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Sleep Apnea Hypopnea Syndrome Classification in SpO_2 Signals using Wavelet Decomposition and Phase Space Reconstruction

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***Abstract*— Sleep Apnea Hypopnea Syndrome (SAHS) is a sleep disorder where patients experience multiple airflow cessations or reductions during the night. It is recognized as a common condition with a population prevalence of 1% to 6.5%. The Apnea Hypopnea Index (AHI) characterizes the severity of SAHS using signals obtained from Polysomnography (PSG); this requires the use of multiple sensors on the patient and an overnight hospital stay. The development of cheaper and more comfortable screening techniques involving wearable devices is, therefore, desirable. This paper presents a method based on wavelet decomposition and phase space reconstruction with embedding dimensions for feature extraction from oxygen saturation measured in SpO_2 signals. The proposed characteristics are the areas spanned by each wavelet level in the phase space calculated using the convex hull algorithm. These areas are then fed into a classifier that groups the patients in categories of AHI higher or lower than 5. The results show an accuracy of 93% using K-Nearest Neighbors (K_{nn}), and 88.61% using Least Square Support Vector Machines (LS-SVM).**

I. Introduction

Sleep Apnea Hypopnea Syndrome (SAHS) is a condition characterized by repetitive airflow reductions or cessations during sleep. The two underlying events of SAHS are apneas: reductions of 90% airflow for at least 10 seconds; and hypopneas: reductions of 30% airflow lasting 10 seconds or more with either a blood oxygen saturation drop of 3% or more, or an arousal [1]. The manifestations of SAHS include excessive sleepiness, poor concentration, and fatigue. In addition, increased cardiovascular risk factors, depression and memory loss are recognized as long-term effects. SAHS is included in the World Health Organization's (WHO) list of chronic respiratory diseases, and is considered the most common sleep disorder. The WHO also reports an increased frequency of accidents associated to patients diagnosed with SAHS [14].

The current standard test for diagnosing SAHS is PSG, which involves the acquisition and analysis of various signals including electroencephalogram (EEG), electrocardiogram (ECG), thoracic and abdominal movement, airflow, electrooculogram (EOG), electromyogram (EMG), and oxygen saturation. This test requires an overnight hospital stay leading to high costs. Furthermore, multiple sensors and wires attached to the body cause discomfort and disturb the normal sleep patterns. The acquired signals can exceed 4 GB of data in one night and are mostly manually annotated, therefore PSG is a labor-intensive examination. This is the motivation for developing home monitoring techniques that are less disruptive. Previous research ideas attempting to tackle these challenges include photoplethysmography (PPG) [5], ECG [13], sound [12] or SpO_2 [9] sensor based home monitoring. The SpO_2 signal is defined as the oxyhemoglobin concentration in the blood recorded by a pulse oximeter. Levels of SpO_2 in healthy adults usually range between 96% and 99%. This signal is highly unstable in patients with SAHS and presents slow desaturations and fast resaturations.

The signals recorded during the PSG are used to calculate the Apnea Hypopnea Index (AHI) which expresses the severity of SAHS. The AHI is the average number of apneic or hypopneic events that occur in one hour of sleep. It allows the classification of SAHS into categories of normal ($AHI < 5$), mild ($5 \leq AHI < 15$), moderate ($15 \leq AHI < 30$) or severe ($AHI \geq 30$).

This study uses features extracted from the phase space reconstruction of the wavelet decomposition of SpO_2 signals to classify patients with different AHI. Section II gives a general overview of the datasets and acquisition methods, section III describes the processing techniques used to extract the features, and sections IV and V discuss the results, conclusions and future work.

II. Materials

Polysomnographic studies from 79 subjects recorded with a Medatec acquisition system at the University Hospital Leuven in Belgium were used. The dataset includes 47 men and 32 women with an average age of 49 $\pm$ 11.7 years, and a mean Body Mass Index (BMI) of 27.57 $\pm$ 4.42 kg/m^2. 57 patients were overweight or obese. 31 patients had severe SAHS, 17 moderate SAHS, 17 mild SAHS, and 14 were normal. The AHI was calculated using the AASM 2012 rules [3]. Somnograms, corresponding to the sleep stages, were also available for the study. The data was anonymized to protect patients privacy. A total of 34 signals were acquired from each patient but only the SpO_2, recorded using with a NONIN™ sensor, was used in this study. The sampling

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frequency of the signals was 500 Hz. MATLAB® R2015b was used for the implementation of the algorithms.

