.014), and our low band – between 0.026 and 0.06 Hz– includes only the lower part of the LF band and the VLF band (Very Low Frequency, between 0.002 and 0.004 Hz).

However, the algorithm is based on patients suffering from OSA having less power in the high band and more power in the low band, because it calculates the ratio between the low band and the high band, and expects that OSA patients have a higher value for this ratio than healthy patients. Furthermore, in our attempt to find bands as close as possible to the LF and HF bands, the classification results are significantly worse than those obtained with the optimal bands – 6 recordings misclassified in the training set, and 8 in the testing test. Therefore, our results suggest that OSA patients have increased activity only in the lower part of the LF band and in the VLF band, and have decreased activity not only in part of the HF band, but also in the 0.06 and 0.014 Hz range of the LF band.

5 CONCLUSIONS

This paper presents a simple but effective algorithm capable of classifying patients as OSA or non-OSA on the basis of a single ECG lead. The algorithm calculates the power spectrum of the time series obtained by filtering and resampling at 4 Hz the RR intervals extracted from the ECG lead. Then the power of the bands between 0.026 and 0.06 Hz and between 0.06 and 0.25 Hz is calculated, and then the ratio between the power of the low band and the high band is obtained. If this ratio is greater than a certain threshold –0.43– the patient is classified as OSA. The boundaries of the bands and the threshold were obtained by means of a semi-automatic training stage where the Apnea-ECG Database training data set was used. The algorithm was validated on the test data set of the same database, incorrectly classifying only 1 of 30 control and OSA recordings.

Our future work aims to obtain a screening test for OSA patients that can be performed at low cost and in the patient's home. This can avoid travels to the hospital, long waiting lists, and other inconveniences for the patient. To this end, the test will be based on MEDIM, a PDA platform with the capability of recording ECGs (Presedo et al., 2009). The algorithm we have developed has a low demand of computational resources, which makes it suitable to be implemented in such a device.

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