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Automatic sleep staging from ventilator signals in non-invasive ventilation

Cristina C.R. Sady [a,*], Ubiratan S. Freitas [b,c], Adriana Portmann [b], Jean-François Muir [b], Christophe Letellier [c], Luis A. Aguirre [a,**]

[a] MACSIN, Laboratório de Modelagem, Análise e Controle de Sistemas Não Lineares, Universidade Federal de Minas Gerais (UFMG), Belo Horizonte MG, Brazil
[b] ADIR, Association, Hôpital de Bois Guillaume, 76031 Rouen, France
[c] CORIA, Université de Rouen, Rouen, France

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ABSTRACT

Non-invasive ventilation (NIV), a recognized treatment for chronic hypercapnic respiratory failure, is predominantly applied at night. Nevertheless, the quality of sleep is rarely evaluated due to the required technological complexity. A new technique for automatic sleep staging is here proposed for patients treated by NIV. This new technique only requires signals (airflow and hemoglobin oxygen saturation) available in domiciliary ventilators plus a photo-plethysmogram, a signal already managed by some ventilators. Consequently, electroencephalogram, electrooculogram, electromyogram, and electrocardiogram recordings are not needed. Cardiorespiratory features are extracted from the three selected signals and used as input to a Support Vector Machine (SVM) multi-class classifier. Two different types of sleep scoring were investigated: the first type was used to distinguish three stages (wake, REM sleep and nonREM sleep), and the second type was used to evaluate five stages (wake, REM sleep, N1, N2 and N3 stages). Patient-dependent and patient-independent classifiers were tested comparing the resulting hypnograms with those obtained from visual/manual scoring by a sleep specialist. An average accuracy of 91% (84%) was obtained with three-stage (five-stage) patient-dependent classifiers. With patient-independent classifiers, an average accuracy of 78% (62%) was obtained when three (five) sleep stages were scored. Also if the PPG-based and flow features are left out, a reduction of 4.5% (resp. 5%) in accuracy is observed for the three-stage (resp. five-stage) cases. Our results suggest that long-term sleep evaluation and nocturnal monitoring at home is feasible in patients treated by NIV. Our technique could even be integrated into ventilators.

1. Introduction

Non-invasive ventilation (NIV) is a recognized treatment for the patient with chronic respiratory failure. It is usually applied during sleep and recently it has been increasingly used at home [1,2]. The main objective of NIV is to control hypoventilation during sleep, thus improving sleep quality. As a consequence, patient's well-being should be improved. However it is quite difficult to confirm objectively this benefit, mainly because NIV may induce undesirable respiratory events disrupting sleep (patient–ventilator interactions [3,4], discomfort due to the mask, etc.) and the sleep may be also influenced by other external physical conditions or clinical reasons. In order to objectively determine whether the patient sleeps sufficiently well or to understand why sometimes the use of NIV is not beneficial, routinely assessing sleep quality during NIV is a crucial step [5].

Polysomnography (PSG) is considered as the gold standard method to evaluate sleep but this is a time consuming procedure that requires expert personnel and which is most often realized in a sleep laboratory with attended recordings. The patient spends the night at the hospital with many sensors connected to the head and other parts of the body. Several physiological signals are recorded such as the neural cortical activity (electroencephalogram, EEG), ocular activity (electrooculogram, EOG), electromyograms (EMG), pulse oximetry (SpO_2), electrocardiogram (ECG) among others cardiorespiratory signals. Special care is required in placing the electrodes and data acquisition should be monitored during the night. Although it is possible to perform home measurements, their quality is very often not sufficient to be of a practical interest [6,7]. Specialized manual intervention is also

* Corresponding author.
** Principal corresponding author at: PPGEE, Programa de Pós-Graduação em Engenharia Elétrica, Universidade Federal de Minas Gerais, Av. Antônio Carlos 6627, 31270-010 - Belo Horizonte - MG, Brazil. Tel.: +55 31 3409 4866; fax +55 31 3409 5480.
E-mail addresses: cristinasady@cpdee.ufmg.br, cristinasady@gmail.com (C.C.R. Sady), aguirre@cpdee.ufmg.br (L.A. Aguirre).

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necessary for a visual sleep scoring according to standard rules and specifications [8]. All these factors make the PSG a complex and expensive procedure and limit sleep monitoring to sleep clinics and hospitals. Electrodes and sensors used to record these signals may affect sleep quality and structure. Moreover, a more simple way to evaluate sleep at reduced costs is therefore invaluable, especially for home treated NIV patients.

There are many studies that describe non-invasive ways for recording a full night of sleep that could, at least in principle, be applied at home [9–15]. Bed sensors like the ballistocardiography are non-contact measuring systems used to measure heart rate and breathing variations [16,17]. Features related to the cardiovascular system were found to be promising for classifying sleep stages. Sleep stages in adults were estimated using cardiorespiratory information obtained from an air mattress designed as a noninvasive measurement system [18]. Sleep disorders in children were diagnosed using pulse time transit (PTT) in [19,20], thus indicating that this signal gives useful information about sleep structure. The detection of REM sleep stage, which can be understood as a binary classification problem, was performed using only breathing signals in [13]. In other works, respiratory signals were used for detecting apnea events [12,14]. Actigraphy has also been widely used as a portable monitoring method for assessing sleep quality to check whether the patient is quiet during sleep [16]. Nevertheless, in none of such studies it was possible to identify more than three different sleep stages and no sufficient information was thus available to evaluate the sleep structure. Moreover, most of these methods require additional sensors.

