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Poincaré analysis of an overnight arterial oxygen saturation signal applied to the diagnosis of sleep apnea hypopnea syndrome

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Abstract

The analysis of oxygen desaturations is a basic variable in polysomnographic studies for the diagnosis of sleep apnea. Several algorithms operating in the time domain already exist for sleep apnea detection via pulse oximetry, but in a disadvantageous way—they achieve either a high sensitivity or a high specificity. The aim of this study was to assess whether an alternative analysis of arterial oxygen saturation (SaO_2) signals from overnight pulse oximetry could yield essential information on the diagnosis of sleep apnea hypopnea syndrome (SAHS). SaO_2 signals from 117 subjects were analyzed. The population was divided into a learning dataset (70 patients) and a test set (47 patients). The learning set was used for tuning thresholds among the applied Poincaré quantitative descriptors. Results showed that the presence of apnea events in SAHS patients caused an increase in the SD_1 Poincaré parameter. This conclusion was assessed prospectively using the test dataset. 90.9% sensitivity and 84.0% specificity were obtained in the test group. We conclude that Poincaré analysis could be useful in the study of SAHS, contributing to reduce the demand for polysomnographic studies in SAHS screening.

Keywords: apnea, SAHS, Poincaré, SaO_2, oximetry

1. Introduction

Sleep breathing disorders are widely underdiagnosed (Kapur *et al* 2002, Endeshaw 2006, Lettieri *et al* 2005). International Classification of Sleep Disorders (ICSD) classifies sleep

apnea–hypopnea syndrome (SAHS) as a dysomnia (disorders of initiating and maintaining sleep and disorders of excessive sleepiness) and more specifically as an intrinsic sleep disorder. SAHS causes a not restful sleep and important daytime repercussions such as sleepiness and psychiatric and cardiorespiratory secondary disorders (American Sleep Disorders Association Task Force 1998).

Nowadays, diagnosis of SAHS is not easy. The whole process usually takes a long time and requires complex diagnostic studies with a high cost.

Overnight full-channel polysomnography (PSG) remains the 'gold standard' for the diagnosis of sleep apnea. It involves monitoring many body functions and performing a comprehensive recording of the biophysiological changes that occur during sleep. Many sensors need to be attached to the patient and a manual scoring of the recorded data performed by specialists is required (Guilleminault and Stoohs 1990).

A significant number of apnea cases remain underdiagnosed. This situation drives to the increasing interest in finding alternative approximations to (early) diagnosis.

Overnight pulse oximetry has opened the way for subsequent systematic investigations of sleep apnea (Bloch 2003), and thus has been proposed as a simpler alternative to PSG in the diagnosis of SAHS because it is readily available, it is cost effective and could be extended as a screening method to overcome the large demand in sleep units (Whitelaw *et al* 2005, Epstein and Dorlac 1998, Chesson *et al* 2003, Levy *et al* 1996). It can be used in a non-supervised environment as it is the case of domiciliary applications.

There are many quantitative indices derived from overnight pulse oximetry in the diagnosis of SAHS. The most widely used include the number of oxygen desaturations below a certain threshold, usually 3% or 4% decline from baseline (Rauscher *et al* 1991, Rusch *et al* 1996), or the cumulative time spent below a threshold of 90% (Martinez *et al* 2005, Grupo Español del Sueño 2005). Based on time domain analysis, SAHS screening algorithms achieve either a high sensitivity or a high specificity (Von Perleth *et al* 2003). This lack of reliability arises from the no standardized definition of desaturation. This absence of a standard definition causes SAHS screening algorithms via pulse oximetry differ within the method of desaturation detection (Von Perleth *et al* 2003, Moser *et al* 1994). Three key definitions of apnea can be found.

- *ODI-1*: a decrease of at least 4% in arterial oxygen saturation in relation to a defined baseline level (Rusch *et al* 1996). Baseline can be a fixed level (ODI-1_A) or it can be evaluated every 1 (ODI-1_B) or 5 min (ODI-1_C) with a moving average filter.
- *ODI-2*: oxygen desaturation of at least 4% in a time interval of 40 s (Rauscher *et al* 1991).
- *ODI-3*: detection of restoration phases in SaO_2 of at least 3% in a time interval of 10 s (Rauscher *et al* 1991).

As a conclusion, SAHS detection by time domain analysis is not as satisfactory as desired. Some frequency (Zamarron *et al* 1999) or entropy (Hornero *et al* 2007) based approaches have been tested to overcome this disappointment. In this study, the useful of Poincaré plot analysis is evaluated.

Poincaré plot is a technique taken from nonlinear dynamics, developed by Henri Poincaré for analyzing complex systems. It is a geometrical representation of a time series into a Cartesian plane (Piskorski and Guzik 2007), where the values of each pair of successive elements of the time series define a point in the plot. It has found its use in such diverse fields as physics and astronomy, geophysics, meteorology, mathematical biology and medical sciences (Ott 1993). In the context of medical sciences, it is mainly used for quantifying the heart rate variability (HRV) becoming an effective measure of this marker (Brennan *et al* 2001, Task Force of the ESC and NASPE 1996).

The goal of this study was to assess whether an alternative Poincaré plot analysis of arterial oxygen saturation (SaO_2) signals from overnight pulse oximetry could yield essential information on the diagnosis of SAHS.

2. Participants

Available data were acquired from a total of 117 adult subjects. They were randomly selected as they were referred to the Sleep Unit of the Hospital Universitario Puerta del Mar de Cadiz (Spain) suspected of suffering from OSAS. All of them had at least one the following symptoms: excessive sleepiness, strong snoring, night awakenings or episodes of breathing cessation during sleep.

