Study of time-frequency characteristics of single snores: extracting new information for sleep apnea diagnosis

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Abstract

Obstructive sleep apnea (OSA) is a highly prevalent chronic disease, especially in elderly and obese population. Despite constituting a huge health and economic problem, most patients remain undiagnosed due to limitations in current strategies. Therefore, it is essential to find cost-effective diagnostic alternatives. One of these novel approaches is the analysis of acoustic snoring signals. Snoring is an early symptom of OSA which carries pathophysiological information of high diagnostic value. For this reason, the main objective of this work is to study the characteristics of single snores of different types, from healthy and OSA subjects. To do that, we analyzed snoring signals from previous databases and developed an experimental protocol to record simulated OSA-related sounds and characterize the response of two commercial tracheal microphones. Automatic programs for filtering, downsampling, event detection and time-frequency analysis were built in MATLAB. We found that time-frequency maps and spectral parameters (central, mean and peak frequency and energy in the 100-500 Hz band) allow distinguishing regular snores of healthy subjects from non-regular snores and snores of OSA subjects. Regarding the two commercial microphones, we found that one of them was a suitable snoring sensor, while the other had a too restricted frequency response. Future work shall include a higher number of episodes and subjects, but our study has contributed to show how important the differences between regular and non-regular snores can be for OSA diagnosis, and how much clinically relevant information can be extracted from time-frequency maps and spectral parameters of single snores.

1. Introduction

Obstructive sleep apnea (OSA) is a chronic respiratory disease with a high prevalence in adult population, especially elderly or obese subjects. Its physiopathology is characterized by brief and repeated upper airways (UA) obstruction episodes during sleep, which lead to intermittent hypoxia and microarousals. These effects increase the cerebrovascular and cardiovascular mortality and morbidity. Sleep fragmentation produces symptoms like fatigue and daily sleepiness, too, with the subsequent risk of traffic, domestic or work-related accidents.

Despite the severe implications of this disease, most patients remain undiagnosed and untreated. The gold-standard technique for OSA diagnosis is nocturnal polysomnography (PSG). It measures a high number of physiological signals to obtain a diagnostic score: the apnea-hypopnea index (AHI), defined as the total number of apnea or hypopnea episodes per hour. However, PSG presents important limitations due to its complexity and high cost. For this reason, there is an increasing pressure to develop novel and cost-effective strategies to enable an early OSA detection and reach many more patients.

Recent works [1-2] have highlighted the current interest towards the analysis of acoustic breathing signals, especially snoring. Snores are vibratory sounds produced at anatomical structures of the pharyngeal airway during sleep. They are one of the most common and earliest symptoms of OSA and constitute a signal of high diagnostic value; since they can indicate the degree and origin of UA obstruction. Besides, the required sensor for recording snoring is simply a microphone, largely available in different models, quality and solutions (air-coupled, contact or ambient, among others).

As reported in a recent meta-analysis [2], many methods and different snoring features have been studied, but further investigation is needed to understand which parameters, or combination of them, contain the best predictive value to identify OSA patients and estimate their severity. Most works focus on detecting and quantifying the number of snores and apnea episodes, but little attention is paid to the intrinsic characteristics of single snores. This bottom-up approach could be essential to extract clinically relevant information for diagnosis. For this reason, this work was intended to study the characteristics of single snores from acoustic signals acquired with different throat microphones. The objective was to compare different types of snores from healthy and OSA subjects. Furthermore, another aim was to characterize and compare two commercial tracheal contact microphones to record snoring sounds. This approach would allow studying how sensor response and acquisition protocol can affect the information in the final signals, especially the spectral characteristics of snores.

2. Materials and Methods

2.1. Dataset

Our dataset included different snoring segments extracted from full-night recordings of healthy volunteers and OSA patients from previous databases of our group. Signals had been acquired through a tracheal air-coupled microphone from Snoryzer equipment (SIBEL, S.A.) [3-4] with a sampling frequency of 5 kHz. We selected five different segments (about 2 minutes long except for post-apneic snores segment, of 15 minutes) containing between 15 and 30 episodes of:

- “Regular” or structured snores from a healthy subject (understanding “regular” as steady snoring, with little variation and little or no interruptions)
- Non-regular snores from the same subject
- Regular snores from an OSA subject (AHI=9)
- Non-regular snores from the same OSA patient
- Post-apneic snores from the same OSA patient

On the other hand, we also had a set of signals containing simulated snores from healthy subjects, acquired according to the experimental procedure described below.

