LAURA RIBEIRO
SONIFICATION OF POLYSOMNOGRAPHIC SLEEP RECORDINGS

Master of Science thesis

Examiner: Prof. Alpo Värri
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ABSTRACT

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Sleep is a topic of fascination and interest and sleep complaints are one of the main reasons to seek medical attention. However, the capacity of sleep clinics to evaluate all those that suffer from sleep disorders, or that just want to learn more about their sleep, is still very limited.

The development of new home available methods of sleep analysis has started to allow an affordable, but extensive recording of sleep data. Nonetheless, a problem arises with these recorded signals, as users without extensive training and experience can have arduous tasks at interpreting them. This problem could be fixed by using sonification, which has long been used in many fields as a way of representing hard to understand data (even long streams of data) into short duration sounds.

In this work we aimed to determine whether or not sonification can be used to make polysomnographic information interpretable for laymen. For this, we developed a new sonification methodology of sleep recordings, using information from the EEG, EOG, EMG and oxygen saturation signals. Our methods rely on the extraction of relevant features from these signals and their combination into functions that modulate characteristics of preexistent sounds. Sleep stage, respiratory and movement information are represented into sounds that intuitively resemble these variables.

Results show that separability among classes for the sonification of sleep stages is quite high, and the respiratory and movement functions have generally higher values for unhealthy patients. Listening tests were carried out in order to determine whether or not participants who went through a short training session were able to take relevant conclusions from the sounds. The results show that 8 out of 10 listeners were able to correctly identify all recordings as healthy or unhealthy, and all the participants would be willing to listen to these sounds on a regular basis.

We have thus concluded that sonification can be a very valuable tool in solving the data interpretation step of sleep recordings.
PREFACE

I would like to thank Professor Alpo Värri for supervising this thesis as well as for all the patience and advice in the course of the work. I thank also my supervisor in Portugal, Professor José Fonseca for the support, without which I would not be able to attend TUT. And Professor Jari Viik, for the availability to discuss with me the results chapter.

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I thank furthermore all those that patiently participated in the listening tests and all the friends that took the questionnaires countless times and helped pointing out the mistakes, as well as my father for all the encouragement and proofreading throughout the thesis.

Tampere, 25.7.2017

Laura Ribeiro
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<tr>
<td>EEG</td>
<td>Electroencephalogram</td>
</tr>
<tr>
<td>PSG</td>
<td>Polysomnogram</td>
</tr>
<tr>
<td>EMG</td>
<td>Electromyogram</td>
</tr>
<tr>
<td>EOG</td>
<td>Electrooculogram</td>
</tr>
<tr>
<td>ECG</td>
<td>Electrocardiogram</td>
</tr>
<tr>
<td>REM</td>
<td>Rapid Eye Movement</td>
</tr>
<tr>
<td>NREM</td>
<td>Non Rapid Eye Movement</td>
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<tr>
<td>SWS</td>
<td>Slow Wave Sleep</td>
</tr>
<tr>
<td>PMSon</td>
<td>Parameter Mapping Sonification</td>
</tr>
<tr>
<td>EDF</td>
<td>European Data Format</td>
</tr>
<tr>
<td>VI</td>
<td>Vigilance Index</td>
</tr>
<tr>
<td>SISA</td>
<td>Spectral Asymmetry</td>
</tr>
<tr>
<td>SEF</td>
<td>Spectral Edge Frequency</td>
</tr>
<tr>
<td>MF</td>
<td>Median Frequency</td>
</tr>
<tr>
<td>SWI</td>
<td>Slow Wave Index</td>
</tr>
<tr>
<td>TWI</td>
<td>Theta Wave Index</td>
</tr>
<tr>
<td>AWI</td>
<td>Alpha Wave Index</td>
</tr>
<tr>
<td>STFT</td>
<td>Short-Time Fourier Transform</td>
</tr>
<tr>
<td>FR</td>
<td>Fisher Ratio</td>
</tr>
<tr>
<td>FIR</td>
<td>Finite Impulse Response</td>
</tr>
<tr>
<td>SatO2</td>
<td>Oxygen Saturation</td>
</tr>
<tr>
<td>MIDI</td>
<td>Musical Instrument Digital Interface.</td>
</tr>
</tbody>
</table>
1. INTRODUCTION

1.1 Motivation

Sleep has always fascinated humans, as a state of apparent simplicity but actual great activity and complexity[1, 2], in which we spend about a third of our lives[3] and that we still do not fully understand. Even though it is one the main reasons to seek medical attention, only preceded by pain[2], the capacity of sleep clinics to evaluate all those that want to know more about their sleep is still very limited[4, 5]. The interpretation of sleep recordings (in particular sleep scoring) is a time consuming, tedious task that can take up to 8 hours for a night’s recording[6, 7]. There is a growing interest in understanding sleep and being able to determine, easily and without much cost how well we slept shown by the amount of research done in the development of new home available recording devices[8]. In this context, there is a growing need for the development of new ways of interpreting polysomnographic data (that are faster, easier and more intuitive).

This work comes in sequence of a work previously developed that proposed the sonification (the use of non speech audio) to represent the sleep electroencephalogram (EEG) as a method of making it interpretable for people with no previous experience with the EEG and only a little training[5]. The listening of the produced sounds would, thus, replace the task of visually inspecting graphical representations of the EEG for a considerable amount of time, trying to recognize patterns that might not be very intuitive to see, or even impossible to the untrained eye.

Sonification is known to allow alternative perceptions and new insight into data interpretation[9] and could make the interpretation of polysomnographic data more intuitive (as the human ear has interesting characteristics of pattern and frequency recognition as well as monitoring several sources of information at the same time[10]) and also faster (as the information could be accelerated to a different time frame[10]).
1.2 Objectives

The main objective of this work is to determine whether or not sonification can be used to determine sleep quality. A new method of sonification of sleep recordings should be developed that can be used by those who are interested in learning more about their sleep quality but have little or no training in this area and do not have a serious condition that requires the analysis by a professional in a sleep clinic. The produced sounds should be faithful to the data, easily interpretable and pleasant to hear. In the development of this method we will need to answer the following questions:

- Which polysomnographic signals to take into account? Considering that this needs to be a compromise between the reliability of the algorithm and the possibility of making the measurements conveniently.
- How to extract relevant information from these signals?
- How to represent the extracted information into sounds?

It is also an objective the elaboration of a user’s manual that can easily train the listener to understand the meaning of the sounds. As a final objective, and considering that auditory perception can be subjective, the pleasantness and perceptibility of the resulting sounds should be evaluated by a set of human listeners.

1.3 Document organization

This document is organized as follows: Chapter 2 gives a brief introduction of relevant concepts of sleep and sonification. Chapter 3 presents a review of the related work and status of the research field. Chapter 4 describes the materials and methods of the implementation of our work and is further divided in five subsections (Sleep Stage Sonification, Oxygen Saturation (SatO2) Sonification, Leg Movement Sonification, Electrocardiogram (ECG) Sonification and Listening Experiences). Our results are presented in Chapter 5 and discussed in Chapter 6. Chapter 7 presents our conclusions and discusses future work. In the end of the document there are two appendices with the materials used for the listening experiences.
2. THEORETICAL BACKGROUND

2.1 Sleep

Sleep is a natural, periodic state of total or partial unconsciousness characterized by a decrease in bodily movements and responsiveness to external stimuli, in which the human body undergoes many physiological changes, important for the recovery, integration, consolidation as well as restitution of functions (like the restoration of tissues and growth, neural maturation, memory and learning)[1, 6, 11, 12]. These changes are usually monitored, with the objective of studying sleep or diagnosing sleep related diseases.

2.1.1 Sleep Monitoring

The gold standard for sleep monitoring has long been the polysomnogram (PSG)[8]. The (PSG) is the result of the recording of multiple biophysiological parameters during sleep. These parameters are typically the EEG, submental electromyogram (EMG), electrooculogram (EOG), anterior tibialis EMG, electrocardiogram (ECG) and respiratory data[3].

The EEG measures the electrical activity of the brain with electrodes at the level of the scalp and the location of the electrodes is defined according to the International 10/20 System. In this system, letters F, T, C, P and O represent, respectively, the frontal, temporal, central, parietal and occipital lobes, while numbers refer to the hemisphere location. 1, 3, 5 and 7 refer to the left hemisphere, while 2, 4, 6 and 8 refer to the right hemisphere and z to the mid line, as represented in figure 2.1. The recommended derivations for the scoring of sleep are F4, C4 and O2 but Fz, Cz and C4 channels are also acceptable to use. A minimum of 3 derivations is always necessary in order to sample information from frontal, central and occipital regions [13][14].

The relevant frequency band of the EEG is of 0.5 - 50 Hz and the amplitude of the order of hundreds of microvolts[15]. The effective frequency range is divided
in: Delta, Theta, Alpha, Beta and Gamma activity that can provide important information and whose characteristics are summarized in Table 2.1 [12]. Other characteristic waveforms are K-complexes (sharp, high voltage transient waves) and sleep spindles (bursts of waves with a frequency of 12 to 15 Hz)[16].

<table>
<thead>
<tr>
<th>EEG waveform</th>
<th>Frequency (Hz)</th>
<th>Amplitude (µV)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Delta Rhythm</td>
<td>0-4</td>
<td>20-100</td>
</tr>
<tr>
<td>Theta Rhythm</td>
<td>4-8</td>
<td>10</td>
</tr>
<tr>
<td>Alpha Rhythm</td>
<td>8-13</td>
<td>2-100</td>
</tr>
<tr>
<td>Beta Rhythm</td>
<td>13-22</td>
<td>5-10</td>
</tr>
<tr>
<td>Gamma Rhythm</td>
<td>30-50</td>
<td>-</td>
</tr>
</tbody>
</table>

The EOG signal measures eye movement with at least two electrodes. The recommended derivations are E1-M2 and E2-M2, although E1-Ppz and E2-Fpz are also acceptable. (E1 and E2 are placed, respectively, 1 centimeter below the left outer canthus and 1 centimeter above the right outer canthus in the first case)[17, 18, 14].

The EMG measures muscle activity or skeletal muscle activation. The recommended chin EMG derivation consists of two electrodes (above and below the mandible) referenced to each other [3][14]. Figure 2.2 shows typical EOG and chin EMG electrode placement sites for sleep analysis.
The ECG measures the electrical activity of the heart and is recommended to be measured with a single modified electrocardiograph Lead II [14].

Respiratory data include airflow (usually with an oronasal thermal sensor), respiratory effort (with, for example, diaphragmatic and intercostal EMG) and blood oxygenation (using pulse oximetry) [14]. Respiratory data include airflow (usually with an oronasal thermal sensor), respiratory effort (with, for example, diaphragmatic and intercostal EMG) and blood oxygenation (using pulse oximetry) [14].

In specific cases other signals can be measured like position, snoring, blood pressure, video and audio recording, among others [19].

Mainly due to the issues of cost and inconvenience of laboratory PSG, many home sleep monitoring devices have recently been developed [8]. Home devices allow the overcoming of some of the typical problems of in lab analysis like cost and atypical sleep environment, allowing the recording of multiple nights in a convenient way [8]. These vary form devices capable of measuring one or more EEG, EMG, EOG channels to devices that only measure a small set of channels that do not allow the possibility of preforming sleep scoring [8]. According to the American Academy of Sleep Medicine (AASM) sleep monitoring devices can be divided in the following categories [20, 21]:

- **Type 1**: Overnight PSG preformed in a sleep clinic in the presence of a technician.

- **Type 2**: Overnight PSG at home using comprehensive portable devices.
2.1. Sleep

- **Type 3**: Monitoring devices that can include respiratory signals, ECG and SatO2, as well as, light or body position detection.

- **Type 4**: Monitoring devices that record a maximum of two bioparameters, like SatO2 and airflow.

In this study we are mainly interested in home devices able to measure at least one EEG, EOG and EMG channels. It is important to take into consideration that the devices we have available are ever changing and devices with new characteristics might came up in the near future.

### 2.1.2 Sleep Staging

Even though sleep was thought for a long time to be a homogenous, inactive state, since 1937 we know it to be an active brain process constituted by different phases, particularly Rapid Eye Movement (REM) sleep and Non Rapid Eye Movement (NREM) sleep, very distinct from each other[1, 2]. The AASM Manual for the Scoring of Sleep and Associated Events divides sleep further into 5 main stages: (Wakefulness (W), Stage N1 (NREM 1), Stage N2 (NREM 2), Stage N3 (NREM 3) and Stage R (REM))[14].

Previous sleep scoring classifications divided sleep in 7 states, subdividing stage N3 in Stage 3 and Stage 4 and considering that epochs in which movements of the subject obscure the polygraph record for more than 50% of the time should be classified as movement time[14]. The new classification considers stages 3 and 4 to have very similar characteristics[3, 17] and the combination of this stages (Stage NREM 3) is called deep sleep or slow wave sleep (SWS), as this is considered to be the most restorative sleep stage[3, 22]. The new classification also eliminated the movement stage, classifying those moments as awake, as movements of that duration and magnitude commonly result in a transition to wakefulness.

**Wakefulness**: The awake state (when the subject is relaxed, with the eyes closed) is characterized by Alpha Waves in the EEG signal, by rapid eye blinks (with frequency of 0.5 to 2 Hz) and irregular slow eye movements. The EMG is usually higher than in all the sleep stages[17, 3, 6].