A previous consent was signed by patients. Relating to gender distribution, there were 30 females and 87 males, with a mean age of 58.4 years. Mean $\pm$ standard deviation (SD) of body mass index (BMI) was 31.4 ± 5.3 kg m^{-2}.

Patients were evaluated by an overnight pulse oximetry test in conjunction with a simultaneous standard in-laboratory overnight polysomnography (PSG). Signals recorded included electroencephalogram, electrooculogram, submental and bilateral tibial electromyogram, electrocardiogram, airflow (nasal thermistor), chest and abdominal piezo bands, and body position. Data were collected and stored using the Standard Sleep Lab Polysomnographic System from Jaeger. In particular, Jaeger Oximeter, model 70750A19, with a finger probe and with a sampling frequency of eight samples per second was used. Oximetry data were separately recorded for a later analysis.

The PSG operated according to the system by Rechtschaffen and Kales (1968). Apnea was defined as the absence of airflow for more than 10 s, and hypopnea 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 calculated for hourly periods of sleep. In this study, an AHI $\geqslant$ 15 events per hour was considered as positive diagnostic of SAHS.

Positive diagnosis of SAHS was confirmed in 54 out of 117 subjects. The subjects under study were divided randomly into two groups: a learning group (70 subjects) and a test group (47 subjects). The learning group was used to find the optimum Poincaré parameters in relation to SAHS diagnosis and for tuning the thresholds for diagnosis. The calculated thresholds were then applied to the test group. Table 1 summarizes the composition of both groups and the clinical features for all subjects under study.

3. Methods

The Poincaré plot is a visual technique which can make use of the human eye's ability to recognize patterns. The Poincaré plot is a scattergram, which is constructed by plotting each SaO_2 value against the previous one. As this procedure was used for realistic data such as arterial oxygen saturation (SaO_2) vectors, shapes like those in figures 1 and 2 were obtained.

The Poincaré plot may be analyzed quantitatively by some descriptors (Piskorski and Guzik 2007). Fitting an ellipse to the Poincare plot's shape is becoming an increasingly popular technique.

As shown in figures 1 and 2, a set of axis oriented with the line of identity is defined. The axes of the Poincaré plot are related to the new set of axes by a rotation of $\theta = \pi/4$ radian,

Table 1. Clinical features for all subjects and for the learning and test groups (mean ± SD). SAHS+ include patients with a positive diagnosis of SAHS; SAHS− include patients with a negative diagnosis of SAHS; BMI: body mass index; AHI: apnea-hypopnea index.

	All	SAHS+	SAHS−
	All participants		
Subjects	117	54	63
Age (years)	58.4 ± 10.5	59.2 ± 11.7	57.2 ± 12.0
Females (%)	25.6	22.2	28.5
BMI (kg m^{-2})	31.4 ± 5.3	32.1 ± 6.2	29.4 ± 5.5
Recording time (min)	317.1 ± 149.9	302.4 ± 143.2	329.9 ± 144.1
AHI		42.6 ± 26.2	6.6 ± 10.6
	Learning group		
Subjects	70	32	38
Age (years)	59.1 ± 9.8	59.9 ± 12.3	58.4 ± 6
Females (%)	23.4	25.0	28.9
BMI (kg m^{-2})	30.5 ± 6.4	34.8 ± 5.9	27.4 ± 6.4
Recording time (min)	317.4 ± 149.9	317.2 ± 147.8	317.3 ± 149.9
AHI		39.7 ± 17.9	7.6 ± 3.4
	Test group		
Subjects	47	22	25
Age (years)	58.1 ± 12.5	58.9 ± 11.4	58.2 ± 9.8
Females (%)	25.5	18.2	28.0
BMI (kg m^{-2})	32.2 ± 7.4	32.4 ± 6.5	30.4 ± 6.3
Recording time (min)	317.1 ± 135.6	306.8 ± 138.8	329.2 ± 136.7
AHI		43.6 ± 20.6	7.2 ± 4.1

according to the rotation matrix defined as

$$\begin{bmatrix} X \\ Y \end{bmatrix} = \begin{bmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{bmatrix} \begin{bmatrix} \mathrm{SaO}_{2\,n} \\ \mathrm{SaO}_{2\,n+1} \end{bmatrix}. \tag{1}$$

In the reference system of the new axes, SD_1 quantify the width of the Poincaré cloud and it is measured as the standard deviation around the Y-axis. It indicates the level of short-term variability of the SaO_2 signal. SD_2 is defined as the standard deviation around the X-axis (Guzik *et al* 2006). SD_2 is the length of the Poincaré cloud and it is related to the long-term variability of the SaO_2 signal. SD_1 and SD_2 allow fitting an ellipse to the cloud.

Additionally, we may define a parameter which reflects the area of the previously defined ellipse (Guzik *et al* 2006):

$$A = 2\pi \mathrm{SD}_1 \mathrm{SD}_2. \tag{2}$$

Some researchers have employed the correlation coefficient of the Poincaré plot (Otzenberger *et al* 1998). The correlation coefficient can be expressed in terms of SD_1 and SD_2 indices as

$$r = \frac{\mathrm{SD}_2^2 - \mathrm{SD}_1^2}{\mathrm{SD}_2^2 + \mathrm{SD}_1^2}. \tag{3}$$

Finally, the ratio $R = \mathrm{SD}_2/\mathrm{SD}_1$ will be also studied.

