Snoring Analysis on Full Night Recordings based in the Energy and Entropy in PSG Basal Studies

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Abstract: Snoring is a widely occurring problem in our society and it is highly associated with pathologies like Obstructive Sleep Apnea Syndrome (OSAS) being, usually, one of the first symptoms to appear. Economically, OSAS has a great impact since sleep disorders affect the daily performance of people in their professional activities. The extensive study of snoring evidences may be useful to improve the knowledge of associated pathologies, such as OSAS or others, at an early state. In this work, we study full night sound recordings of patients undergoing polysomnography (PSG) procedures. Recordings are offline processed to characterize time series of snoring events through the record length and correlated with the PSG data. The main goal of the proposed algorithms is to understand the behaviour of the full night sound recording and to identify snoring event patterns that may help and refine the diagnostics process. To achieve this goal, the relationship between the energy and the entropy was studied, for each respiratory event, in both snoring and non-snoring cases. Recordings are offline processed to characterize time series of snoring events through the record length and correlated with the PSG data. In the future, the relationship between these two physical variables can be used to predict the clinical evolution between a simple snorer patient and a patient with OSAS.

1 INTRODUCTION

Sleeping is a natural process in the life of a human being and its importance is well known in several processes of the human biology, such as memory consolidation, blood pressure regulation, learning motor sequence and normal immune function (Barkoukis and Avidan, 2007)(Shneerson, 2005). This process is dynamic and throughout the life, sleep patterns change in a natural way (Shneerson, 2005).

However, there are some changes in sleep patterns induced by either pathological factors or drugs. Sleep disorders are a common problem in our society affecting both men and women, especially elderly, as well as children (Pevernagie et al., 2010) (Spicuzza et al., 2009) (Grunstein et al., 2001) (Ye et al., 2009) (Launois et al., 2007). One of such disorders is the Sleep Apnea Syndrome (SAS). SAS has a high impact in the quality of life and in the world economy (Leger et al., 2012) (Wittmann and Rodenstein, 2004). SAS can be obstructive (OSAS), central (CSAS) or both. OSAS is much more common than CSAS and it is highly linked with snoring.

Snoring is the result of the mechanical vibration of the anatomical structures of the upper airway and usually precedes almost all the others OSAS symptoms (Banno and Kryger, 2007). It is a complex signal since it changes between different people and it may change throughout the same night in the same person. Factors like route of breathing, site of narrowing, sleep stage and sleep position contribute to changes in the features of snoring (Pevernagie et al., 2010). According to (Beck et al., 1995) there are 2 basic dominant patterns in snoring: the simple-waveform and the complex-waveform. The second one is characterized by ”a repetitive, equally-spaced, train of sound structures, each composed of a few oscillations, starting with a large deflection which is followed by a decaying amplitude wave.”. The first one is characterized as follows: ”In the time domain, simple-waveform snores have a quasi-sinusoidal pattern and almost no secondary internal oscillations within the periodic wave.”.

Since snoring is highly linked to OSAS, our work

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focuses its goal in the study of this condition. Previous works demonstrated differences in acoustic properties between simple snorers patients and patients with OSAS in the sound power spectrum (Fiz et al., 1996). The first step is the determination of the energy of a full night sound recording in patients with polysomnographic basal studies, splitting the sound recordings in small segments of settable length (between 0.01s and 1s). The second step is the determination of the entropy for every respiratory event, with or without a snoring signal. Entropy is a measure of the disorder of a system. In information theory, the concept of entropy was first explored by Claude Shannon and it measures the uncertainty associated with a random variable (Yadollahi and Moussavi, 2006) (Zhang et al., 2009).

In the end, a relationship between the energy and the entropy of all the respiratory events detected by the algorithm was established.

2 METHODS

2.1 Data Acquisition

Full night sound recordings took place at the Centro de Medicina do Sono of the Centro Hospitalar e Universitário de Coimbra with clinical supervision of MD J. Moutinho dos Santos and the collaboration of his clinical team.

Prior to each data acquisition, the patient is given an informed consent. To the development of this work 36 patients agreed to participate (22 men and 14 women). The arithmetic mean of their ages was 50.83 years with a standard deviation of 12.66 years.

