Sleep staging using contactless audio-based methods

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Abstract

Sleep stage classification is essential for evaluating sleep and its disorders. Most sleep studies make use of contact sensors which may interfere with natural sleep although recently the potential for sleep staging from audio signals has been acknowledged. This project presents a non-contact audio-based method for sleep staging.

The objective of this work is to develop a method that can classify sleep stages from non-contact audio signals. To achieve the aforementioned objective a measurement acquisition setup has been presented alongside a validation of the acquired respiratory signal and a sleep staging algorithm. 11 subjects have been measured with the proposed method. The validation process compares the pre-processed acquired audio signal with a reference respiratory signal yielding good results in terms of error metrics, with a low deviation between the acquired respiratory cycles using the audio method and the reference method. The sleep stage algorithm classifies sixty-second epochs into NREM or REM stages with good results in terms of REM and NREM detection, with REM and NREM cycle duration similar to the ones that can be found in other studies present in the literature, thus validation the obtained results.

Resum

La classificació de les etapes del son és essencial per la seva avaluació i la dels seus trastorns. La majoria dels estudis del son fan ús de sensors de contacte que podrien interferir en la natura del son, tot i que recentment, s'ha reconegut el potencial de mètodes de classificació de les etapes del son basats en senyals d'àudio sense contacte. Aquest projecte presenta un mètode de classificació de les etapes del son basat en senyals d'àudio sense contacte.

L'objectiu d'aquest treball és desenvolupar un mètode que permeti classificar les diferents etapes del son a partir de senyals d'àudio sense contacte. Per assolir aquest objectiu s'ha definit una configuració de mesura juntament amb una validació del senyal de respiració i un algorisme de classificació de les etapes del son. S'han mesurat 11 subjectes utilitzant la configuració proposada. El procés de validació compara el senyal d'àudio capturat, una vegada preprocessat, amb un senyal de respiració com a referència, donant bons resultats en termes de mètriques d'error, amb una desviació baixa entre els cicles respiratoris obtinguts mitjançant el mètode d'àudio i el mètode de referència. L'algorisme de classificació de les etapes del son, classifica trames de seixanta segons en REM o NREM amb bons resultats en termes de detecció REM o NREM, amb una durada de cicle REM i NREM similar a les que es poden trobar en altres estudis presents en la literatura, validant així els resultats obtinguts.

Resumen

La clasificación por fases del sueño es esencial para su evaluación y para la evaluación de sus trastornos. La mayoría de los estudios del sueño requieren del uso de sensores de contacto que podrían alterar la natura de este, aunque recientemente, se ha reconocido el potencial de otros métodos basados en señales de audio sin contacto. Este proyecto presenta un método de clasificación de las fases del sueño basado en señales de audio sin contacto.

El objetivo del trabajo es desarrollar un método que permita clasificar las diferentes fases del sueño a partir de señales de audio sin contacto. Para alcanzar este objetivo se ha definido una configuración de medida junto a una validación de la señal respiratoria y un algoritmo de clasificación de las fases del sueño. Se han medido 11 sujetos usando la configuración de medida propuesta. Este proceso de validación compara la señal de audio con una señal de respiración de referencia, dando buenos resultados en términos de métrica de errores, con una baja desviación entre los ciclos respiratorios obtenidos mediante el método de audio propuesto y el método de referencia. El algoritmo de clasificación, clasifica en NREM y REM con buenos resultados en términos de detección de las fases, con una duración de ciclo REM y NREM similar a las que se pueden encontrar en otros estudios presentados en la literatura, validando así los resultados obtenidos.

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I would like to thank Marc Mateu and Mireya Fernandez for all their help and support in the course of the project, especially Marc for his patience and spent afternoons in the laboratory. Also thank my parents, my sisters and the rest of my family and close friends, old and new, who have been by my side for these past four years.

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1. Introduction

Sleep accounts for almost one-third of the human lifespan and is a crucial biological function for both physical and mental energy restoration. That is why sleep quality is as important as the number of hours of sleep we get [1]. Sleep stage detection is crucial for the diagnostic and monitoring process of sleep quality and sleep diseases such as obstructive sleep apnoea (OSA) and insomnia.

The gold standard for sleep staging is Polysomnography (PSG) which is a multiparametric test conducted in a sleep laboratory [2]. This test requires the attachment of sensors on the subject's body, which added to the fact that needs to be conducted in a laboratory, can affect the subject's night sleep.