It is remarkable that although the Poincaré plot displays nonlinear aspects of the interval sequence, most of the previously defined indices are linear measures (Brennan *et al* 2001, Task Force of the ESC and NASPE 1996).

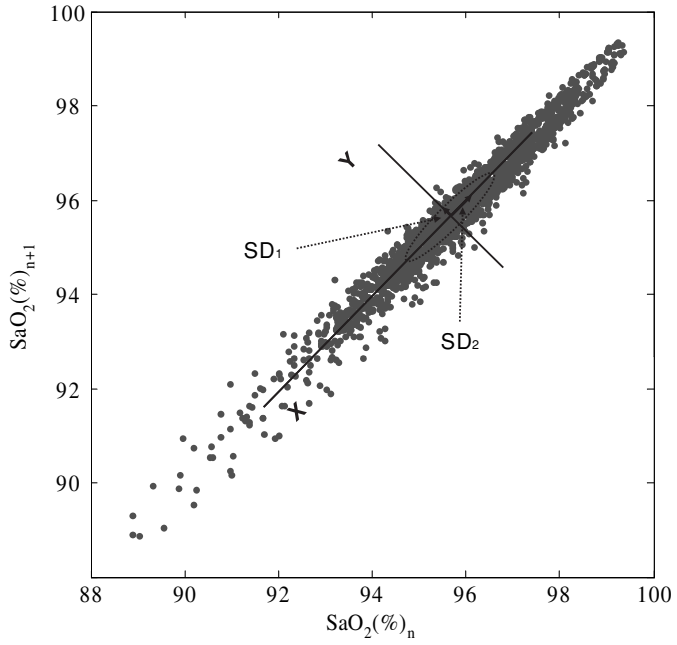

Figure 1. The Poincaré plot of an 8 h recording of arterial oxygen saturation, previous to the mean removal, of a healthy subject with an apnea hypopnea index (AHI) = 4. SD_1 and SD_2 determine the width and length of the fitted ellipse.

In this study, SaO_2 signals were recorded at the hospital with a sampling rate of eight samples per second. Before processing, each SaO_2 signal was decimated using a 30th-order lowpass FIR filter. Oxygen saturation changes have a low dynamic, so one sample per second is an adequate sampling rate. Some studies carried out (Warley *et al* 1987) showed that this sampling rate or even lower frequency (one sample every 5 s) provides reasonable resolution in SaO_2 variability.

Each oximetry recording was firstly scanned to remove artifacts and drops to zero due to poor contact from the finger probe or patient movements. Values above or below 6% of precedent were replaced by the average value in the 10 s before. Zero-valued samples were excluded from the signal. The calculated vector was filtered using an average mobile filter, in order to reduce noise during the acquisition process. Mean was then removed from the SaO_2 vectors.

For signal processing, statistics and other processing, and graphical representation, the MathWorks MATLAB® software was used.

The parameters SD_1, SD_2, r, R and A were calculated from the pre-processed SaO_2 signals. In order to test the accuracy of these indices for differentiating SAHS-positive and -negative patients, a preliminary statistical processing was applied. A wide variety of mathematical methods exist for determining whether the means of different groups are statistically different. First, the chi-square test for normal distribution was applied. The results rejected normality ($P < 0.0001$) so non-parametric tests should be used for checking statistical significance (figure 3). The Mann–Whitney non-parametric U-test assesses whether the means of two groups are statistically different from each other. This test was used for calculating the significance level for each of the Poincaré descriptors.

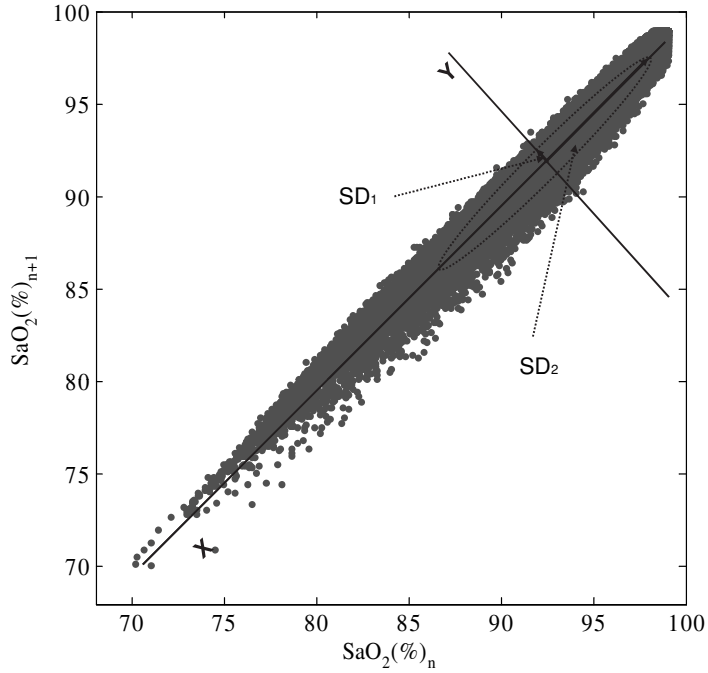

Figure 2. The Poincaré plot of an 8 h recording of arterial oxygen saturation, previous to the mean removal, of a SAHS positive patient with an apnea hypopnea index (AHI) = 87. SD_1 and SD_2 determine the width and length of the fitted ellipse.