2.2. Experimental Approach

We carried out a small experimental approach aimed at characterizing and comparing the responses of two commercial contact microphones: Biopac acoustical transducer (TSD108) and Sleepmate snoring sensor (G-09-01EPP). Four healthy subjects (two men and two women) were asked to simulate some sounds, including vowels, words, breathing, apneas and snores; in supine position. Microphones were attached over the trachea of these subjects, at the level of cricoid cartilage, through adhesives (Bionic S.A.). Signals were recorded using Biopac acquisition system (MP150) and advanced transducer (DA100C), at a sampling frequency of 12.5 kHz. One of the female recordings was discarded since a realistic simulation of snores was not obtained.

2.3. Signals Processing and Conditioning

All signals were processed and analyzed using MATLAB (Mathworks®). First, they were downsampled to 5 kHz, applying an anti-aliasing Chebyshev low-pass filter with a cut-frequency of 2500 Hz (fs/2). Power-line noise (50 Hz and its harmonics) was removed through a Notch filter. We also applied an 8^{th} order Butterworth band-pass filter between 70 Hz and 2 kHz to remove cardiorespiratory and high-frequency noise and keep the band of interest for snores and breathing sounds. Signals from Snoryzer had been previously conditioned, with the same process we used with new signals. Finally, in order to better compare the results, we normalized all the signals.

2.4. Analysis of Snores

All the episodes of single snores were identified and isolated using an automatic events detector. Then we focused on the analysis of spectral and time-frequency parameters of each snore. First, we represented the whole segments with their spectrograms (using 1024 points for the Fast Fourier Transform calculation (NFFT), Hanning window of 500 points and overlap of 450).

Regarding single snores, we used the Welch periodogram with a Hanning window of 1000 points, 50% overlap and NFFT=1024 as Power Spectral Density (PSD) representation and we extracted a series of quantitative parameters from this spectrum for each snore, as detailed in Table 1. We averaged the values for each type of snore and used the Mann-Whitney U-test to study if there were significant differences between each pair of classes. Lastly, we computed a time-expanded representation (window 0.1s) of each snore to find its repetitive pattern.

Parameter	Description
fc	Central frequency
fm	Mean frequency
fp	Peak frequency
fvar	PSD Standard deviation
fq1	First quartile frequency
fq3	Third quartile frequency
IQR	Interquartile range
fmax	Frequency with 95% of energy
%PSD <500 Hz	Percentage of PSD energy below 500 Hz
%PSD 100-500 Hz	Percentage of PSD energy between 100 and 500 Hz
%PSD >800 Hz	Percentage of PSD energy over 800 Hz

Table 1. *Spectral parameters computed for each snore from the Welch periodogram*

3. Results and Discussion

3.1. Microphones characterization

Spectral and time-frequency representations of the acquired acoustic signals were analyzed for microphone characterization. They evidenced that Sleepmate sensor seriously attenuated high frequencies, what was expected according to its limited frequency response (50-250 Hz). Consequently, although it is described as a “snoring sensor” by the manufacturer, it is not appropriate for recording snore sounds, which can have frequency components up to 2 kHz. Biopac microphone, instead, had a frequency band suitable for recording snores (35-3500 Hz). However, it seemed to have a resonance peak around 1 kHz and not a perfect flat frequency response, apart from capturing higher frequencies than the air-coupled microphone of Snoryzer equipment. This effect has to be taken into account to avoid confusing it with physiological information when interpreting the results.

Biopac microphone had also a higher sensibility than Sleepmate sensor and provided a better signal-to-noise ratio (SNR). This can be critical for OSA detection, since quiet breathing produces very low-amplitude sounds and the effect of background noise can make difficult to distinguish them from apnea episodes. Figure 1 shows how, once the same filtering process has been applied to both channels, the quality of the signal obtained with Biopac microphone is much better than with Sleepmate sensor. For these reasons, we decided to use just this sensor for posterior analysis of snores characteristics.