Recently, respiratory sound, which can be accurately acquired with microphones, has been acknowledged to differentiate sleep stages with the proper signal treatment and processing [3]–[6]. Moreover, with the development of consumer electronic devices and smartphones, an easy access to microphones has been provided, leading to the development of contactless audio-based methods for monitoring sleep which are inexpensive, suitable for mass screaning and do not affect normal sleep, which make these methods a promising field of study.

In this project, a method for sleep stage classification based on non-contact audio signals is proposed with the aim to verify sleep stage classification from audio signals. Moreover, an acquisition system set up is proposed alongside a validation of the acquired respiratory signal.

1.1. Objectives

The project is carried out at the Electronic and Biomedical Instrumentation Group (IEB) of *Universitat Politècnica de Catalunya* (UPC).

This project consists of evaluating the relationship between the different sleep stages and acquired ambient audio signals, based on comparing the different respiration and ambient audio signals. The main goal of the project is to develop algorithms that can determine the sleep stage of the subject using contactless methods based on audio signal analysis.

The project's main goals are:

1. Evaluation of the state of art regarding sleep stages measured with polysomnography.
2. Study of different respiratory and ambient audio signals to label the different sleep stages within a subject.
3. Algorithm development and signal processing to obtain the different sleep stages from the audio signals.
4. Measurement setup design for the validation of the proposed algorithm.

1.2. Requirements and specifications

Project requirements:

- Sleep staging extraction from audio signals.
- Sleep staging annotation and validation using different physiological signals (polysomnography, respiration...).

The expected requirements should verify the hypothesis that the ambient audio of a sleeping person can be used to correctly characterize the different sleeping stages. Moreover, the proposed work aims to develop an algorithm to correctly label the sleep stages by the means of the obtained audio signals.

Project specifications:

- The proposed algorithm must be developed using MATLAB software.
- The proposed algorithm should be agnostic regarding the audio format at the input.
- The proposed algorithm must provide a mean to adjust the first stage filtering, in order to easily select the frequency bands of interest.
- As a result of the algorithm, a full report must be provided including the following parameters: different sleep stages, the timestamps of the audio signal in which are present and other derivate parameters of the algorithm.
- As a result of the algorithm, the processed audio signal must be saved as well as an annotation of the timestamps and type of the sleep stages.

1.3. Project framework

This project is performed in the Electronic and biomedical Instrumentation research group (IEB), UPC, as part of the sleep analysis study within MINECO project "Métodos no intrusivos para monitorizar el proceso de esfuerzo/recuperación basados en el análisis de la calidad del sueño y la estimación" PID2019-107473RB-C22.

The project is started from scratch, as there has not been a prior analysis using this type of technology (audio) within the research group. At the same time, an algorithm provided by the Electronic and Biomedical Instrumentation research group (UPC) has been used in the project for the respiratory signal validation.

Project structure

The present project is structured in 6 chapters including the introduction, which encompasses a state-of-the-art revision, the development of the project, the budget, and finally, the conclusions and future work.

A state of the art is included in Chapter 2, where an introduction to sleep stages is reviewed, as well as different methods and signal processing techniques that can be used to classify sleep stages based on non-contact audio methods.

Chapter 3 describes the methods and materials used for the project. A measurement system setup is presented, alongside an audio pre-processing algorithm, a respiratory signal validation method and a sleep stage classification method.

In Chapter 4 the results and discussions for the respiratory signal validation and sleep staging methods are presented.

Chapter 5 includes the budget for this project.

Finally, Chapter 6 presents the conclusions and future work of the project.

1.4. Work plan

This section describes the work plan and its modifications along the development of the project.

Work Plan packages containing task details can be found in Annex A.

Work plan modifications

The first two proposed work packages in the initial work plan did not suffer any changes and have been completed according to plan.

As access to night ambient audio databases is very limited, a new work package was added in the third place. It consists of proposing a measurement setup, acquiring and retrieving data from various subjects and validating the respiration signal with a reference signal. The following and fourth work package is signal processing and algorithm development, which was the third work package in the initial plan. It has the same tasks but it has been postponed. The last work package did not suffer any modifications.

