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Automated detection of obstructive sleep apnoea syndrome from oxygen saturation recordings using linear discriminant analysis

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Nocturnal polysomnography (PSG) is the gold-standard to diagnose obstructive sleep apnoea syndrome (OSAS). However, it is complex, expensive, and time-consuming. We present an automatic OSAS detection algorithm based on classification of nocturnal oxygen saturation (SaO_2) recordings. The algorithm makes use of spectral and nonlinear analysis for feature extraction, principal component analysis (PCA) for preprocessing and linear discriminant analysis (LDA) for classification. We conducted a study to characterize and prospectively validate our OSAS detection algorithm. The population under study was composed of subjects suspected of suffering from OSAS. A total of 214 SaO_2 signals were available. These signals were randomly divided into a training set (85 signals) and a test set (129 signals) to prospectively validate the proposed method. The OSAS detection algorithm achieved a diagnostic accuracy of 93.02% (97.00% sensitivity and 79.31% specificity) on the test set. It outperformed other alternative implementations that either use spectral and nonlinear features separately or are based on logistic regression. The proposed method could be a useful tool to assist in early OSAS diagnosis, contributing to overcome the difficulties of conventional PSG.

Obstructive sleep apnoea syndrome, oxygen saturation, linear discriminant analysis, spectral analysis, nonlinear analysis, pattern classification

1 Introduction

Obstructive sleep apnoea syndrome (OSAS) is the most common form of sleep disordered-breathing [38]. Epidemiological studies estimate its prevalence up to 5% of adult men in western countries [37]. OSAS is characterized by repetitive occlusion of the upper airway during sleep, causing intermittent cessations of breathing (apnoeas) or reduction in airflow (hypopnoeas) [29]. Events of apnoea are accompanied by hypoxaemia and bradycardia. They are often terminated in arousals, and the resulting sleep fragmentation can lead to excessive daytime sleepiness [38]. As a result, OSAS has been pointed out as a major cause of traffic and industrial accidents [32]. Additionally, long-term effects are related to the cardiovascular system, including hypertension, arrhythmias, congestive heart failure and cerebrovascular disease [29]. A high percentage of patients, 83% of men and 93% of women, remains undiagnosed [36]. Therefore, OSAS can be considered as a risk factor for public health.

Nowadays, nocturnal polisomnography (PSG) is the gold-standard for OSAS diagnosis. It must be performed in a special sleep unit and under supervision of a trained technician. PSG monitors different physiological recordings such as electrocardiogram (ECG), electroencephalogram (EEG), electrooculogram (EOG), electromyogram (EMG), oxygen saturation, abdominal ventilatory effort and snoring [32]. These recordings must be subsequently analyzed by a medical expert to obtain a final diagnosis. Despite its high diagnostic performance, PSG presents some drawbacks since it is complex, expensive and time-consuming. As a result, the research focused on the development of alternative diagnostic techniques has notably increased in recent years.

Most of these studies were based on nocturnal pulse oximetry [26]. It allows to monitor respiratory dynamics during sleep by measuring arterial oxygen saturation (SaO_2). This recording provides useful information about OSAS. Events of apnoea are characterized by a decrease in the SaO_2 value, which reflects airflow reduction and hypoxaemia. Subsequently, respiration is restored and the saturation value increases until its baseline level [3]. As a result, SaO_2 signals from OSAS patients tend to be more unstable than those from control subjects due

to the recurrence of apnoeas during sleep. This different behaviour can be exploited to diagnose OSAS.

Diverse methodologies have been proposed to perform OSAS diagnosis from SaO_2 data. The simplest one is visual inspection [30]. However, it is tedious and subjective. Conventional oximetry indices such as the oxygen desaturation index over 2% (ODI2), 3% (ODI3) and 4% (ODI4), and the cumulative time spent below 90% of saturation (CT90) represent a first approach for automated analysis of SaO_2 signals [14, 22, 26, 34]. A more advanced interpretation of oximetry data can be obtained by using signal processing techniques [1, 6, 16, 39]. According to this approach, several diagnostic algorithms have been developed by using pattern classification methods [23, 24, 25].

In this paper, we describe a novel automatic OSAS detection algorithm based on classification of nocturnal SaO_2 recordings. The results of our previous studies in this research area [25] indicate that it may be possible to design a fully automatic OSAS detection algorithm with adequate performance for clinical use by combining spectral and nonlinear analysis for feature extraction, principal component analysis (PCA) for preprocessing, and linear discriminant analysis (LDA) for classification. In addition to providing a detailed description of the algorithm to ensure reproducibility, we report the results of the study designed to characterize and prospectively validate the proposed novel algorithm using a new database.