Sound acquisitions are performed with a commercial recording device in order to bypass developing times and because such instruments provide the best sound quality and noise immunity while still being portable (Zoom, 2012). The instrument has 2 independent channels with near-Lambertian spatial sensitivity (directional microphones) which significantly reduces ambient sounds and other stray noises present on the exam location. The recordings are stored on an SD card and afterwards downloaded to a processing workstation for analysis.

Each full night recording stores an uncompressed 16 bit single channel with at 44.1KHz sampling rate. Due to the used acquisition configuration, there is an upper limit of 6h45m to the record length of a data taking session. This is indeed compatible with the PSG protocol and doesn't represent a limitation to data availability.

The use of a non-contact microphone may add some challenges to this work since the source and the destination of the sound do not have the same relative position and distance throughout the night. In fact, there are some works pointing their goals to this issue. One of such works was developed by (Herzog et al., 2009). Its investigation team used 4 non-contact microphones and 2 contact microphones. Non-contact microphones were at different distances and at different relative positions from the source. The results show an independence relationship between intensity (% of maximum intensity) and the position of the non-contact microphones since the intensity profile is almost the same throughout all the studied frequencies for all the non-contact microphones. Although there is a suggestion that the recording took place with the patient in the supine position there isn't a clear evidence if the sleeping position was controlled. If not, the results can be biased, because different sleeping positions mean different distances between the source of the sound and the microphones. Another consequence of studying different sleeping positions is the sound reflection on the wall of the room, different for each one.

Since this research work only used one acquisition device, the best place to acquire sound was just above the head of the patient. This choice should minimize sound losses due to the different sleeping positions adopted throughout the night. The sound acquisition support was placed behind and above the bed to keep the vertical distance, around 0.7m, between the bed and the microphone. This support has 3 degrees of freedom to allow a correct orientation of the acquisition device to the sound source. An infrared is used to check the orientation (Figure 1).

2.2 Data Processing

To develop this work it was used a high-level programming language, MATLAB, working in a computer with the following features: Operating System: Windows 7 (64 bits), Central Processing Unit: i7-3610QM 2.3GHz, RAM: 6GB.

Energy calculation was the first step in sound processing. In this study, the full night sound recording was split in smaller pieces of data with length of 0.1s. Since the frequency acquisition was 44100Hz, each energy calculation contained 4410 sound samples. To calculate the energy of each set of 4410 sound samples, the mathematical equation implemented in the algorithm was:

$$E(x) = \sum_{i=1}^{N} x_i^2 \tag{1}$$

Figure 1: Data acquisition setup.

The variable x_i represents the amplitude of the i^{th} sound sample. The energy distribution, stored in an array with a length of one tenth of the length of the original data sound file, was filtered. The filtering process started with a convolution between the energy array and the [1 0 -1] array. The result of this high-pass filtering was an array with elements in $\mathbb{R}$. To avoid working with negative values the absolute values were taken and then a moving average filtering was applied. Each energy element was average by its 10 nearest neighbors to remove low amplitude peaks.

With the purpose of detecting each respiratory event, a Gaussian fit was applied to the filtered data. To perform the Gaussian fit, a 4 second sliding window with a time step of 0.5 seconds was chosen to try to get one respiratory event each time. On the other hand, a smaller window could be ineffective to respiratory events detection. The Gaussian fit does not start at the beginning of the array but only 10 minutes after the sound recording starts and it goes until the end of the filtered energy array. The 10 minutes delay was implemented to ignore the first minutes where the patient was still awake. It was usual the patient awakes in the middle of the study and, therefore, all the results inside these time periods must be considered as interference. During the Gaussian fit process, the algorithm calculates the center of mass, R, of the current window to know where the respiratory event is most likely to be:

$$R = \frac{\sum_{i=1}^{k} m_i r_i}{M} \tag{2}$$

$$M = \sum_{i=1}^{k} m_i \tag{3}$$

In (2) and (3) m_i and r_i represents, respectively, the i^{th} element of the energy filtered subset and of the time subset. Since the sliding window has a duration of 4 seconds and each energy value represents 0.1s then R is calculated for 40 points, k, each time.