Milestones

WP#	Task#	Short title	Milestone / deliverable	Date (week)
1	3	Write state of the art	State of the art	30/03/2021
3	1	Definition measurement setup	Measurement setup	4^{th} week of April
4		Developed algorithm	Developed algorithm	Last week of May
5	2	Final report	Final report	16/06/2021
5	3	Final presentation	Final presentation slides	24/06/2021

Final Gantt diagram

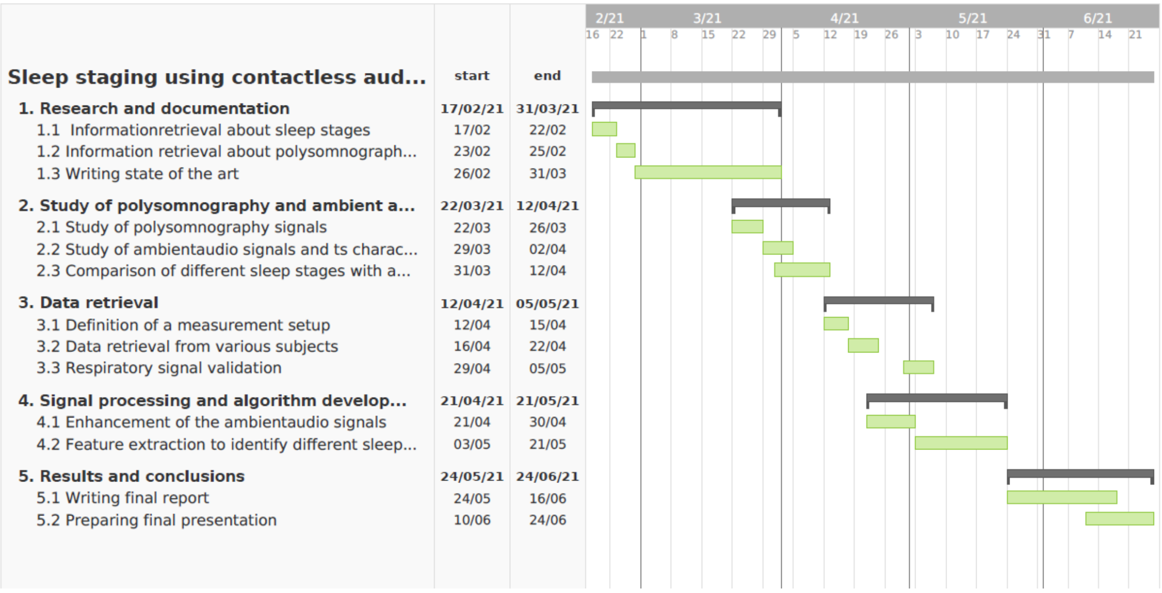

Figure 1.1: Final Gantt diagram

2. State of the art of the technology used or applied in this thesis:

2.1. Sleep stages

Sleep is a naturally recurring state characterized by reduced or absent consciousness, relatively suspended sensory activity and inactivity of nearly all voluntary muscles [2].

Sleep is not uniform and throughout the night, our sleep is composed over several rounds of the sleep cycle which is composed of four different stages. In a six to eight hours night sleep the number of cycles varies from four to six, each cycle having a duration of 90 to 110 minutes. Moreover, there can occur brief micro-arousals, that last from 1.5 to 3 seconds, and short awakenings, that last more than 15 seconds [7].

There are four sleep stages: one for Rapid-Eye Movement (REM) and four for Non-Rapid Eye Movement (NREM).

NREM Sleep patterns

NREM sleep is composed of four different stages, which represent 75 to 90% of the total night sleep. The first two stages (Stage 1 and Stage 2) are known to be the light sleep stages while Stage 3 and 4 are known as deep sleep or Slow Wave Sleep (SWS) [7].

Stage 1 is the lightest stage of sleep. It usually lasts one to five minutes and it represents 3 to 5% of the total NREM sleep [1], [7]. Breathing occurs at a regular rate [8].

Stage 2 follows stage 1 and it represents 50 to 60% of total NREM sleep [7]. Brain activity, heart rate and breathing slow down during this stage [1] .

Stage 3 and 4 are the deep sleep stages where brain activity has an identifiable pattern know as delta waves, and breathing and heart rate are even slower as the body relaxes even further [1]. Each of these stages represents 10 to 20% of total NREM sleep[7] .

REM Sleep patterns

REM sleep stage is the last one of a night sleep's cycle and is associated with dreaming. It comprises 10 to 25% of a total night 's sleep. During this stage, breathing is more erratic and irregular and heart rate often increases [8].

