Biomedical Signal Processing and Control 25 (2016) 130–142

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

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

Characterization of REM/NREM sleep using breath sounds in OSA

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ARTICLE INFO

Article history:
Received 6 March 2015
Received in revised form 7 October 2015
Accepted 17 November 2015
Available online 17 December 2015

Keywords:
Obstructive sleep apnea
Non-rapid eye movement
Rapid eye movement
Snoring
Sleep disorder

ABSTRACT

Obstructive Sleep Apnea (OSA) is a serious sleep disorder where patient experiences frequent upper airway collapse leading to breathing obstructions and arousals. Severity of OSA is assessed by averaging the number of incidences throughout the sleep. In a routine OSA diagnosis test, overnight sleep is broadly categorized into rapid eye movement (REM) and non-REM (NREM) stages and the number of events are considered accordingly to calculate the severity. A typical respiratory event is mostly accompanied by sounds such as loud breathing or snoring interrupted by choking, gasps for air. However, respiratory controls and ventilations are known to differ with sleep states. In this study, we assumed that the effect of sleep on respiration will alter characteristics of respiratory sounds as well as snoring in OSA patients. Our objective is to investigate whether the characteristics are sufficient to label snores of REM and NREM sleep. For investigation, we collected overnight audio recording from 12 patients undergoing routine OSA diagnostic test. We derived features from snoring sounds and its surrounding audio signal. We computed time series statistics such as mean, variance, inter-quartile-range to capture distinctive pattern from REM and NREM snores. We designed a Naïve Bayes classifier to explore the usability of patterns to predict corresponding sleep states. Our method achieved a sensitivity of 92% (±9%) and specificity of 81% (±9%) in labeling snores into REM/NREM group which indicates the potential of snoring sounds to differentiate sleep states. This may be valuable to develop non-contact snore based technology for OSA diagnosis.

1. Introduction

Obstructive Sleep Apnea (OSA) syndrome results from repetitive closure of upper airway (UA) during sleep. Partial closure is termed as hypopnea and complete closure is termed as apnea. Total number of apnea and hypopnea events divided by total sleep time in hours, is known as the Apnea–Hypopnea Index (AHI). AHI can be as high as 100 in OSA patients. Frequent OSA events and associated arousals can seriously disrupt overall sleep architecture of the patient. A common and immediate diurnal symptom of OSA is excessive daytime sleepiness (EDS).

OSA is a common sleep disorder with increased risk of developing cardiovascular disease, diabetes, stroke and neuro-cognitive deficits [1]. The disease is considered to have serious concern for public health systems. Health care resource consumption is found to be doubled to treat co-morbidities long before the actual diagnosis of OSA [2].

Current reference for OSA diagnosis is Polysomnography (PSG). PSG test monitors overnight sleep by recording multiple neurophysiological and cardio-respiratory signals from the patient. Main outcomes of PSG are severity indices such as AHI and Arousal Index (AI). Details of the temporal course of sleep during PSG is measured by segmenting sleep into Rapid-Eye-Movement (REM) and non-REM (NREM) states [3]. These states are collectively known as Macro Sleep States (MSS). MSS scoring require trained sleep technician to visually score events using multiple electrophysiological signals; at-least 2 channels each of EEG, EOG and EMG, simultaneously applying various complex rules [3]. Then, separate severity indices are measured for REM and NREM sleep (i.e. REM AHI, NREM AHI, REM AI or NREM AI).

Sleep stage and body positions are known to influence the activity of UA muscles [1]. Airway muscles are known to vary with REM and NREM sleep stages [4–6] both in normal and OSA population. In OSA patients, reduced neural stimulation to UA muscles at sleep onset [4,7] in association with REM related increased airflow resistance [8] and less compliant airway [5] against pharyngeal pressure may make REM sleep more vulnerable to airway collapse. Recent research indicate the implication of these co-existing factors in OSA diagnosis. In particular, misclassification is more commonly attributed by 10% for sleep stage dominance while 20–40% for body

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http://dx.doi.org/10.1016/j.bspc.2015.11.007
1746-8094/

position [9]. Therefore separate sleep specific severity index provides further details about sleep quality, which is unavailable via overall AHI and AI parameters.

OSA is prevalent in general population and at least 80% of the middle-aged adults with moderate to severe OSA remained undiagnosed [10]. Considering the spectrum of undiagnosed population, associated co-morbidities and timely access to the facilities, there is growing interest among researchers to develop alternative techniques for mass screening. In general, devices targeted for population screening does not consider MSS scoring due to its time-consuming, costly, laborious intensive nature, complexity of instrumentation and contact sensors for multiple physiological signals.