III. Methods

This section describes the steps to extract the features from the SpO_2 signal and build the classifiers. First, a preprocessing procedure is applied. Then, the wavelet decomposition in 7 levels is performed using the Haar wavelet. After that, the phase space of each level is constructed using the embedding dimension technique. The area spanned by the cloud of points is calculated using the convex hull algorithm. Finally, these areas are used as features to build a classifier.

A. Preprocessing

There are various reasons for the preprocessing the SpO_2 signals. Firstly, the sampling frequency is much higher than that of the observed oscillations. Secondly, two artifacts are clearly identified: ripples occurring with sudden changes in the oxygen saturation and a zero level reading due to sensor movement [8]. Finally, wake segments present unstable SpO_2 waveforms, and are thereby removed.

1) Smoothing: The ripples observed when the oxygen saturation shows a sudden change are first removed. These occur due to the fast shifts in voltage measurements corresponding to varying oxygen levels. A Moving Averaging Filter with a window length of 100 milliseconds is applied to correct for this. The selection of the window for the filter corresponds to the observed duration of the ripples in the signal.

2) Downsampling: While the sampling frequency is 500 Hz, the fastest changes occur in periods of 4-6 seconds. Therefore, the signal is downsampled to 1 Hz. The important information is preserved avoiding aliasing effects and reducing the computational cost.

3) Zero SpO_2 levels removal: As described in [8], the artifacts detected in SpO_2 are caused by signal interruptions (loss of focus). They appear as zero levels in the oxygen saturation. A linear interpolation is applied to reduce their effect on the lower frequency levels of the wavelet decomposition.

4) Non-Sleeping segment removal: Non-sleeping periods are characterized by unstable oxygen saturations, which can be confused with apneas. The desaturations produce outliers in the features derived from the phase space. Hence, the non-sleeping periods are segmented using the somnogram, and they are then removed from the analysis. This is done under the assumption that a method to classify sleep stages using home monitoring is available.

B. Wavelet Decomposition

The SpO_2 signal has non-stationary characteristics which cause temporal changes in statistical properties. The wavelet transform is used to represent components that reflect the behavior of the observations in different time and frequency scales [9]. The mother wave should resemble the structure of the original signal. Hence, the Haar wavelet is chosen to accommodate the observed rapid changes in oxygen saturation. 7 levels are analyzed since, as discussed in [15], the duration of the apneas can last up to 2 minutes; 6 levels are sufficient to cover this period of time, however, an extra level is added as buffer. The last level considers periods of 2.13 to 4.26 minutes. Figure 1 shows the last 4 levels for the SpO_2 signal of 1 patient in the dataset. This paper exploits the distinctive characteristics found in the wavelet components of patients with different SAHS severity.

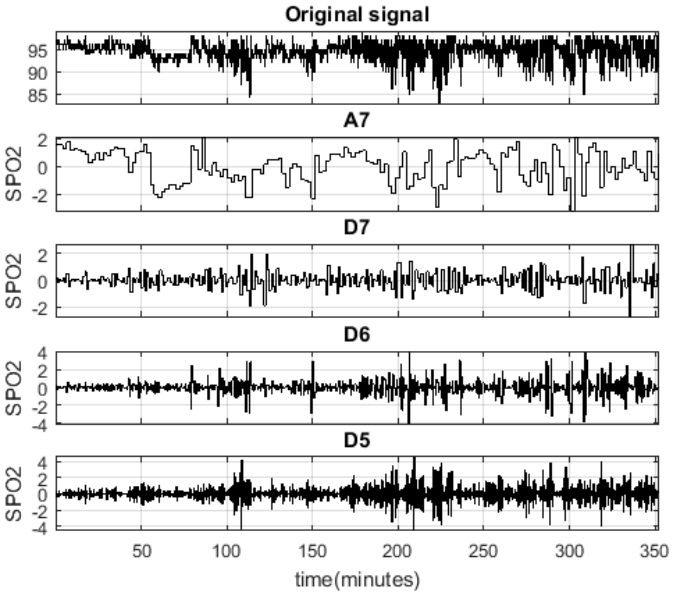

Fig. 1. Haar wavelet decomposition of an SpO_2 signal

C. Phase Space Reconstruction

The Phase Space (PS) is a useful visual approach for analyzing non-stationary signals with chaotic characteristics. It has been used for classification of heart beats in ECG [6] and detection of seizure events in EEG [10] [7]. PS allows the analysis of nonlinear dynamics of a signal by providing a visual representation of the evolution of the system over time. The PS is constructed using the embedding dimension method. The SpO_2 signal can be represented as a time series vector $X = \{x_1, x_2, x_3, ..., x_n\}$ with n the number of samples in the signal. The phase space can be reconstructed by generating m vectors as

