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A classification algorithm based on spectral features from nocturnal oximetry and support vector machines to assist in the diagnosis of obstructive sleep apnea

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***Abstract*—The aim of this study is to develop and evaluate an algorithm to help in the diagnosis of the obstructive sleep apnea syndrome (OSAS). Arterial oxygen saturation (SaO_2) signals from nocturnal pulse oximetry were used to identify OSAS patients. A total of 149 SaO_2 recordings from subjects suspected of OSAS were available. The initial population was divided into a training set (74 subjects) and a test set (75 subjects) to optimize and evaluate our algorithm. Support vector machines (SVM) with Gaussian kernel were used to classify spectral features from SaO_2 signals. Several configurations of SVM were assessed by varying the regularization (C) and the kernel width (σ) parameters. Finally, the selected SVM classifier (C = 235 and σ = 0.4) provided an accuracy of 88.00% (84.44% sensitivity and 93.33% specificity) and an AROC of 0.921. Our results suggest that the proposed algorithm could be useful for OSAS screening.**

I. Introduction

OBSTRUCTIVE sleep apnea syndrome (OSAS) is characterized by repetitive collapse of the upper airway during sleep [1]. Events of apnea are associated with hypoxemia and hypercapnia. The increasing inspiratory effort leads to the termination of the apnea event, resulting in arousal and marked sleep fragmentation. This leads to excessive daytime sleepiness, which is a primary cause of traffic and work accidents. Moreover, OSAS could adversely affects cardiovascular and cerebrovascular systems [1]. The prevalence of OSAS is estimated between 1-5% of adult men in western countries [2]. Nowadays, nocturnal polysomnography (PSG) is the gold standard in OSAS diagnosis. However, it is a complex, time-consuming and expensive procedure. PSG must be performed in a special sleep unit under supervision of a trained technician. Subsequently, a medical expert must analyze a large amount of physiological data to provide a final diagnosis [1].

Nocturnal pulse oximetry represents an alternative to PSG since it is readily available, relatively inexpensive and can be performed at home [3]. Pulse oximetry allows to monitor arterial oxygen saturation (SaO_2) during sleep. It is a widely used technique to analyze respiratory dynamics [4]. Episodes of apnea are reflected in SaO_2 recordings by means of recurrent drops and following restorations of the saturation value. As a result, oximetry signals from OSAS positive subjects are characterized by frequent fluctuations. In contrast, signals from control subjects tend to remain constant with a saturation value near 97% [4]. Therefore, SaO_2 signals can be used to detect OSAS.

Previously, other research studies have been focused on OSAS diagnosis from SaO_2 signals. Visual inspection of these signals represents a straightforward approach [5]. Other studies assessed the utility in OSAS diagnosis of traditional oximetry indices such as the oxygen desaturation index over 2% (ODI2), 3% (ODI3) and 4% (ODI4), and the cumulative time spent below a given level of saturation [4, 6-8]. Additionally, signal processing techniques have been applied on oximetry data. Specifically, analyses based on spectral and nonlinear methods have provided promising results [9-11].

In this study, we present an algorithm based on support vector machines (SVM) and spectral features from SaO_2 signals to help in OSAS diagnosis. SVM represent an efficient tool for classification purposes. They have been successfully applied in different domains including biomedical engineering [12]. Indeed, other researchers previously applied SVM to OSAS diagnosis from ECG features [13,14]. SVM are characterized by high generalization capability and low sensitivity to the curse of dimensionality [12,15]. The former is achieved according to the principle of structural risk minimization (SRM) [15]. This consists in minimizing the generalization error, which is bounded by the sum of the training error and a term depending of the Vapnik-Chervonenkis (VC) dimension [16]. The latter is due to the optimization process of SVM classifiers. These are based on maximizing the margin between classes. In contrast, traditional statistical classifiers aim to capture the statistical distribution of data in each class, which requires a large amount of training data [12].

We modeled OSAS diagnosis as a classification problem by applying SVM. Each subject must be assigned to one of two possible groups: OSAS positive or negative. Spectral features from SaO_2 signals were used as inputs to the SVM classifier. The repetition of apnea events during sleep

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originates differences in the power spectral density of oximetry signals from OSAS negative and positive subjects [9]. The aim of this study is to evaluate the utility of SVM in OSAS diagnosis by only using information from SaO_2 recordings.