**NREM Sleep**: In general, NREM sleep is characterized by a synchronous EEG signal, low muscle tonus and minimal psychological activity[17, 3, 6]: Stage N1 is characterized by the diminishing of alpha rhythm in the EEG and the appearance of slow wave activity (4 to 7 Hz) and sharp waves, as well as reasonably regular
slow eye movements and relatively lower muscle activity. *Stage N2* is characterized by the observation of K-complexes and spindles (with frequency of 11-16 Hz) in the EEG signal, none or relatively few slow eye movements in the EOG and low muscular activity. *Stage N3*, also known as Deep Sleep or Slow Wave Sleep (SWS) is characterized by slow wave activity in the EEG signal, non-existent eye movement and even lower muscular activity.

*REM Sleep*: REM sleep is characterized by a desynchronized EEG that might show some alpha activity, bursts of irregular, REMs, lowest chin EMG tone conjugated with muscle twitches detected in the chin and tibial derivations of EMG and cardiorespiratory irregularities. Both the EEG and EOG might display information of activity of muscles in the respective regions.[17, 3, 6]

The characteristics of each sleep stage are summarized in Table 2.2[16, 23]

<table>
<thead>
<tr>
<th>Stage</th>
<th>EEG waveform</th>
<th>EOG</th>
<th>EMG</th>
</tr>
</thead>
<tbody>
<tr>
<td>Awake</td>
<td>Beta, Alpha</td>
<td>SEM (0.1 - 0.3 Hz)</td>
<td>Highest</td>
</tr>
<tr>
<td>N1</td>
<td>Alpha, Theta</td>
<td>Absent EM</td>
<td>-</td>
</tr>
<tr>
<td>N2</td>
<td>Alpha, Theta, K complex, Spindle waves</td>
<td>Absent EM</td>
<td>-</td>
</tr>
<tr>
<td>SWS</td>
<td>Delta, Spindle Waves</td>
<td>Absent EM</td>
<td>-</td>
</tr>
<tr>
<td>REM</td>
<td>Pattern similar to N1</td>
<td>REM (0.3 - 0.45 Hz)</td>
<td>Lowest</td>
</tr>
</tbody>
</table>

In most laboratories, the PSG is divided into epochs of 10, 20, 30, or 60 s which are then visually classified into one of the stages by a sleep expert. The resulting time evolutionary description of sleep stages, termed *hypnogram*, is used by physicians for diagnosis purposes[24, 7]. Figure 2.3 is a representation of a typical hypnogram.

![Hypnogram](image)

*Figure 2.3 Representation of sleep stage progression throughout the night (hypnogram), starting from wakefulness and progressing to deeper stages of sleep. (Taken from:[15]).*

However, visual scoring of the PSG is, by no means, a simple task. It requires much
practice and the results are not always consistent[12]. It is important to take into consideration that the classification of sleep into discrete stages is a simplification, used as a way of standardizing sleep analysis. The actual progression from light to deep sleep is a continuous, uniform biological process[7].

Usually sleep starts in NREM Sleep (Stage N1) and progresses to deeper stages of NREM Sleep (N2, N3) and then to REM sleep, before it starts another cycle. A healthy adult is usually awake for only about 5% of the night, spends most of the night in NREM sleep (mostly in stage N2 - 45% to 55% of the sleep) and 20% to 25% in REM sleep[25].

### 2.1.3 Sleep Diseases

According to the International Classification of Sleep Disorders, sleep disorders can be classified into 6 main categories: Insomnia, Sleep Related Breathing Disorders, Central Disorders of Hyper somnolence, Circadian rhythm sleep-wake disorders, Parasomnias and Sleep-related movement disorders[26]

*Insomnia* is the most common sleep complaint and is characterized by the persistent difficulty initiating or maintaining sleep[26, 2].

*Sleep related breathing disorders* can be divided in several categories: obstructive sleep apnea disorders, central sleep apnea disorders, sleep-related hypoventilation disorder and sleep-related hypoxemia disorder[26]. Obstructive sleep apnoea (OSA) is characterized by collapse of the upper airway during sleep that may lead to a fall in the blood oxygen level and results in repetitive brief arousals (up to 100 per hour of sleep) to re-establish upper airway airflow[2]

*Central disorders of hyper somnolence* like narcolepsy are characterized by excessive sleepiness and the inability to stay awake during the day[26].

*Circadian rhythm sleep-wake disorders* (like shift work disorder or jet lag disorder) are associated with alterations of the circadian system and the notion of time[26].

*Parasomnias* are characterized by the occurrence of complex motor or behavioral events or experiences and are divided into NREM-related parasomnias, REM-related parasomnias and other parasomnias[26].

*Sleep-related movement disorders*, including restless leg syndrome (RLS) and Periodic Limb Movements (PLM) are stereotyped movements that occur during sleep or on its onset.
Many other disorders, like depression, schizophrenia and Alzheimer disease manifest themselves through sleep disturbances[1]. It is important to take into account that non-pathological factors like age, prior sleep history, circadian rhythms, temperature, drug ingestion etc., may also have influence on the quality of sleep[25].

2.2 Sound and Sonification

Sonification consists on the auditory representation of a signal[27]. It allows a different representation of data than the usual visual representation and can, sometimes, lead to an easier, more intuitive or more interesting interpretation of the available information as the ear can easily be trained to recognize patterns that would be unrecognizable otherwise[10]. There are three main groups of sonification techniques: Audification, Parameter Mapping and Model Based Audification[10].

Audification is the simplest way of sonification. It consists essentially in converting a specific wave, exactly as it is, to an audible form. That might entail changing the velocity of the signal to fit a frequency range audible for humans. It can only display one-dimensional data[10].

Parameter Mapping Sonification (PMSon) focuses more on the characteristics of the wave, than in its exact physical form. It allows us to display multidimensional data as we associate a certain characteristic we deem relevant to a certain sound[10]. Most auditory graph representations are based on PMSon[28].

Model Based Sonification is a type of sonification technique usually used with non time-indexed data that entails feedback and changes of the acoustic response in time as a function of the interaction with the user[10].

Each sonification technique has its advantages and disadvantages related to the nature of the data we want to analyze and the choice of the sonification technique must always have the nature of the data into account[9]. There are many dimensions of sound to which the data we want to represent can be modulated to, like frequency (that we perceive as pitch), amplitude (that we perceive as loudness), timbre, position or rhythm[27]. Each one has its own advantages and disadvantages. Pitch perception can differ between people, loudness perception lacks the same resolution as pitch and timber is not clearly correlated to any physical stimulus[10]. Its important to choose those characteristics carefully and actually many of those characteristics can be chosen as a way of displaying multidimensional data[29].

In the sonification of any signal it is important to take into account that the frequency range of human hearing is usually 20Hz to 20kHz varying from person to
person (and taking into account that many people have difficulty hearing in both ends of the scale) with frequency resolution of 4Hz and temporal resolution of 20 to 50 ms[10]. Relating to amplitude, even though the thresholds of hearing and pain are respectively 0 dB and 120 dB, the typical thresholds for background noise and confront are usually of about 50 dB and 100 dB and its important to consider that the perception of loudness is frequency dependent[10].

Furthermore, it is considered to be a major challenge in sonification the design of sounds that are not only effective at communication, but aesthetically pleasant, engaging to the listeners and intuitively related to the underlying data in order to sustain the listeners attention and allow comprehension[30].
3. LITERATURE REVIEW

3.1 Computerized methods of sleep analysis

Since 1970 many have been the efforts to develop appropriate computerized methods of sleep analysis like automatic sleep scoring[7, 3, 6], methods of quantification of sleep depth[31, 32] and computer-assisted detection of events like leg movements [33] or sleep apnea[34, 35]. Many of this methods rely on the extraction of features from sleep signals, whether they use a classification algorithm to identify the sleep stage [12] or they leave the interpretation of the features to the user[31, 32]. These features can be divided into time domain features, frequency domain features, time-frequency domain features, nonlinear parameters and complexity parameters[12]. Many of the challenges appointed to these methods are associated with suitable and efficient feature extraction, reliability of classification algorithms, computational times or low generalization[12].

3.2 Sonification of biological signals

Even though visual representation of signals has, in general, always prevailed over auditory representations, the use of tools to listen to the human body actually goes back to the invention of the stethoscope, a device that allows a very inexpensive, noninvasive listening to body functions and that is still used to this day[10]. There is actually much work done in the sonification of biological signals for purposes of neuro-feedback, brain computer interfaces, diagnosis, as well as for purposes of art and entertainment[36, 37, 38, 39]. We briefly point out some examples:

- In some variations of the pulse oximeter a physician is alerted for a drop in the level of oxygen in the patients blood by the change in the pitch of a sound[40, 41].

- Both PMSon and model based sonification, as well as audification, have been explored for EEG sonification. Are examples of this: The extensive work done
3.3. Sonification of sleep recordings

by the Ambient Intelligence group in the University of Bielefeld, including in
the detection of rhythmic patterns characteristic of epileptic pathologies[42,
43, 44, 45]; And the encephalophone, an instrument in which alpha-frequency
power of the EEG signals is converted into a musical scale and controls a syn-
thesized piano, which can be manipulated by the individual in real time.[46];

- ECG sonification is mainly used to represent information of heart rate variabil-
ity (HRV) and have been used mainly for artistic, diagnosis and bio-feedback
purposes[47, 48]

- EMG sonifications are usually obtained through parameter mapping of ex-
thracted features and are mainly used for purposes of biofeedback[49, 50, 51].
Matsubara et al. compared the results of the mapping of EMG extracted fea-
tures to pitch, a combination of loudness and polyphonic timbre and timbre
comparing the comprehensibility of the results for participants with and with-
out musical experience concluding that the second sonification strategy showed
best results for both groups, that preference for the sound does not always
correspond to better comprehensibility and the use of musical instruments in-
stead of synthesized sounds could improve the pleasantness and interest in the
sounds[49].

3.3 Sonification of sleep recordings

There is also work done in the sonification of biological signals in order to study
sleep, even though there is still a lot to be done in this area:

In 2000[52], Ballora et al. proposed the listening of sonified HRV data in order to
diagnose obstructive sleep apnea. Through the auditory display they could represent
multidimensional data obtained by different signal processing operations (like inter
beat intervals, mean of a window of 15 beats, mean of a window of 5 beats and
standard deviation of a window of 300 beats) with the purpose of trying to find
correlations that would not be seen otherwise. This work explored the modulation
in rhythm which seemed to produce interesting results and the user of the developed
program was able to adjust the playback rate and relative volume of the dimensions
to fit his better perception of the data, which was important to make the diagnosis
possible regardless of the variability between patients. Even though the main goal
of this sonification was diagnosis, aesthetics was also a concern (the different tracks
were based in the same pitch mapping as to avoid total cacophony) and the authors
were interested in the artistic possibilities of their implementation.
Another project developed in 2004[53] aimed to do a simple and direct audition of polysomnographic signals. The authors developed a software that allowed signals stored in European Data Format (EDF) files to be easily converted to sound and accelerated by the desired factor in order to reduce the assessment time of the PSG and reach audible frequencies. In their experiments, they listened to EEG, EOG, ECG and respiratory signals of sleep recordings and pointed out that some frequency characteristics of REM sleep, SWS and wakefulness, like alpha waves, spindles and REMs could actually be perceived in the sonified EEG and EOG. In the recordings of apneic patients, they were able to identify the arousal events from the sonified respiratory and ECG signals and even from EEG and EOG. The results of this work were not very pleasing to hear and also not very easy to interpret but the sound were very easy to produce and showed that the listening to polysomnographic signals is useful and worth developing further.

In 2012[54] Tulilaulu et al. presented the concept of Sleep Musicalization in which data retrieved from a commercially available mattress sensor (which detects force, temperature, noise level and brightness in order to calculate respiration, heart rate and movement information and score sleep into stages with use of a classifier) was used to automatically compose music that was aimed to complement visualization of the measurements. The sequence of chords (within a certain scale) and the intervals that form the melody are chosen using stochastic processes and the theme and accompaniment varies according to the sleep stage. The respiratory signal modulates rhythm, while the movement signal is modulated in intensity of the sounds and the cardiac signal modulates tempo. Even though the results obtained in this work are quite pleasant to hear and have a high aesthetic standard, they are aimed to give a sense of the sleep and to complement visual representation and do not seem to have much diagnose purpose on their own.

In the work that we plan to continue[5], developed in 2015, the authors proposed the sonification of the sleep EEG for the purpose of recognizing the presence of REM and SWS thorough the calculation of descriptive features that would characterize those states.

They extracted the following features from the C4 and O2 EEG channels: Relative Power Density from 6 different EEG bands: Delta (0.5-4 Hz), Theta (4-8 Hz), Alpha (8-13 Hz), Sigma(13-16 Hz), Beta (16-30 Hz) and Gamma (30-45 Hz); Vigilance Index (VI); Spectral Asymmetry (SISA); Spectral Edge Frequency (SEF); Median Frequency (MF); Slow Wave Index (SWI); Theta Wave Index (TWI); Alpha Wave Index (AWI); total Short Time Fourier Transform (STFT) power; Band Entropy and Hjorth Parameters(Activity, Mobility and Complexity).
They used the EEG Fp1 channel as a EOG channel and from this channel extracted the following features: Hjorth Parameters (Activity, Mobility and Complexity), lower (0.3-2 Hz) medium (2-4 Hz) and high (6-8 Hz) frequency band of EOG, V1 and band entropy.

*Feature selection* was done through the pairwise comparison of class separability using the Fisher Ratio (FR) and the visual comparison of the features’ plots with the corresponding hypnogram. They concluded that generally a FR above one was required to obtain enough separation.

Two main *sonification methods* were explored in this work:

1. Automatic sleep stage classification and modulation of the related sound’s amplitude to the certainty of belonging to a certain class.

2. Modulation of the related sound’s amplitude according to a function that, combining one or more extracted features, shows discriminative power between the desired class and other classes.