Modern ventilators used in NIV commonly measure and record data in the ventilatory circuit (at least airflow and pressure). Several models are also equipped with a pulse oximeter to study the patient's cardiorespiratory system. It is important to investigate whether these data could allow sleep scoring and, consequently, sleep assessment of patients ventilated at home. Moreover, this sleep evaluation could potentially be much less disturbing compared to PSG, since the patient already sleeps with the ventilator and no extra sensor would be required, apart from a pulse oximeter which is already used in some cases.

The main goal of this work is to develop and to assess the performance of a sleep classification technique for patients under NIV that only uses signals available to ventilators. The key point is to consider an amplitude signal derived from pulse plethysmography (PPG). This type of signal so far has not been fully exploited in spite of its apparent potential as mentioned in [21]. In order to be able to accurately assess the sleep structure, up to five sleep stages will be scored. Sleep staging (classification) is accomplished by a multi-class support vector machine (SVM) scheme. The technique described in this paper could eventually be integrated to the ventilators themselves, thus allowing for continuous sleep monitoring at home for patients treated by NIV.

The paper is organized as follows. Section 2 describes the protocol and the preprocessing of the three signals used to train a classifier based on SVMs, which is described in Section 3. Results are presented in Section 4 and discussed in Section 5, where the main conclusions are provided.

2. Methods: data and signal processing

The data used in this work were collected during an observational study conducted at the Pulmonary and Respiratory Unit of the Rouen University Hospital (France) [22].[1] This study was authorized as part of a protocol for routine care by the Committee to Protection People (CPP North West 1, approval dated October 16, 2009) and the patients gave informed consent to the work. The aim of this study was to evaluate patient–ventilator interactions and changes in sleep structure during the first nights after initiation to NIV. Some details of 13 patients that suffer from chronic respiratory failure and selected from the aforementioned study will be described in the sequel. Data of a 14 patient (P_5), originally included in [22], were not used in the present study.

2.1. Patients

Clinical characteristics of 13 patients are listed in Table 1. Seven patients (P_3, P_4, P_7, P_8, P_{11}, P_{12}, P_{13}) had obesity hypoventilation syndrome (OHS) associated with obstructive sleep apnea syndrome (OSAS) of variable severity (Apnea/Hypopnea Index (AHI) ranging from 34 to 142 events/hour). Four patients (P_2, P_6, P_{10}, P_{14}) had amyotrophic lateral sclerosis (ALS) among which the first three had a peripheral presentation and OSAS, the fourth having a bulbar presentation. Two other patients presented restrictive pathologies: one patient (P_1) suffers from tuberculosis sequel and another one (P_9) from kyphoscoliosis associated with OSAS.

All patients performed three full PSG. The first diagnostic PSG was carried out under spontaneous breathing (night 1) and the two others (night 2 and night 15, that is, two weeks later) were made under NIV. Only the latter two PSG recordings were considered in the present work due to our interest in investigating sleep in patients under NIV [22]. One PSG recording (night 15) is missing for patient P_{13}.

2.2. Recorded data

The recorded signals included electrophysiological signals (EEG, EMG, EOG and ECG) and ventilation physiological data (pressure, airflow, oxygen saturation, among others). The acquisition system used was a CID102-L8D (CIDELEC SA, France). Each data set was analyzed by a neurologist and sleep was coded in 30-s epochs according to the guidelines of the American Association of Sleep Medicine [8]. Five stages were distinguished: Wake (W), Rapid Eye Movements (REM) sleep, sleep stages N1 and N2 and slow wave sleep (N3).

From all signals recorded in PSG, only three were used: (i) photo-plethysmogram (PPG); (ii) hemoglobin oxygen saturation (SpO_2) and (iii) airflow. The first two were measured by a sensor placed at patient's index finger. The sampling frequency of PPG was 64 Hz and that of SpO_2 was 1 Hz. Airflow was measured by a pneumotachograph inserted in the ventilation circuit and was sampled at 128 Hz. Although the ventilator has an internal pneumotachograph like most modern ventilators, its raw measurements are not easily accessible. Unlike the oxygen saturation signal SpO_2, the PPG and airflow signals required preprocessing as described in the next two subsections.

2.3. Photo-plethysmogram preprocessing

All features related to the cardiac activity were determined by analyzing photo-plethysmogram signal (ECG signal was not used in this work). Although the use of PPG to determine heartbeat intervals for sleep classification was suggested in [21] to avoid ECG measurement and the required electrodes, it was not yet implemented. This is the key-signal used in this work which enables sleep stage classification for patients under NIV, possibly at home and without the need of any electrode.

The PPG signal was first preprocessed by applying a third order band-pass Butterworth filter with corner frequencies at 0.667 Hz and 5 Hz, which correspond to 40 and 300 beats per minute, respectively. The filtered signal is then used to detect heartbeats

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