II. Subjects and Signals

A total of 149 subjects took part in the study. PSG and pulse oximetry were simultaneously performed on each of them. Sleep study was typically carried out from midnight to 8:00 AM in the Sleep Unit of the Hospital Clínico de Santiago de Compostela, Spain. A Criticare 504 oximeter (CSI, Waukeska, W.I., U.S.A.) with a sampling frequency of 0.2 Hz was used to record SaO_2 signals. A polygraph (Ultrasom Network, Nicolet, Madison, W.I., U.S.A.) was used to obtain recordings from PSG. A medical expert analyzed these recordings according to the system proposed by Rechtschaffen and Kales [17] in order to provide a diagnosis for each subject. Apnea was defined as a cessation of airflow for 10 seconds or longer. Hypopnea was characterized by a reduction, without complete cessation, in airflow of at least 50%, accompanied by a decrease of more than 4% in the saturation of hemoglobin. The apnea-hypopnea index (AHI) was the average calculated from the number of apneic events detected in PSG and the total time, in hours, of sleep. Finally, a threshold of AHI ≥ 10 events/h was considered to diagnose OSAS.

A positive diagnosis of OSAS was confirmed in 89 subjects. There were no significant differences in age, body mass index (BMI) and recording time between OSAS positives and negatives. A training set with 74 subjects (49.7%) and a test set with 75 subjects (50.3%) were randomly derived from the initial population to develop and evaluate our algorithm. Table I summarizes the demographic and clinical data of these sets and of the whole population under study.

TABLE I
Demographic and Clinical Features for All Subjects under Study, the Training Set and the Test Set

All Subjects			
	All	OSAS Positive	OSAS Negative
Subjects (n)	149	89	60
Age (years)	57.9 ± 13.4	58.2 ± 13.3	57.5 ± 13.6
Males (%)	75.8	82.0	66.7
BMI (kg/m^2)	29.6 ± 5.6	30.4 ± 5.0	28.5 ± 6.2
RT (h)	8.2 ± 0.7	8.2 ± 0.8	8.2 ± 0.3
AHI (events/h)		39.7 ± 19.6	2.3 ± 2.5
Training Set			
	All	OSAS Positive	OSAS Negative
Subjects (n)	74	44	30
Age (years)	58.2 ± 12.1	56.7 ± 13.6	59.6 ± 10.2
Males (%)	75.7	79.6	70.0
BMI (kg/m^2)	29.6 ± 5.7	30.2 ± 5.1	28.9 ± 6.4
RT (h)	8.2 ± 0.4	8.2 ± 0.5	8.3 ± 0.3
AHI (events/h)		38.1 ± 18.2	2.6 ± 2.5
Test Set			
	All	OSAS Positive	OSAS Negative
Subjects (n)	75	45	30
Age (years)	57.6 ± 14.7	59.6 ± 13.0	55.0 ± 16.6
Males (%)	76.0	84.4	63.3
BMI (kg/m^2)	29.5 ± 5.6	30.6 ± 5.1	28.0 ± 6.0
RT (h)	8.1 ± 0.9	8.1 ± 1.1	8.2 ± 0.4
AHI (events/h)		41.2 ± 21.0	2.0 ± 2.4

Data presented as mean ± standard deviation. OSAS Positive/ Negative: patients with a positive/negative diagnosis of obstructive sleep apnea syndrome; BMI: body mass index; RT: recording time; AHI: apnea-hypopnea index calculated for hourly periods.

III. Methods

A. Feature extraction

Oximetry signals tend to present a different behavior for OSAS positive and negative subjects. Events of apnea are reflected in SaO_2 signals by means of drops and subsequent restorations of the saturation value. As a result, recordings from subjects affected by OSAS are usually characterized by instability. In contrast, SaO_2 signals from OSAS negative subjects tend to have a constant value near 97% [4]. However, subjects referred to a sleep study may present uncertain oximetry data. Indeed, visual inspection has shown to be insufficient to provide an accurate diagnosis [5].

In this study, we suggest to perform spectral analysis of SaO_2 recordings to quantify differences between both groups of subjects. The duration of an apnea usually ranges from 30 s to 2 min, including the awakening response after apnea. Thus, the minimum and maximum frequencies for the occurrence of apnea events would approximately correspond to 0.010 and 0.033 Hz, respectively. The repetition of apneas during sleep originates phase-lagged changes in SaO_2 signals. As a result, the signal power associated with frequency components located in that band is higher in subjects with OSAS than in normal controls [9].

We applied the nonparametric Welch's method to estimate the power spectral density (PSD) of oximetry recordings [18]. A 50% overlapping Hanning window (300 samples) was used. We focused our analysis in the frequency band 0.010-0.033 Hz. The following spectral parameters were computed: the total area under the PSD (S_T), the area enclosed in the band under study (S_B) and, the peak amplitude of the PSD in this band (PA).