2 Methods

2.1 Algorithm Description

A pattern classification approach was used to model the OSAS diagnosis problem. The proposed algorithm comprises three stages: feature extraction, preprocessing, and classification using LDA. Figure 1 shows a block diagram of the proposed OSAS detection algorithm.

INSERT FIGURE 1 AROUND HERE

Step 1 - Feature extraction

The feature extraction stage maps the SaO_2 signal into a reduced set of variables or features to summarize the information in the recording. The extracted features measure relevant properties of oximetry data in order to discriminate signals from OSAS positive subjects. Previously, it was shown that spectral and nonlinear analyses of SaO_2 signals provide valuable information to detect OSAS [1, 6, 16, 39]. Statistically significant differences were found between OSAS positive and negative subjects by evaluating different spectral [39] and nonlinear features [1, 6, 16]. Consequently, our proposed automatic OSAS detection algorithm uses both spectral analysis and nonlinear analysis for feature extraction.

Spectral analysis

Periodicities of ventilation originate phase-lagged changes in SaO_2 data [26]. The duration of apnoea events ranges from 30 s to 2 min, including the awakening response after the event. These events are reflected in oximetry recordings by a fluctuation (decrease and subsequent restoration of the saturation value) with the same duration. As indicated in previous studies [10, 39], the recurrence of apnoeas during sleep infers some periodic behaviour in SaO_2 signals. Due to the duration of the events, the repetition of changes in these signals occurs with a rate between 30 s and 2 min. The frequency band associated to these periods of fluctuation ranges between 0.010 and 0.033 Hz. Thus, the signal power contained in this band is usually higher in subjects with OSAS than in controls [39].

The proposed OSAS detection algorithm calculates the following spectral features computed from the power spectral density (PSD) of SaO_2 data:

- Feature 1. Total area under the PSD (S_T). This feature provides an estimate of the signal power.
- Feature 2. Area enclosed in the band of interest (S_B). This feature approximates the amount of signal power contained in the band between 0.010 and 0.033 Hz.

- Feature 3. Peak amplitude of the PSD in the band of interest (*PA*). It represents the most significant frequency component contained in the band between 0.010 and 0.033 Hz.

According to the dynamical behaviour of SaO_2 recordings, these spectral features are expected to be higher in signals corresponding to OSAS positive subjects.

Nonlinear analysis

SaO_2 signals from patients affected by OSAS tend to present frequent changes and fluctuations due to the repetition of apnoeas. In contrast, oximetry recordings corresponding to control subjects tend to have a near-constant value of saturation around 97% [26]. According to our previous research, nonlinear analysis of oximetry data can capture these differences, representing a useful means to quantitatively distinguish OSAS patients from control subjects [1, 6, 16]. The proposed OSAS detection algorithm calculates the following nonlinear methods from the SaO_2 recordings during the feature extraction stage:

- Feature 4. Approximate entropy (*ApEn*). It provides an estimate of the irregularity of a signal [28]. High values of *ApEn* correspond to irregular signals. Two input parameters must be specified to compute *ApEn*: a run length *m* and a tolerance window *r*. Briefly, *ApEn* measures the logarithmic likelihood that runs of patterns that are close (within *r*) for *m* contiguous observations remain close (within the same tolerance width *r*) on subsequent incremental comparisons [28].
- Feature 5. Central tendency measure (*CTM*). It quantifies the variability of a time series [5], assigning low values to signals with a high degree of chaos. Second-order difference plots are generated by plotting $(s_{t+2} - s_{t+1})$ vs. $(s_{t+1} - s_t)$, where $\mathbf{s} = (s_1, \ldots, s_t, \ldots, s_T)$ is the time series of length *T*. Then, *CTM* is computed by selecting a circular region of radius ρ round the origin, counting the number of points that fall within the radius and dividing by the total number of points [5].
- Feature 6. Lempel-Ziv complexity (*LZC*). It is a non-parametric, simple-to-calculate measure of complexity in a one-dimensional signal [21]. Complex signals generate high values of *LZC*. This feature is related to the number of distinct substrings and the rate of their recurrence along a given sequence. The signal must be transformed into a finite symbol sequence

before calculating the complexity measure. The transformation is carried out by comparing each sample with a fixed threshold. Usually, the median value is used to obtain a 0-1 sequence. Then, this binary sequence is scanned from left to right and the complexity counter is increased by one unit every time a new subsequence of consecutive characters is encountered [21].

The presence of OSAS is related to irregularity, variability and complexity of SaO_2 measured by *ApEn*, *CTM* and *LZC*, respectively [1, 6, 16]. As a result, high values of *ApEn* and *LZC* as well as low *CTM* values are expected for recordings from OSAS positive subjects.