In both cases the resulting sound should be the combination of the three modulated sounds correspondent to the three classes (REM, SWS and Wakefulness). For the second method (without use of the classifier) it was shown that the best combinations of features to represent *SWS, REM sleep* and *Wakefulness* were, respectively, equations 3.1, 3.2 and 3.3:

\[
\frac{SWI(O2) \times \text{Complexity}(O2)}{\text{Mobility}(O2) \times \text{Entropy}(O2)} \quad (3.1)
\]

\[
\frac{TWI(O2)}{\text{Activity}(Fp1)} \quad (3.2)
\]

\[
V1(O2) \quad (3.3)
\]

They stated that the modulation of sinusoidal signals was not pleasant for human hearing and the use of musical instruments made the listening experience more pleasant. In the modulation of the amplitude of musical instruments they used piano sounds to indicate REM sleep, drums to indicate wakefulness and xylophone to indicate SWS. The results were added together in a stereophonic output, according to equations 3.4 and 3.5.

\[
Left_{channel} = \text{drums} \times V1(O2) + \text{piano} \times \frac{TWI(O2)}{\text{Activity}(Fp1)} \quad (3.4)
\]
3.3. Sonification of sleep recordings

\[ \text{Right}_{\text{channel}} = \text{drums} \times V1(O2) + \text{xylophone} \times \frac{\text{SWI}(O2) \times \text{Complexity}(O2)}{\text{Mobility}(O2) \times \text{Entropy}(O2)} \] (3.5)

Some of the future improvements they appointed were:

- The use of a larger set of recordings, in order to test if disturbed sleep can be distinguished from normal sleep with this methods.

- The development of the classifier further (for the first sonification method). If it could be made reliable enough, then they would probably not make use of the human pattern recognition capabilities at all.

- The extraction of REM related features from the EMG and EOG, to better distinguish this stage.

- Experiment with the modulation of different musical instruments and other sounds that could better represent the different classes.

- The arranging of listening test for laymen, determining how well they can distinguish good from poor sleep using sonification.
4. MATERIALS AND METHODS

4.1 Materials

The main resource of this work were the sleep recordings that we analyzed and from which we produced sounds. As there was not enough time and resources to record our own data, we used in our experiments data from available sleep databases. Seventeen full night recordings were selected from both the SIESTA polygraphic database[55] and the CAP Sleep Database of Physionet[56]. All recordings were visually inspected before they were selected and the ones in which we found severe disturbances, were taken from further use. When two night recordings were available for the same patient, we chose the second recording as we considered that this would better represent a normal night of sleep, having less changes due to an atypical sleep environment. For the sonification of sleep stages one EEG channel (O2-M1 or O2-P4 when the first one was not available), one EOG channel (Pos8-M1 or ROC-LOC when the first one was not available) and chin EMG signal were used. For the sonification of breathing difficulties and leg movement the SatO2 and Left Leg EMG signals were used. The ECG signal was extracted and experimented with but not used for the final results. Data from both databases was stored in the EDF, sampling frequency of the signals and further description of the records are presented in Table 4.1.

Hypnograms were available in both databases, obtained through visual scoring by sleep experts, epoch by epoch, in 30 second intervals according to the RK rules [17]. Sleep was divided into seven stages: stage wake (Wake), stage 1 (S1), stage 2 (S2), stage 3 (S3), stage 4 (S4), REM stage and Movemont time (Mov). Table 4.2 shows the number of epochs each subject spent in each stage according to the available hypnograms.

The main tool for the development of this project was the software Matlab®9.1.0 (R2016b). For the sonification, several sounds were experimented with, even though only 4 sound tracks were used to produce the final results. All the used sounds were publicly available in the Freesound website [57].
### Table 4.1 Description of Sleep Records used in the course of the work. The numbers in the sampling frequency vector represent, respectively, the EEG, EOG, Chin EMG, SatO2, Leg EMG and ECG sampling frequencies.

<table>
<thead>
<tr>
<th>Database</th>
<th>Subject</th>
<th>Description</th>
<th>Sampling Frequencies(Hz)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SIESTA</td>
<td>N33</td>
<td>RLS + PLM</td>
<td>[256,256,256,1,256,256]</td>
</tr>
<tr>
<td>SIESTA</td>
<td>N34</td>
<td>PLM</td>
<td>[256,256,256,1,256,256]</td>
</tr>
<tr>
<td>SIESTA</td>
<td>N35</td>
<td>RLS + PLM</td>
<td>[256,256,256,1,256,256]</td>
</tr>
<tr>
<td>SIESTA</td>
<td>C27</td>
<td>Apnea</td>
<td>[200,200,200,1,200,200]</td>
</tr>
<tr>
<td>SIESTA</td>
<td>C28</td>
<td>Apnea</td>
<td>[200,200,200,1,200,200]</td>
</tr>
<tr>
<td>SIESTA</td>
<td>C29</td>
<td>Apnea</td>
<td>[200,200,200,1,200,200]</td>
</tr>
<tr>
<td>SIESTA</td>
<td>B01</td>
<td>Healthy</td>
<td>[200,200,200,1,200,200]</td>
</tr>
<tr>
<td>SIESTA</td>
<td>B04</td>
<td>Healthy</td>
<td>[200,200,200,1,200,200]</td>
</tr>
<tr>
<td>SIESTA</td>
<td>B05</td>
<td>Healthy</td>
<td>[200,200,200,1,200,200]</td>
</tr>
<tr>
<td>SIESTA</td>
<td>B06</td>
<td>Healthy</td>
<td>[200,200,200,1,200,200]</td>
</tr>
<tr>
<td>SIESTA</td>
<td>B07</td>
<td>Healthy</td>
<td>[200,200,200,1,200,200]</td>
</tr>
<tr>
<td>SIESTA</td>
<td>B08</td>
<td>Healthy</td>
<td>[200,200,200,1,200,200]</td>
</tr>
<tr>
<td>SIESTA</td>
<td>C21</td>
<td>PLM + Apnea</td>
<td>[200,200,200,1,200,200]</td>
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<td>Insomnia</td>
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</tr>
<tr>
<td>CAP Sleep Database</td>
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<td>Insomnia</td>
<td>512,128,256,1,256,256</td>
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<td>Narcolepsy</td>
<td>512,128,512,1,256,256</td>
</tr>
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<td>CAP Sleep Database</td>
<td>plm9</td>
<td>PLM</td>
<td>512,128,512,1,256,256</td>
</tr>
</tbody>
</table>

### Table 4.2 Number of 30s epochs of each sleep stage in each recording. Total represents the total number of epochs in the recording. The percentages of wakefulness, REM and SWS (%W, %R, %S) are obtained by dividing the number of epochs classified as the respective stages/stages by total number of epochs.

<table>
<thead>
<tr>
<th>Subject</th>
<th>W</th>
<th>S1</th>
<th>S2</th>
<th>S3</th>
<th>S4</th>
<th>REM</th>
<th>Mov</th>
<th>Total</th>
<th>%W</th>
<th>%R</th>
<th>%S</th>
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<td>83</td>
<td>213</td>
<td>594</td>
<td>39</td>
<td>95</td>
<td>2</td>
<td></td>
<td>1026</td>
<td>8.1</td>
<td>9.3</td>
<td>3.8</td>
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<td>190</td>
<td>157</td>
<td>492</td>
<td>47</td>
<td>2</td>
<td>157</td>
<td>1</td>
<td>1046</td>
<td>18.2</td>
<td>15.0</td>
<td>4.7</td>
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<tr>
<td>N35</td>
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<td>74</td>
<td>428</td>
<td>94</td>
<td>0</td>
<td>207</td>
<td>0</td>
<td>1007</td>
<td>20.3</td>
<td>20.6</td>
<td>9.3</td>
</tr>
<tr>
<td>C27</td>
<td>140</td>
<td>81</td>
<td>601</td>
<td>14</td>
<td>0</td>
<td>136</td>
<td>3</td>
<td>975</td>
<td>14.4</td>
<td>13.9</td>
<td>1.4</td>
</tr>
<tr>
<td>C28</td>
<td>260</td>
<td>65</td>
<td>428</td>
<td>33</td>
<td>0</td>
<td>189</td>
<td>0</td>
<td>975</td>
<td>26.7</td>
<td>19.4</td>
<td>3.4</td>
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<tr>
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<td>119</td>
<td>72</td>
<td>501</td>
<td>97</td>
<td>61</td>
<td>147</td>
<td>0</td>
<td>997</td>
<td>11.9</td>
<td>14.7</td>
<td>15.8</td>
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<tr>
<td>B01</td>
<td>29</td>
<td>72</td>
<td>535</td>
<td>71</td>
<td>66</td>
<td>173</td>
<td>18</td>
<td>964</td>
<td>3.0</td>
<td>17.9</td>
<td>14.2</td>
</tr>
<tr>
<td>B04</td>
<td>120</td>
<td>71</td>
<td>314</td>
<td>90</td>
<td>105</td>
<td>182</td>
<td>3</td>
<td>885</td>
<td>13.6</td>
<td>20.6</td>
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<tr>
<td>B05</td>
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<td>36</td>
<td>531</td>
<td>82</td>
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<td>202</td>
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<tr>
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<td>35</td>
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<td>96</td>
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<td>0</td>
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<td>145</td>
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<td>233</td>
<td>0</td>
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<td>50.0</td>
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<td>229</td>
<td>136</td>
<td>193</td>
<td>67</td>
<td>107</td>
<td>135</td>
<td>0</td>
<td>867</td>
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<td>169</td>
<td>63</td>
<td>25</td>
<td>216</td>
<td>0</td>
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<td>39.9</td>
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<td>10.8</td>
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<td>169</td>
<td>173</td>
<td>266</td>
<td>0</td>
<td>1006</td>
<td>9.5</td>
<td>26.4</td>
<td>34.0</td>
</tr>
</tbody>
</table>
4.2 Methods

This work started with the analysis and familiarization with the software and methods developed by Franco et al. [58] for the sonification of the sleep EEG. We took into consideration the future improvements they appointed in their work and our own objectives and established the following priorities: improvement of the non classification sonification of sleep stages and development of new methods for the sonification of other relevant sleep variables.

Based on these objectives, our methods are divided in 4 main categories: Sleep Stage Sonification, Oxygen Saturation Sonification, Leg Movement Sonification and Heart Rate Variability sonification. Each section comprises the following steps: Data Analysis and Pre-processing, Feature Extraction, Feature Selection, Development of Modulation Functions and Sonification and a brief introduction on why the information is useful in sleep analysis.

In a final section, Listening Tests, we present the methods used to determine whether or not sonification can be used by layman to determine, based only on listening to our sounds, how well the subjects in the available recordings slept.

4.2.1 Sleep Stage Sonification

Sleep scoring is one of the most important methods for the diagnosis and treatment of sleep disorders[59, 24] and, thus, sleep stage representation is the most important part of this work. Many sleep diseases manifest themselves in the alteration of sleep patterns. Examples of this are: Obstructive sleep apnea, in which the amount of stages 3 and REM sleep is commonly reduced; Narcolepsy, in which the time from the first epoch of sleep to the first epoch of REM is commonly decreased and Chronic insomnia, characterized by a long sleep latency, increased awakenings after sleep onset and commonly decreased stages 3 and REM sleep[60].

For the sonification of sleep stages we applied one of the methods developed by Franco et al[58]. From their experiments, we chose the sonification method that does not require the use of a classifier, but rather represents the results of a combination of descriptive features as sound characteristics. We considered that this method could allow faster computational times and avoid some of the disadvantages and difficulties of automatic sleep stage classification. Known difficulties of automatic sleep stage classification include the fact that sleep scoring is artificial and does not capture the intrinsic continuous changes in the signals recorded during sleep[61], associated with the fact that no classifier to this day has the same
reliability as human scoring, and even among human scorers the classification is not always consistent[62]. Furthermore, the development of a reliable enough sleep stage classifier was considered to be a too wide task to be covered in the scope of this work.

In this work we hypothesize that the listener’s pattern recognition capabilities can be used to perform a mental scoring based on the presented features and take general conclusions about sleep quality.

Data Analysis and Pre-processing

The use of pre-processing methods previous to feature extraction has been considered to be useful in removing artifacts from the signals and minimizing their influence in the extracted features[12]. We implemented 100th order finite impulse response (FIR) filters with linear phase using a Hamming window, as these were commonly used in the literature and are more stable than other options[12, 63]. The cutoff frequencies for the various signals were the following:

*EEG Signal*: Bandpass filtered with cutoff frequency of 0.5 Hz in the lower band and 50 Hz in the upper band.

*EOG Signal*: Bandpass filtered with cutoff frequency of 0.1 Hz in the lower band and 10 Hz in the upper band.

*EMG Signal*: High pass filtered with cutoff frequency of 20 Hz and band-stop filter of with cutoff frequency of 45 Hz in the lower band and 55 Hz in the upper band

The cutoff frequencies were chosen taking into account the relevant frequency bands of the respective signals (already discussed in the theoretical introduction of this work). The 50 Hz frequency band was in all the signals removed in order to avoid interference from electrical fields originating in the electrical power supply.

Feature Extraction

Both time and frequency domain features were extracted from the *EEG O2 channel* as in the work of Franco et al. it was concluded that this channel provided better results[58]. All the extracted features were evaluated in intervals of 30 seconds, as this is a commonly used window in sleep scoring.
4.2. Methods

**Frequency domain features:** EEG is traditionally analyzed in the frequency domain, since each sleep stage is characterized by a specific pattern of frequency contents[64]. STFT is one of the most conventional feature extraction methods. While Fourier transform shows the relative power of each frequency of the signal without dependency in specific time, STFT represents the Fourier transform of the local windowed signal and shows frequency response according to time variation. It can, thus, be used to extract features from non-stationary signals like the EEG[65, 66, 58].