2.2. Classification methods for sleep staging

2.2.1. Polysomnography

Polysomnography (PSG) is regarded as the gold standard for sleep staging. It is a multiparametric test conducted to study sleep and its disorders. This procedure requires various contact sensors attached to the study subjects to acquire physiological signals such as electroencephalography (EEG), electrooculography (EOG), electromyography (EMG), electrocardiography (ECG) as well as respiration [2]. Moreover, the study is time-consuming, needs to be carried out in a laboratory, which may affect the patient's normal sleep, and a sleep expert is required to analyse the full night signals.

2.2.2. Non-contact audio-based methods

In the recent years, the development of smartphones and consumer electronics has provided easy access to microphones, which can be used to acquire breathing audio signals that can be useful for monitoring sleep. Multiple sleep monitoring methods have been presented in the recent years, most of them based on machine learning techniques [2], [4]–[6], [9]–[11].

Audio signal acquisition and pre-processing

Some methods have common things regarding audio signal acquisition. The acquired audio signals are recorded using a directional condenser microphone placed one meter above the subject's head and a recorder [2], [4], [5], [9], [11]. Other methods propose placing the microphone 0.25 meters above the patient's head [10]. Commonly, in the aforementioned studies the audio signals are acquired at the standard sample rate, 44.1kHz, which in some methods are down sampled to 16kHz [2], [5], [9] commonly with PCM modulation and 16 bits per sample.

In addition, some methods[5] propose simultaneously carrying out a PSG, scored manually by a technician, to compare the proposed methods' sleep stage detection to the PSG score.

The main problems that come up with non-contact audio methods is that the acquired signal is not clean and needs to be processed to reduce the impact of ambient noise, as well as motion artefacts. These noise sources and artefacts can be attributed to unvoluntary body movements during sleep, external ambient or background noise due to external sound sources within the vicinity of the acquisition device. Overall, if not taken into account, attenuated and filtered, these factors can potentially interfere with the acquisition system and even render unusable the acquired data. For these reasons, in the literature, different signal processing approaches can be found that mitigate the effect of the aforementioned errors. Wiener filter-based algorithms based on spectral subtraction are commonly used in audio signals enhancement. The Wiener filter is a linear estimator and it minimizes the mean-squared error between the original and enhanced signal. Some examples of these filters can be found in Single Channel Speech Enhancement: Using Wiener Filtering with Recursive Noise Estimation by N. Upadhyay et.al. [[12]].

Breathing/non-breathing event detection

Once the audio signal is pre-processed, breathing or snoring events and non-breathing events are detected [[5], [9]–[11]. Inspiration and expiration are identified as breathing events while non-breathing sounds such as: vocally self-generated sounds, like speech, body movement or third-party sounds [4], [5], [9] are identified as well and categorized as noise sources. Moreover, as it can be appreciated in some of the studies in the literature, the audio signal is segmented into 30 second epochs in order to match the polysomnography epoch segmentation [4], [5], [11].

Feature extraction

In order to classify the segmented epochs into the different sleep stages, these methods propose the extraction of mainly three different feature types: time domain features, frequency domain features or entropy-based features.

Time domain features include:

- Respiratory/Breathing rate (RR): defined as the number of detected breathing events in an interval [9].
- Respiratory/breathing cycle (RC): defined as the duration of a breathing cycle. It can be defined as the time difference between one exhalation to the following one [10].
- Respiratory/breathing cycle power: defined as the power of the audio signal in a cycle (inhalation and exhalation) [5].

Frequency domain features such as: formants and MFCC coefficients (Mel-Frequency Cepstrum coefficients) are widely used as an effective feature for speech recognition and can be useful for snore/non-snore classification [10]. Moreover, zero-crossing rates are useful to differentiate voiced and unvoiced sounds, and for sleep analysis might be useful for inhale-exhale differentiation [10].

Finally, entropy features like Approximate Entropy or Shannon Entropy can be useful to discriminate chaotic and stationary signals and to measure the uncertainty of a time series.

NREM/REM classification

The classification between NREM and REM sleep stages can be done based on different approaches. On the one hand, most recent studies, are based on machine learning techniques and neural networks in order to train a classification system [2], [4]–[6], [9]–[11]. These can use decision trees based on most likelihood scores [5], [11] binary-random forest classifiers [9] and others.

On the other hand, other studies follow a much simpler approach for the sleep stage classification. As an example, some of these studies are based on the measurement of breaths per minute (BPM) [13] or on the acquisition of the respiratory rate (RR) [3]. Moreover, these studies show that there is a remarkable change in breath rates for awake and REM stages. However, the breathing rate of a subject in NREM stage remains almost the same. Table 2.1 shows the breathing rate of a subject in BPM for different sleep stages[14].