The Gaussian function template to the fit process had one variable, x, and 3 parameters to be calculated, a, b and c. The algorithm used the following Gaussian function, $F(x)$:

$$F(x) = a.e^{-(\frac{x-b}{c})^2} \tag{4}$$

When the fitting process is finished, the algorithm calculates the maximum of the Gaussian function, (4). Throughout the window sliding process, the algorithm tried to find each respiratory event and store it.

With the respiratory events detected, the final algorithm step was to find the entropy of each one in the sound file. In information theory, a very common formula is given by the Shannon's Entropy, $H(x)$:

$$H(x) = -\sum_{i=1}^{l} p(x_i) log_d \, p(x_i) \tag{5}$$

If a probability of an event was 0, $p(x_i) = 0$, then the entropy of such event was 0:

$$0.log_d 0 = 0 \tag{6}$$

Every time the sound recording device made an acquisition, such data was stored in a signed variable of 16 bits. The sample space, Ω, in a variable of 16 bits is a set of 65536 possible outcomes, l, each one representing an elementary event, x_i. To know the probability of each event, a data acquisition profile was calculated, for each sound file, to know how many times each event occurred. The calculation of the Shannon's Entropy was performed for the neighborhood of each respiratory event. The length of the neighborhood was $T = 3.1s$. For a neighborhood of length T and a respiratory event at time t, then the Shannon's Entropy would be calculated with samples between $\left[t - \frac{T}{2} \quad t + \frac{T}{2}\right]$. Finally, the Shannon's Entropy was calculated with a logarithm of base 2. The maximum energy value, E_m, around each detected respiratory event with time t was determined using a time span of 1s $[t - 0.5 \quad t + 0.5]$. In the end, the plot between E_m and entropy was taken.

In the development of this data processing tool, other features have been created as a background support or as a different parallel processing path (Figure

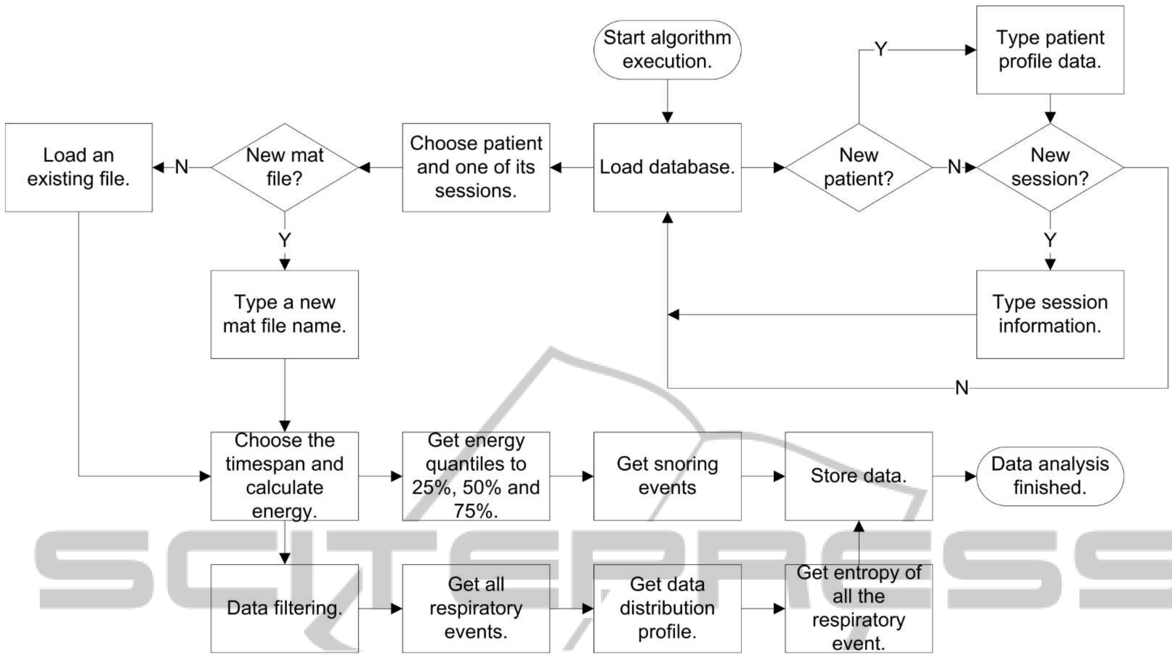

Figure 2: Algorithm workflow.

