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Feature selection from nocturnal oximetry using genetic algorithms to assist in obstructive sleep apnoea diagnosis

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ABSTRACT

Nocturnal pulse oximetry (NPO) has demonstrated to be a powerful tool to help in obstructive sleep apnoea (OSA) detection. However, additional analysis is needed to use NPO alone as an alternative to nocturnal polysomnography (NPSG), which is the gold standard for a definitive diagnosis. In the present study, we exhaustively analysed a database of blood oxygen saturation (SpO_2) recordings (80 OSA-negative and 160 OSA-positive) to obtain further knowledge on the usefulness of NPO. Population set was randomly divided into training and test sets. A feature extraction stage was carried out: 16 features (time and frequency statistics and spectral and nonlinear features) were computed. A genetic algorithm (GA) approach was applied in the feature selection stage. Our methodology achieved 87.5% accuracy (90.6% sensitivity and 81.3% specificity) in the test set using a logistic regression (LR) classifier with a reduced number of complementary features (3 time domain statistics, 1 frequency domain statistic, 1 conventional spectral feature and 1 nonlinear feature) automatically selected by means of GAs. Our results improved diagnostic performance achieved with conventional oximetric indexes commonly used by physicians. We concluded that GAs could be an effective and robust tool to search for essential oximetric features that could enhance NPO in the context of OSA diagnosis.

1. Introduction

The obstructive sleep apnoea (OSA) syndrome is a sleep-related disorder characterised by frequent breathing pauses, which lead to deep oxyhaemoglobin desaturations, blood pressure and heart rate acute changes, increased sympathetic activity and cortical arousals [1]. A wide variety of significant consequences affect people suffering from OSA including hypersomnolence, neurocognitive dysfunction, metabolic deregulation or respiratory failure [2]. Moreover, OSA is frequently linked with conditions associated to the main causes of mortality in adults, such as hypertension, stroke or myocardial infarction [2,3]. It is estimated that approximately 20% of adults have at least mild OSA and 7% of adults have moderate-to-severe OSA [4]. Unlike its high prevalence, 90% of cases in men and 98% of cases in women may go undiagnosed for many years [2].

The gold standard method for a definitive OSA diagnosis is in-hospital, technician-attended nocturnal polysomnography (NPSG) [5]. However, this methodology is labor-intensive, expensive and time-consuming [5]. The main alternatives to NPSG are aimed at reducing the number of recordings to be analysed, focusing on the use of portable monitoring [5,6]. Several studies have been developed to assess automated analysis of single cardiorespiratory-related signals [7–15]. Single-lead electrocardiogram (ECG) [7,8], single-channel airflow (AF) [9–11] and blood oxygen saturation (SpO_2) from nocturnal pulse oximetry (NPO) [12–14] have been predominantly studied. Previous studies based on single-lead ECG do not use portable devices [7,8]. Single-channel AF-based studies commonly use the respiratory disturbance index (RDI) to detect OSA [9]. However, the RDI often includes all other abnormal respiratory events [9] and portable devices using nasal pressure or thermal sensors are less accurate than standard pneumotachometers [6]. On the other hand, portable NPO is handier, less expensive, easy-to-use and highly reliable [12]. SpO_2 from NPO could provide relevant information to detect apnoeas, making NPO an essential tool to obtain simple ambulatory methodologies aimed at reducing waiting lists [6,12]. However, some limitations decrease its ability as a single tool for OSA diagnosis at patient's home [12]. Regarding the diagnosis of OSA syndrome, the American Academy of Sleep Medicine (AASM) suggests that portable monitoring should not be used in patient groups with significant comorbid medical conditions, patients suspected of having other sleep disorders and for general screening of asymptomatic populations [6]. Furthermore, the AASM recommends that the use of portable monitoring should be limited to patients with a high pre-test probability of moderate-to-severe OSA based on clinical evaluation [6]. Thus, there is still

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a great demand on new studies that can provide additional information to improve the usefulness of SpO_2 from NPO to help in OSA diagnosis.

In the present study, feature extraction and feature selection procedures were carried out to analyse SpO_2 recordings. A large set of features was developed to obtain as much information as possible from oximetry signals. Statistical, spectral and nonlinear analyses were carried out to compose an initial feature set. Previous studies showed the usefulness of multivariate pattern analysis in OSA diagnosis [14,16]. Additionally, feature selection techniques could be very useful to derive a smaller but optimal subset for classification purposes. There are many potential benefits of variable selection after feature extraction, both computational and in prediction performance [17,18]. Previous studies on the usefulness of SpO_2 recordings in the context of OSA diagnosis commonly assessed single features or small subsets [13,19,20]. When larger feature sets are evaluated, a feature selection stage is not implemented [21–23] or suboptimal variable selection is carried out [14,16]. In this research, we hypothesised that an exhaustive analysis of the search space by means of GAs could provide further knowledge on SpO_2 dynamics. GAs provide a parameter optimisation strategy that has demonstrated to be a powerful tool for variable selection [24]. GAs were used to find the optimum feature subset with a given number of variables. Since the goal of our study was to maximise OSA diagnostic accuracy, we used the classification performance of a predefined classifier to guide the search. A logistic regression (LR) classifier was used to investigate classification performance. Our study was aimed at enhancing diagnostic ability of NPO to improve diagnostic accuracy reached by conventional oximetric indexes. To achieve this goal, the present research focuses on assessing the usefulness of GAs to provide suitable reduced oximetric feature subsets in the context of OSA diagnosis from a wide feature space of oximetry measures: time *vs.* spectral and linear *vs.* nonlinear.

