Biomedical Signal Processing and Control 33 (2017) 358–367

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

Discriminative methods based on sparse representations of pulse oximetry signals for sleep apnea–hypopnea detection

R.E. Rolón[a], L.D. Larrateguy[b], L.E. Di Persia[a], R.D. Spies[c], H.L. Rufiner[a,d]

[a] Instituto de Investigación en Señales, Sistemas e Inteligencia Computacional, sinc(i), FICH-UNL/CONICET, Santa Fe, Argentina
[b] Centro de Medicina Respiratoria de Paraná, Argentina
[c] Instituto de Matemática Aplicada del Litoral, IMAL, FIQ-UNL/CONICET, Santa Fe, Argentina
[d] Laboratorio de Cibernética, Fac. de Ing., Univ. Nacional de Entre Ríos, Argentina

A R T I C L E I N F O

Article history:
Received 10 August 2016
Received in revised form
13 December 2016
Accepted 16 December 2016

Keywords:
Sleep apnea–hypopnea syndrome
Sparse representations
Dictionary learning
Neural networks

A B S T R A C T

The obstructive sleep apnea–hypopnea (OSAH) syndrome is a very common and generally undiagnosed sleep disorder. It is caused by repeated events of partial or total obstruction of the upper airway while sleeping. This work introduces two novel approaches called most dicriminative activation selection (MDAS) and most discriminative column selection (MDCS) for the detection of apnea–hypopnea events using only pulse oximetry signals. These approaches use discriminative information of sparse representations of the signals to detect apnea–hypopnea events. Complete (CD) and overcomplete (OD) dictionaries, and three different strategies (FULL sparse representation, MDAS, and MDCS), are considered. Thus, six methods (FULL-OD, MDAS-OD, MDCS-OD, FULL-CD, MDAS-CD, and MDCS-CD) emerge. It is shown that MDCS-OD outperforms all the others methods. A receiver operating characteristic (ROC) curve analysis of this method shows an area under the curve of 0.937 and diagnostic sensitivity and specificity percentages of 85.65 and 85.92, respectively. This shows that sparse representation of pulse oximetry signals is a very valuable tool for estimating apnea–hypopnea indices. The implementation of the MDCS-OD method could be embedded into the oximeter so as to be used by primary attention clinical physicians in the search and detection of patients suspected of suffering from OSAH.

1. Introduction

In the year 2014 the American academy of sleep medicine (AASM) released the third edition of the international classification of sleep disorders [1]. One of the most common sleep disorders is the obstructive sleep apnea–hypopnea (OSAH) syndrome, which is caused by repeated events of partial (hypopnea) or total (apnea) obstruction of the upper airway while sleeping. To establish the degree of severity of the syndrome, the apnea–hypopnea index (AHI) is created. The AHI represents the number of apnea–hypopnea events per hour of sleep. The OSAH is classified as normal, mild, moderate or severe if belongs to the interval $[0, 5)$, $[5, 15)$, $[15, 30)$, or $[30, \infty)$, respectively.

Nowadays, the gold standard test for diagnosing sleep disorders is a polysomnography (PSG) in a sleep medical center. However, the accessibility to this type of study is usually very limited as well as costly in terms of both time and money. A complete PSG consists of simultaneous measurement of several physiological signals such as electrical activity of the brain along the scalp, electrical activity of the heart using electrodes placed on the body's surface, electrical activity produced by skeletal muscles, respiratory effort, airflow and blood oxygen saturation (SaO_2) signals, among others. Mainly due to its ease of acquisition, we are particularly interested in the latter. In a typical PSG study, after a normal period of sleep the recorded signals are provided to medical experts. Due to its complexity, different alternatives to PSG have been developed. One of the most popular alternatives to PSG is the so called home respiratory polygraphy [2]. Although some studies have shown that there is a very high correlation between AHIs generated by polygraphy and PSG studies and polygraphy requires no neurophysiological signals [3], it still needs several others physiological signals, whose acquisition affects the normal sleeping of the persons. It is therefore highly desirable to develop a reliable system which makes use of as few as possible physiological signals. Since pulse oximetry is a well know, quite cheap and non-invasive technique, it has become a very valuable alternative to detect persons suspected of suffering from OSAH [4]. A recent work has shown that statistical analysis and feature extraction methods applied to pulse oximetry signals provide satisfactory diagnostic performance in detecting severe OSAH patients [5]. Cessation of breathing associated with apnea–hypopnea events are always accompanied by

E-mail address: rrolon@sinc.unl.edu.ar (R.E. Rolón).

http://dx.doi.org/10.1016/j.bspc.2016.12.013
1746-8094/

a drop in the oxygen saturation level. It is appropriate to mention however that this drop level can be very small and impossible to detect by a human observer, reason for which advanced signal processing techniques such as artificial intelligence methods could provide a very valuable alternative. A decrease in blood oxygen saturation usually produces changes in the pulse oximetry record corresponding to intermittent hypoxemia. The intermittent hypoxemia, with hypoxemia–reoxygenation cycles, very often indicates OSAH syndrome.