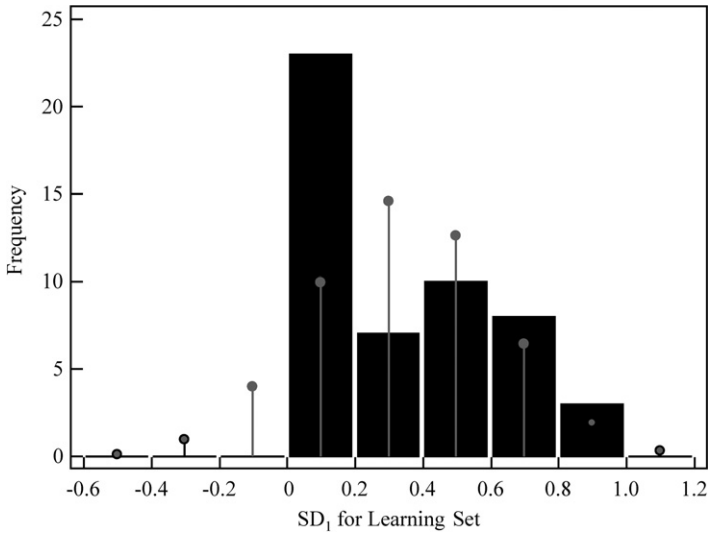

Figure 3. Histogram of SD_1 values in the learning group. The chi-square test rejected normality in distribution, as can be appreciated (normal distribution appears marked with dots). The same happened to all analyzed parameters.

Table 2. Poincaré indices estimated from SaO_2 signals of subjects in the learning group. Data are presented as mean ± SD. SAHS+ include patients with a positive diagnosis of SAHS; SAHS− include patients with a negative diagnosis of SAHS. SD_1 and SD_2 are measured as arterial hemoglobin oxygen saturation percentages

Indices	SAHS+	SAHS−	Two-tailed probability (Mann–Whitney test)
SD_1 (percentage)	0.23 ± 0.11	0.11 ± 0.05	$P < 0.0001$
SD_2 (percentage)	3.96 ± 2.02	2.07 ± 1.02	$P < 0.0001$
A (squared percentage)	6.82 ± 6.23	1.68 ± 1.73	$P < 0.0001$
r	0.99 ± 0.00	0.99 ± 0.00	$P = 0.2050$
R	0.06 ± 0.01	0.05 ± 0.01	$P = 0.1589$

Table 3. Optimum thresholds, area under the ROC curve (AUC), standard error (SE), 95% confidence intervals (95% CI), sensitivity (Se) and specificity (Sp) calculated for the selected descriptors.

Indices	Threshold	AUC	SE	95% CI	Se (%)	Sp (%)
SD_1 (percentage)	0.13	0.87	0.045	0.77–0.94	84.4	81.6
SD_2 (percentage)	2.03	0.84	0.050	0.73–0.92	96.9	65.8
A (squared percentage)	1.56	0.87	0.045	0.77–0.94	96.9	71.1

4. Results

4.1. Learning phase

The results obtained on the learning group are presented in table 2. Poincaré indices were calculated from the SaO_2 signals in the learning group in order to compare results from subjects with positive and negative SAHS diagnosis. Significant differences ($P < 0.05$) with the Mann–Whitney non-parametric U-test were achieved, except for the correlation coefficient (r) and for the ratio SD_1/SD_2 (R).

In consequence, the accuracy of the parameters SD_1, SD_2 and A, for differentiating SAHS positive and negative patients, was studied. In the learning group, the optimum threshold was selected in each case to improve the sensitivity/specificity pair according to the receiver operating characteristic (ROC) plots (Zweig and Campbell 1993). Matlab software was used. A routine was programmed for an automatically optimum threshold selection, calculating the sensitivity/specificity pair for different cutoff points and finding the best value. The optimum value was determined as being the point closest to the left top point (100% sensitivity and 100% specificity).

Figure 4 shows the ROC curves for the learning set. Table 3 includes ROC parameters for the analyzed descriptors. It can be appreciated that the best area under ROC curve corresponds to SD_1 as well as the high sensitivity/specificity pair and the lowest standard error.

A pairwise comparison of ROC curves can be appreciated in table 4, where the differences between areas, error and significant levels are one-to-one compared.

Values for subjects in the learning group with positive and negative SAHS diagnosis are shown in figure 5. The optimum cutoff point is represented in each case. It can be appreciated that patients without SAHS had lower SD_1 values ($0.11 \pm 0.05\%$) than patients in the positive group ($0.23 \pm 0.11\%$).

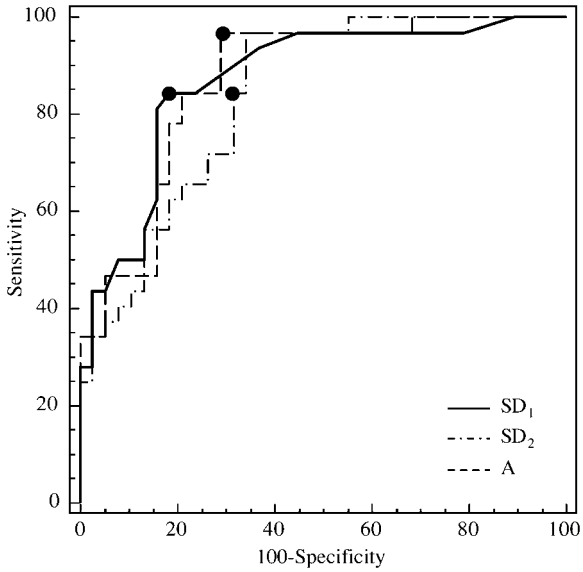

Figure 4. ROC curves for the analyzed Poincaré descriptors calculated from SaO_2 signals in the learning group for the diagnosis of SAHS. The symbol • indicates the optimum threshold.