2. Subjects and signals under study

The population set consisted of 240 subjects (186 males and 54 females) derived to the Sleep Unit of the Hospital Universitario Río del Río Hortega of Valladolid (Spain). All subjects showed high suspicion of suffering from OSA based on clinical evaluation. Complete in-hospital NPSG studies were carried out from midnight to 08:00 AM. Patients were monitored using a polysomnograph Alice 5 by Respironics (Philips Healthcare, The Netherlands). Rechtschaffen and Kales standard rules were used to study sleep architecture. The standard apnoea–hypopnoea index (AHI) was used to diagnose OSA and characterise its severity [5]. According to the AASM rules [25], apnoea was defined as a drop in the peak thermal airflow sensor greater than or equal to 90% from baseline lasting at least 10 s, whereas hypopnoea was defined as a nasal pressure signal excursion drop greater than or equal to 50% during at least 10 s, accompanied by a desaturation greater than or equal to 3% from pre-event baseline and/or the event is associated with an arousal. An AHI $\geq$ 10 events per hour (e/h) was considered as diagnostic of OSA.

A positive diagnosis of OSA was confirmed in 160 patients, with an average AHI of 36.6 ± 25.7 e/h. The remaining 80 subjects composed the OSA-negative group, with an average AHI of 3.9 ± 2.4 e/h. The initial population set was randomly divided into two independent groups: the training set (40%) and the test set (60%). The training set was used to obtain different feature subsets and LR models from the variable selection procedure. On the other hand, the test set was used to assess the optimum models from the training stage, in order to validate our methodology. Table 1 displays demographic and clinical features for the initial, training and test population groups.

Table 1
Summary of demographic and clinical features for patient groups.

Features	All subjects	OSA-negative	OSA-positive
Subjects (n)	240	80	160
Age (years)	52.3 ± 13.7	47.2 ± 12.2	54.8 ± 13.8
Males (%)	77.5	65.0	83.8
BMI (kg/m^2)	29.8 ± 4.4	27.8 ± 3.7	30.8 ± 4.3
Records (h)	7.3 ± 0.6	7.3 ± 0.3	7.2 ± 0.6
AHI (e/h)		3.9 ± 2.4	36.6 ± 25.7
Features	**Training set**	**OSA-negative**	**OSA-positive**
Subjects (n)	96	32	64
Age (years)	52.4 ± 13.8	47.3 ± 10.6	54.9 ± 14.5
Males (%)	77.1	62.5	84.4
BMI (kg/m^2)	29.8 ± 4.2	28.3 ± 4.4	30.6 ± 3.9
Records (h)	7.3 ± 0.3	7.3 ± 0.3	7.2 ± 0.4
AHI (e/h)		4.2 ± 2.2	35.0 ± 25.2
Features	**Test set**	**OSA-negative**	**OSA-positive**
Subjects (n)	144	48	96
Age (years)	52.2 ± 13.7	47.2 ± 13.2	54.7 ± 13.4
Males (%)	77.8	66.7	83.3
BMI (kg/m^2)	29.8 ± 4.5	27.5 ± 3.3	31.0 ± 4.7
Records (h)	7.3 ± 0.7	7.3 ± 0.3	7.2 ± 0.8
AHI (e/h)		3.7 ± 2.5	37.7 ± 26.2

Data are presented as mean $\pm$ SD, number (n) or percentage (%). kg/m^2, kilogram per square meter; e/h, events per hour; BMI, body mass index; AHI, apnoea–hypopnoea index.

The polysomnograph equipment used in the present study included a Nonin PureSAT® pulse oximeter (Nonin Medical Inc., USA), with 3 s or faster averaging interval at a minimum heart rate of 60 beats per minute or greater. Thus, the NPO equipment outperforms the recommendations of the Task Force on Respiratory Scoring of the AASM, which requires a maximum signal averaging time of $\leq$3 s at a heart rate of 80 beats per minute or more [6,25]. A finger probe with a pair of red (for measuring deoxygenated haemoglobin) and infrared (for measuring oxygenated haemoglobin) light sources was used for measuring peripheral SpO_2. A commercial PureLight® sensor (Nonin Medical Inc., USA) was used, with high-performance in the presence of motion artefacts and low perfusion for adult, paediatric and neonate patients. SpO_2 was recorded at a sampling rate of 1 Hz. All SpO_2 recordings from NPSG were saved to separate files and processed offline. SpO_2 signals presented zero samples at the beginning of the acquisition process and drops to zero due to patient movements along the recording time. An automatic pre-processing stage was carried out to remove these artefacts.

3. Methods

The present study was divided into three main stages: feature extraction, feature selection and classification. In the feature extraction stage, oximetric recordings were exhaustively analysed to parameterise SpO_2 dynamics from NPO. The outcome of this step was a wide oximetric feature set, which was the input to the subsequent feature selection stage. Genetic algorithms (GAs) were evaluated for variable selection. Additionally, a logistic regression (LR) classifier was used in the classification stage. The Matlab® software version 7.6 (R2008a) was used to implement feature extraction methods and to develop the feature selection (*Genetic Algorithm and Direct Search Toolbox*™) and classification (*Statistics Toolbox*™) stages. The full-model (all variables are included) and all single-feature models were also computed. Additionally, we applied this methodology to a conventional oximetric feature set composed of oximetric indexes commonly used by physicians.