$$V_i = (x_i, x_{i+\tau}, x_{i+2\tau}, ..., x_{(i+(m-1)\tau)}), \quad (1)$$

where $i = 1, 2, ..., n-(m-1)\tau$, m is the embedding dimension of the phase space, and τ is the time delay. The function *phasespace* available in the community forum of Mathworks [17] was used to perform the calculations. In figure 2, a comparison of the PS obtained in the A7 wavelet level for 2 patients with different AHI is shown. More periodicities are expected in the signal when desaturations are present. This results in changes in the shape and area of the PS representation according to the AHI. The selection of the ideal delay to compute the phase space is a critical decision. This is further discussed together with the classifier construction in the following sections. An embedding dimension of 2 is

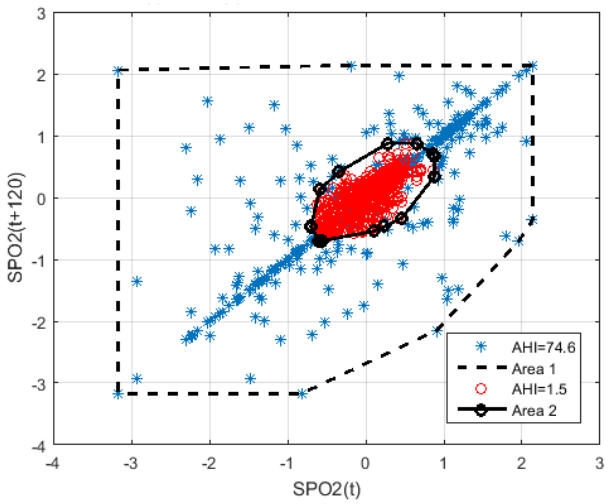

Fig. 2. Convex hull computation on the cloud of points in the Phase Space. The plot corresponds to level 7 of the wavelet decomposition

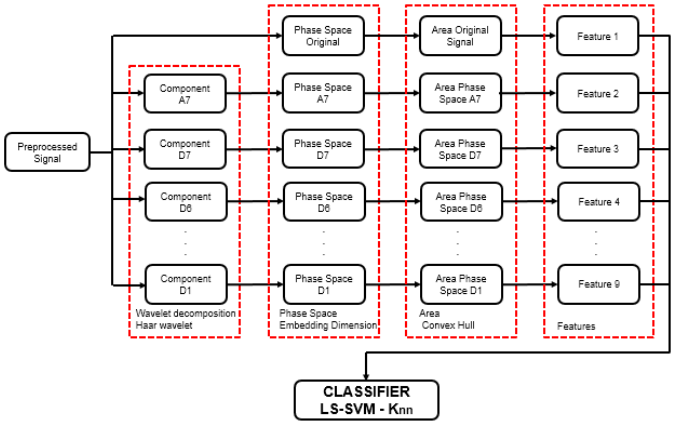

Fig. 3. Steps Followed for the feature extraction

chosen in order to be able to calculate the area occupied by the cloud of points.

D. Convex Hull Algorithm

After building the PS, the area spanned by the cloud of points in each level must be calculated. The convex hull method, defined as the minimal convex set that contains a given collection of points, is used. Various algorithms exist to compute it. This work uses the function *convhull* in MATLAB®, which employs the Quick Hull algorithm [16] [2]. Figure 2 shows the PS and the computation of the area for two patients with different AHI. The convex hull has a length equal to the minimum perimeter needed to contain the cloud of points.

E. Classifiers

The K_{nn} and LS-SVM algorithms are used to build the classifiers. The discrimination between healthy and unhealthy subjects is done using an AHI of 5. This threshold defines the limit between normal and SAHS patients, therefore it is a good choice to use in screening systems. The optimal delay to build the phase space is chosen using the F1-score. This technique measures the discrimination of two sets of real numbers. Given the training vectors z_k, $k = 1, ..., l$, where l is the number of patients, the F1 score of the ith feature is defined as [4]

$$F1(i) = \frac{\left(\bar{z}_i^{(+)} - \bar{z}_i\right)^2 + \left(\bar{z}_i^{(-)} - \bar{z}_i\right)^2}{\frac{1}{l_+ - 1}\sum_{k=1}^{l_+}(z_{k,i}^{(+)} - \bar{z}_i^{(+)})^2 + \frac{1}{l_- - 1}\sum_{k=1}^{l_-}(z_{k,i}^{(-)} - \bar{z}_i^{(-)})^2}, \quad (2)$$