Table 2.1: Sleep stages associated to BPM

Sleep stage	Breaths per minute (BPM)
Awake	12-18 breaths per minute
NREM	3-4 breaths per minute
REM	24-36 breaths per minute

Finally, to improve stage classification, some methods use simple sleep heuristics [3], [6]. This post-processing stage, helps in the classification of the different sleep stages based on the knowledge of sleep structure.

Overall, the methods found in the literature make use of similar pre-processing techniques on the acquired audio signal to remove artefacts and noise, as well as improve the sleep staging detection.

3. Materials and methods:

This chapter contains the description of the proposed algorithms for sleep staging and verification of the respiratory signal extraction, as well as the acquisition set up description and the measurement protocols.

3.1. Proposed algorithm

The project is divided into two distinctive parts: validation of the respiratory signal and sleep staging analysis.

First of all, a validation of the respiratory signal from the acquired audio signal has been performed. The acquired audio signal is pre-processed to obtain respiratory information. In order to validate this process, a reference respiratory signal is also acquired and compared to the pre-processed audio signal.

The second part is the sleep staging, which is divided into 3 different steps. The first task being the pre-processing of the acquired audio signal in order to extract respiratory information, the second the feature extraction and the third the sleep stage classification and labelling. Figure 3.1 depicts the different steps for the sleep staging.

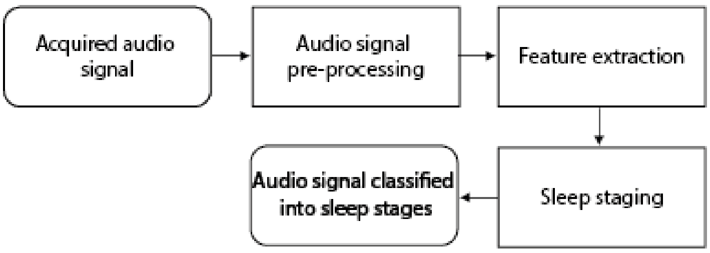

Figure 3.1: Block diagram for sleep staging proposed algorithm

Audio signal pre-processing

The acquired audio signal needs to be pre-processed in order to extract respiratory information. Moreover, the signal needs to be resampled and filtered for better handling of the resulting signal, which will be used for sleep staging. This process consists of filtering, down sampling, normalising and extracting the envelope of the signal.

These pre-processing steps are common for both sleep staging and validation of the respiratory signal extraction.

Respiratory signal validation

To assure that the sleep staging algorithm, that uses respiratory information of the signal, is being applied to a respiratory signal or to a signal containing respiratory information, a prior step is required in order to verify the correct extraction of the respiratory signal from the acquired audio signal.

In order to do so, the pre-processed acquired audio signal is compared to a reference respiratory signal. This comparation is carried out using an algorithm based on the comparison of detected respiratory cycle series provided by the Electronic and Biomedical Instrumentation group (UPC).

Feature extraction and sleep staging

The pre-processed audio signal is analysed by epochs, each epoch lasting sixty seconds. For every epoch, different time-domain features are computed. Some of these features are going to be used to classify every epoch into NREM or REM stage[3] . The other features are going to be useful to help validate the results of the sleep stage classification and to compare them with other studies [10], [15], [16]. As a result of the sleep staging analysis, the input audio file is going to be returned alongside a text file containing the classification of the stages with the corresponding time stamps.

3.2. Acquisition system setup

The acquisition system setup used, was composed of a condenser microphone placed 50 cm above the subject's head to record the ambient audio, a diadem microphone placed 5 cm from the subject's mouth and an inductive respiration band. Both microphones presented a cardioid polar diagram and a flat frequency response, and both were connected to an audio interface. The condenser microphone was connected directly to the audio interface through a XLR cable and the diadem microphone sent its signal to a receiver which was connected to the audio interface, also via an XLR cable.

The condenser microphone used was a Behringer C2, the diadem microphone was the t.bone HeadmiKe -D and the audio interface used was Zoom H4n audio recorder. The inductive respiration band was the RespiBand from BioSignalsPlux^{TM} [17].

The audio interface was connected to a computer via USB cable, and the RespiBand, was connected via classic Bluetooth using RFCOMM protocol.