Table 4. Comparison of ROC curves. DBA: difference between areas; SE: standard error; 95% CI: 95% confidence interval; SL: significance level. SD_1 and SD_2 units are percentages. *A* is measured as a squared percentage.

Indices	DBA	SE	95% CI	SL
SD_1 versus SD_2	0.03	0.03	−0.03 to 0.10	$P = 0.28$
SD_1 versus *A*	0.00	0.02	−0.03 to 0.03	$P = 0.90$
SD_2 versus *A*	0.03	0.02	0.00 to 0.07	$P = 0.09$

To assess the improvement provided by the proposed algorithms, the classification performance of the Poincaré descriptors was compared with that reached by means of the previously detailed classic oximetry indices. Algorithms for calculating the indices ODI-1_A, ODI-1_B, ODI-1_C, ODI-2, and ODI-3 were programmed. As previously described, the threshold for each of these indices was selected from the training set to improve the sensitivity/specificity pair according to the ROC plots, as can be appreciated in figure 6. The thresholds that provided the highest accuracy (minimal false negative and false positive results) on the training set were selected as optimum. A threshold value of 4.7 events h^{-1}, 3.5 events h^{-1}, 5 events h^{-1}, 8.9 events h^{-1} and 6.4 events h^{-1} was established for ODI-1_A, ODI-1_B, ODI-1_C, ODI-2 and ODI-3, respectively. Table 5 includes ROC parameters for the classic descriptors.

4.2. Test phase

The parameters calculated from the learning phase were used in the test group. Features of the descriptors for the test group are shown in table 6. Figure 7 shows the ROC curves for the test set. Figure 8 shows values for the positive and negative subjects in the test group, including the optimum cutoff point previously calculated.

Again, SD_1 values for the SAHS negative group were lower ($0.11 \pm 0.05\%$) than those for patients in the positive group ($0.30 \pm 0.27\%$) for the test group. These results corroborate

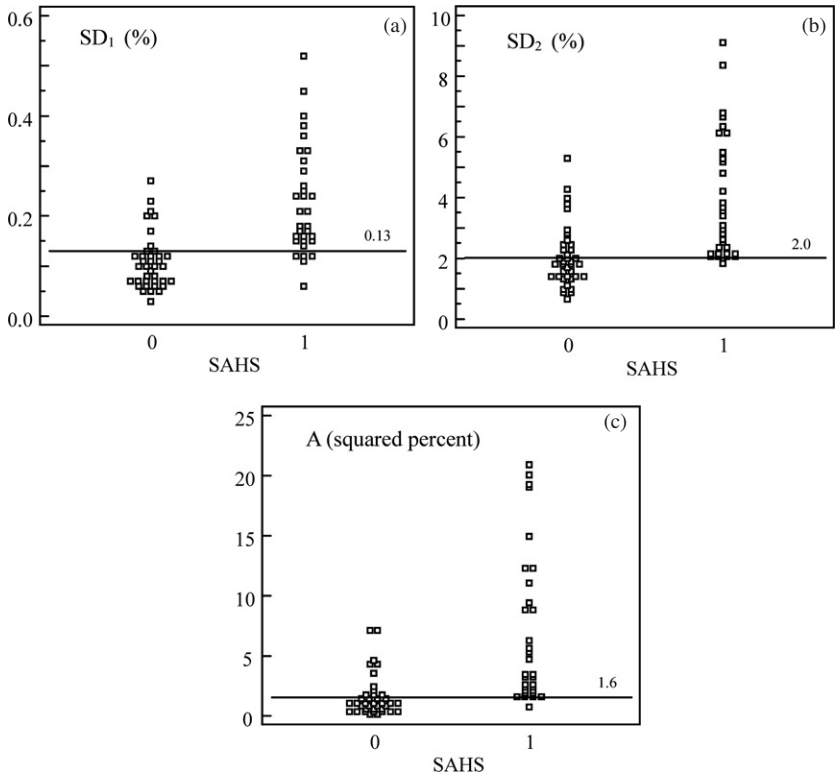

Figure 5. SD_1 (a), SD_2 (b) and A (c) values for the SAHS positive and negative subjects in the learning group. The optimum cutoff point is represented as a continuous line for every case. SD_1 and SD_2 units are percentages. A is measured as a squared percentage.

Table 5. Optimum thresholds, area under the ROC curve (AUC), standard error (SE), 95% confidence intervals (95% CI), sensitivity (Se) and specificity (Sp) calculated for ODI classical descriptors in the learning set.

Indices	Threshold	AUC	SE	95% CI	Se (%)	Sp (%)
$ODI\text{-}1_A$	4.70	0.88	0.042	0.71–0.96	87.1	78.2
$ODI\text{-}1_B$	3.50	0.86	0.045	0.63–0.92	81.3	78.1
$ODI\text{-}1_C$	5.00	0.88	0.045	0.75–0.97	89.1	76.0
ODI-2	8.90	0.89	0.041	0.79–0.99	90.0	77.2
ODI-3	6.40	0.86	0.045	0.62–0.90	87.2	78.3

that SD_1 is higher in SAHS positive patients and lower in healthy subjects. A sensitivity of 90.9%, a specificity of 84.0% and an area under curve of 0.95 were achieved (table 7).

Although the average values of the parameters SD_2 and A seem different between populations with positive and negative SAHS, their high standard deviation do foresee that their efficiency in diagnosis will be poor.