Step 2 – Preprocessing: Principal component analysis (PCA)

Once the algorithm obtains the spectral (S_T, S_B, *PA*) and nonlinear (*ApEn*, *CTM*, *LZC*) features during the feature extraction stage, it performs PCA before the pattern classification stage. PCA defines an orthonormal basis in the *d*-dimensional space spanned by the extracted features [18]. For the present study, patterns $\mathbf{x}$ composed by spectral and nonlinear features from SaO_2 recordings can be viewed as vectors in a space with dimension $d = 6$. A new set of *d* uncorrelated variables is obtained from PCA by projecting these original vectors onto the new basis.

The eigenvectors of the covariance matrix ($\mathbf{\Sigma_x}$) of variable $\mathbf{x}$ are computed by PCA to find an orthonormal basis for the input feature space [18]. A relevant property of PCA is that the new *d* components are ranked in decreasing importance since the amount of variance along a particular eigenvector is represented by its associated eigenvalue. Thus, the first *l* most relevant components ($l \leq d$) can be selected in order to remove redundant information, resulting in improved classification performance.

Step 3 – Classification: Linear discriminant analysis (LDA)

In this step, the *l* variables selected from PCA are the inputs to the statistical classifier based on LDA. In statistical pattern recognition, a feature or pattern vector $\mathbf{y} = [\mathbf{y}_1, \ldots, \mathbf{y}_l] \in \Re^l$ must be assigned to one of *c* categories $\{\omega_1, \ldots, \omega_c\}$. Each pattern $\mathbf{y}$ belonging to class ω_j ($j = 1, \ldots, c$) is viewed as an observation

drawn randomly from the class-conditional probability function $p(\mathbf{y}|\omega_j)$. The classifier can be regarded as a function $f:\Re^l \to \{\omega_1,\ldots,\omega_c\}$. The Bayes decision rule allows to minimize the probability of error in the classification task [2]. It can be stated as follows:

$$\text{Decide } \omega_j \text{ for } \mathbf{y} \text{ if } p(\mathbf{y}|\omega_j)P(\omega_j) = \max_{j=1,\ldots,c} p(\mathbf{y}|\omega_j)P(\omega_j) \tag{1}$$

where $P(\omega_j)$ denotes the prior probability of class ω_j. LDA models each class-conditional density function $p(\mathbf{y}|\omega_j)$ as a multivariate normal distribution. Additionally, it is supposed that all the class covariance matrices are identical (homocedasticity) [17].

Substituting the estimated multivariate normal $p(\mathbf{y}|\omega_j)$ into Eq. 1 and taking the natural logarithm leads to the rule:

$$\text{Decide } \omega_j \text{ for } \mathbf{y} \text{ if } h_j(\mathbf{y}) = \max_{j=1,\ldots,c} h_j(\mathbf{y}) \tag{2}$$

where $h_j(\mathbf{y})$ is called the discriminant score for class ω_j. It is given by:

$$h_j(\mathbf{y}) = \boldsymbol{\mu}_j^T \boldsymbol{\Sigma}^{-1}\mathbf{y} - \frac{1}{2}\boldsymbol{\mu}_j^T \boldsymbol{\Sigma}^{-1}\boldsymbol{\mu}_j + \ln P(\omega_j) \tag{3}$$

where $\boldsymbol{\mu}_j$ are the class ω_j mean vector and $\boldsymbol{\Sigma}$ is the covariance matrix of the pooled data. This classification rule is referred to as LDA since it defines linear decision boundaries in the feature space.

Training a classifier based on LDA requires to adjust parameters $\boldsymbol{\mu}_j$ and $\boldsymbol{\Sigma}$ associated with the class-conditional densities. The maximum likelihood estimates of both parameters can be directly computed from training data [12]. In addition, prior probabilities $P(\omega_j)$ can be obtained as:

$$P(\omega_j) = \frac{N_j}{N} \tag{4}$$

where N is the number of samples in the training set and N_j is the total number of training samples belonging to class ω_j.

2.2 Subjects and Signals

The population used for algorithm characterization and validation consisted of

214 patients (171 males and 43 females) with a mean ± standard deviation (SD) age of 53.53 ± 13.17 years. All subjects were suspected of suffering from OSAS because of daytime hypersomnolence, loud snoring, nocturnal choking and awakenings or apneic events reported by the subject or a bedmate. Overnight conventional polysomnographies (PSG) were carried out from midnight to 08:00 AM in the Sleep Unit of Hospital Universitario Pío del Río Hortega of Valladolid, Spain. The Review Board on Human Studies approved the protocol, and each subject gave his or her informed consent to participate in the study. Patients were continuously monitored using a polysomnograph (Alice 5, Respironics, Philips Healthcare, The Netherlands) and included EEG, EOG, chin EMG, airflow, ECG, measurement of chest wall movement and oximetry. Apnea was defined as the absence of airflow for more than 10 s, and hypopnea was defined as a decrease in respiratory flow of at least 50%, accompanied by a decrease of more than 4% in the saturation of hemoglobin. The average apnea-hypopnea index (AHI) was computed for hourly periods of sleep. An AHI of 10 or more events per hour was considered as OSAS positive.