The audio recorder, was configured to capture audio at a sample frequency of 44100 Hz.

As for the acquisition software, an ad-hoc acquisition software based on ROS[18] Melodic Morenia, Intel Core^{TM} i5-4210M CPU @2.60GHz x4 with 8Gb RAM running Ubuntu 20.04 LTS, was used.

3.3. Measurement protocols

Eleven subjects volunteered for the study, 5 of which were female and 6 male. Table 3.1 shows the anthropometric data from the subjects which includes age, height and weight expressed as mean ± SD. Each subject gave their written informed consent to freely participate in the study, and all the tests complied with the regulations of the Universitat Politècnica de Catalunya (UPC). All measurements were performed in a relatively quiet and controlled environment.

Table 3.1: Anthropometric data from subjects expressed as mean ± SD.

Age [years]	Height [cm]	Weight [kg]
20.09 ± 1.14	169.6 ± 8.66	66.0 ± 17.16

Two different tests were performed. Both consisted in recording the subject in a controlled environment for different periods of time in a supine position. While the test was performed, several audio sources were recorded (ambient audio signal and diadem microphone placed at the nose's height) as well as the respiration signal acquired with the inductive band system.

Prior to any measurement, every subject was asked to put on the RIP strap from the RespiBand system below the chest near the abdominal region and to put on the diadem microphone. The subject was also asked to lay on a supine position.

For the first test, ten subjects were recorded for a five-minute period. They were asked to lay in supine position and to remain still for all the test. This test was performed to verify that the acquired audio signal that will further be processed and used for sleep staging corresponds to a respiration signal.

The second test, only performed on two of the subjects, consisted in recording a whole night sleep. As in the previous measures, two audio sources (ambient audio microphone and diadem microphone) were captured along the respiration acquired with a commercial inductive band system. These measures will be used to test how the developed sleep staging algorithm performs.

3.4. Signal processing

Once the raw audio and respiratory signals had been extracted using the proposed method, first the breathing information had to be extracted from the audio and was compared with the respiratory signal acquired by the inductive band. All signal processing was carried out using MATLAB R2020b.

3.4.1. Basic concepts

The next subsection of the chapter describes useful concepts for a better understanding of the proposed algorithm.

Hilbert Transform

The Hilbert Transform of a signal *g(t)* is the convolution of the signal *g(t)* with the signal $1/\pi t$ and it is defined as

$$H[g(t)] = g(t) * \frac{1}{\pi t} = \frac{1}{\pi}\int_{-\infty}^{\infty} \frac{g(\tau)}{t-\tau}\, d\tau = \frac{1}{\pi}\int_{-\infty}^{\infty} \frac{g(t-\tau)}{\tau}\, d\tau \quad (3.1)$$

This transform is useful for calculating the audio envelope of an audio signal [19].

Envelope of a signal

The envelope of a signal are the boundary curves, upper and lower, within the signal is contained. Analytically, the envelope *e(t)* of a signal *x(t)* is defined as the magnitude of the analytic signal

$$env(t) = \sqrt{x(t)^2 + \hat{x}(t)^2} \tag{3.2}$$

where $\hat{x}(t)$ denotes the Hilbert transform of *x(t).*

In figure 3.4.1 the upper envelope of an audio signal is represented in green while the lower envelope is plotted in yellow.

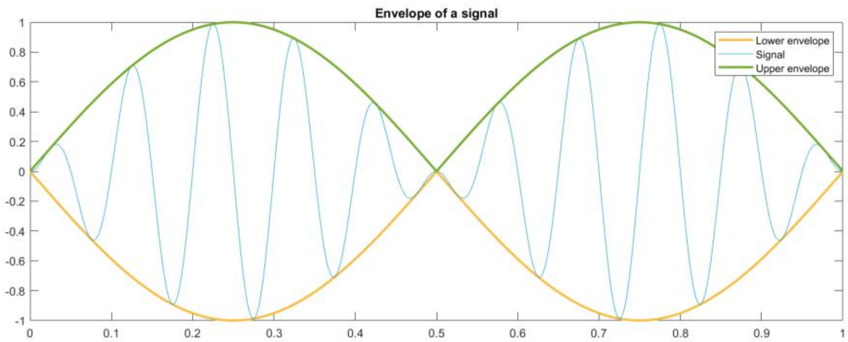

Figure 3.2: Envelope of a signal

Down and up sampling

Down sampling is the process of reducing the sample rate of a signal. This process reduces the size of the data and it is useful to handle fewer samples of a signal for its analysis. However, there is risk of data loss.