The five classical indices provided high sensitivity and low specificity. As it can be appreciated in table 7, the best AUC value was obtained by means of ODI-2 and ODI-3, with 0.94. The best performance between the Poincaré parameters is given by SD_1. Sensitivity, specificity, accuracy and AUC achieved by the classical indices were outperformed by the SD_1 descriptor.

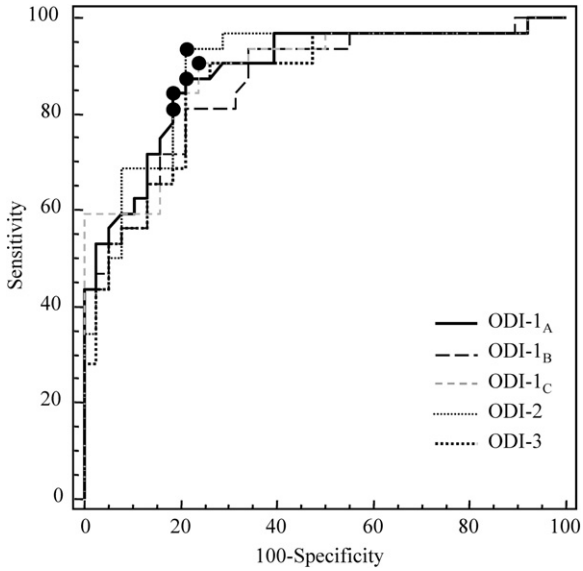

Figure 6. ROC curve for the classic oximetry indices, calculated from SaO_2 signals in the learning group for the diagnosis of SAHS. The symbol • indicates the optimum threshold.

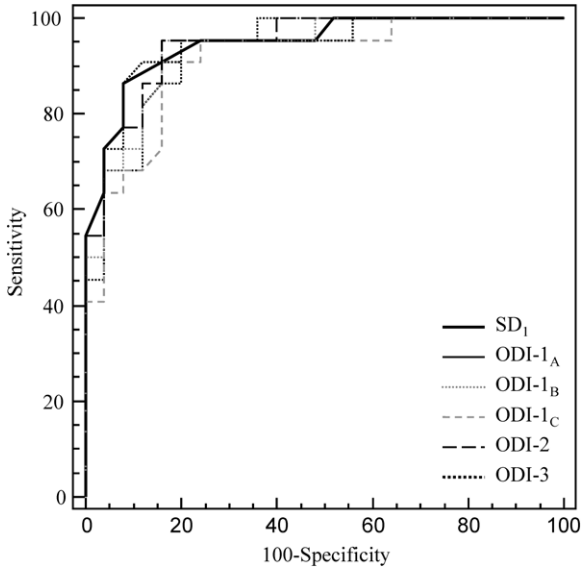

Figure 7. ROC curves computed on the test set for the SD_1 Poincaré descriptor and classic oximetry indices.

5. Discussion

Oximeter has now become one of the most widely used biomedical sensors. Many authors define pulse oximetry as the fifth vital indicator (Mower *et al* 1997). Particularly in the diagnosis of sleep apnea, it is basic in respiratory event detection.

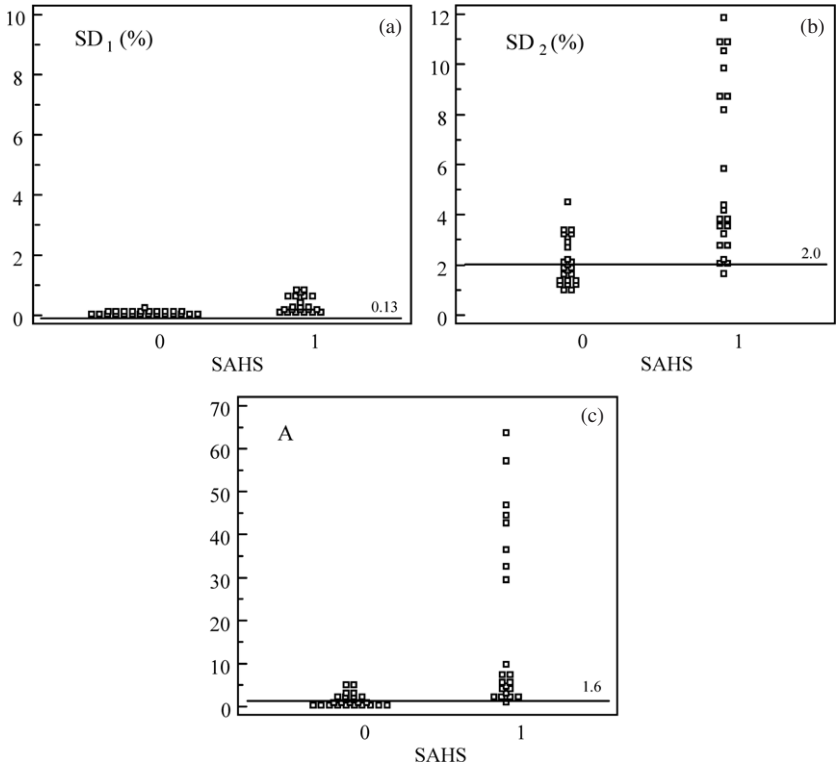

Figure 8. SD_1 (a), SD_2 (b) and A (c) values for the SAHS positive and negative subjects in the test group. The cutoff point, tuned in the learning phase, is depicted as a continuous line for every case.