2). The alternative parallel processing path used a set of conditions, e. g. calculation of the energy's quantile to 25%, 50% and 75%, to find only snoring events. The results achieved allow a profile of snoring distribution during the sleep and a profile of the time space between 2 consecutives snoring events. This last profile allows the user to select a time span and see where such snoring events occur during the night. Another feature in the algorithm allows the user to select another time span in the energy plot and either appears a list with the times of the respiratory events or a list with the times of the snoring events of such time span. If the selected data type is respiratory events, there is the possibility to listening an individual event and classify it as breath, snore or interference.

3 RESULTS

Each full night sound recording had near 2GB of data. Such amount of data was huge and not easy to handle in an ordinary computer. Even if a computer has enough RAM memory to load this amount of data it would be unwise because it would affect its performance. On the other hand, if the algorithm picked up a suitable time span to calculate the energy, no respiratory event would be lost and higher amplitude signals would be distinguish even better than lower amplitude signals because of the energy's definition, $\sum_{i=1}^{N} x_i^2$. A good time span, not too big to lost respiratory events and not too little to get a small energy array, was required and the time chosen was 0.1 seconds. An example of the energy array of a full night sound recording, for a time span of 0.1 seconds, is available in Figure 3 and in Figure 4.

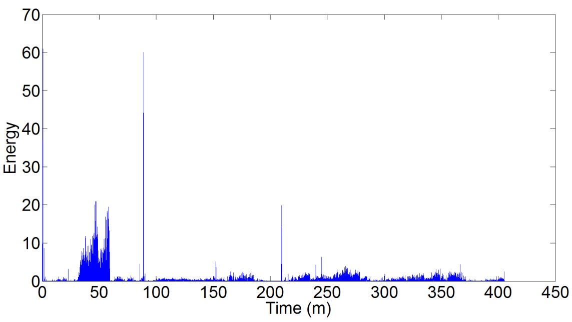

Figure 3: Sound energy of a full night sound recording with y-axis in linear scale.

In Figure 4 it is possible to identify some oscillations in the baseline of the signal energy. The first half of the energy distribution is very different from the second half. Even within the first half of the energy distribution the baseline is not stable, with periodic oscillations between 2 values. Both values are higher than the energy baseline of the second half.

In signal acquisition is very difficult to have a signal without interference. In this work several interference sources may exist. The most common ones are coughing, changing bed sleep position, road traffic and sleep technicians talking with patients or resolv-

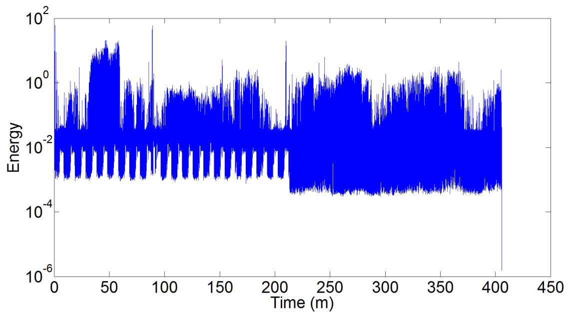

Figure 4: Sound energy of a full night sound recording with y-axis in log scale.

ing data acquisition problems. Another interference sources are poor weather conditions, like heavy rain or strong winds, air conditioning (AC) and capnograph. In Figure 4 the source of interference is most likely to be the AC. Performed tests to evaluate the functional behaviour of the AC show a similar profile. In the first half of the energy distribution, AC switches between the working and the idle mode. In the second half the AC was shut down since the energy baseline achieve even lower values. An example of a recording free of interference from an AC system is available in Figure 5.

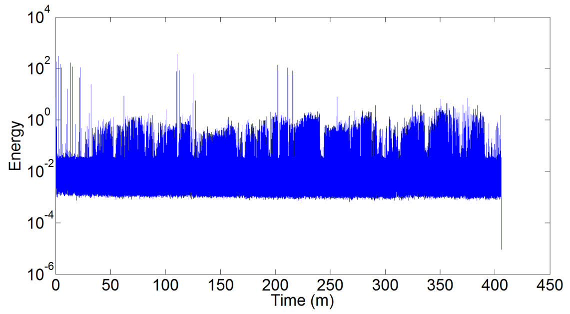

Figure 5: Full night energy profile when AC is always off.