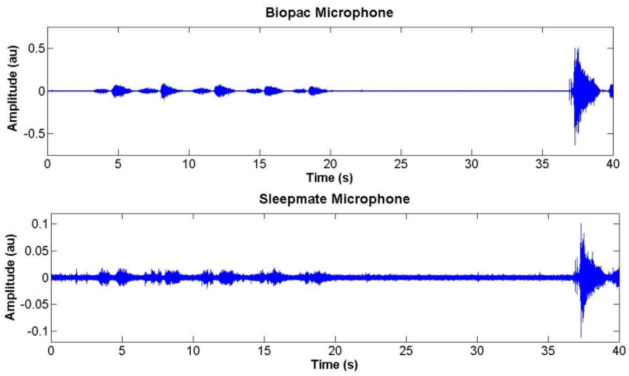

Figure 1. *Acoustic signal of breaths and apneas of one subject, recorded with both microphones. Biopac provides a better SNR.*

3.2. Analysis of Snores

Figure 2 shows a segment of each type of snore; together with their spectrograms and the Welch periodogram of one episode. Two patterns can be clearly identified. On the one hand, regular snores have most power below 200 Hz and acoustic energy is concentrated around particular frequencies, corresponding to the so-called "formants" of snores (a fundamental frequency around 80 Hz and its harmonics). In contrast, non-regular snores (both from healthy and OSA patients, since their patterns were found to be equivalent), similarly to regular snores from the OSA patient, have a much more scattered spectrum, extending up to 600 Hz and with maximum intensities located at higher frequencies (around 250 Hz). This can also be seen in the periodograms of single snores and agrees with previous studies pointing out the presence of higher frequencies in snores from OSA patients [4]. Post-apneic snores are shorter and explosive sounds and their spectral behavior (not shown here) was found to be similar to the one of non-regular snores. Simulated snores at low frequencies are similar to the healthy regular ones, but they also present some higher frequency components, probably due to the different frequency responses of the microphones and the resonance peak around 1 kHz. It also has to do with the fact that these are not real but simulated snores.

Figure 3 summarizes the quantitative spectral parameters extracted from the Welch periodograms of single snores and the results of the statistical tests comparing classes. Regular snores have a significantly lower central, mean, peak and first and third quartile frequencies than the non-regular, post-apneic and OSA patients regular snores, whose parameters are similar. Regarding the amount of energy at different frequency bands, all the snores, as expected, concentrate their power below 500 Hz and have small contribution over 800 Hz (slightly larger for simulated snores). However, the percentage of energy at 100-500 Hz is a good indicator to classify snores: regular snores have a PSD concentrated at lower frequencies and thus a smaller contribution at this band than non-regular or OSA snores. According to this parameter, our simulated snores are also classified as regular and healthy.