We calculated the STFT in 30 seconds epochs using a Hamming window with no overlap, according to Equation 4.1 where \( w/n \) represents the windowing function.

\[
X(m, w) = \sum_{-\infty}^{+\infty} x[n]w[n-m]e^{-jwn}
\]  

(4.1)

STFT calculation was used to extract a wide range of frequency domain features from the EEG signal, including several percentiles of the normalized power spectrum and indexes that traduce relationships between frequency bands that were commonly used in the literature:

- Relative power density from 6 EEG bands (Delta(0.5 to 4 Hz), Theta(4 to 8 Hz), Alpha (8 to 13 Hz), Sigma (13 to 16 Hz), Beta (16 to 30 Hz) and Gamma(30 to 45 Hz))[58].
- SEF: Frequency \( freq \) which the range 0 to \( freq \) contains 95% of the total power of the signal[58]
- MF: Frequency \( freq \) which the range 0 to \( freq \) contains 50% of the total power of the signal[58].
- VI: Fraction of higher frequencies over lower frequencies, calculated according to Equation 4.2[58]

\[
VI = \frac{P_{\text{gamma}} + P_{\text{beta}}}{P_{\text{theta}} + P_{\text{delta}}}
\]

(4.2)

- SISA: Asymmetry of the spectral power from the left side of the Alpha band and the right side of the Alpha band, calculated according to Equation 4.3[58]

\[
VI = \frac{P_{\text{gamma}} + P_{\text{beta}} + P_{\text{sigma}} - P_{\text{theta}} - P_{\text{delta}}}{P_{\text{gamma}} + P_{\text{beta}} + P_{\text{sigma}} + P_{\text{theta}} + P_{\text{delta}}}
\]

(4.3)
4.2. Methods

- SWI, calculated according to Equation 4.4[58].

\[
SWI = \frac{P_{\text{delta}}}{P_{\text{theta}} + P_{\text{alpha}}}
\]  

(4.4)

- TWI, calculated according to Equation 4.5[67].

\[
TWI = \frac{P_{\text{theta}}}{P_{\text{alpha}} + P_{\text{delta}}}
\]  

(4.5)

- AWI, calculated according to Equation 4.6[68].

\[
AWI = \frac{P_{\text{alpha}}}{P_{\text{theta}} + P_{\text{delta}}}
\]  

(4.6)

- Total STFT Power[58].

- Band entropy: Entropy represents how concentrated the STFT power is and is calculated according to Equation 4.7[58]

\[
Entropy = \sum_{i=1}^{N_{\text{bands}}} \text{power}(t) * \log(\text{power}(t))
\]  

(4.7)

- Sum of Delta and Sigma relative power[69].

Time domain features:

- Hjorth Parameters: Activity, Mobility and Complexity, calculated according to Equations 4.8 4.9 4.10[65].

\[
Activity = \text{var}(y(t))
\]  

(4.8)

\[
Mobility = \sqrt{\frac{\text{var}(y'(t))}{\text{var}(y(t))}}
\]  

(4.9)

\[
Complexity = \frac{\text{Mobility}(y'(t))}{\text{Mobility}(y(t))}
\]  

(4.10)

- Standard deviation of the Beta band of the EEG calculated according to Equation 4.11 where X(n) is the current epoch, E[X] is the mean value of the signal and N is the number of samples in the segment, after isolation of the Beta band of the EEG with a FIR filter of order 100[24].
\[ std = \frac{\sum_{i=1}^{N} [X(n) - E[X]]^2}{N - 1} \quad (4.11) \]

- Energy of the Beta band of the EEG calculated according to Equation 4.12 where \( X(n) \) is the current epoch, \( E[X] \) is the mean value of the signal and \( N \) is the number of samples in the segment[23], after isolation of the Beta band with a FIR filter of order 100.

\[ Energy = \frac{\sum_{i=1}^{N} [X(n) - E[X]]^2}{N} \quad (4.12) \]

In order to obtain better performance, specially in the distinction between Wakefulness and REM sleep, we further extracted features from the EMG and EOG signals. According to the work of Estrada et al.[23] the extraction of characteristics from these signals can be used as a switch to better distinguish between REM Sleep, Wakefulness and other sleep stages, as REM sleep and stage S1 have similar EEG characteristics, making them hardly distinguishable from the EEG alone.

From the **EMG channel** we extracted two time domain features: Energy and Standard deviation, according to Equations 4.11 and 4.12. The EMG muscular activity is strongly linked to both this features and, for both, we expect that a high value corresponds to a high muscular activity. It is also expected that this features will have high values for wakefulness and progressively lower values for deeper stages of sleep.

From the **EOG channel** we extracted the relative power density from the 0.3 to 0.45 Hz frequency band, as this is the frequency range of REMs[23]. We expect that this feature will be higher for REM sleep.

**Feature Selection and Modulation Functions**

In a similar way to what was done by Franco et al.[58] our objective was to create functions to represent REM sleep, SWS and Wakefulness, that would have high values in the epochs corresponding to the respective class, and low values in the remaining epochs.

Our main methods for determining the discriminative power of the extracted features were:

1. The **FR**, calculated according to Equation 4.13[65]. This measure provides
4.2. Methods

a good class separability measure because it is maximized with the interclass
difference being maximized and the intraclass spread being minimized\cite{70}.

\[ FR(1, 2) = \frac{|m_1 - m_2|^2}{\sigma_1^2 + \sigma_2^2} \] (4.13)

2. Evaluation of the mean, standard deviation, minimum and maximum values
of the features for each sleep stage, calculated through the collection of the
extracted features into different groups according to the corresponding hypno-
grams.

3. Visual inspection of the time evolution of the extracted features relating it to
the corresponding hypnograms.

Regarding the function that represents SWS:

To represent SWS we used the same combination of features proposed by Franco et
al.\cite{58} (Equation 4.14) as its performance in this work was considered to be very
good. Comparing the two graphical representations of figure 4.1 we can see that
this combination of features has relatively high values for the moments of SWS and
relatively low values for the remaining moments.

\[ \frac{SWI(O2) \times Complexity(O2)}{Mobility(O2) \times Entropy(O2)} \] (4.14)

Regarding the function that represents REM Sleep:

In the previous work\cite{58} the authors reported some difficulty in the separation of
REM sleep from other sleep stages and experimented with the retrieval of EOG
information from the EEG Fp1 channel as an solution to overcome this issue. Re-
garding this, we considered that the convenience of using an extra EEG channel and
an actual EOG channel was similar and thus, used the features extracted from the
actual EOG signal, as these are expected to provide better results.

We developed the combination of features represented in Equation 4.15, taking
into account that the REM representing function should have higher values in the
presence of REMs and lower values in the presence of high EMG activity.

\[ \frac{EOGPower(0.35 - 0.4Hz)}{Energy(chinEMG)} \] (4.15)
Results of the application of this function can be seen in figure 4.2 (blue line), where we notice that it can generally discriminate the moments of REM sleep, despite having some high values in moments of S2 and S3 sleep.

We tried to improve this function using the following method: We considered meanSWS the mean value of the EMG energy for the epochs in which the SWS function is higher than 0.5. Considering that the SWS function is reliable enough, meanSWS represents the overall value of EMG activity for SWS. If we now consider that the overall EMG activity is higher in SWS than in REM sleep (as stated in the previous sections), it makes sense that the REM representing function is set to zero when the EMG energy of a certain epoch is higher than meanSWS. The final function to represent REM sleep would then be calculated as follows:

```java
if (energychinEMG(t)<=meanSWS)
    rem(t)=EOGPowerty(t)/energychinEMG(t);
else
    rem(t)= 0;
```
4.2. Methods

![REM Sleep Modulation Function](image)

![Hypnogram](image)

**Figure 4.2** Normalized REM Modulation Function (blue line, above) normalized EOG Power (green line, above), normalized EMG energy (red line, above) and corresponding hypnogram (below), for recording N34. In the hypnogram representation classes 0, 1, 2, 3, 4, 5 and 6 in the vertical axis represent, respectively, stages W, S1, S2, S3, S4, REM and Movement, according to the RK classification system. In the horizontal axis time is represented in hours.

However, even though this improvement allowed us to have better results for some patients (in particular for healthy patients), the value meanSWS is not very reliable for the recordings with a very reduced amount of SWS and led to the setting of the REM function to zero in moments that corresponded to actual REM sleep. We considered that it would be best to represent the combination of features (equation 4.15), even if at some point its performance is not ideal, rather than wrongly artificially setting it to zero.

*Regarding the function that represents Wakefulness:*

The main difficulty encountered in the representation of Wakefulness was that the function developed in the previous work[58], VI, had usually high values, not only for the moments of wakefulness, but also for stages S1 and S2. Considering that stage S2 is an important stage of sleep, that usually occupies most of the night, we considered that it could, by no means, be represented in the same group as wakefulness, that
is considered alarming if heard for most of the night. Furthermore, as in this work there is no sound that represents S2, it is particularly important that the other stages are not heard during these periods. In an attempt to develop the wakefulness function further we followed the following steps:

In a first stage the FR (calculated between the classes wakefulness and all other stages) was used to evaluate the discriminative power of all the features extracted from the EEG. Figure 4.3 shows the calculated FR for the 21 extracted features. The same ratios were also calculated between the classes wakefulness and Stage S2 as the distinction between these stages is, as discussed before, particularly important. We can see from analyzing figures 4.3 and 4.4 that all the features that seem to have consistent discriminative power among the analyzed recordings are Mobility, VI, SEF and SISA.

Figure 4.3 FR calculated between the classes Wakefulness and Other Stages for the 21 features extracted from the EEG, analyzed for 6 recordings: N34, N35, C27, N34, B01 and C21.

In a second stage the selected features were evaluated by visually comparing their time evolution with the corresponding hypnograms. As none of the extracted features seemed to have distinctively better results than the VI, we worked on combining this feature with the information from the EMG signal in order to increase its
4.2. Methods

![Fisher Ratio W vs S2](image)

**Figure 4.4** FR calculated between the classes Wakefulness and Stage S2 for the 21 features extracted from the EEG, analyzed for 6 recordings: N34, N35, C27, N34, B01 and C21.

performance.

Let’s consider *modeChinEMG* the most common value (mode) of the standard deviation of the chin EMG. Considering (as stated before) that the EMG activity during Wakefulness is higher than during sleep and assuming that the subject is asleep for most of the night, we can consider that, if the EMG activity in a certain moment is lower than *modeChinEMG*, the subject is probably not awake. The function that represents wakefulness can thus be set to zero in those moments. The final function can then be calculated as follows:

\[
\begin{align*}
\text{energychinEMG}(t) &= \text{energychinEMG}(t) - \text{mode}(
\text{energychinEMG}) ; \\
\text{stdchinEMG}(t) &= \text{stdchinEMG}(t) - \text{mode}(
\text{stdchinEMG}) ; \\
\text{if} \ (\text{energychinEMG}(t)<=0 \ \text{or} \ \text{stdchinEMG}(t)<=0) \\
&\quad \text{wakefulness}(t)=0; \\
\text{else} \\
&\quad \text{wakefulness}(t) = (\text{VI}(t) + \text{stdchinEMG}(t))/2;
\end{align*}
\]

We can see in figure 4.5 that while the VI feature (green line) has high values for
some moments of S1 and S2 the new feature (blue line) does not, even if it’s not able to detect some of the brief periods of wakefulness.

Figure 4.5: Graphical representation of the standard deviation of the chin EMG signal after subtraction of the most common value (red line, above), VI (green line, above), wakefulness modulation function (blue line, above) and corresponding hypnogram (below) for recording B07. In the hypnogram representation classes 0, 1, 2, 3, 4, 5 and 6 in the vertical axis represent, respectively, stages W, S1, S2, S3, S4, REM and Movement, according to the RK classification system. In the horizontal axis time is represented in hours.

Sonification

All the previously represented modulation functions were normalized and low pass filtered with a moving average filter of order 30 and with a median filter of order 7, in a similar way to what was done by Franco et al. [58]. This is done to avoid too sudden changes in sound characteristics that would make the sounds unpleasant to hear. The graphical representation of the features was analyzed in order to determine if the important characteristics of the functions were preserved after smoothing.
In a first phase we did some experiments with the production of Musical Instrument Digital Interface (MIDI) files and the modulation of functions to variations in frequency. However, continuous variation in frequency were considered to be extremely unpleasant and the modulation into a scale of notes forced us to discretise the information, which was not our objective. Our objective was to represent the smooth variation of the features throughout the night. Furthermore, variations in frequency seemed to us very difficult to perceive for users with no musical training and "real", not computer produced, sounds seemed to improve the pleasantness of the results. Based on our previous considerations, and taking into account the limited time frame of this project, we concluded that the the simplest approach should be followed and proceeded with the amplitude modulation of pre-existent sounds.

These preliminary experiences were very brief and our evaluation of the sounds was subjective so we do not discard the possibility that some of these sonification methods could be pursued further for better results. In particular, the production of sounds in the MIDI format shows some promise, as this format would allow more control over the characteristics of the produced sounds, as well as more versatility of the results (that could be easily edited and experimented with for aesthetic purposes).

In the next phase, we analyzed the results of the previous work, in which the amplitude of pre-existent piano, xylophone and drums sounds was modulated according to the calculated functions. We found that in this approach we would need to be very careful about which sounds we would join together, as when the tracks of the different instruments do not agree with each other, the results are extremely unpleasant. Furthermore, the chosen sound tracks should have as constant amplitude as possible, in order to not compromise the understanding of the variations.