Computing the energy of a signed signal shifts its baseline from near zero to a higher value since all energy values are non-negative. Before the implementation of a Gaussian fit, pre-processing techniques must be implemented to have an energy signal with a baseline near zero around the respiratory event. Since the Gaussian function has near zero values for points far enough of the expected value, μ, a filtering process was developed in the algorithm. The filtering process developed can be split in two steps. In the first one, a convolution was implemented to shift the baseline to values nearer to zero. The second step implements a moving average filter to reduce or even eliminate low level amplitude signals. Figure 6 shows the energy distribution before, in a blue line, and after filtering, in a red line.

After the filtering process, the algorithm applied

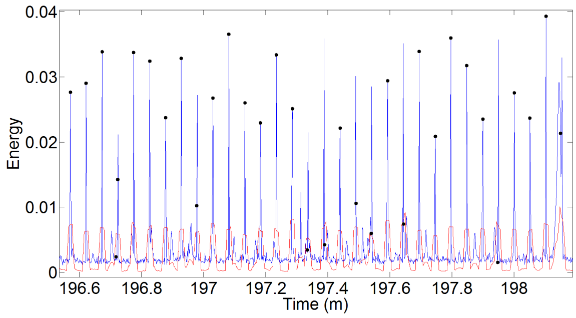

Figure 6: Sound energy before (blue line) and after (red line) filtering and respiratory events detection (dark dots).

the Gaussian fit to the filtered data and it tried to find the time location of all the respiratory events. The Gaussian fit was very accurate and it found almost all the respiratory events and its maxima. Figure 6 shows how the algorithm performed in the detection of such events, dark dots.

With a set of data identifying the respiratory events of a full night sound recording, the algorithm applied the definition of the Shannon's Entropy to calculate the entropy of each respiratory event in its neighborhood. The Shannon's Entropy is calculated using the original data from the full night sound recording.

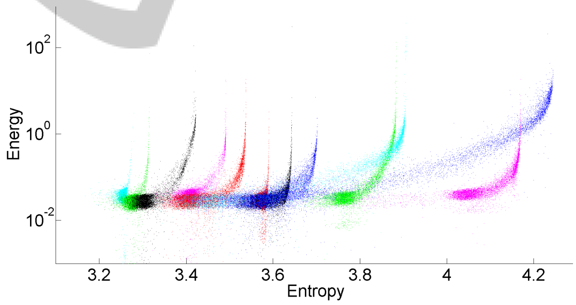

Figure 7: Relationship between energy and entropy for patient 1 to 12.

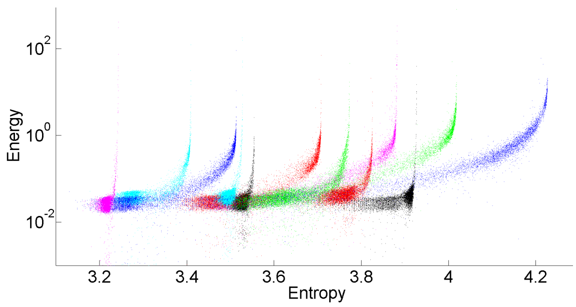

Figure 8: Relationship between energy and entropy for patient 13 to 24.

The relationship between energy and entropy for all the patients from this research may be seen in Fig-

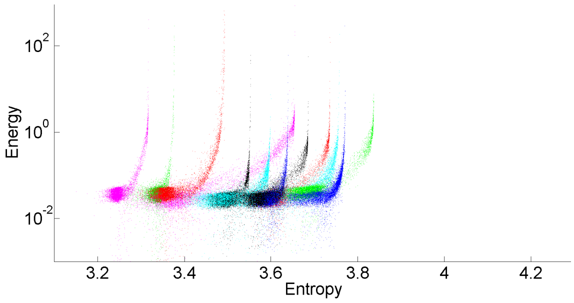

Figure 9: Relationship between energy and entropy for patient 25 to 36.

ure 7, Figure 8 and Figure 9. In Figure 10 it is possible to see the relationship between entropy and energy for 2 different patients. The red profile shows an example of a patient with a medical diagnosis of snoring. The blue profile shows an example of a non-snoring patient.

