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Dynamics of snoring sounds and its connection with obstructive sleep apnea

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ABSTRACT

Snoring is extremely common in the general population and when irregular may indicate the presence of obstructive sleep apnea. We analyze the overnight sequence of wave packets — the snore sound — recorded during full polysomnography in patients referred to the Sleep Laboratory due to suspected obstructive sleep apnea. We hypothesize that irregular snore, with duration in the range between 10 and 100 s, correlates with respiratory obstructive events. We find that the number of irregular snores — easily accessible, and quantified by what we call the snore time interval index (STII) — is in good agreement with the well-known apnea–hypopnea index, which expresses the severity of obstructive sleep apnea and is extracted only from polysomnography. In addition, the Hurst analysis of the snore sound itself, which calculates the fluctuations in the signal as a function of time interval, is used to build a classifier that is able to distinguish between patients with no or mild apnea and patients with moderate or severe apnea.

1. Introduction

Temporal patterns of natural events can be used to detect hidden dynamics [1]. In fact, this connection dates back to Hurst's work [2] on the long-term memory (i.e. the autocorrelation) of a time series. This approach has been used to analyze respiratory sound events, and for instance the time interval between consecutive crackling sounds, generated when a collapsed airway opens, has been related to both lung structure and surface properties of the lung coating fluids [3,4]. The dynamics of various other physiological signals has been investigated with the help of tools derived from information theory and statistical mechanics (see e.g. [5,6] and references therein).

Snoring is perhaps the best known respiratory sound, and is characterized by a loud sound with frequency content between 20 and 300 Hz. It is caused by the vibration of soft tissues from the upper airway, including soft palate, uvula, tonsils, tonsilar pillars, base of tongue, lateral pharyngeal walls and mucous membranes [7]. Snoring occurs during sleep, when the pharyngeal muscles relax and may block the airway. Snoring is common in the general population, and does not necessarily indicate a disease. In contrast, irregular snoring is one of the hallmark signs suggestive of Obstructive Sleep Apnea (OSA). OSA is the most common sleep-disordered breathing, and is characterized by repetitive events of upper airway obstruction during sleep, causing total or partial cessation of airflow (apneas and hypopneas, respectively) [8].

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A respiratory event is defined as apnea or hypopnea if its duration exceeds 10 s. Apnea is characterized by the cessation of airflow, while hypopnea is defined as a substantial reduction — of at least 50% — in airflow. OSA is a major public-health problem due to the high prevalence in the adult population (ranging from 4% to 10%), and due to the poor outcome when not recognized and treated. OSA is associated with recurrent asphyxia, fragmented sleep and generation of negative intrathoracic pressure during futile efforts to breath [9]. Although the patient is by and large unaware of these recurrent respiratory episodes during sleep, the consequences are multiple and may include excessive daytime sleepiness, fatigue, poor cognitive function and quality of life, as well as increased risk of motor vehicle accidents, metabolic and cardiovascular diseases. Full polysomnography is the gold standard method for OSA diagnosis, and the most important index expressing the severity of OSA is the apnea–hypopnea index (AHI), which is the average number of apnea or hypopnea events per hour. Sleep apnea is usually classified into mild, moderate or severe, depending on whether the AHI lies between 5 and 15 (mild), 15 and 30 (moderate), or above 30 events/h (severe) [10]. The major limitation of polysomnography is that it is an expensive and laborious test, which requires an overnight sleep in a specialized laboratory under the supervision of a sleep technician. Therefore, the development of alternative and simpler methods for the diagnosis of OSA is a priority [11].

Irregular snoring and witnessed apneas are the major signals indicating OSA and there is an increasing amount of research trying to relate OSA with snoring patterns. Most methods in the literature try to establish a correlation between OSA and either the number of snore events or the wave features of the snore such as intensity, sound frequency, number of snore events, spectral density, or a combination of these features [12–14]. Recently, Cavusoglu et al. [15,16] proposed the use of sequential properties of snoring episodes for OSA identification. They built sequences of snoring episode duration, snoring episode time separations and average snoring episode power, and were able to show that, using statistical properties of these sequences to measure snore regularity, OSA patients exhibit a greater degree of irregularity as compared with simple snorers. Following a related path, in this work we focus on the dynamics of irregular snoring episodes, and define a new Index, called the Snore Time Interval Index (STII), showing a strong positive correlation with the well-known apnea–hypopnea index. Furthermore, by a fluctuation analysis of the snore sound, through Hurst's R/S analysis, we build an automated classifier which is able to distinguish between patients with no or mild OSA and patients with moderate or severe OSA. In a similar spirit, a number of studies focused on the study of dynamic properties of sleep electroencephalogram (EEG) signals and their relation to OSA [17–19]. Here we work directly with acoustic signals, whose acquisition, in contrast with EEG signals, requires very simple equipment and no direct contact with the patients.

The remainder of this paper is organized as follows. In Section 2 we describe details regarding data acquisition and processing, and introduce the mathematical definitions used in this work. In Section 3 we present the results, and the paper ends in Section 4, in which we provide a discussion and our conclusions.

2. Methods

2.1. Experimental and pre-processing details

We analyzed snore records from patients referred to the sleep laboratory due to suspected OSA. The patients slept in a bed at the Sleep Laboratory of the Heart Institute at Clinics Hospital in São Paulo, Brazil, and we recorded the sounds in the room while the patients were simultaneously evaluated by a full polysomnography exam.

The population of 17 patients for which sound and polysomnography data are available was characterized by a male/female ratio of 11/6, average age 50 $\pm$ 10 years, average body mass index 30.7 $\pm$ 6.7 kg/m^2, and average apnea–hypopnea index 25.5 $\pm$ 22.5 events/h. Out of the 17 patients in the present study, 4 suffered from mild OSA, 6 from moderate OSA, and 7 from severe OSA.

The sound-recording system is based on a 16-bit audio codec (PCM 2901, Texas Instruments, USA) with a 4th order low-pass Butterworth analog filter (cutoff frequency of 5 kHz) and a 4th order high-pass Butterworth analog filter (cutoff frequency of 20 Hz). The audio codec is responsible for the acquisition (sampling frequency of 44.1 kHz) of the sound captured by the microphones, and the transmission of the recorded data to a laptop computer by a USB serial input. The sound was captured by two microphones located at the headboard of the bed, at a distance of 90 cm from each other.

The microphones acquired the sound $S(t)$ emitted by the patient plus the ambient noise, with a total time T, and recorded the data into a microcomputer for later analysis. Since the frequency content of the snore signal is predominantly between 20 and 300 Hz, the first step of the analyses was to digitally filter the signal, reducing the noise ratio. We found that the most suitable filter for dismissing the unwanted ambient noise while still keeping a strong snore signal was a 1024th-order band pass filter between 80 and 300 Hz.

Following the filtering, we square the filtered signal $S_f(t)$ and sum over all $[S_f(t)]^2$ in a time window Δt, with a window overlap of 50% between consecutive windows, building a new series of sound intensities I_m,

$$I_m = \sum_{t=\frac{m}{2}\Delta t}^{(\frac{m}{2}+1)\Delta t} [S_f(t)]^2, \tag{1}$$

with m going from zero to $2(T/\Delta t - 1)$, i.e., the series $\{I_m\}$ has a total of $2(T/\Delta t) - 1$ elements. We choose $\Delta t = 1$ s, since the normal breathing period is approximately 5 s, and we found that this discretization gives us a good overall precision for