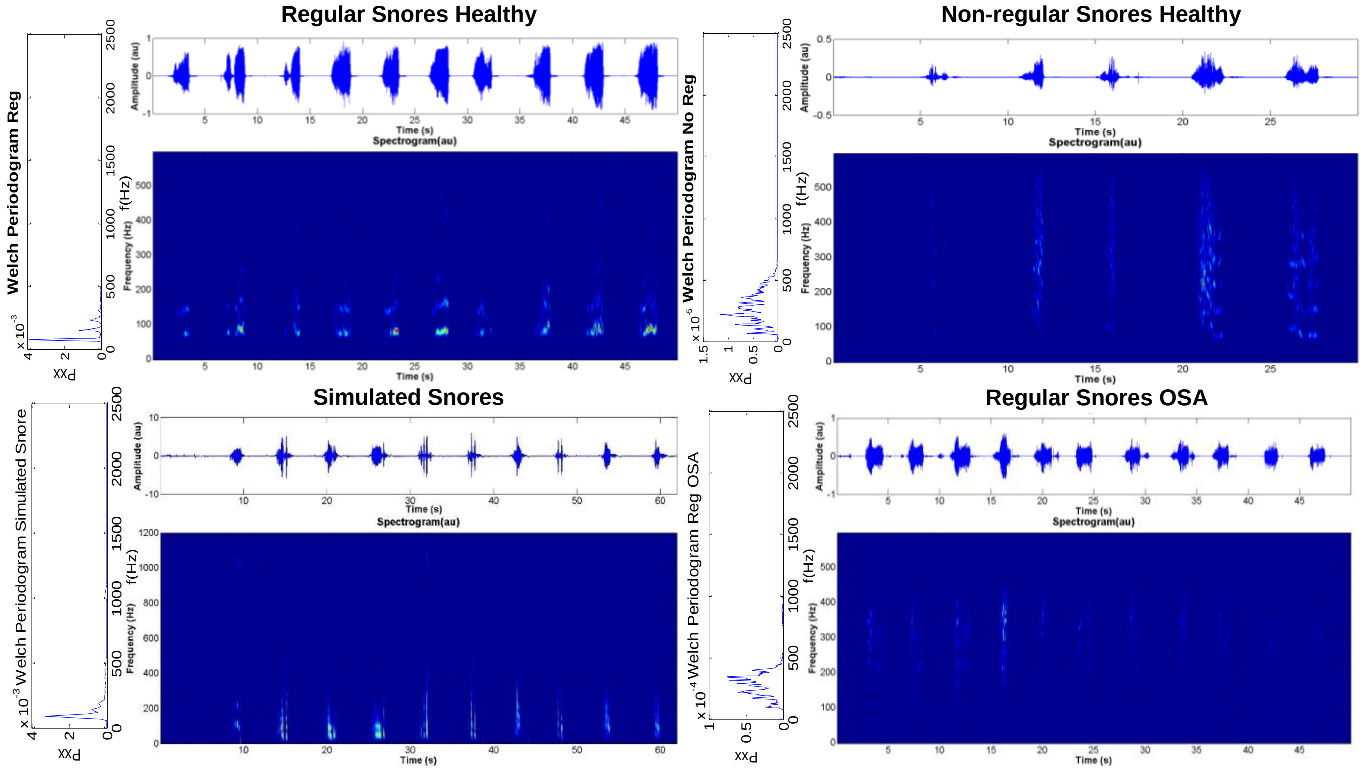

Figure 2: *Segments of different types of snore with their spectrograms and the Welch periodogram of one episode. Time-frequency maps are cut at those frequencies concentrating most of the energy, to enable a good visualization.*

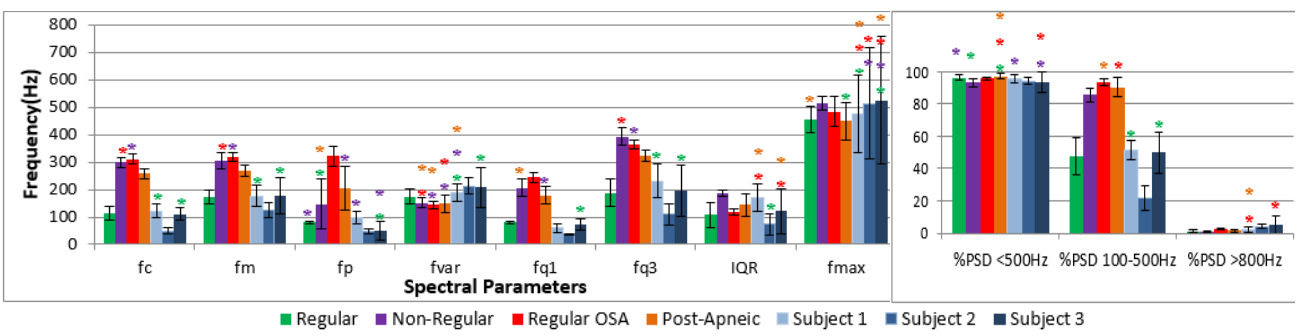

Figure 3: *Spectral parameters (mean±standard deviation) extracted from Welch periodograms of each type of snore. Asterisks indicate classes with NO significant differences according to Mann-Whitney U-test (p-value=0.05)*

We also plotted a time expanded representation of each snore in order to find their basic repetition pattern and compare them (Figure 4). Regular snores have a very clear deterministic pattern, which is quite similar for all the examples of this class. Their pitch (frequency of repetition) is around 70-80 Hz. However, the pattern of non-regular, post-apneic (not shown) and OSA regular snores have an important stochastic component and it is more difficult to establish the basic pattern and the pitch and there are also important intraclass differences. Simulated snores present a clear deterministic pattern like regular snores, but with noticeable differences in waveforms and pitches (usually lower). These differences were expected, since simulating a snore is difficult and the generation mechanism can involve different anatomical structures than in real snores, so the vibratory pattern is clearly affected.