In order to develop alternatives, snoring in OSA patients has gained attention to researchers because of its non-contact instrumentation, cheap and easy to access nature. Snoring is the earliest symptom of OSA. Snoring originates from vibration of soft tissues (e.g. tongue, soft palate, pharyngeal wall) in UA [11] while OSA results from UA collapse. Loud breathing or snoring followed by period of silence and then sudden gasps for air are common concomitant events in OSA. Hence, sounds during respiration such as snoring, loud breathing in OSA patients should carry vital information about UA patency which may be valuable to develop OSA screening techniques.

In the context of sounds, variation in snore sound properties (formants [12], periodicities [13], intervals [14] and Gaussianity [15]) were studied to characterize OSA patients. Indeed, these efforts indicate potential of snoring sounds for population screening. However, sleep related variation in UA muscles should cause alteration in acoustical properties of UA (and hence the sounds of respiration). Very few studies [16,17] have attempted to explore sounds for MSS specific information which may provide further details about OSA.

Snore sounds in NREM sleep were described as intense and longer than those in REM sleep for OSA patients [17]. However, no definitive framework was proposed in [17] for the usage of such variations to extract REM/NREM states. The pioneering work in [17] was limited to a presentation of descriptive statistics of snores from known sleep states and findings were not validated on a new dataset. Later, REM/NREM differentiation were found to be only 64% achievable using patient specific models [16]. These efforts indicate possibility of MSS related information in sleep sounds. However, performance achieved by them requires improvement before actual field use.

Sleep studies commonly characterizes REM sleep by variable nature of breathing. Rapid and irregular breathing pattern with increased eye-movement activity [18] are classic features of REM. Moreover, reduced minute ventilation and tidal volume [19] were also observed in REM sleep. Previously, numerous attempts were made to utilize breathing variability (volume, durations [20] and intervals [21]) to separate REM/NREM. Whilst, investigation performances were inspiring, most of them require multiple sensors with at least one physical contact. Hence our focus is to develop a technique to separate MSS states by exploiting non-contact sounds from OSA patients. We assumed there must be some indication attributed to REM sleep in overnight snoring and breathing sounds from OSA patients. If so, then this could assist labeling snores into REM and NREM groups. To this point, our hypothesis is that activation of upper airway muscles with sleep states and corresponding variability in breathing/snoring are embedded in snoring sounds properties and its surrounding breathing patterns. This can be used to extract MSS states.

We aimed to investigate snoring and breathing related sound (SBS) signal from OSA patients and explore their efficacy to classify a snore episode (SE) into REM/NREM classes. Our approach is to acquire simultaneous PSG and non-contact SBS recording and diagnostic information from hospital. PSG based sleep staging is our reference to characterize REM and NREM snores. We trained a model with REM/NREM snores from our database and cross-validated the model iteratively by leaving-one-out technique. It was generalized for entire patient population. We computed standard matrices such as sensitivity, specificity, accuracy, positive predictive value (PPV) and negative predictive value (NPV) to compare method performance with previous researches. As our method is solely depend on sounds, it can be easily integrated into snore based automated techniques developed for OSA screening both in contact and non-contact nature.

2. Methodology

Fig. 1 represents the overall methodology proposed in this paper. A detail of our method is described in following Sections 2.1–2.5.

2.1. Data acquisition protocol

Data acquisition environment for the work of this paper was Sleep Diagnostic Laboratory of The Princess Alexandra Hospital, Brisbane, Australia. Both oral and written consent from the patients was collected according to the approval of the human ethics committees of Princess Alexandra Hospital and The University of Queensland. Our subject population includes patients referred to the hospital for a routine Polysomnography (PSG) test. Routine PSG recordings were made using clinical PSG equipment (Siesta, Compumedics®, Sydney, Australia). Typical PSG recording followed

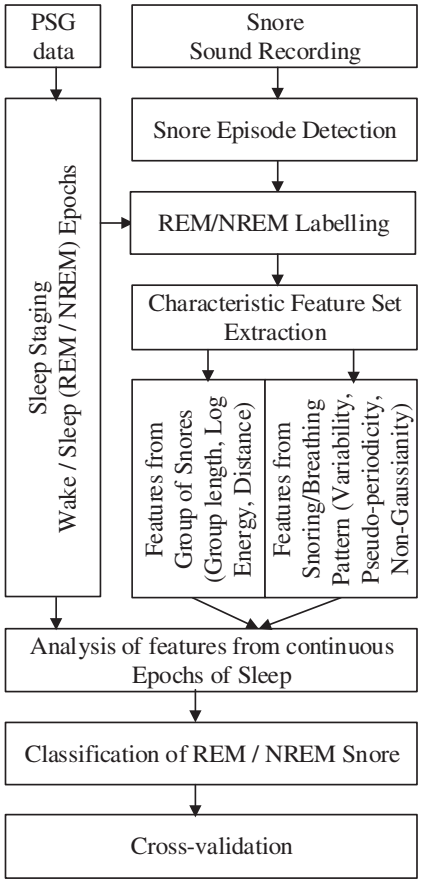

Fig. 1. A schematic diagram of the method proposed in this paper.