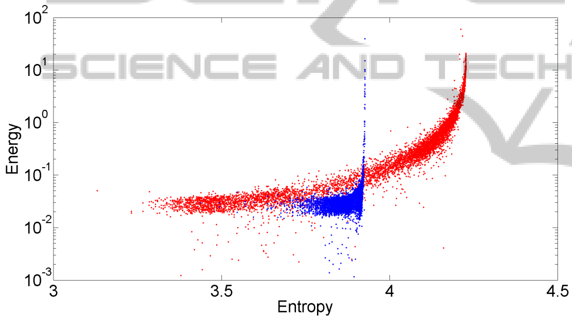

Figure 10: Relationship between energy and entropy of each respiratory event for a non-snoring patient (blue) and for a snoring patient (red).

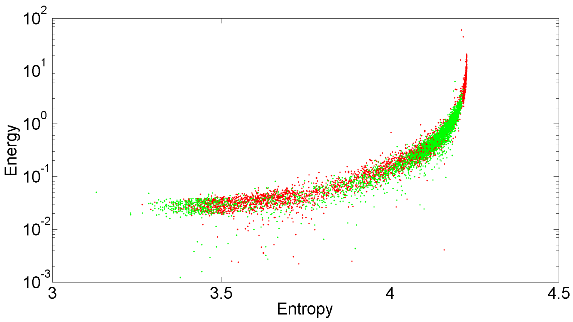

Figure 11: Relationship between energy and entropy while AC is off (green) an on (red) switching between working and idle state.

The interference of the AC during data acquisition can be analyzed in Figure 11. Although there are deviations in the data distribution, the trend line of the relationship between both variables it is not affected.

The relationship between the energy and the entropy of a respiratory event seems to have an upper limit, a vertical asymptote function. This limit is justified by (5). For a chosen logarithm base, the entropy is only a function of the probability of an event, $H(x) \propto p(x_i)$. So, whatever the energy value, the maximum entropy is achieved when the number of different events in the neighborhood of a respiratory event is equal to the number of different events of an entire full night sound recording.

4 CONCLUSIONS

The relationship between both variables for a full night data recording suggests the existence of a trend line. Although the paper does not introduce a mathematical equation of such trend line, Figures 7, 8 and 9 show a common behaviour. For low entropy values an almost horizontal line represents quietly respiratory events. Such respiratory events are non-snoring, meaning a normal breath from the patient. It is possible to see a high density in this area of the plot in Figure 10, especially in the blue profile.

In the case of a non-snoring patient the trend line should be an equation of the type $y = b$, with b the best representative value of all the energies of the respiratory events. Figure 10, blue profile, is an example of a non-snoring patient accordingly with the medical opinion. There isn't a perfect horizontal trend line but almost all the points are below the energy value of 0.1. The points missing the equation $y = b$ represents interference generated during the recording and also snores. Despite the classification as a non-snore patient it doesn't mean the patient doesn't snore. It means the patient doesn't snore or he snores just a little bit.

As quietly respiratory events start to be replaced by loud respiratory events, a snoring event, the energy also increases. The increase in energy induces an increase in the disorganization of the normal breathing. As a consequence entropy increases.

Although there is a clear trend line in the plots entropy vs. energy, some dots miss such relationship. Such deviations can be explained by the interference and by the Gaussian fit process. During the night, the patient can change their sleeping position, can cough or the sleep technician can go to the bedroom. On the other hand, the Gaussian fit can find some false respiratory events.

In the future, the relationship between energy and entropy can be used by the physicians to understand the development of OSAS. Since OSAS means a total or partial obstruction of the upper airways, the moment when the muscle re-acquire tonus to let the air go into the lungs can give useful information about the disorganization of the process.

Further work must be developed to understand data distribution and its variability in the plots entropy vs. energy. A second feature to be explored in these plots is the slope of a mathematical equation representing each data set. To know how fast and earlier in time the curve starts to rise can reveal new useful information. These information may bring new insights in the study of snoring and OSAS.

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