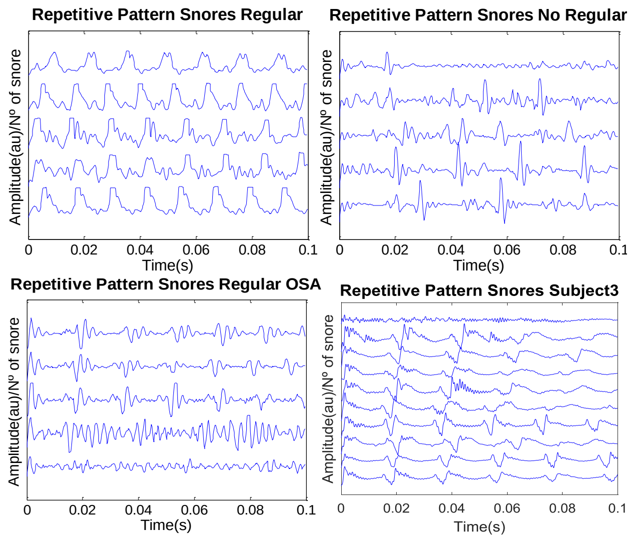

Figure 4: *Time-expanded representations showing the basic repetitive pattern of different types of snore*

Differences between healthy and OSA regular snores rely on the anatomico-pathological basis of this sleep disorder. While simple snoring in the adult is caused mainly by vibrations of the soft palate, apneic snoring is a tongue based sound related to UA obstruction and impeded movement of the soft palate [1,5]. This had already been studied and could help to discriminate patients, but the important point is that not all the snores of a healthy subject behave like that. On the contrary, most aspects of non-regular snores make them practically equivalent to snores of OSA subjects. Non-regular snores are produced occasionally by simple snorers due to an abnormal desynchronization. This situation is comparable to the pathology, which produces a higher scatter and variability by desynchronizing the natural mechanism of generation of snores and making the patients breath in an unstructured way. That is probably the reason explaining the different patterns that we found and the complex waveforms of non-regular and apneic snores.

4. Conclusions

This work was focused on analyzing the characteristics of single snores of different types, to extract information related to sleep disorders. We found that time-frequency representations, which are rarely used with snoring signals, are in fact a very useful tool to study their content. Together with certain spectral parameters, they allowed discriminating regular snores of healthy subjects from non-regular snores and all the snores of OSA patients. This is in good agreement with previous works comparing simple and apneic snoring but, most remarkably, highlights the importance of differentiating regular and non-regular snores in diagnostic applications.

On the other hand, we characterized the response of two commercial contact microphones. The importance of this point relies on the fact that selecting an appropriate sensor is the first step to obtain high-quality signals. While Biopac microphone was found to be a good snoring sensor, which could be integrated in platforms of diagnostic devices; Sleepmate sensor had a very limited frequency response, not suitable for this application. Simulated snore patterns looked like healthy regular ones, but we encountered some problems due to the huge variability between subjects when simulating snores.

Therefore, in this work we have characterized the response of two commercial microphones and we have developed an automatic methodology to quantify parameters from single snores, enabling a distinction between snores of different types that could be used for screening or differential diagnosis of sleep-breathing disorders. Future improvements would include studying more episodes of single snores and from more patients, with different degrees of OSA severity. Nevertheless, this approach has shown how time-frequency maps and spectral features differentiating regular and non-regular snores are a powerful source of clinical information. This kind of analysis could help in the near future to develop new non-invasive tools for screening OSA patients and improving the management of their disease.

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References

[1] Pevernagie D, Aarts RM, De Meyer M. The acoustics of snoring. *Sleep Med Rev* 2010, 14: 131–144

[2] Jin H, Lee LA, Song L et al. Acoustic analysis of snoring in the diagnosis of obstructive sleep apnea syndrome: a call for more rigorous studies. *J Clin Sleep Med*. 2015, Jul 15;11(7):765-71

[3] Jané R, Fiz JA, Sola-Soler J et al., Automatic snoring signal analysis in sleep studies, *Conf Proc IEEE Eng Med Biol Soc.* 2003, vol 1, pp 366-369

[4] Fiz JA, Jané R, Sola-Soler J et al., Continuous analysis and monitoring of snores and their relationship to the apnea-hypopnea index, *Laryngoscope* 2010;120(4):854-62

[5] Miyazaki S, Itasaka Y, Ishikawa K et al., Acoustic analysis of snoring and the site of airway obstruction in sleep-related respiratory disorders, *Acta Otolaryngol Suppl* 1998;537;47-51