Table 6. Poincaré descriptors estimated from SaO_2 signals of subjects in the test group. Data are presented as mean ± SD. SAHS+ include patients with a positive diagnosis of SAHS; SAHS− include patients with a negative diagnosis of SAHS. SD_1 and SD_2 units are percentages. A is measured as a squared percentage.

Descriptor	SAHS+	SAHS−
SD_1	0.30 ± 0.27	0.11 ± 0.05
SD_2	5.72 ± 3.49	2.16 ± 0.92
A	18.97 ± 20.78	1.67 ± 1.36

Due to the need for reliable SAHS screening systems, many SAHS screening algorithms based on pulse oximetry have been proposed. Classic oximetry indices facilitate SaO_2 analysis. Oximeters can provide a measure of ODI-1_A, ODI-1_B, ODI-1_C, ODI-2 and ODI-3. Several studies where the diagnostic capability of these indices was assessed have been reviewed (Rusch *et al* 1996, Rauscher *et al* 1991). The reported values of sensitivity ranged from 30% to 98% and of specificity, from 41% to 100%. Most of the SAHS screening algorithms using oximetry are based on this classic time domain analysis, but frequency (Zamarron *et al* 1999) and nonlinear, based on approximate entropy (Hornero *et al* 2007) or neural networks (Marcos *et al* 2008), can also be found. In these studies, the sensitivity of the test ranged from 71.3%

Table 7. Results provided on the test set by the Poincaré descriptors and the classic oximetry indices. SE: sensitivity; Sp: specificity; AUC: area under ROC curve; SE: standard error; +LR: positive likelihood ratio; −LR: negative likelihood ratio; ODI-1_A: oxygen desaturation over a 4% fixed baseline; ODI-1_B: oxygen desaturation over a 1 min 4% mobile baseline; ODI-1_C: oxygen desaturation over a 5 min 4% mobile baseline; ODI-2: oxygen desaturation over 4% in time intervals of 40 s; ODI-3: oxygen desaturation over 3% restoration phases in time interval of 10 s. SD_1 and SD_2 units are percentages. *A* is measured as a squared percentage.

Descriptor	Se (%)	Sp (%)	AUC	SE	+LR	−LR
SD_1	90.91	84.00	0.95	0.035	5.68	0.11
SD_2	95.45	56.00	0.87	0.050	2.17	0.08
A	95.45	64.00	0.90	0.050	2.65	0.07
ODI-1_A	95.45	72.00	0.93	0.043	3.41	0.06
ODI-1_B	95.45	72.00	0.93	0.044	3.41	0.06
ODI-1_C	95.45	72.00	0.91	0.042	3.20	0.06
ODI-2	95.45	64.00	0.94	0.042	2.65	0.07
ODI-3	95.45	60.00	0.94	0.046	2.39	0.08

(Chiner *et al* 1999) to 90.2% (Levy *et al* 1996) and the specificity ranged from 64% (Baltzan *et al* 2000) to 75% (Levy *et al* 1996) for AHI = 15 as an upper limit of non-SAHS diagnosis.

But a few studies have been published on the relationship between the variability SaO_2 signal and SAHS. Some authors have used related methodologies, such as central tendency measure (Marcos *et al* 2008) or the delta index (Levy *et al* 1996, Olson *et al* 1999, Magalang *et al* 2003). The first study about quantifying arterial oxygen saturation (SaO_2) variability for SAHS diagnosis deserves a special mention. It was performed in Levy *et al* (1996). The delta index (average of absolute deviations from the mean) was used over a sampling of 300 patients. Conclusions were that a nocturnal oximetry test with a delta index below 0.6 could be helpful in ruling out the diagnosis of SAHS in patients being screened for this condition. A sensitivity of 98% was achieved but with a poor specificity (46%). An alternative operating point was analyzed. Using a delta value of 0.8 led to sensitivity of 90% but with a higher specificity of 75%.

In this study, the SaO_2 signals from 117 subjects were analyzed by using a new approach, based on the Poincaré plot analysis.

The whole group was divided into two subgroups: a learning set with 70 subjects (32 patients with SAHS and 38 healthy subjects) and a test set with 47 subjects (22 patients with SAHS and 25 healthy subjects). The learning group was used to find the useful Poincaré descriptors and for tuning the optimum threshold for the selected parameters in relation to SAHS diagnosis. SD_1, SD_2 and the area of the fitted ellipse (*A*) were selected among the proposed descriptors. Optimum cutoff values of 0.13%, 2.03% and 1.56 (squared percent), respectively, were calculated.

The application of the results in the learning group to the test set emphasizes the diagnosis accuracy of the SD_1 descriptor (90.91% sensitivity and 84.00% specificity) with an AUC of 0.95. Thus, the proposed algorithm achieves sensitivity, specificity and accuracy similar to that provided by classic oximetry indices, as it can be observed from the results achieved in the test set (table 7).

Sensitivity is the critical parameter in medical diagnosis. The penalty for misclassifying an OSAS-positive subject is greater than that for misclassifying an OSAS-negative. Here, SD_1 provides sensitivity above 90%.

The AHI thresholds are still a problem. No standard criterion exists and used values vary from 5 to 20 events per hour to denote SAHS-positive diagnosis. This fact makes it impossible to strictly compare many existing algorithms and techniques with our study. It is possible

to find some approaches with either a high sensitivity or a high specificity. In our study, we generated and presented a method characterized by a high sensitivity–specificity pair.

Finding the best balance between sensitivity and specificity depends on the selection of the thresholds. ROC analysis allows the selection of thresholds. In this sense, the advantages of the proposed approach can be demonstrated by fixing sensitivity (number of subjects with SAHS correctly identified by the algorithm) and comparing the caseloads and specificities of the new and the classical techniques.