In order to fulfill these requirements, we listened to and experimented with a wide range of freely available sound tracks and chose the ones that allowed us to obtain better results. Our goal was to modulate the characteristics to sounds that intuitively resembled the desired interpretation. As both REM and SWS are considered to be restorative stages of sleep, we modulated both this functions to piano sounds, using the stereo to distinguish between them. The progression between SWS and REM sleep will thus be heard as the progression of piano sounds from right to left side, and this was considered to give a good feeling of the progression of sleep. For the same reasons, wakefulness was modulated to the amplitude of drumming sounds. All the produced sounds had a duration of 1 minute, as in the work of Franco.

The input sounds were edited in order to fulfill the 1 minute duration requirement.
The sounds were modulated by interpolating the normalized modulation function over the duration of the sounds and multiplying its values, element by element, by the sound vector. The results corresponding to REM sleep and wakefulness are added to compose the left channel and the vector corresponding to SWS composes the right channel of the output sound. Both input and output sounds have sampling frequencies of 44100 Hz.
4.2.2 Oxygen Saturation Sonification

In order to obtain information about sleep related breathing disorders and be able to display more parameters that enable the users to better distinguish between healthy and unhealthy sleep we took into consideration the information of the SatO2 signal. This signal can be measured in a non invasive, convenient way using a pulse oximeter\cite{71}.

A very common sleep related breathing disorder is sleep apnea. Sleep apnea is characterized by periods of interrupted breathing (apnea) and periods of reduced breathing (hypoapnea). Obstructive sleep apnea, the most common form of sleep apnea, is caused by the partial or complete constriction of the patients upper airway leading to hypoxemia, asphyxia and awakenings\cite{71}. Cooper et al. \cite{72} showed that oximetry alone allowed recognition of a moderate or severe sleep apnea syndrome, in a study where experienced observers classified the recordings based on the pattern recognition of repetitive dips in SatO2 of more than 5%.

Normal SatO2 levels for adult patients are typically between 96% and 100%, even though it can have lower values for short periods of time\cite{73, 74}. According to the AASM Manual hypopnea should be scored when there is a desaturation $\geq$ 4% from pre-event baseline\cite{14}. Furthermore, the drop in the SatO2 commonly follows apnea termination by approximately 6 to 8 seconds due to circulation time and instrumental delay (as the oximeter averages over several cycles before producing a reading)\cite{60}.

Data Analysis and Processing

In this phase, our objective was to extract the information of blood oxygenation from the SatO2 signal, separating the moments where the signal is broken due to the displacement of the probe, movement and other artifacts. Visual inspection of a set of recordings showed that the signal has usually several artifacts, recording values of saturation as unreliable as 1% and 251% as represented in figure 4.6. In order to remove this samples, we processed the signal in such a way that the non credible values (values below 70% surrounded by normal values, values near 0% or of more than 100%) are replaced for the value 100% as a way of signalizing that these should be ignored for sonification purposes. In a second stage a median filter of length 3 seconds is applied. Results are presented in figure 4.6.
4.2. Methods

![Saturation O2 - Raw Signal](image)

**Figure 4.6** Saturation of O2 signal for recording C25 (diagnosed with apnea) before processing (above) and after processing (below).

**Feature Extraction and Selection**

The SatO2 signal is evaluated in windows of 149 seconds (approximately 2.4 minutes) in order to be possible to represent the results of whole night recordings into short time sounds. After experimenting with both the extraction of the mean value and minimum value of each windows, we concluded that the second option showed the best results, as our objective is to detect drops in the saturation values.

**Modulation Function**

From analysis and interpretation of the literature[75, 73, 74] we considered that the range of saturation values considered to be healthy should be of about 95% to 100%. Values between 70% and 95% percent should be assassinated in the sounds produced as potentially unhealthy[75] We shall, thus, produce a function that has a high value for saturation value of 70% and values of 0 for saturation values above 95%. After experimenting with various functions, we concluded that better performance was achieved for those that had a less step inclination in the 90% to 95% (less severe saturation drops) and a steeper inclination in the 70% to 90% area. Considering
4.2. Methods

This, a polynomial function of 3th degree (described in Equation 4.16 and figure 4.7) was used to make a correspondence between the extracted feature and the modulation function.

\[
\begin{cases}
0.000025l^3 - 0.005625l^2 + 0.38875l - 7.6 & \text{if } \text{lowest} \leq \text{threshold} \\
0 & \text{otherwise.}
\end{cases}
\] (4.16)

The resulting modulation functions are represented in figure 4.8 and 4.9 respectively for a patient with apnea and a healthy patient. We can see that the function behaves as expected, having frequent high values for the unhealthy recording and values of zero for most of the healthy recording.

**Sonification**

In a similar way to what was described for the sonification of sleep stages, the choice of the sound that represents breathing difficulties tried to be as intuitively related to the represented variable as possible. In this case we used a recording of gasping sounds that is sounded, like an alarm, every time the SatO2 is below the acceptable value. The amplitude of the sound is modulate by the severity of the desaturation, given by the modulation function that we discussed previously. The methods to modulate the sounds were in all similar to what was described for the sonification of sleep stages. The resulting sound vector is added to the information already displayed in the left channel of the output sounds.
4.2. Methods

Figure 4.8 Saturation of O2 signal for recording C25, diagnosed with apnea (above) and the calculated modulation function (below).

Figure 4.9 Saturation of O2 signal for recording B07, Healthy (above) and the calculated modulation function (below).
4.2. Methods

4.2.3 Leg Movement Sonification

An important parameter in the detection of Leg Movements (LMs) and diagnosis of sleep-related movement disorders is the left leg EMG signal[60]. In this section we explore the sonification of information of this signal aiming to quantify limb movements and represent motor symptoms.

According to the AASM manual[14] a LM is defined as an increase in the EMG signal of at least 8 μV above the amplitude exhibited during bio calibration that lasts between 0.5 and 10 seconds. Periodic LMs (PLMs) should be differentiated from the bursts of spike-like phasic activity that occur during REM sleep and to be considered a PLM, the movement must occur in a group of four or more movements, each separated by 5 to 90 seconds[60].

LMs that occur during wakefulness or associated with the termination of respiratory events are usually either not counted or tabulated separately. Frequent LMs during wake, especially at sleep onset, may suggest the presence of restless legs syndrome (RLS)[60]. RLS is characterized primarily by a vague and difficult-to-describe unpleasant sensation in the legs. This discomfort appears primarily during periods of inactivity, particularly during the transition from wake to sleep in the evening. [2]

Although Periodic Leg Movements in Sleep (PLMS) are found more frequently in RLS, they often occur in other pathological conditions such as sleep apnea, narcolepsy and REM sleep behavior disorder and may even occur without any other definite sleep pathology, resulting in a separate clinical entity called periodic leg movements in sleep syndrome [76, 77]. The occurrence of PLMS in patients with otherwise not explained insomnia or hypersonnia is classified as periodic limb movement disorder (PLMD)[77]. PLM may occur also during wakefulness and it was found that these have more specificity and sensitivity in the diagnosis of RLS than PLMS[77].

The automatic or computer assisted methods of leg movement detection found in the literature [78, 79, 76] usually use thresholds to detect the starting and ending point of each movement and determine its duration and spacing. In the mentioned studies, different threshold values were experimented with and Periodic Leg Movements during Wakefulness were not represented.

Our objectives in this section are not to automatic detect leg movements but rather represent muscular activity and leave the interpretation of the information to the user.
4.2. Methods

Data Analysis and Processing

The signal was pre processed as described in the previous sections for the other EMG signals.

Feature Extraction and Selection

We extracted the following time domain features from the Left Leg EMG signal: Hjorth Parameters (Activity, Mobility and Complexity), Energy and Standard Deviation in 0.5 second windows. We chose this window as this is, as stated before, the shortest possible duration of a leg movement.

The features were selected by visual inspection of their time evolution, evaluating which ones allowed better distinction between the peaks of EMG activity and the background activity. We also tried to visually evaluate which ones were more obviously distinct between healthy patients and patients with movement disorders.

Figures 4.10 and 4.11 are examples of the analyzed graphs and show that standard deviation seems to have the best results. Thus, the selected feature was the standard deviation.

The selected feature had a constant low amplitude background (as can be seen in the second graph of figure 4.12) corresponding to the background activity of the EMG signal. In order to remove this information we subtracted in each point the double of the most common value of all the samples, 2*mode. We assume that for the majority of recorded time the subject was not moving the leg and thus, the most common value corresponds to resting activity. The subtraction of 2*mode showed best results than the mode as can be seen in figure 4.12.

Modulation Function

The development of an appropriate modulation function to characterize leg movement had, from the beginning, some difficulties related with the duration of this movements. In a first stage, our objective was to represent into sounds the information of the previously described feature, but the duration of leg movements (0.5 - 10 seconds) made it impossible to represent the information in short (approximately 1 minute) sounds as 10 seconds in a recording of approximately 8 hours corresponds to a 0.002 second sound, which is barely hearable. In order to make the sounds more
4.2. Methods

Figure 4.10 Left Leg EMG Signal for recording N34 (diagnosed with PLM) and corresponding extracted features: Standard Deviation, Energy and Hjorth Parameters (Activity, Mobility, Complexity).
4.2. Methods

![EMG Signal](image)

**Figure 4.11** Left Leg EMG Signal for recording B06 (Healthy) and corresponding extracted features: Standard Deviation, Energy and Hjorth Parameters (Activity, Mobility, Complexity).
perceptible, various solutions were pursued. The first attempts involved the smoothing of these features with a moving average filter. This made the representation lose time resolution and led to the loss of almost all useful information.

Experiments were also done with the use of activation functions that would have their maximum value for each peak of EMG activity and have a progressive decrease until the next peak was found. Both Quadratic and Gaussian functions were experimented with and their outputs for one activity peak are represented in figure 4.13. The results of this experiments were often unpleasant to hear as the variation of the characteristics of the sounds were too sudden. Furthermore it was very hard to distinguish healthy recordings and recordings of patients with moving disorders using these methods. This path was not pursued further.

Lastly, we noticed that what actually distinguishes our selected feature in healthy and unhealthy recordings is the fact that in the second case we see a large amount of low amplitude spikes closely spaced together (compare Standard Deviation representations in figures 4.10 and 4.11). Considering this, we calculated the following binary response function:
4.2. Methods

Figure 4.13 From top to bottom, extracted feature, quadratic response and gaussian response features for a small section of an EMG signal.

\[
\text{BinaryResponse} = \begin{cases} 
1 & \text{if } \text{std-2*mode} \geq 0 \\ 
0 & \text{otherwise.} 
\end{cases} 
\]  \hspace{1cm} (4.17)

As the relevant information to be displayed is the time distribution of the moments of EMG activity, we calculated the mean of this binary function in windows of 100 seconds. The length of this window is related to what was previously described about PLMs: if we consider that the maximum length of a LM is 10 seconds and the maximum separation between LMs in PLM is 90 seconds, we can consider that in periods of PLM there will always be at least one moment of EMG activity in a 100 second window. The resulting modulation functions were low pass filtered with a moving average filter of order 30 and a median filter of order 5, as a way of removing the spiky behavior that would produce unpleasant sonification results. Results of these calculation can be seen in figures 4.14 and 4.15.
4.2. Methods

![EMG Left Signal](image1)

**Figure 4.14** From top to bottom, raw EMG signal, extracted feature, binary response and final modulation function for recording N34 (of a patient diagnosed with PLM). In the bottom representation the blue and red lines represent, respectively, the calculated modulation function before and after filtering.
Figure 4.15 From top to bottom, raw EMG signal, extracted feature, binary response and calculated modulation function for recording B07 (of a healthy subject). In the bottom representation the blue and red lines represent, respectively, the calculated modulation function before and after filtering.
It is important to notice that this resulting modulation function has certainly high values for the moments of PLM but also for moments of other type of movements, as the restrictions in spacing and number of movements for a sequence to be classified as PLM are not taken into account.

Sonification

In a first phase, experiments were made with the audification of the EMG signal but this hypothesis was quickly discarded after the hearing of the first results as the sounds were unpleasing, disturbed severely the simultaneous hearing of other sounds and the fact that the typical frequencies of the EMG are in the same range as humans hearing frequencies and the attempts done of condensation the results into one to two minute sounds generated almost unhearable outputs. In a similar way to what was done in the previous sections we tried to find a sound that intuitively resembled leg movements, modulated its amplitude with the method previously described and added this information to the right channel of the output sound.

4.2.4 ECG Sonification

We considered the sonification of the ECG signal as this signal was proved in other studies to be valuable for extracting sleep related information[80, 81, 82]. Sleep related diseases, in particular obstructive sleep apnea, can manifest themselves through the alteration of ECG characteristics. Obstructive sleep apnea is characterized by a cyclic variation of heart rate (progressive decrease of heart rate, followed by abrupt increase of heart rate, until normal breathing is restored)[82].

Data Analysis and Pre-processing

The ECG signal was filtered with a 100th order FIR bandpass filter with cutoff frequencies of 0.1 and 3 Hz, applying the same methods that were described in previous sections.

Feature Extraction

We extracted the heart rate information from the ECG signal using the following methods: The Pan Tompkins algorithm[83] was used to calculate the location of
all R waves in windows of 2 minutes. The calculated heart rate corresponds to the
number of R waves for unit of time, and was averaged in windows of 2 minutes.
For the implementation of the Pan Tompkins algorithm we used a Matlab script
developed by Hooman Sedghamiz at Linkoping university available in the Math-
Works file exchange page[84]. In the preliminary visual inspection of the extracted
feature we did not seem to find any prominent characteristic that would distinguish
between healthy and unhealthy records. Our research on heart rate characteristics
of healthy and unhealthy patients was not extensive due to the problems faced in
the sonification of the first extracted features, that led us to abandon this path of
work.