The SaO_2 profiles from PSG were recorded using a sampling frequency of 1 Hz. Oximetry recordings were scanned to remove artifacts and drops to zero due to poor contact from the finger probe. The initial population was randomly divided into training and test sets. 85 subjects (19 OSAS negative and 66 OSAS positive) composed the training set, which was used to develop the algorithm. The remaining 129 subjects (29 OSAS negative and 100 OSAS positive) composed the test set, which was used for prospective validation of the proposed OSAS detection algorithm. Both groups showed similar age, gender, body mass index (BMI) and recording time. Table 1 summarizes the demographic and clinical data for the population under study as well as for training and test sets.

INSERT TABLE 1 AROUND HERE

3 Results

In this section we describe the results of the study conducted to characterize the proposed OSAS detection algorithm, as well as the results of its prospective validation.

3.1 Feature extraction

All SaO_2 signals in our database were automatically analyzed by the algorithm to compute the spectral (S_T, S_B and PA) and nonlinear (*ApEn*, *CTM* and *LZC*) features. The following user specified parameters were selected for the algorithm's implementation:

- Spectral analysis. The non-parametric Welch's method was used to estimate the PSD of our signals [35]. A Hanning window of 512 samples with an overlapping of 50% was applied. Fast Fourier Transforms were computed for a length of 1024 samples.
- Nonlinear analysis. SaO_2 signals were divided into epochs of 512 samples to obtain an estimate for *ApEn*, *CTM* and *LZC*. The measures obtained from all the epochs were averaged to compute the final estimate for each of them. As suggested in previous studies [1, 6, 16], different values of the user-specified parameters were evaluated for each of these methods. The configurations with the best discriminant capability on the training set were selected. In the case of *ApEn*, parameters m and r were set to 1 and 0.25 times the standard deviation of the original sequence, respectively. To compute *CTM*, a radius $\rho = 1$ was selected as optimum. Finally, *LZC* was computed by converting SaO_2 signals into 0–1 sequences. Each SaO_2 value was compared with the median of the samples in the corresponding epoch to transform the data.

We analyzed the statistical properties of the extracted features. Normality and homocedasticity were evaluated by applying the Kolmogorov–Smirnov and the Levene tests, respectively. We observed that *CTM* presented a non-normal distribution. In addition, the three spectral features were transformed by means of the base 10 logarithm function to have a normal and homocedastic distribution.

3.2 Preprocessing

In the preprocessing stage, a new set of variables or components was obtained from PCA. The original patterns composed of spectral and nonlinear features were projected onto a new orthonormal basis in the input space. Figure 2 represents the percentage of the variance explained by each of the components from PCA.

INSERT FIGURE 2 AROUND HERE

As can be observed, most of the variance is explained by the first principal component. However, information contained in the other components may significantly contribute to improve classification performance. Otherwise, redundant components can be removed.

3.3 Classification

Training

We used the training set with 85 subjects to select the optimum value for l, i.e. the number of components retained from PCA. Its effect on classification performance was analyzed. A total of six different input patterns were considered by selecting the first l components from the preprocessing stage, with l = 1, 2, …, 6. For each of the defined input patterns, a LDA classifier was implemented from data in the training set. The accuracy (percentage of subjects correctly classified) achieved on this dataset was used to compare the classification capability of the six different schemes. These results are shown in Figure 3.

INSERT FIGURE 3 AROUND HERE

The highest accuracy on the training set was provided by the algorithms with l = 5 and l = 6. Both achieved a correct classification rate of 91.77%. Although a high percentage (94.69%) of the input variance is explained by the first principal component, our results suggest that the information provided by the other ones is relevant for classification. Moreover, we found that adding the sixth component from PCA did not increase the discriminant capability of the algorithm. Thus, the optimum number of components was fixed to l = 5.

Test (Prospective Validation)

The algorithm was prospectively validated on an independent test set with 129 subjects. Sensitivity, specificity and accuracy were computed. Moreover, we applied receiver operating characteristic (ROC) analysis [15]. The area under the ROC curve (AUROC) was used as a measure of classification performance. It represents the probability of correct classification for a randomly chosen pair of OSAS positive and OSAS negative subjects [15]. Table 2 shows the confusion matrix with the diagnostic results achieved on test data.