B. Preprocessing

Each feature was normalized to have zero mean and unit variance to be properly applied to the classifier. This normalization process avoids possible differences in the magnitude of the features.

C. Support vector machines (SVM)

The normalized spectral features were applied as inputs to a SVM classifier in order to obtain a final diagnosis about OSAS. SVM are built from a training set D composed of pairs $\{(\mathbf{x}_i, y_i)\}_{i=1}^{N}$, with each input $\mathbf{x} \in \Re^m$ and the output label $y \in \{\pm 1\}$. SVM maps input data to a higher dimensional space $(\Im)$ by means of a nonlinear transformation $\mathbf{z} = \phi(\mathbf{x})$. The aim of SVM is to find an optimal separating hyperplane (OSH) of the form $\mathbf{w}^T\mathbf{z} + b$

in the space $\Im$ [15]. In the case of linearly nonseparable data in $\Im$, there exist **w** and *b* that satisfy:

$$y_i(\mathbf{w}\mathbf{z}_i + b) \geq 1 - \xi_i \quad (1)$$

where $\xi_i \geq 0$ are called slack variables and measure the deviation of a data point from the ideal condition of pattern separability. In this study, we applied $\xi_i = 5 \cdot 10^{-5}$. The OSH is found according to the SRM principle. The goal is to maximize the margin of separation between the two classes and to minimize the training error [15,16]. There is a trade-off between both objectives. It is controlled by means of a regularization parameter *C*. High values of *C* lead to complex SVM classifiers with low training error. However, overfitting could be produced. In contrast, low values of *C* provide SVM classifiers with a large training error, which means that the classifier is underfitted [12].

The optimization problem of SVM is formulated through a Lagrangian function [15]. The Lagrange multipliers $(\alpha_1, \ldots, \alpha_N)$ can be found by maximizing the following expression:

$$Q(\alpha) = \sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j y_i y_j K(\mathbf{x}_i, \mathbf{x}_j) \quad (2)$$

subject to the constraints

$$\sum_{i=1}^{N} \alpha_i y_i = 0 \text{ and } 0 \leq \alpha_i \leq C, \quad i = 1, \ldots, N \quad (3)$$

The final discriminant rule $f(\mathbf{x})$ is expressed as a function of data in the original space:

$$f(\mathbf{x}) = \sum_{i \in S} \alpha_i y_i K(\mathbf{x}_i, \mathbf{x}) + b \quad (4)$$

where *S* is a subset of the indices {1, …, *N*} corresponding to the nonzero Lagrange multipliers α_i, which define the support vectors, and $K(x_i, x_j) = \phi(x_i)\phi(x_j)$ is the kernel function. In this study, the Gaussian kernel was used [16]. The variance (σ) of the Gaussian functions must be specified by the user. This parameter influences the generalization capability of SVM classifiers. When $\sigma \to 0$ all the training data points are regarded as support vectors and are correctly classified. However, the classifier is overfitted. If $\sigma \to \infty$ all the training data points are regarded as one point and the SVM cannot recognize any new data point [19].

IV. Results

We used the Matlab 7.0 software to implement our algorithms. The training set with 74 subjects was used to optimize SVM classifiers. Values of *C* and σ had to be adjusted. As suggested in [20], we assigned exponentially growing sequences to both parameters, with $C \in \{2^{-6}, 2^{-5}, \ldots, 2^{12}\}$ and $\sigma \in \{2^{-6}, 2^{-5}, \ldots, 2^{12}\}$. A new SVM algorithm was built for each pair of values from data in the training set. Then, we measured the accuracy reached by the algorithm on the test set. The highest classification accuracy was achieved for values in the region $2^3 \leq C \leq 2^8$ and $2^{-2} \leq \sigma \leq 2^0$. A refined search was carried out by varying both parameters according to $C \in \{0,5,\ldots,250\}$ and $\sigma \in \{0.2,0.3,\ldots,1\}$. Finally, the SVM classifier with *C* = 235 and σ = 0.4 provided the best result on the test set. The selected algorithm achieved a sensitivity of 84.44%, a specificity of 93.33% and an accuracy of 88.00%. Additionally, we performed receiver operating characteristic (ROC) analysis. The area under the ROC curve (AROC) reflects the generalization capability of the classifier. The proposed algorithm achieved an AROC of 0.921 from data in the test set. The ROC curve obtained for the proposed diagnostic algorithm is displayed in Fig. 1

V. Discussion

We developed and evaluated a novel diagnostic algorithm to help in OSAS diagnosis. It was based on SVM classifiers and spectral features from SaO_2 signals. Spectral analysis was focused on the band between 0.010 and 0.033 Hz, due to the duration of apnea events and their repetition during sleep. Our algorithm achieved an accuracy of 88.00% (84.44% sensitivity and 93.33% specificity) and an AROC of 0.921 on the test set with 75 subjects.