where l_+ and l_- are the amount of positive and negative samples; $\bar{z}_i$, $\bar{z}_i^+$ and $\bar{z}_i^-$ are the averages of the ith feature of the whole, positive and negative groups, respectively; $z_{k,i}^{(+)}$ and $z_{k,i}^{(-)}$ are the ith feature of the kth positive and negative sets, respectively. The numerator expresses the discrimination between positive and negative groups while the denominator is the differentiation within each of the two sets. A higher score suggests that the ith feature has more discriminative power. Areas spanned by the clouds of points are calculated for delays ranging from 100 to 20000 seconds. This range is selected to focus on the repeatability of apneic events. More desaturations are expected in patients with higher AHI. This in turn results in a higher probability of observing periodicities when SAHS is present. The F1 score is calculated with all delays for each feature. The optimal delay is chosen separately for each feature and level of the wavelet decomposition as the delay with the maximal F1 score.

Figure 3 shows the summary of the steps followed to compute the features. The function *fitcknn* is used to build the K_{nn} classifier with 5 neighbors while using the Euclidian distance; for the LS-SVM [11], LS-SVMlab1.8 is used [18], with an RBF kernel with γ=64 and σ^2=12. γ determines the smoothness of the estimated function while σ^2 is the kernel function parameter. They are chosen maximizing the performance through several trials. This performance is calculated using Leave-One-Out, accuracy, specificity and sensitivity.

IV. Results and Discussion

Table I shows the results of the classification. The accuracies, specificities and sensitivities are higher using K_{nn}. However, the performance of this algorithm is not trustworthy when the problem is unbalanced, as in this dataset where only 17.7% of the subjects have an AHI lower than 5. The bias present in the database is difficult to correct because, normally, the PSG is not performed on patients with normal sleep. LS-SVM shows a poorer performance but, with a smarter parametrization of the LS-SVM, the results can be improved.

The obtained results are good for a screening technique based only on SpO_2 signals and a limited amount of features and mathematical tools. Accuracies are similar to those obtained in [13], and the procedure is relatively easy to understand and implement. The algorithm is executed in a computer with a core i7 processor (2.7 GHz), 2 cores and 4

TABLE I

RESULTS OF THE TWO CLASSIFICATION METHODS WITH THE LEAVE-ONE-OUT VALIDATION

Leave-One-Out validation			
Algorithm	**Specificity**	**Sensitivity**	**Accuracy**
Knn	78.57%	96.92%	93.67%
LS-SVM	64.29%	93.85%	88.61%

TABLE II

EXECUTION TIMES PER PATIENT

Execution times/analyzed hour		
Step	**Average**	**Standard Deviation**
Filtering	21.65 ms	3.40 ms
Wavelet Decomposition	22.77 ms	4.22ms
PS and convex hull	235.77 ms	41.23 ms

GB of RAM. The execution times obtained to analyze one hour of recordings are shown in table II. One can observe that the procedure is computationally cheap. The longest times occur during the phase space reconstruction as this has to be repeated for each of the 8 levels of the wavelet decomposition.

This paper assumes that there is an accurate method to segment non-sleeping segments and discard them from the analysis. The integration and evaluation of two algorithms to perform both tasks is necessary. Also, the dataset employed to build the algorithms is small. More tests with more patients are needed to validate these results.

V. CONCLUSION AND FUTURE WORK

An algorithm to classify patients with an AHI higher or lower than 5 using features extracted from wavelet decomposition and phase space representation was presented. This method is not computationally expensive, is easy to implement, easy to understand, and only a few features derived from a single signal are used. These factors are important in the development of wearable devices which have limited hardware specifications.

The obtained accuracies, specificities and sensitivities encourage an undertaking of an in-depth study of improvements to the used algorithms. Firstly, a tool for feature selection can be implemented, since there is the possibility of having redundancy that may create collinearity problems. Secondly, the algorithm should be tested in bigger databases and different AHI thresholds should be used in order to overcome the issue of the imbalance. Additionally, more classifiers can be designed to look for methods with better performances. A proper tuning of the configuration parameters of the LS-SVM should also be done to reduce the number of miss-classifications. Furthermore, the range of delays used to find the phase spaces with the highest discriminative power can be modified. This to consider delays, such that 10-120 seconds, which can be directly related to typical durations of sleep apnea events. Finally, the physiological meaning of the characteristics of the levels of the wavelet decomposition needs to be further investigated.

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