INSERT TABLE 2 AROUND HERE

Our diagnostic algorithm reached an accuracy of 93.02% (sensitivity of 97.00% and specificity of 79.31%) and an AUROC of 0.95 on data in the test set. A total of 6 OSAS negative subjects were misclassified. Their mean AHI was 4.98 h^{-1} and 3 of these subjects had an AHI > 5 h^{-1}. On the other hand, the algorithm provided an incorrect decision for 3 OSAS positive subjects. The mean AHI for this group was 12.40 h^{-1}. All of them had an AHI < 15 h^{-1}, which is considered the threshold between mild and moderate OSAS [29].

4 Discussion

The proposed algorithm provided significant results in the OSAS diagnosis problem. It outperformed other techniques for automated OSAS detection previously developed by our research group. All of them were based on the analysis of nocturnal oximetry signals. Specifically, classification of spectral features from SaO_2 data by using LDA provided an accuracy of 87.61% and an AUROC of 0.93 [25]. A similar scheme was implemented by using a logistic regression (LR) classifier, which achieved 86.73% accuracy and 0.92 AUROC [25]. Additionally, we evaluated the utility of neural networks classifiers in the OSAS diagnosis problem. Multilayer perceptron (MLP) and radial basis function (RBF) networks were used together with nonlinear features from oximetry data. Both networks provided similar diagnostic results. The MLP achieved an accuracy of 85.50% and an AUROC of 0.90 [23] whereas the algorithm based on RBF reached an accuracy of 86.10% and an AUROC of 0.91 [24].

However, the comparison with previous results may be biased. A different database composed of 187 SaO_2 recordings was used in the cited studies. In addition, spectral and nonlinear features from SaO_2 data were separately applied. In the present research, it is proposed to combine information from both sets of features. Moreover, PCA was applied as a previous stage to pattern classification. In this study, PCA was used to rank the transformed features or components. A subset of these components was selected based on the achieved classification performance. In order to quantify the benefit obtained from this approach, a similar algorithm based on PCA and LDA was implemented from each of the two feature sets. The optimum number of components was selected by computing the classification accuracy on the training set. For both algorithms, the best performance was achieved when all the components were used as inputs to the LDA classifier. The PCA-LDA algorithm based on spectral features provided a diagnostic accuracy of 86.82% on the test set (94.00% sensitivity and 62.07% specificity) and an AUROC of 0.93. A diagnostic accuracy of 75.97% (95.00% sensitivity and 10.34% specificity) and an AUROC of 0.71 were reached using nonlinear features. Additionally, we evaluated the effect of substituting our PCA-LDA method by a LR classifier [17]. Three different LR-based algorithms were assessed according to the feature set used as input: spectral features, nonlinear features and the combination of both. The highest classification accuracy on the test set was obtained when spectral and nonlinear features were combined. The LR algorithm with this configuration achieved a diagnostic accuracy of 81.40% (92.00% sensitivity and 44.83% specificity) and an AUROC of 0.89. As can be observed, the proposed PCA-LDA algorithm outperformed the evaluated alternatives. Table 3 summarizes the results achieved by the algorithms compared in this study. These suggest that there exists a significant advantage on combining both feature sets (spectral and nonlinear) for classifying SaO_2 signals as OSAS positive or negative. Moreover, PCA-LDA has shown to be more efficient than LR for the proposed pattern classification problem.

INSERT TABLE 3 AROUND HERE

Oximetry signals have been widely used to obtain information related to OSAS. Traditionally, visual inspection and conventional oximetry indices have been evaluated for diagnostic purposes [26, 30]. ODI2, ODI3, ODI4 and CT90 provide an automated means for interpretation of SaO_2 signals. However, their diagnostic utility extremely varied from one study to another, with sensitivity ranging from 31% to 98% and specificity from 41% to 100% [26]. ODI4 was identified as the best predictor of OSAS out of the four conventional indices. Vázquez et al. [34] reported a sensitivity of 98% and a specificity of 88% for this index using a threshold of AHI $\geq$ 15 h^{-1} to define OSAS. Nevertheless, these results substantially differed from other similar studies. Golpe et al. [14] estimated the diagnostic performance of ODI4 in a sensitivity of 32% and a specificity of 97%. On the other hand, Magalang et al. [22] proposed to combine these indices to provide an estimation of the AHI using linear regression methods. A sensitivity of 90% and a specificity of 70% were achieved.