The proposed algorithm provided significant results in the OSAS diagnosis problem. A total of 8 subjects from the test set were misclassified (2 OSAS negatives and 6 OSAS positives), yielding higher specificity than sensitivity. However, the opposite may be preferred since the cost for misclassifying an OSAS positive is greater than that for misclassifying an OSAS negative. Undiagnosed positive subjects could be affected by long term implications of OSAS. Thus, an early diagnosis is desirable.

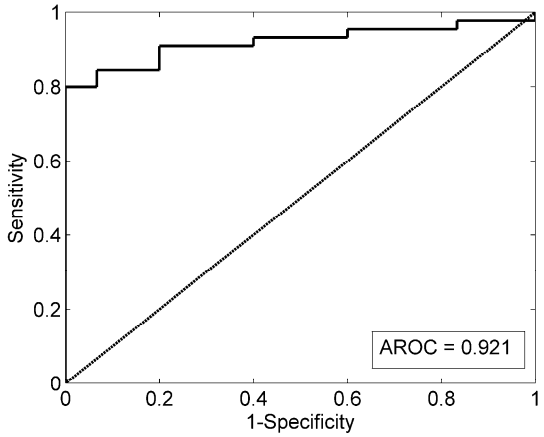

Fig. 1. ROC curve computed on the test set for the proposed SVM classifier.

Previously, other studies analyzed the diagnostic utility of SaO_2 data. Visual inspection of oximetry recordings provided 91% sensitivity and 69% specificity [5]. However, it represents a time-consuming task. On the other hand, oximetry indices have been widely applied to OSAS diagnosis [4]. A sensitivity of 98% and a specificity of 88% were reached by means of ODI4 [6]. The combination of several indices achieved 90% sensitivity and 70% specificity [7]. Finally, information from oximetry was used together with clinical data to perform OSAS diagnosis [8]. An accuracy of 62.1% was reported.

Conventional oximetry indices represent a straightforward approach to automated analysis of SaO_2. However, there exists a significant variability for diagnostic results reported by them [4]. In this study, we propose to apply advanced signal processing techniques to carry out OSAS diagnosis. In preceding studies, we developed other algorithms by using multilayer perceptron (MLP) and radial basis function (RBF) neural network classifiers [21,22]. They reached an accuracy of 85.5% and 86.1%, respectively. The SVM developed here improved the diagnostic capability of these networks. However, it was assessed on a different test set. Furthermore, SVM were used to classify features from ECG in other studies [13,14]. An accuracy of 100% was reached on a test set with 30 subjects [14]. However, borderline subjects were previously removed from the study.

Some limitations can be found in our study. Firstly, larger training and test sets are desirable in order to improve optimization and evaluation processes. Additionally, oximetry signals could be affected by noise and artifacts. These could affect the spectral properties of SaO_2 recordings, leading to incorrect classification. Finally, parameters C and σ of SVM were optimized on the test set. Therefore, results may be biased. The proposed algorithm should be evaluated on a different dataset.

In summary, SVM represent a powerful tool for classification purposes. They provided relevant results in OSAS diagnosis. An accuracy of 88.00% and an AROC of 0.921 were achieved by these classifiers using spectral features from SaO_2 as inputs. The proposed method could be applied as a screening tool for early OSAS diagnosis. As a result, it could contribute to reduce the number of PSG.

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REFERENCES

[1] A. Qureshi and R. D. Ballard, "Obstructive sleep apnea," *J. Allergy Clin. Immunol.*, vol. 112, pp. 643-651, 2003.

[2] T. Young, P. E. Peppard and D. J. Gottlieb, "Epidemiology of obstructive sleep apnea: a population health perspective," *Am. J. Respir. Crit. Care Med.*, vol. 165, pp. 1217-1239, 2002.

[3] K. E. Bloch, "Getting the most out of nocturnal pulse oximetry," *Chest*, vol. 124, pp. 1628-1630, 2003.

[4] N. Netzer, A. H. Eliasson, C. Netzer and D. A. Kristo, "Overnight pulse oximetry for sleep-disordered breathing in adults: a review," *Chest*, vol. 120, pp. 625-633, 2001.