Sonification

We aimed to represent the heart rate variability information by modulating the
rhythm of a sound that resembles the heart beat. Preliminary experiences with this
showed that variations in rhythm are much harder to perceive than variations in
amplitude. Furthermore, the incrementation of the number of different sounds in
each recording seemed to decrease the concentration in each characteristic, making
the results more tiring and difficult to interpret. We concluded that this path did
not add much to what was already done in previous works and would not allow us
to obtain acceptable results in a reasonable amount of time, so we decided to not
pursue ECG sonification further.

4.2.5 Listening Experiments

Listening experiments were conducted to determine the efficacy of our sonification
methods. Twelve students and staff from Tampere University of Technology suc-
cessfully completed the listening tests. Their ages ranged from 20 to 37 years old
(mean 27,25). Five reported having considerable musical education or experience
preforming with musical instruments and seven reported having few or no experi-
ence.

The setup of the experiments (represented in figure 4.16) was composed by a
Lenovo G50 laptop computer and a wireless mouse. The participants heard the
sounds through Audio-technica ATH-M50x headphones.

A short training session was carried out in which the participants were instructed
about the meaning of the different sounds and given some basic notions about
healthy and unhealthy sleep. In the following stage the participants are presented
with four example sounds and its interpretation. The example sounds were obtained from recordings B01 (Healthy), C21 (Apnea and PLM), C27 (Apnea) and narco5 (Narcolepsy). The training session presentation is shown in Appendix A.

After the hearing of the examples the participants were asked to listen and classify four sounds and fill in a questionnaire for each sound. The description of the sounds can be seen in Table 4.3. They took a two to three minute pause and after this time were asked to listen and classify two more sounds (that were a repetition of two of the previous ones). Participants one to six repeated the listening of sounds one and four and participants seven to twelve repeated sounds two and three. Listeners did not know that the last sounds were repetitions of the first ones. One questionnaire was filled after the hearing of each sound and a final questionnaire was filled in the end of the session. Blank questionnaires are shown in Appendix B.

Table 4.3 Description of the four sounds presented to the listeners for classification.

<table>
<thead>
<tr>
<th>Sound</th>
<th>Recording</th>
<th>Classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sound 1</td>
<td>C29</td>
<td>Apnea</td>
</tr>
<tr>
<td>Sound 2</td>
<td>B04</td>
<td>Healthy</td>
</tr>
<tr>
<td>Sound 3</td>
<td>N33</td>
<td>PLM</td>
</tr>
<tr>
<td>Sound 4</td>
<td>ins2</td>
<td>Insomnia</td>
</tr>
</tbody>
</table>

The first three questions of the sound questionnaires were related to the sonification of sleep stages. The fourth and fifth questions were related, respectively, to the sonification of respiratory difficulty and leg movement.
5. RESULTS

5.1 Developed Program

One of the results of this work was the development of the program developed by Franco et al. further. The final program (schematically described in figure 5.1) is organized in three main case processes that can be run separately:

1. Database Parser: In this function the data stored in an .edf or .txt file is parsed, the useful channels are extracted, filtered and stored in a data file Signals_name.mat that can be more easily manipulated.

2. Feature Calculation: The file produced by the last function is loaded, relevant features are extracted from the respective signals and saved to the files: FeaturesEEG_name.mat, FeaturesEOG_name.mat, FeaturesChinEMG_name.mat, FeaturesSatO2_name.mat and FeaturesLeftEMG_name.mat.

3. Modulation Functions: The modulation function for the sonification of sleep stages, leg movement and breathing are calculated and sent, as variables, to the following function.

Sonification: The received data is used to modulate sound characteristics and produce the output sounds in the .wav format.

Figure 5.1 Simplified fluxogram of the developed program.
5.2 Realized Experiments

The program was run and sounds were produced for a set of 17 recordings: six normal recordings, five in which PLMs can be observed, four displaying breathing difficulties and three recordings with a clear lack of deep sleep.

Sleep Stage Sonification

After the separation of the values of the resulting modulation functions into classes according to the information of the available hypnograms, we calculated various statistical measures, trying to evaluate its tendencies for each stage. In Tables 5.1, 5.2 and 5.3 we represent the mean value of the three modulation functions for each sleep stage, for the analyzed recordings. Recordings ins3 and pbm9 are not shown, as we did not have the information of the whole night hypnograms. Box Plot representations showing the behavior of each feature for each recording were also produced. In figure 5.2 we show this representation for recording ins2. In this representation the central red mark represents the median, the bottom and top edges of the boxes represent the 25th and 75th percentiles. The whiskers extend to the most extreme data points not considered outliers, and the outliers are plotted individually using the ‘+’ symbol.

![Box Plot representation of the values of the REM, SWS and Wakefulness modulation functions for each sleep stage, for recording ins2.](image)

1No epochs were classified as S4 in the available hypnogram.
### Table 5.1 Mean values of REM Modulation Function for each sleep stage.

<table>
<thead>
<tr>
<th>Subject</th>
<th>B01</th>
<th>B04</th>
<th>B05</th>
<th>B06</th>
<th>B07</th>
<th>B08</th>
<th>N35</th>
<th>N34</th>
<th>N33</th>
<th>C29</th>
<th>C28</th>
<th>C27</th>
<th>C21</th>
<th>ins2</th>
<th>narco5</th>
</tr>
</thead>
<tbody>
<tr>
<td>W</td>
<td>0.059</td>
<td>0.084</td>
<td>0.004</td>
<td>0.007</td>
<td>0.046</td>
<td>0.004</td>
<td>0.018</td>
<td>0.007</td>
<td>0.059</td>
<td>0.048</td>
<td>0.041</td>
<td>0.057</td>
<td>0.051</td>
<td>0.045</td>
<td>0.058</td>
</tr>
<tr>
<td>S1</td>
<td>0.235</td>
<td>0.197</td>
<td>0.089</td>
<td>0.042</td>
<td>0.078</td>
<td>0.096</td>
<td>0.051</td>
<td>0.021</td>
<td>0.045</td>
<td>0.088</td>
<td>0.058</td>
<td>0.114</td>
<td>0.092</td>
<td>0.086</td>
<td>0.076</td>
</tr>
<tr>
<td>S2</td>
<td>0.135</td>
<td>0.092</td>
<td>0.116</td>
<td>0.125</td>
<td>0.117</td>
<td>0.212</td>
<td>0.084</td>
<td>0.037</td>
<td>0.100</td>
<td>0.073</td>
<td>0.034</td>
<td>0.070</td>
<td>0.062</td>
<td>0.138</td>
<td>0.061</td>
</tr>
<tr>
<td>S3</td>
<td>0.092</td>
<td>0.161</td>
<td>0.342</td>
<td>0.254</td>
<td>0.193</td>
<td>0.178</td>
<td>0.122</td>
<td>0.147</td>
<td>0.201</td>
<td>0.075</td>
<td>0.037</td>
<td>0.132</td>
<td>0.122</td>
<td>0.273</td>
<td>0.031</td>
</tr>
<tr>
<td>S4</td>
<td>0.039</td>
<td>0.237</td>
<td>0.399</td>
<td>0.248</td>
<td>0.097</td>
<td>0.151</td>
<td>0.076</td>
<td>0.062</td>
<td>0.132</td>
<td>0.122</td>
<td>0.273</td>
<td>0.031</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>REM</td>
<td>0.501</td>
<td>0.424</td>
<td>0.488</td>
<td>0.400</td>
<td>0.165</td>
<td>0.374</td>
<td>0.393</td>
<td>0.250</td>
<td>0.332</td>
<td>0.380</td>
<td>0.286</td>
<td>0.482</td>
<td>0.273</td>
<td>0.510</td>
<td>0.300</td>
</tr>
</tbody>
</table>

### Table 5.2 Mean values of SWS Modulation Function for each sleep stage.

<table>
<thead>
<tr>
<th>Subject</th>
<th>B01</th>
<th>B04</th>
<th>B05</th>
<th>B06</th>
<th>B07</th>
<th>B08</th>
<th>N35</th>
<th>N34</th>
<th>N33</th>
<th>C29</th>
<th>C28</th>
<th>C27</th>
<th>C21</th>
<th>ins2</th>
<th>narco5</th>
</tr>
</thead>
<tbody>
<tr>
<td>W</td>
<td>0.017</td>
<td>0.013</td>
<td>0.038</td>
<td>0.031</td>
<td>0.010</td>
<td>0.019</td>
<td>0.081</td>
<td>0.052</td>
<td>0.068</td>
<td>0.025</td>
<td>0.055</td>
<td>0.062</td>
<td>0.108</td>
<td>0.053</td>
<td>0.179</td>
</tr>
<tr>
<td>S1</td>
<td>0.035</td>
<td>0.054</td>
<td>0.110</td>
<td>0.049</td>
<td>0.018</td>
<td>0.037</td>
<td>0.085</td>
<td>0.068</td>
<td>0.083</td>
<td>0.033</td>
<td>0.095</td>
<td>0.081</td>
<td>0.197</td>
<td>0.034</td>
<td>0.133</td>
</tr>
<tr>
<td>S2</td>
<td>0.067</td>
<td>0.080</td>
<td>0.140</td>
<td>0.134</td>
<td>0.037</td>
<td>0.125</td>
<td>0.201</td>
<td>0.210</td>
<td>0.174</td>
<td>0.081</td>
<td>0.165</td>
<td>0.255</td>
<td>0.091</td>
<td>0.057</td>
<td>0.141</td>
</tr>
<tr>
<td>S3</td>
<td>0.404</td>
<td>0.373</td>
<td>0.496</td>
<td>0.664</td>
<td>0.200</td>
<td>0.477</td>
<td>0.579</td>
<td>0.687</td>
<td>0.779</td>
<td>0.504</td>
<td>0.705</td>
<td>0.758</td>
<td>0.276</td>
<td>0.242</td>
<td>0.242</td>
</tr>
<tr>
<td>S4</td>
<td>0.710</td>
<td>0.598</td>
<td>0.731</td>
<td>0.447</td>
<td>0.647</td>
<td>0.808</td>
<td>1.000</td>
<td>0.802</td>
<td>1.000</td>
<td>0.802</td>
<td>1.000</td>
<td>0.802</td>
<td>1.000</td>
<td>0.802</td>
<td>1.000</td>
</tr>
<tr>
<td>REM</td>
<td>0.029</td>
<td>0.039</td>
<td>0.127</td>
<td>0.071</td>
<td>0.016</td>
<td>0.033</td>
<td>0.096</td>
<td>0.061</td>
<td>0.112</td>
<td>0.056</td>
<td>0.058</td>
<td>0.065</td>
<td>0.018</td>
<td>0.026</td>
<td>0.068</td>
</tr>
</tbody>
</table>

### Table 5.3 Mean values of Awake Modulation Function for each sleep stage.

<table>
<thead>
<tr>
<th>Subject</th>
<th>B01</th>
<th>B04</th>
<th>B05</th>
<th>B06</th>
<th>B07</th>
<th>B08</th>
<th>N35</th>
<th>N34</th>
<th>N33</th>
<th>C29</th>
<th>C28</th>
<th>C27</th>
<th>C21</th>
<th>ins2</th>
<th>narco5</th>
</tr>
</thead>
<tbody>
<tr>
<td>W</td>
<td>0.551</td>
<td>0.263</td>
<td>0.399</td>
<td>0.399</td>
<td>0.382</td>
<td>0.197</td>
<td>0.382</td>
<td>0.542</td>
<td>0.337</td>
<td>0.468</td>
<td>0.356</td>
<td>0.400</td>
<td>0.466</td>
<td>0.287</td>
<td>0.293</td>
</tr>
<tr>
<td>S1</td>
<td>0.129</td>
<td>0.070</td>
<td>0.305</td>
<td>0.257</td>
<td>0.022</td>
<td>0.223</td>
<td>0.267</td>
<td>0.176</td>
<td>0.340</td>
<td>0.136</td>
<td>0.104</td>
<td>0.069</td>
<td>0.085</td>
<td>0.000</td>
<td>0.016</td>
</tr>
<tr>
<td>S2</td>
<td>0.070</td>
<td>0.052</td>
<td>0.074</td>
<td>0.032</td>
<td>0.009</td>
<td>0.005</td>
<td>0.065</td>
<td>0.066</td>
<td>0.100</td>
<td>0.088</td>
<td>0.069</td>
<td>0.018</td>
<td>0.025</td>
<td>0.002</td>
<td>0.001</td>
</tr>
<tr>
<td>S3</td>
<td>0.088</td>
<td>0.033</td>
<td>0.040</td>
<td>0.007</td>
<td>0.009</td>
<td>0.002</td>
<td>0.029</td>
<td>0.022</td>
<td>0.001</td>
<td>0.063</td>
<td>0.027</td>
<td>0.000</td>
<td>0.008</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>S4</td>
<td>0.100</td>
<td>0.035</td>
<td>0.027</td>
<td>0.006</td>
<td>0.007</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>REM</td>
<td>0.009</td>
<td>0.000</td>
<td>0.003</td>
<td>0.009</td>
<td>0.000</td>
<td>0.000</td>
<td>0.004</td>
<td>0.009</td>
<td>0.057</td>
<td>0.004</td>
<td>0.000</td>
<td>0.002</td>
<td>0.002</td>
<td>0.000</td>
<td>0.002</td>
</tr>
</tbody>
</table>
Produced Sounds: The following representations were obtained by splitting the output sounds. It is important to notice that the actual sounds are a combination of all the represented information.