In addition to oximetry analysis, a wide variety of methods have been proposed to overcome the difficulties related to OSAS diagnosis. Home unattended PSG enables to reduce cost and waiting lists associated to in-laboratory sleep studies [13, 31]. However, this approach is still complex and time-consuming since it cannot avoid manual scoring of the recorded data. As in the present study, signal processing techniques have been applied to other physiological data to characterize OSAS. Morphological and clinical features [4, 9], ECG [27, 7], nasal airflow [33], snoring [11], tracheal breathing sound [19, 20] or speech [40] have been previously used for OSAS detection or identification of apnoea events during the night. Specifically, several studies focused on ECG analysis to assist in OSAS diagnosis. Most of them were based on the detection of cardiac arrhythmias induced by events of apnoea [32]. A diagnostic accuracy of 100% was reported in the study by de Chazal et al. [7]. Time and spectral features from the RR series and the ECG-derived respiratory signal were used as inputs to a LDA classifier. Nevertheless, the method was evaluated on a test set with 30 subjects from which borderline cases were removed.

Some limitations can be found in our research. Our diagnostic algorithm provided substantially higher sensitivity (97.00%) than specificity (79.31%). The different

prior probabilities $P(\omega_j)$ associated to both groups (OSAS positive and OSAS negative) influence the decision obtained from the Bayes rule. As a result, the algorithm tended to label doubtful subjects as OSAS positive. Our recordings correspond to subjects suspected of suffering from OSAS. Therefore, it is more likely to find positive cases in such a population. On the other hand, LDA assumes the input variables to have a normal and homocedastic distribution, in contrast to other pattern classifiers such as neural networks or LR. Nevertheless, these methods represent a black-box approach to model statistical pattern classification problems [8]. From our previous results, LDA was selected for its efficiency and reduced complexity. In our study, only *CTM* did not meet the assumption of normality. However, the proposed method achieved significant diagnostic results.

In summary, the OSAS diagnosis problem was modeled as a pattern classification task. Nocturnal oximetry signals corresponding to subjects suspected of suffering from OSAS were classified into two groups: OSAS positive or negative. A novel algorithm based on LDA was implemented for this purpose. Input patterns were obtained from the linear combination of spectral and nonlinear features from SaO_2 recordings using PCA. The algorithm provided an accuracy of 93.02% and an AUROC of 0.95 on an independent test set with 129 subjects. It was shown that the combination of spectral and nonlinear features from oximetry data improved the classification performance of the algorithm. In addition, the presented PCA-LDA method outperformed LR in the proposed classification problem. Therefore, our method represents an efficient technique for automated OSAS diagnosis using only SaO_2 data. It could be used as a screening test to assist doctors for early OSAS detection. As a result, it could contribute to overcome the difficulties of PSG as well as to reduce the demand for these studies.

References

[1] Álvarez D, Hornero R, Abásolo D, Del Campo F, Zamarrón C (2006) Nonlinear characteristics of blood oxygen saturation from nocturnal oximetry for obstructive sleep apnoea detection. Physiol Meas 27:399-412

[2] Bishop CM (1995) Neural networks for Pattern Recognition. Oxford University Press, Oxford, UK.

[3] Bloch KE (2003) Getting the most out of nocturnal pulse oximetry. Chest 124:1628-1630

[4] Caballero P, Álvarez-Sala R, García-Río F, Prados C, Hernán MA, Villamar J, Álvarez-Sala JL (1998) CT in the evaluation of the upper airway in healthy subjects and in patients with obstructive sleep apnea syndrome. Chest 113:111-116

[5] Cohen ME, Hudson DL, Deedwania PC (1996) Applying continuous chaotic modelling to cardiac signals. IEEE Eng Med Biol Mag 15:97-102

[6] Del Campo F, Hornero R, Zamarrón C, Abásolo DE, Álvarez D (2006) Oxygen saturation regularity analysis in the diagnosis of obstructive sleep apnea. Artif Intell Med 37:111-118

[7] de Chazal P, Heneghan C, Sheridan E, Reilly R, Nolan P, O'Malley M (2003) Automated processing of the single-lead electrocardiogram for the detection of obstructive sleep apnoea. IEEE Trans Biomed Eng 50:686-696

[8] Dreiseitl S, Ohno-Machado L (2002) Logistic regression and artificial neural network classification models: a methodology review. J Biomed Inform 35:352-359

[9] El-Solh AA, Mador MJ, Ten-Brock E, Shucard DW, Abul-Khoudoud M, Grant BJB (1999) Validity of neural network in sleep apnea. Sleep 22:105-111

[10] El-Solh AA, Magalang UJ, Mador MJ, Dmochowski J, Veeramachaneni S, Saberi A, Draw AM, Lieber BB, Grant BJB (2003) The utility of neural network in the diagnosis of Cheyne-Stokes respiration. Journal of Medical Engineering and Technology 27:54-58

[11] Fiz JA, Jané R, Solá-Soler J, Abad J, García MA, Morera J (2010) Continuous analysis and monitoring of snores and their relationship to the apnea-hypopnea index. Laryngoscope 120:854-862