On the basis of the receiver operating curves in figure 7, a caseload of 84% is required to achieve 90% sensitivity using the Poincaré proposed descriptor, while a caseload of 71%, 65%, 76%, 78% and 73% is needed to achieve the same sensitivity using the classical ODI-1_A, ODI-1_B, ODI-1_C, ODI-2 and ODI-3 oximetry indices, respectively.

On the background, our findings indicate that Poincaré analysis provides greater variability values in SaO_2 signals corresponding to SAHS-positive patients compared to variability in SAHS-negative subjects. In SAHS, oxygen desaturations associated with respiratory events cause fluctuations in the oxygen saturation signal leading to higher Poincaré indices values.

Here, we must clearly distinguish the concepts of variability in the short and long term. Cyclical oxygen desaturations associated with respiratory events, classical in SAHS patients, cause short-term variability. Healthy patients of SAHS do not show abrupt changes in their oximetric levels. Otherwise, sudden downturns in oximetry values continued with relatively fast recoveries are characteristics of apneics. Respiratory patterns for a patient with apneic syndrome show apneas with a typical saw-tooth morphology of the pulse oximetry curve. This phenomenon reflects into values related to short-term variability indices (SD_1) lower than that for SAHS patients.

On the other hand, oxygen desaturation during sleep is greater during rapid eye movement (REM) sleep compared with non-REM sleep. During first part of the night, oxygen saturation may remain in the normal range (i.e. different from the subsequent hours) if a patient does not go to sleep or has very little sleep during the first hour, as normal in healthy subjects. On the other hand, oxygen saturation is expected to decrease right from the beginning in a patient who has reduced sleep latency and, hence, early onset of apneas.

Oxygen desaturation is expected to increase with night because of the higher percentage of REM sleep during this time. It has been shown that the mean apneic duration and the sleep time spent in the apneic state increase as the night progresses (Orr *et al* 1979, Charbonneau *et al* 1994).

Behind these circumstances is the increase observed in SaO_2 variability and expressed through the Poincaré parameters.

A significant contribution in our study is the comparison of many methods over the same database. Analysis of older methods for different thresholds is useful as other methods do not report exploratory analysis about sensitivity and specificity.

Although the results achieved with the proposed algorithm are very similar to those achievable by common techniques applied to conventional oximeters in the market, we should remark the double additional potential for this approach. First, it provides a tool that allows a quick visual identification of the reality of the patient (Poincaré plots of subjects with SAHS are quite different compared to those of patients without) and second, this method would allow a possible insight into short-term and long-term variability SaO_2. It must not be forgotten that the aim of the nocturnal oximetry for the diagnosis of SAHS is the reduction in the number of polysomnography tests in sleep units, and the proposed method can be useful in addressing this objective.

The obtained results can be conditioned by some factors. Several conditions adversely affect pulse oximetry readings during sleep (Kelleher 1989). SaO_2 of zero may be acquired,

due to the fact that the probe is not plugged into unit, the probe is not properly placed on patient or light transmission is blocked (e.g. blue or black nail polish). The recording of an erratic signal is also common due to poor perfusion, motion artifact, unstable hemodynamics (irregular pulse) or dyshemoglobinemia.

Motion artifacts can interfere with signal detection and interpretation of the signal by the device because of an unstable waveform. Improperly seated sensors, shivering or seizures can cause movement, creating an inaccurate reading. Adjustment of the device to a longer signal-averaging time may reduce the effects of motion artifact (Barker and Tremper 1987).

In our study, a method for removing some of the previously detailed artifacts was implemented but some other items need to be taken into account. The main question is related to supervision during data collections. All data in our study were collected at a sleep unit, under supervised methods. In relation to this question, a deeper study in non-supervised environments needs to be developed. Oximetry test for the detection of SAHS is often developed in the homes of patients without medical supervision. Thus, it is important to take into account the percentage of failed experiments by a defective action of the patient.

In summary, in the present study, we applied the Poincaré plot analysis looking for differences in variability between SAHS-positive and SAHS-negative patients. Our study is aimed to estimate the variability of overnight oximetric recording by means of Poincaré descriptors, in order to assess its utility in SAHS diagnosis. It was corroborated that desaturation events in SAHS patients caused fluctuations in SaO_2 levels leading to higher SD_1 values. SD_1, the dispersion of points perpendicular to the line-of-identity in the Poincaré plot, reflects the level of short-term variability.

Thus, the proposed method estimates the short-term SaO_2 signal variability with a low computational cost and provides both high sensitivity and specificity values. It also has high predictive values.

To our knowledge, this is the first study using the Poincaré plot analysis, commonly used in HRV analysis, in application to SAHS diagnosis with the SaO_2 variable. We assessed its usefulness to physicians in screening for sleep apnea syndrome, comparing it with classical oximetric indices, so the technique could be used as a supplementary method in a domiciliary approach to SAHS diagnosis.

However, and although the results were significant, further work is required to test the potential value of the proposed technique. First, algorithms have to be validated with a larger group of patients. Second, results should be taken with caution because of the limitations of the study. There is no doubt, from the clinical point of view, that there is an increased variability of SaO_2 signal in patients with apnea. However, it may be true that some of the measured SaO_2 variability is secondary to the applied method and is strongly related to the heart rate.

Finally, the results could be even better by focusing on a multivariate analysis approach. A combination of linear and non-linear parameters from SaO_2 signals addresses an interesting research line, so studies need to be developed.

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