**Figure 5.3** Graphical representation of the amplitude of the three components of the resulting sound for the sonification of sleep stages, corresponding to recording B04. In the hypnogram representation classes 0, 1, 2, 3, 4, 5 and 6 in the vertical axis represent, respectively, stages W, S1, S2, S3, S4, REM and Movement, according to the RK classification system. In the horizontal axis time is represented in hours. Piano left, piano right and drums represent, respectively, REM sleep, SWS and wakefulness.
Figure 5.4 Graphical representation of the amplitude of the three components of the resulting sound for the sonification of sleep stages, corresponding to recording ins2. In the hypnogram representation classes 0, 1, 2, 3, 4, 5 and 6 in the vertical axis represent, respectively, stages W, S1, S2, S3, S4, REM and Movement, according to the RK classification system. In the horizontal axis time is represented in hours. Piano left, piano right and drums represent, respectively, REM sleep, SWS and wakefulness.

Comparing figures 5.3 and 5.4 we can see that the amplitude of both right side and left side piano sounds are higher for the recording of the healthy patient. The
amplitude of the sound that represents wakefulness (drums) is clearly higher for the patient with insomnia, specially in the beginning of the recording.

**Oxygen Saturation Sonification**

Comparing figures 5.6 and 5.6, we can see that the gasping sound has frequent high amplitudes in the recording of the patient with apnea, and amplitudes close to zero for the recording of the healthy patient.

![Gasping Sound](image)

**Figure 5.5** Graphical representation of the amplitude of the oxygen saturation alarm sound, corresponding to recording C21 (diagnosed with apnea and PLM).

![Gasping Sound](image)

**Figure 5.6** Graphical representation of the amplitude of the oxygen saturation alarm sound, corresponding to recording B01 (healthy).
Leg Movement Sonification

Comparing figures 5.7 and 5.8, we can see that, even though there are movement sounds produced in the recording of the healthy subject, these have clearly a higher amplitude and they are more frequent in the recording of the patient with PLM.

**Figure 5.7** Graphical representation of the amplitude of the leg movement alarm sound, corresponding to recording C21 (diagnosed with apnea PLM).

**Figure 5.8** Graphical representation of the amplitude of the leg movement alarm sound, corresponding to recording B01 (healthy).
5.3 Listening Experiments

5.3.1 Questions relating to the sonification of sleep stages

The listeners were asked to classify, respectively, the overall amount of *REM* and *Deep Sleep* in each recording, in a scale of 1 (very few) to 5 (very frequent) and the amount of *wakefulness* in scale of 1 (long periods) to 4 (mostly for short, cyclic periods). The number of classifications for each class are presented in figures 5.9 5.10 and 5.11.

![Figure 5.9](image1.png) *Figure 5.9* Representation of the number of answers of the twelve participants to Question 1, regarding the amount of REM sleep in the recording, for each sound. In the vertical axis we represent the number of participants and in the horizontal axis the possible answers to the question. NR indicates that the listener gave no answer to the question.

![Figure 5.10](image2.png) *Figure 5.10* Representation of the number of answers of the twelve participants to Question 2, regarding the amount of SWS in the recording, for each sound. In the vertical axis we represent the number of participants and in the horizontal axis the possible answers to the question. NR indicates that the listener gave no answer to the question.
Most listeners considered sound 2, corresponding to the healthy recording, to have enough REM and deep sleep and a healthy distribution of wakefulness. The sounds corresponding to unhealthy recordings (1,3 and 4) were generally classified to have less amount of REM and deep sleep. Most participants considered that sound 4, corresponding to the recording of insomnia, had quite long periods of wakefulness.

In order to evaluate the level of agreement of the listeners with their own answers and the direction in which they change their classifications, we calculated the difference between the classification given in the second and first time they listened to the sounds. This variable will have, for example, a value of 3 if they changed their answers from 1 to 4, or -1 if they change their answer from 4 to 3.

In figures 5.12, 5.13 and 5.14 we represent the histograms of this variable for each sound. In this representation, it is possible to see that the agreement of the listeners with their own answers is generally high. Their answers do not usually change more than one class. Furthermore, it seems that the level of certainty of their answers is higher for sound 2 (healthy recording) than for other sounds, as most listeners did not change their answers.
5.3. **Listening Experiments**

![Histograms](image)

**Figure 5.12** Representation of the agreement between the first and second answers of each participant to Question 1 (regarding the amount of REM sleep). In the vertical axis we represent the number of participants and in the horizontal axis the difference between the second and first answers. NR indicates that the listener gave no answer one or both times he was asked the question.

![Histograms](image)

**Figure 5.13** Representation of the agreement between the first and second answers of each participant to Question 2 (regarding the amount of SWS). In the vertical axis we represent the number of participants and in the horizontal axis the difference between the second and first answers. NR indicates that the listener gave no answer one or both times he was asked the question.
5.3. Listening Experiments

Figure 5.14 Representation of the agreement between the first and second answer of each participant to Question 3 (regarding the amount of wakefulness). In the vertical axis we represent the number of participants and in the horizontal axis the difference between the second and first answers. NR indicates that the listener gave no answer one or both times he was asked the question.

5.3.2 Question relating to the sonification of breathing difficulty

In Question 4 the listeners were asked to classify the subjects breathing in the heard recording in a scale of 1 (very frequent breathing difficulty) to 4 (no breathing difficulties). In figure 5.15 we represent the number of answers for each class and in figure 5.16 we represent the difference in classification between the first and second listening, in a similar way to what was done before.

We can see in this representations that there is a clear distinction between the apnea recording (Sound 1) and the remaining sounds, as most participants classified sound 1 as having very frequent breathing difficulties and the remaining sounds to have none or very few. For this question only a very few number of participants gave different answers in the first and second listening.
5.3. Listening Experiments

Figure 5.15 Representation of the number of answers of the twelve participants to Question 4, regarding the amount of breathing difficulties in the recording, for each sound. In the vertical we represent the number of participants and in the horizontal axis the possible answers to the question. NR indicates that the listener gave no answer to the question.

Figure 5.16 Representation of the agreement between the first and second answer of each participant to Question 4 (regarding the amount of breathing difficulties). In the vertical axis we represent the number of participants and in the horizontal axis the difference between the second and first answers. NR indicates that the listener gave no answer one or both times he was asked the question.

5.3.3 Questions relating to the sonification of leg movement

In Question 5 the listeners were asked to classify the subjects leg movement in the heard recording in a scale of 1 (very frequent leg movements) to 4 (no leg movements). In figure 5.17 we represent the number of answers for each class and in figure 5.18 we represent the difference in classification between the first and second listening, in a similar way to what was done before.

We can see in this representations that most listeners identified very frequent leg movements in the recording of the PLM patient (sound 3), very few leg movement
in the recording of the healthy patient (sound 2) and gave classification somewhat in between for sounds 1 and 4. The agreement between listeners and of the listeners with themselves seems to be low for adjacent classes.

**Figure 5.17** Representation of the number of answers of the twelve participants to Question 5, regarding the amount of leg movements in the recording, for each sound. In the vertical we represent the number of participants and in the horizontal axis the possible answers to the question. NR indicates that the listener gave no answer to the question.

**Figure 5.18** Representation of the agreement between the first and second answer of each participant to Question 5 (regarding the amount of leg movements). In the vertical axis we represent the number of participants and in the horizontal axis the difference between the second and first answers. NR indicates that the listener gave no answer one or both times he was asked the question.

### 5.3.4 Questions relating to the overall classification of the recording

The last two questions of the questionnaire were related to the overall classification of the recording as healthy or unhealthy. In question 6 they were asked to classify the recording in a scale of 1 (unhealthy) to 4 (healthy) and in question 7 they were asked
to classify the recording as healthy or unhealthy. The results of this experiment are presented in figures 5.19, 5.20, 5.21 and 5.22, in a similar way to what was presented before.

**Figure 5.19** Representation of the number of answers of the twelve participants to Question 6, regarding the overall classification of the recording, for each sound. In the vertical axis we represent the number of participants and in the horizontal axis the possible answers to the question. NR indicates that the listener gave no answer to the question.

**Figure 5.20** Representation of the agreement between the first and second answers of each participant to Question 6 (regarding the overall classification of the recording). In the vertical axis we represent the number of participants and in the horizontal axis the difference between the second and first answers. NR indicates that the listener gave no answer one or both times he was asked the question.
5.3. Listening Experiments

Figure 5.21 Representation of the number of answers of the twelve participants to Question 7, regarding the classification of the recording as healthy or unhealthy, for each sound. In the vertical axis we represent the number of participants and in the horizontal axis the possible answers to the question. NR indicates that the listener gave no answer to the question.

Figure 5.22 Representation of the agreement between the first and second answers of each participant to Question 7 (regarding the classification of the recording as healthy or unhealthy). In the vertical axis we represent the number of participants and in the horizontal axis the difference between the second and first answers. NR indicates that the listener gave no answer one or both times he was asked the question.

5.3.5 Questions relating to interest, pleasantness and fatigue

When asked to answer if they would be willing to listen to this sounds for more time or on a regular basis all the participants responded yes. When asked to rate the pleasantness of the sounds in a scale of 1 to 4, half the participants gave a classification of 3 and half a classification of 4. This indicates that regarding fatigue and interest the results are satisfactory. In the end of the questionnaire there was an open question, in which the participants were asked to give their opinion about the project and whether they found what they heard interesting or not.
all the participants reported they found the experience interesting or exciting, one participant suggested the visual representation of the sounds, one wrote that the REM and deep sleep sounds could be more distinct and one participant reported that it was hard in the beginning to preform the evaluating as there were so many different sounds.
6. DISCUSSION

Regarding the functions that represent sleep stages:

Considering the mean value of the sleep stage modulation functions for each stage of the hypnogram (presented in section 5.2), we can observe a good separability of classes, although they highly dependable on which patient is being analyzed. For example, in the recording B07, the separability of the classes (specially for REM sleep and wakefulness) is not very satisfactory, and contrasts with the other recordings. This can also be observed in the FR representations of section 4.2.1. For the same feature, the FR has very different values for each patient, demonstrating the difficulty of finding features that allow a good separability throughout all recordings.

Additionally, it is important to take into account that the mean is not always the best statistical measure to evaluate the discriminative power of the functions, and should be interpreted with caution. From the box plot representation of the modulation functions of recording ins2 (shown in section 4.2.1) we see that the SWS modulation function has for the awake stage a mean value of around 0, but its distribution of values goes actually from 0 to 1. Despite this, we conclude that the separability is still quite good, as most of these values are considered to be outliers, and most are concentrated in the close to zero region. However, for the REM modulation function we have values for REM sleep that range from around 0.2 to 1. It would be desirable that this distribution would be more narrow. This box plot is represented as an example and the behavior is similar for the remaining recordings.

Regarding breathing difficulty and movement sonification:

The evaluation of the breathing and movement functions separability was done differently, as we had no epoch by epoch information of these variables. The results were evaluated by plotting the amplitude of the sounds for apnea, PLM and healthy recordings. We concluded that there is a clear difference in the amplitude of the sounds for healthy and unhealthy patients, which was already discussed in detail in the previous sections.

Regarding the listening tests:
Analyzing the results of the listening tests presented section, we conclude that listeners were able to distinguish between healthy and unhealthy recoding with a satisfactory score. This is shown by the fact that for the unhealthy recordings (Sounds 1, 3 and 4) the values of the responses to question 6 "Generally, how would you classify this night of sleep?" are significantly lower than for sound 2 (healthy recording). Furthermore, when asked to classify the recordings as "healthy" or "unhealthy" most of the listeners were able to give a correct answer - in the worst case 3 out of 12 listeners classified unhealthy recordings as healthy and no listener classified the healthy recording as unhealthy.

The classification of the first sound (of a patient with apnea) had the best overall score, when compared to the other sounds. One of the possible interpretations of this is that the alarm for respiratory difficulty was designed more effectively than the other sounds. In fact, three of the participants stated in the end of the test that this alarm transmitted them a very strong idea of restlessness.

We can also see that the listeners identified very frequent leg movements in Sound 3 (recording of the PLM patient), but also quite frequent leg movements in the recording of the patient with apnea and insomnia. This was expected as the muscular activity is high in this recordings, in particular in the recording of insomnia, where the subject is awake for a long period in the beginning of the night. The movement alarm, as it was constructed in this work, is not a suitable of whether or not the subject suffers from PLM. It is, however, another indicator to whether or not the recording is healthy (as EMG activity during the night is usually a sign of unhealthy sleep).

The sonification of sleep stages, in which the listener is supposed to identify the absence of the refreshing stages of sleep, by the absence of piano sounds or excess drumming sounds, hasn't, as expected, as precise results as the alarms. Evaluating the progression of sleep stages throughout the night is naturally more difficult and subjective than noticing the presence of an alarm sound. Despite this, the listeners identified correctly the existence of too much wakefulness in the recording of insomnia and considered that the healthy patient had more frequent periods of REM and SWS sleep than the insomnia, apnea and PLM recordings, which is considered to be quite a satisfactory result.

In the preparation phase of the listening tests we realized that the listeners behavior is very variable. Even though the environment in which the tests were carried out tried to be as less stimulating as possible, it was interesting to notice that while some subject kept their eyes closed,others visually scanned everything around them.
We gave freedom to the test subjects to repeat and experiments with the sounds as they saw fit, and while some of them chose to listen multiple times to the sounds and fill the questionnaires progressively, others chose to listen to all sounds only one time. Even though many of these variables could have been studied, and it would be interesting to determine how different behaviors affect the results, this type of studies were part of the objective of this work.

We also noticed, from the answers given to the open question in the end of the questionnaires, that some subjects seem to lack visual representation of the information as one the listeners suggested "more graphical descriptions such as plotting the frequency of the sounds". This might be related to the fact that most participants were engineering students, which are used to monitor data through graphical representation in their daily activities. For those, the adaptation to auditory representation might be difficult and the graphical representation of the extracted features would perhaps allow better results. However, this work was directed also for users that are not used to monitor data and many of the listeners didn’t seem to have problems with the lack of visual stimulus.