[12] Friedman JH (1989) Regularized discriminant analysis. J Am Stat Assoc 84:165-175

[13] Gagnadoux F, Pelletier-Fleury N, Philippe C, Rakatonanahary D, Bernard F (2002) Home unattended vs hospital telemonitored polysomnography in suspected obstructive sleep apnea syndrome: a randomized crossover trial. Chest 121:753-758

[14] Golpe R, Jiménez A, Carpizo R, Cifrian JM (1999) Utility of home oximetry as a screening test for patients with moderate to severe symptoms of obstructive sleep apnea. Sleep 22:932-937

[15] Hanley JA, McNeil BJ (1982) The meaning and use of the area under a receiving operating characteristic (ROC) curve. Radiology 143:29-36

[16] Hornero R, Álvarez D, Abásolo D, Del Campo F, Zamarrón C (2007) Utility of aproximate entropy from overnight pulse oximetry data in the diagnosis of the obstructive sleep apnea syndrome. IEEE Trans Biomed Eng 54:107-113

[17] Jobson JD (1991) Applied Multivariate Data Analysis. Volume II: Categorical and Multivariate Methods. Springer, New York.

[18] Jolliffe IT (2002) Principal Component Analysis. Springer-Verlag, New York.

[19] Kulkas A, Rauhala E, Huupponen E, Virkkala J, Tenhunen M, Saastamoinen A, Himanen SL (2008) Detection of compressed tracheal sound patterns with large amplitude variation during sleep. Med Biol Eng Comput 46:315-321

[20] Kulkas A, Huupponen E, Virkkala J, Tenhunen M, Saastamoinen A, Rauhala E, Himanen SL (2009) New tracheal sound feature for apnoea analysis. Med Biol Eng Comput 47:405-412

[21] Lempel A, Ziv J (1976) On the complexity of finite sequences. IEEE Trans Inf Theory 22:75-81

[22] Magalang UJ, Dmochowski J, Veeramachaneni S, Draw A, Mador MJ, El-Solh A, Grant BJB (2003) Prediction of the apnea-hypopnea index from overnight pulse oximetry. Chest 124:1694-1701

[23] Marcos JV, Hornero R, Álvarez D, Del Campo F, Zamarrón C, López M (2008) Utility of multilayer perceptron neural network classifiers in the diagnosis of the obstructive sleep apnoea syndrome from nocturnal oximetry. Comput Meth Programs Biomed 92:79-89

[24] Marcos JV, Hornero R, Álvarez D, Del Campo F, López M, Zamarrón C (2008) Radial basis function classifiers to help in the diagnosis of the obstructive sleep apnoea syndrome from nocturnal oximetry. Med Biol Eng Comput 46:323-332

[25] Marcos JV, Hornero R, Álvarez D, Del Campo F, Zamarrón C (2009) Assessment of four statistical pattern recognition techniques to assist in obstructive sleep apnoea diagnosis. Med Eng Phys 31:971-978

[26] Netzer N, Eliasson AH, Netzer C, Kristo DA (2001) Overnight pulse oximetry for sleep-disordered-breathing in adults: a review. Chest 120:625-633

[27] Penzel T, McNames J, de Chazal P, Raymond B, Murray A, Moody G (2002) Systematic comparison of different algorithms for apnoea detection based on electrocardiogram recordings. Med Biol Eng Comput 40:402-407

[28] Pincus SM (2001) Assessing serial irregularity and its implications for health. Ann N Y Acad Sci 954:245-267

[29] Qureshi A, Ballard RD (2003) Obstructive sleep apnea. J Allergy Clin Immunol 112:643-651

[30] Rodríguez JM, De Lucas P, Sánchez MJ, Izquierdo JL, Peralta R, Cubillo JM (1996) Usefulness of the visual analysis of night oximetry as a screening method in patients with suspected clinical obstructive sleep apnea syndrome. Arch Bronconeumol 32:437-441

[31] Tiihonen P, Pääkkönen A, Mervaala E, Hukkanen T, Töyräs J (2009) Design, construction and evaluation of an ambulatory device for screening of sleep apnea. Med Biol Eng Comput 47:59-56

[32] Van Houwelingen KG, Van Uffelen R, Van Vliet ACM (1999) The sleep apnoea syndromes. Eur Heart J 20:858-866

[33] Várady P, Micsik T, Benedek S, Benyó Z (2002) A novel method for the detection of apnea and hypopnea events in respiration signals. IEEE Trans Biomed Eng 49:936-942

[34] Vázquez JC, Tsai WH, Flemons WW, Masuda A, Brant R, Hajduk E, Whitelaw WA, Remmers JE (2000) Automated analysis of digital oximetry in the diagnosis of obstructive sleep apnoea. Thorax 55:302-307