Pulse oximetry, besides providing information about blood oxygen saturation during sleeping, is used for computing some parameters which quantify desaturation levels in the SaO_2 signal. The seek of patients suspected of suffering from OSAH can be addressed by means of two different approaches. A *global* approach consists of obtaining general characteristics of the SaO_2 signal, such as its mean, variance and entropy values, among others with the only objective of classifying a person as healthy or sick without taking into consideration the degree of severity of the illness. In this work a *local* approach, which allows a more thorough analysis of the SaO_2 signal, is taken. This approach consists of detecting the apnea–hypopnea events from sparse representations of segments of SaO_2 signals using a neural network classifier. The local approach was previously used for estimating three parameters denoted by ODI4, ODI3, and ODI2, which are defined as the number of times per hour of sleep that the SaO_2 signal decreases below 4%, 3%, and 2% of a baseline level, respectively. It is timely to point out, however that although the concept of "baseline level" is very intuitive, it is not uniquely defined and different criteria and definitions have been adopted by different authors [6,7].

In the last fifteen years, a wide variety of machine learning algorithms were used for detecting several health disorders [8]. Implementations of these algorithms were applied to detect particular sleep disorders and different signal processing techniques originating new methods based on non-linear systems, higher-order statistics, spectral analysis, including independent component analysis (ICA) [9–11]. Moreover pattern recognition algorithms based on artificial neural network (ANN) were successfully applied to assist OSAH diagnosis and classification [12]. Nowadays, a powerful method based on sparse representations of signals finds the solution corresponding to the most compact representation by means of a linear combination of atoms in a dictionary [13,14]. It was found that this approach, when applied to biological sensory systems, results in internal representations having properties similar to the real ones, in particular similar to those found in the primary auditive or visual cortex of the mammals [15,16]. Some of the advantages of the sparse representations are super resolution, robustness to noise and dimension reduction, among others. The sparse representations of signals provide new grounds for treating both the signal modeling and the representation problems. The dictionary is learned for the purpose of obtaining the best representation of a given set of signals, although the atoms involved in such representation are not necessarily the atoms which capture discriminative information. It is therefore clear that if the SaO_2 signal is to be used as the only input for detection of apnea–hypopnea events, advanced signal processing algorithms capable of extracting discriminative information from sparse representations of signals will be needed.

In this work we present two novel methods called "most discriminative activation selection" (MDAS) and "most discriminative column selection" (MDCS) based on sparse representations of SaO_2 signals. A preliminary related approach of this work has been reported in [17]. The methods MDAS and MDCS involve finding an optimal subset of most discriminative atoms and the corresponding configuration of a multilayer perceptron (MLP) neural network classifier for detecting apnea–hypopnea events from sparse representations of segments of SaO_2 signals. The apnea–hypopnea events were appropriately labeled by medical experts, who have been carefully analyzed the complete PSG. Our methods allow for a significant reduction in the dimension of the inputs to the MLP neural network, preserving the most important characteristics of the SaO_2 signal.

This article is organized as follows: in Section 2 the materials and methods used for obtaining sparse representations of SaO_2 signals are explained. In Section 3 the results are described and the discussion and conclusions are finally included in Section 4 and Section 5, respectively.

2. Materials and methods

A sparse representation problem can be divided into two separate sub-problems: a *learning* problem and an *inference* problem. The first one, which is quite often more complex, consists of finding an "optimal" dictionary Φ to represent a given set of signals $\{\mathbf{x}_i\}$. A dictionary Φ is called complete (CD) or overcomplete (OD) depending on the number of basic waveforms be equal or greater, respectively than the signal's space dimension. The second problem consists of selecting a set of representation vectors $\{\mathbf{a}_i\}$ satisfying a given sparsity constraint. The MDAS and MDCS methods involve finding a set of discriminative coefficients (feature vector) to be used as inputs of a MLP neural network [18]. In order to achieve this objective all possible number of inputs (F) and a large number of neurons in its hidden layer (NHL) are tested. Finally the optimal configuration is obtained by choosing the F and NHL values resulting in the best performance.

Fig. 1 shows a simplified block diagram of the proposed system. In the first block (I) the signals are filtered and segmented by

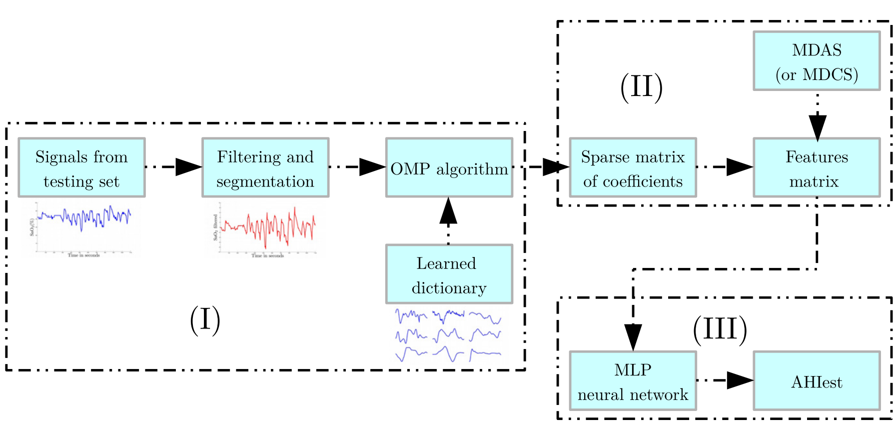

Fig. 1. A simplified block diagram of the classification process.