Up sampling is the contrary process of down sampling, it consists of increasing the number of samples within a signal, hence increasing its effective sampling frequency.

3.4.2. Audio signal pre-processing

This section describes the signal pre-processing applied to the audio signal for the extraction of the audio envelope.

Normalisation and envelope calculation

This process is used to filter any undesired components and noise, to reduce the number of samples in order to reduce the computational cost of the algorithm and to extract the envelope of the signal, which includes breathing events information. The steps followed are described below.

1. The input audio signal is filtered with a bidirectional 2nd order low-pass Butterworth filter with cut off frequency of 8 kHz. It is used to eliminate any undesired high frequency components.

2. The audio signal is down sampled to a sample frequency of 16 kHz in order to work with less samples. In this case, information is not lost in the down sampling.

3. The upper envelope of the filtered and down sampled audio signal is computed. The envelope is calculated using the Hilbert transform, detailed in equation 3.1.

4. The previous envelope, with sample frequency of 16 kHz, is down sampled to a sample frequency of 1 kHz. Again, this step reduces the number of samples to process.

5. The down sampled envelope is filtered with a 2nd order bidirectional Butterworth filter with cut-off frequencies between 0.05 Hz and 1 Hz. This filtering stage is applied in order to isolate the frequency components of the respiratory signal, to remove the possible offset and base-line wandering of the signal and eliminate undesired high frequency components.

6. The envelope is normalised using a non-linear function based on the arctan properties to comprise its amplitude to a -1 to 1 range. The following equation, 3.2, describes the function used to normalise [20].

$$S_n[n] = \arctan \frac{S[n]}{\sqrt{\frac{\sum_{i=1}^{N}(S[i]-\bar{S})^2}{N-1}} \cdot \sqrt{2}} \qquad (3.3)$$

7. Finally, as the expirations can be identified as the peaks in the audio envelope, the envelope is inverted, so that when comparing both signals, the signals coincide.

Figure 3.4 shows the normalised audio envelope in colour green and the acquired audio signal in red colour. As it can be seen, the peaks of the envelope coincide with the maximums of the audio signal.

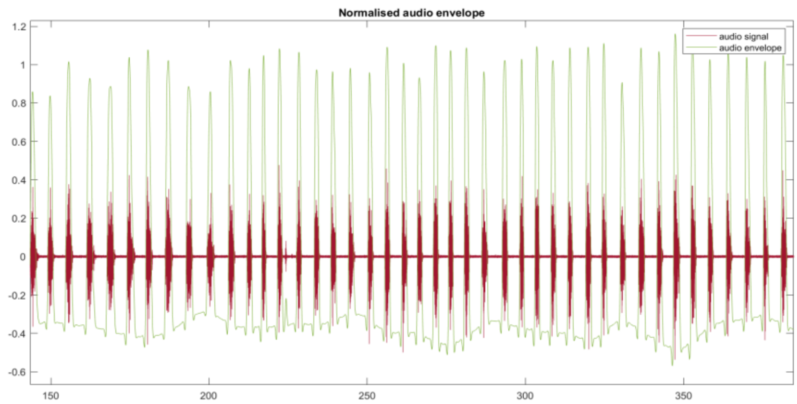

Figure 3.3: Normalised audio envelope

3.4.3. Respiratory signal validation

The previously pre-processed acquired audio signal is compared to a reference respiratory signal. First of all, the acquired audio signal is pre-processed, following the methodology described in the previous section, in order to obtain a respiratory signal. This signal is compared with a reference respiratory signal, acquired with an inductive respiration band, with an algorithm provided by the Electronic and Biomedical Instrumentation group (UPC).

This algorithm aligns both signals with the Intraclass Fisher Correlation. Once aligned, it uses the rising flanks to obtain the respiratory cycle (RC) of both signals, it compares them and returns the common cycles for both signals.

Error assessment

In order to assess the error between the RC series computed for the acquired audio signal and the reference respiration signal, a cycle-to-cycle comparison has been performed. The statistical methods used are shown in the following equations [20].

$$e_k[i] = S_k[i] - P_k[i] \tag{3.4}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|e_k[i]| \tag{3.5}$$

$$MAPE = \frac{\frac{1}{N}\sum_{i=1}^{N}|e_k[i]|}{\frac{1}{N}\sum_{i=1}^{N}|P_k[i]|} \cdot 100 \tag{3.6}$$

$$SDE = \sqrt{\frac{\sum_{i=1}^{N}(e_k[i] - \bar{e}_k)^2}{N-1}} \tag{3.7}$$

where MAE (Equation 3.4) stands for mean absolute error, MAPE (Equation 3.5) stands for mean absolute percentage error and SDE (Equation 3.7) stands for standard deviation of the error.