[35] Welch PD (1967) The use of fast Fourier transform for the estimation of power spectra: a method based on time averaging over short, modified periodogram. IEEE Trans Audio Electroacoust 15:70-73

[36] Young T, Evans L, Finn L, Palta M (1997) Estimation of the clinically diagnosed proportion of sleep apnea syndrome in middle-aged men and women. Sleep 20:705-706

[37] Young T, Peppard PE, Gottlieb DJ (2002) Epidemiology of obstructive sleep apnea: a population health perspective. Am J Respir Crit Care Med 165:1217-1239

[38] Young T, Peppard PE, Taheri S (2005) Excess weigth and sleep-disordered breathing. J Appl Physiol 99:1592-1599

[39] Zamarrón C, Gude F, Barcala J, Rodríguez JR, Romero PV (2003) Utility of oxygen saturation and heart rate spectral analysis obtained from pulse oximetric recordings in the diagnosis of sleep apnea syndrome. Chest 123:1567-1576

[40] Zigel Y, Tarasiuk A, Goldshtein A (2008) Analysis of speech signals among obstructive sleep apnea patients. In: Proceedings of the IEEE 25th Convention of Electrical and Electronic Engineers, Israel, pp 760-764

Tables

ALL SUBJECTS			
	All	OSAS Positive	OSAS Negative
Subjects	214	166	48
Age (years)	53.53 ± 13.17	54.97 ± 13.54	47.71 ± 9.76
Males (%)	79.91	83.73	66.67
BMI (kg/m^2)	30.28 ± 5.62	30.72 ± 5.21	28.52 ± 6.84
Recording Time (h)	7.23 ± 0.59	7.23 ± 0.63	7.24 ± 0.43
AHI (h^{-1})		37.15 ± 25.81	4.13 ± 2.39
TRAINING SET			
	All	OSAS Positive	OSAS Negative
Subjects	85	66	19
Age (years)	53.62 ± 13.54	56.09 ± 13.66	44.87 ± 8.92
Males (%)	82.35	83.33	78.95
BMI (kg/m^2)	30.89 ± 6.67	31.42 ± 6.58	29.11 ± 6.95
Recording Time (h)	7.18 ± 0.80	7.16 ± 0.90	7.25 ± 0.30
AHI (h^{-1})		37.89 ± 28.99	4.16 ± 2.43
TEST SET			
	All	OSAS Positive	OSAS Negative
Subjects	129	100	29
Age (years)	53.47 ± 12.99	54.26 ± 13.49	49.95 ± 10.04
Males (%)	78.29	84.00	58.62
BMI (kg/m^2)	29.88 ± 4.81	30.29 ± 4.14	28.04 ± 6.93
Recording Time (h)	7.27 ± 0.40	7.28 ± 0.37	7.23 ± 0.50
AHI (events/h)		36.67 ± 23.61	4.11 ± 2.40

Table 1. Demographic and clinical features for all subjects under study, training set and test set. Data are presented as mean ± standard deviation. OSAS Positive: patients with a positive diagnosis of obstructive sleep apnoea syndrome. OSAS Negative: patients with a negative diagnosis of obstructive sleep apnoea syndrome. BMI (kg/m2): body mass index. AHI (events/h): apnoea/hypopnoea index calculated for hourly periods.

Predicted	Real	
	OSAS Positive	OSAS Negative
OSAS Positive	97	6
OSAS Negative	3	23

Table 2. Classification results provided by the diagnostic algorithm on the test set.

Method	Input Feature Set	Se (%)	Sp (%)	Acc (%)	AUROC
PCA-LDA	Spec + NonLin	97.00	79.31	93.02	0.95
PCA-LDA	Spec	94.00	62.07	86.82	0.93
PCA-LDA	NonLin	95.00	10.34	75.97	0.71
LR	Spec + NonLin	92.00	44.83	81.40	0.89
LR	Spec	100.00	3.45	78.29	0.93
LR	NonLin	92.00	31.03	78.29	0.86

Table 3. Results achieved on the test set by the algorithm proposed in the preent study and its evaluated alternatives. Spec: feature set composed by the three spectral features S_T, S_B and *PA*; NonLin: feature set composed by the three nonlinear features *ApEn*, *CTM* and *LZC*; Se: sensitivity; Sp: specificity; Acc: accuracy; AUROC: area under the ROC curve.

Figures

Fig. 1. Block diagram describing the diagnostic methodology proposed in the study.

Fig. 2. Percentage of variance explained by each of the components obtained from PCA.

Fig. 3. Classification accuracy reached on the training set as a function of the number of components selected from PCA.