Most listeners reported that they found the experience exciting and we seem to have caught their interest by the fact that sonification is not a very usually way of displaying data, as many of them reported not doing anything like this before.

One participant reported having difficulty evaluating the first sounds, but less difficulty evaluating the ones that followed. However, analyzing the responses given by the participants in the second time they are asked to classify the same sounds, we did not notice an overall significant improvement in the classification. Others stated that the display of so many different sounds made the interpretation harder. This issues can possibly be surpassed with the setup of a longer learning period and with the possibility of producing the sounds with or without the alarms information.

We should note, that the number of listeners in this experiments can be increased to make more accurate conclusions.
7. CONCLUSIONS AND FUTURE WORK

We have introduced a method to extract features from polysomnographic signals and represent them as sound characteristics in order to provide laymen a tool to determine the overall quality of their sleep.

According to our results, sonification can be used to determine how well we slept, as 8 out of 11 listeners were able to correctly classify all heard recordings as healthy or unhealthy using our methods. Most listeners had no previous knowledge of sleep or interpretation of biological signals and would not be able to reach any conclusions from the visual analysis of the EMG, EEG, EOG and Saturation data that was used as input for the production of the sounds. Furthermore, most participants expressed interest in the experiments and would be willing to listen to the sounds in a regular basis.

We thus conclude that the work was successful and brought the field of sonification of sleep recordings further, even though there any many further developments that could be researched in the future.

Relating to the recording of the signals, the algorithm should be tested and adapted for the use with input data gathered with actual home available devices. The fact that all our experiments were conducted with data recorded with laboratory equipment restrains the use of the sonification at home.

Relating to extraction of features, further research could be done relating to the use of less input channels, or even in extracting more information from the channels that we currently use in order to make the modulation functions more reliable.

Regarding to the leg movements sonification, it would be interesting to produce different sounds for leg movements during wakefulness and during sleep and appropriate methods of determining the existence of PLMs.

Relating to sound production, our current methods rely on the amplitude modulation and superimposition of pre existent sounds. We considered this to be the more simple and easily interpretable method. However, the production of MIDI files could
be explored further as this would allow a higher control over all characteristics of the sounds. More sounds could be researched that would represent more intuitively the different variables. Given that the characteristics of each user are different, the next version of this program could entail the possibility of choosing between the modulation into different sound tracks or even into different dimensions, like rhythm and frequency. The possibility to change characteristics could make the use more exciting for those who have musical training, without compromising the interpretation for other users.
BIBLIOGRAPHY


APPENDIX A. TRAINING SESSION AND INSTRUCTIONS FOR THE LISTENING TESTS.

SONIFICATION OF POLYSOMNOGRAPHIC SLEEP RECORDINGS

USER MANUAL

FACULDADE DE CIÊNCIAS E TECNOLOGIA
UNIVERSIDADE NOVA DE LISBOA

TAMPERE UNIVERSITY OF TECHNOLOGY

SLEEP SONIFICATION

This project has as objective the sonification (representation into sounds) of sleep recordings.

It is intended that people without any medical education can determine generally the quality of their sleep by hearing this sounds.
There are **three** essential parameters represented in the sounds.

- **Sleep Stages**
- **Breathing Problems**
- **Leg Movements**

Sleep stages

Sleep is divided in stages that alternate cyclically.

In a normal night, the subject goes from wakefulness to progressively deeper stages (Stage S1, Stage S2, deep SLEEP, REM sleep) before it starts another cycle.

![Sleep Cycle Diagram]
SLEEP STAGES

IN OUR WORK HOLE NIGHT RECORDINGS (OF 8/9 HOURS) ARE REPRESENTED IN 1 MINUTE SOUNDS.

THE TIME PROGRESSION OF THE SOUNDS CORRESPONDS TO THE TIME PROGRESSION THROUGHOUT THE NIGHT.

MEANING: THE BEGINNING OF THE SOUND CORRESPONDS TO THE BEGINNING OF THE NIGHT AND THE SUBJECT WILL PROBABLY BE AWAKE.

SLEEP STAGES

IN THIS SOUNDS:

DRUMS COMING FROM THE LEFT SIDE REPRESENT WAKEFULNESS OR NOT VERY RELAXING STAGES OF SLEEP.

PIANO MUSIC COMING FROM THE RIGHT SIDE REPRESENTS DEEP SLEEP.

PIANO MUSIC COMING FROM THE LEFT SIDE REPRESENTS REM SLEEP.
SLEEP STAGES

PLEASE LISTEN CAREFULLY TO THE FOLLOWING EXAMPLE OF A HEALTHY SUBJECT FALLING ASLEEP.

NOTICE THERE IS A BRIEF PERIOD OF WAKEFULNESS - DRUMS ON LEFT SIDE FOLLOWED BY A PROGRESSIVE TRANSITION INTO DEEP SLEEP - PIANO ON RIGHT SIDE FOLLOWED BY THE TRANSITION TO REM SLEEP – PIANO ON THE LEFT SIDE

SLEEP STAGES

THE BEGINNING OF THIS MIGHT CAN BE CONSIDERED:

HEALTHY! 😊

WANT TO LISTEN AGAIN?
**SLEEP STAGES**

**BUT DON'T FORGET!**

8H/9H OF SLEEP ARE REPRESENTED IN 1 MIN SOUNDS.

DRUMMING FOR 1 SECOND MEANS THE SUBJECT WAS AWAKE FOR SOME MINUTES.

DRUMMING FOR 10 SECONDS MEANS THE SUBJECT WAS AWAKE FOR MORE THAN 1 HOUR: A LONG TIME...

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**SLEEP STAGES**

TAKING TOO LONG TO FALL ASLEEP OR BEING AWAKE FOR LONG, FREQUENT PERIODS DURING THE NIGHT IS CONSIDERED TO BE

UNHEALTHY! 😞

WANT TO LISTEN AGAIN?
BREATHING PROBLEMS

GASPING SOUNDS COMING FROM THE LEFT SIDE REPRESENT A LOW SATURATION OF OXYGEN AND MAY INDICATE BREATHING DIFFICULTIES.

NOTICE THAT SOMETIMES THE OCCURRENCE OF BREATHING DIFFICULTIES IS FOLLOWED BY WAKEFULNESS...

BREATHING PROBLEMS

IT IS NORMAL THAT THERE IS A VERY SPORADIC DETECTION OF A BREATHING PROBLEM (ONCE/TWICE IN A HOLE NIGHT).

BUT HAVING BREATHING DIFFICULTIES VERY FREQUENTLY DURING THE NIGHT IS CONSIDERED TO BE...

UNHEALTHY! 😞
**LEG MOVEMENT**

Movement noises coming from the right side represent leg movement.

**Example** - Leg movements during wakefulness

**Example** - Leg movements during sleep

**LEG MOVEMENT**

Very frequent leg movements throughout the night is considered to be:

**Unhealthy! 😞**
PLEASE
LISTEN
CAREFULLY
TO THE
FOLLOWING
EXAMPLE
SOUNDS

DON’T FILL IN ANY
QUESTIONNAIRES YET
EXAMPLE 1

HOW WOULD YOU CLASSIFY THIS RECORDING?
ENOUGH DEEP SLEEP?
TOO MUCH WAKFULNESS?
FREQUENT BREATHING DIFFICULTIES?
FREQUENT LEG MOVEMENT DURING SLEEP?
PROCEED TO FOLLOWING SLIDE TO SEE CLASSIFICATION

HEALTHY! 😊

✓ DRUMMING IN THE BEGINNING OF THE RECORDING, BUT THE SUBJECT QUICKLY FALLS ASLEEP.
✓ FEW DRUMMING THROUGHOUT THE RECORDING (MAINLY FOR SHORT PERIODS).
✓ NONE / FEW LEG MOVEMENTS.
✓ NONE / FEW MOMENTS OF BREATHING DIFFICULTY.
✓ LOUD PIANO SOUNDS THROUGH THE NIGHT BOTH IN THE LEFT AND RIGHT SIDE.

FEEL FREE TO LISTEN AGAIN
EXAMPLE 2

HOW WOULD YOU CLASSIFY THIS RECORDING?
ENOUGH DEEP SLEEP?
TOO MUCH WAKEFULNESS?
FREQUENT BREATHING DIFFICULTIES?
FREQUENT LEG MOVEMENT DURING SLEEP?
PROCEED TO FOLLOWING SLIDE TO SEE CLASSIFICATION

UNHEALTHY! 😞

- Drumming in the beginning of the recording, but the subject quickly falls asleep.
- Frequent moments of breathing difficulty.
- Moments of breathing difficulty lead to arousals (drumming sounds heard frequently after breathing noises, mainly in the second half of the recording).
- Few leg movements.
- Loud piano sounds through the night both in the left and right side.
- Normal drumming in the end of the recording indicating the end of the night.

Feel free to listen again
EXAMPLE 3

HOW WOULD YOU CLASSIFY THIS RECORDING?
ENOUGH DEEP SLEEP?
TOO MUCH WAKEFULNESS?
FREQUENT BREATHING DIFFICULTIES?
FREQUENT LEG MOVEMENT DURING SLEEP?
PROCEED TO FOLLOWING SLIDE TO SEE CLASSIFICATION

UNHEALTHY! 😞

✓ SUBJECT IS MOSTLY AWAKE FOR THE FIRST HALF OF THE NIGHT.
✓ FREQUENT LEG MOVEMENTS (MAINLY DURING WAKEFULNESS).
✓ NONE / FEW MOMENTS OF BREATHING DIFFICULTY.
✓ LOUD PIANO SOUNDS THROUGH THE NIGHT BOTH IN THE LEFT AND RIGHT SIDE.

FEEL FREE TO LISTEN AGAIN
EXAMPLE 4

HOW WOULD YOU CLASSIFY THIS RECORDING?
ENOUGH DEEP SLEEP?
TOO MUCH WAKEFULNESS?
FREQUENT BREATHING DIFFICULTIES?
FREQUENT LEG MOVEMENT DURING SLEEP?
PROCEED TO FOLLOWING SLIDE TO SEE CLASSIFICATION

UNHEALTHY! 😞

- Drumming in the beginning of the recording, but the subject quickly falls asleep.
- Frequent leg movements during sleeping.
- Frequent moments of breathing difficulty.
- Moments of breathing difficulty lead to arousals (drumming sounds heard frequently after breathing noises).
- Loud piano sounds throughout the night both in the left and right side.

Feel free to listen again 🎵
NOW PLEASE READ THE FIRST QUESTIONNAIRE THAT WAS GIVEN TO YOU

CLASSIFY THE FOLLOWING SOUNDS AS BEST AS YOU CAN
SOUND 1

PLEASE FILL QUESTIONNAIRE 1

FEEL FREE TO LISTEN AGAIN
SOUND 2

PLEASE FILL QUESTIONNAIRE 2

FEEL FREE TO LISTEN AGAIN
APPENDIX A. Training session and instructions for the listening tests.

SOUND 3

PLEASE FILL QUESTIONNAIRE 3

FEEL FREE TO LISTEN AGAIN
SOUND 4

PLEASE FILL
QUESTIONNAIRE 4

FEEL FREE TO LISTEN
AGAIN
PLEASE HAVE A
SHORT BREAK

SOUND 5
PLEASE FILL
QUESTIONNAIRE 5

FEEL FREE TO LISTEN
AGAIN

SOUND 6
PLEASE FILL QUESTIONNAIRE 6

FEEL FREE TO LISTEN AGAIN

PLEASE FILL THE END OF SESSION QUESTIONNAIRE THAT WAS GIVEN TO YOU
APPENDIX B. QUESTIONNAIRES FOR THE LISTENING TESTS.

SOUND 1

Participant ID Number:

Please listen carefully to the sounds and answer as honestly as possible to the questions below.

How would you classify the amount of periods of Deep sleep (Piano sounds from the right side) in this recording?

☐ 1   ☐ 2   ☐ 3   ☐ 4

Very few.   Very frequent.

How would you classify the amount of periods of REM sleep (Piano sounds from the left side) in this recording?

☐ 1   ☐ 2   ☐ 3   ☐ 4

Very few.   Very frequent.

How would you classify the amount of Wakefulness (Drumming sounds from the left side) in this recording?

☐ 1   ☐ 2   ☐ 3   ☐ 4

Long periods.   Mostly for cyclic, short periods.

How would you classify the subjects breathing in this recording?

☐ 1   ☐ 2   ☐ 3   ☐ 4

Very frequent breathing difficulties.   No breathing difficulties.

How would you classify the subject’s leg movement in this recording?

☐ 1   ☐ 2   ☐ 3   ☐ 4

Very frequent Leg Movements.   No Leg Movements.

Generally, how would you classify this night of sleep?

☐ 1   ☐ 2   ☐ 3   ☐ 4

Not normal (unhealthy).   Normal (healthy).

Please classify this recording in one of the following options:

☐ UNHEALTHY   ☐ HEALTHY
END SESSION

Participant ID Number:

Sex:

□ F □ M

Age:

Please answer as honestly as possible to the questions below.

How would you classify your musical education or experience performing with musical instruments?

☐ 1  ☐ 2  ☐ 3  ☐ 4

No experience  Much Experience

Did you find the sounds you heard pleasant?

☐ 1  ☐ 2  ☐ 3  ☐ 4

Unpleasant  Pleasant

Would you be able to listen to similar sounds for more time or in a regular basis (example – for 1 minute, once a day)?

☐ Yes  ☐ No

Did you find this experience interesting? Do you have any suggestions or remarks about the project?

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