[5] J. M. Rodríguez, P. De Lucas, M. J. Sánchez, J. L. Izquierdo, R. Peralta and J. M. Cubillo, "Usefulness of the visual analysis of night oximetry as a screening method in patients with suspected clinical obstructive sleep apnea syndrome," *Arch. Bronconeumol.*, vol. 32, pp. 437-441, 1996.

[6] J. C. Vázquez, W. H. Tsai, W. W. Flemons, A. Masuda, R. Brant, E. Hajduk, W. A. Whitelaw and J. E. Remmers, "Automated analysis of digital oximetry in the diagnosis of obstructive sleep apnoea," *Thorax*, vol. 55,pp. 302–307, 2000.

[7] U. J. Magalang, J. Dmochowski, S. Veeramachaneni, A. Draw, M. J. Mador, A. El-Solh and B. J. B. Grant, "Prediction of the apnea-hypopnea index from overnight pulse oximetry," *Chest*, vol. 124, pp. 1694-1701, 2003.

[8] N. Roche, B. Herer, C. Roig and G. Huchon, "Prospective testing of two models based on clinical and oximetric variables for prediction of obstructive sleep apnea," *Chest*, vol. 121, pp. 747–752, 2002.

[9] C. Zamarrón, F. Gude, J. Barcala, J. R. Rodríguez and P. V. Romero, "Utility of oxygen saturation and heart rate spectral analysis obtained from pulse oximetric recordings in the diagnosis of sleep apnea syndrome," *Chest*, vol. 123, pp. 1567-1576, 2003.

[10] D. Álvarez, R. Hornero, D. Abásolo, F. Del Campo and C. Zamarrón, "Nonlinear characteristics of blood oxygen saturation from nocturnal oximetry for obstructive sleep apnoea detection," *Physiol. Meas.*, vol. 27, pp. 399–412, 2006.

[11] R. Hornero, D. Álvarez, D. Abásolo, F. Del Campo and C. Zamarrón, "Utility of approximate entropy from overnight pulse oximetry data in the diagnosis of the obstructive sleep apnea syndrome," *IEEE Trans. Biomed. Eng.*, vol. 54, pp. 107–113, 2007.

[12] R. K. Begg, M. Palaniwami and B. Owen, "Support vector machines for automated gait classification," *IEEE Trans. Biomed. Eng.*, vol. 52, pp. 828-838, 2005.

[13] A. H. Khandoker, M. Palaniswami and C. K. Karmakar, "Support vector machines for automated recognition of obstructive sleep apnea syndrome from ECG recordings," *IEEE Trans. Inf. Technol. Biomed.*, vol. 13, pp. 37-48, 2009.

[14] A. H. Khandoker, C. K. Karmakar and M. Palaniswami, "Automated recognition of patients with obstructive sleep apnoea using wavelet-based features of electrocardiogram recordings," *Comput. Biol. Med.*, vol. 39, pp. 88-96, 2009.

[15] C. Cortes and V. Vapnik, "Support-vector networks," *Mach. Learn.*, vol. 20, pp. 273-297, 1995.

[16] S. Haykin, Neural networks: a comprehensive foundation. Engewood Cliffs, NJ: Prentice Hall, 1999.

[17] A. Rechtschaffen and A. Kales, *A manual of standardized terminology, techniques and scoring system for sleep stages of human subjects*. Los Angeles: Brain Information Services, Brain Research Institute, University of California, 1968.

[18] P. Welch, "The use of fast Fourier transform for the estimation of power spectra: a method based on time averaging over short, modified periodograms," *IEEE Trans. Acous. Speech*, vol. 15, pp. 70-73, 1967.

[19] W. Wang, Z. Xu, W. Lu and X. Zhang, "Determination of the spread parameter in the Gaussian kernel for classification and regression," *Neurocomputing*, vol. 55, pp. 643-653, 2003.

[20] C. Hsu, C. C. Chang, and C. J. Lin, "A Practical Guide to Support Vector Classification," Dept. Comput. Sci. Inf. Eng., Nat. Taiwan Univ., 2003.

[21] J. V. Marcos, R. Hornero, D. Álvarez, F. Del Campo, C. Zamarrón and M. López, "Utility of multilayer perceptron neural network classifiers in the diagnosis of the obstructive sleep apnoea syndrome from nocturnal oximetry," *Comput. Methods Programs Biomed.*, vol. 92, pp. 79-89, 2008.

[22] J. V. Marcos, R. Hornero, D. Álvarez, F. Del Campo, M. López and C. Zamarrón, "Radial basis function classifiers to help in the diagnosis of the obstructive sleep apnoea syndrome from nocturnal oximetry," *Med. Biol. Eng. Comput.*, vol. 46, pp. 323–332, 2008.