In all equations, S_k represents the RC series for the acquired audio signal with the proposed method and P_k represents the RC series for the reference respiratory signal.

3.4.4. Audio processing for sleep staging

Once the audio signal is pre-processed, the filtered and down sampled envelope of the audio signal, which contains respiratory information, is obtained.

Only signal fragments corresponding to the sleep period of the subjects are processed and analysed. The signal is divided into 1-minute epochs, which will be classified into REM and NREM stages. The followed steps are described below.

1. The audio signal is segmented into 60 second epochs. Each of these epochs will be classified into REM or NREM.

2. For each epoch, the expiration events of the audio envelope are detected in order to calculate different parameters. The expirations are represented as peaks in the envelope. For each expiration, the sample index and the amplitude (comprised between -1 and 1 due normalisation) are obtained.

3. The Breaths per Minute (BPM), the Respiratory Rate (RR), the Respiratory Cycles (RC) and the power of the signal are calculated for each epoch and are added one after the other to create different series. RR series will be used to classify into NREM or REM stages [3]. The Respiratory Cycles are obtained by calculating the time difference between two consecutive detected peaks. The Respiratory Rate is computed using the following equation [3].

$$RR[k] = \frac{60}{N} \sum_{k=1}^{N} \frac{1}{RC[k]} \tag{3.8}$$

4. The RR feature is detrended to remove the non-linear trend. Then two thresholds are calculated so that when the detrended RR value for an epoch is out of range, that epoch is going to be classified as REM [3]. These thresholds are set as the third quartile minus the standard deviation and as the first quartile plus the standard deviation.

5. Moreover, simple heuristics based on knowledge of normal sleep structure are used in order to improve classification [3], [6].
   - All REM epochs during the first 60 minutes of sleep are scored as NREM.
   - An isolated scored REM epoch in an interval of 15 epochs is scored as NREM.
   - If an interval between REM epochs is less than 15 epochs, all epoch included in the interval is scored as REM [6]
   - The duration of a REM is approximately of 30 minutes, so each detected REM period containing less than 20 one-minute epochs is scored as NREM [3].

6. The BPM and RC are added into two different series, each corresponding to the classified stage of the epoch.

Once classified all epochs into the NREM/REM stage, a full report containing the timestamps of the audio signal with the corresponding sleep stage is generated and saved into a .txt file.

3.5. Graphical interface

A graphical interface has been designed for better user interaction. It consists of a main menu, where the user can choose between two functions: sleep staging or validation of the respiratory signal. A screenshot of the main menu can be found in Appendix B.1, figure B.1.

When the validation of the respiratory signal function is chosen a new page opens. This page allows the user to load both audio signal and reference respiration signal, which corresponds to the signal acquired with the Plux inductive respiration band. When choosing which files to upload, an explore tab opens up, so that the user can navigate through his or her files and select the desired one. For each signal, there is a button '*Plot audio signal*' *or 'Plot Plux signal'* that when pressed plots the pre-processed input signal and its spectrogram. For the audio signal, the pre-processing applied is the one described in section 3.2.1. As for the Plux signal, the pre-processing consists of filtering the signal with a 2^{nd} order bidirectional Butterworth zero-phase bandpass filter, with cut-off frequencies between 0.05 and 1Hz so any base-line drifts or undesired high frequency components are removed [20].

Moreover, the user is asked to define an interval. It is the interval for which both signals, once aligned, are going to be analysed and compared. An information button has been added regarding the interval definition.

Finally, a button for the validation has been added. When pressed, the validation process described in section 3.4.3 is carried out. As a result, both aligned and pre-processed signals are shown in the same plot and an error assessment table is displayed. Moreover, a button for plotting both signals has been added, in case the user wants to change in between the different signal graphs.

All screenshots for the Respiration Signal Validation can be found in Appendix B.2.

Going back to the main menu, when the sleep staging function is selected by the user a new window opens up. This window, allows the user to load an audio file by pressing the button '*LOAD AUDIO FILE'* that when pressed opens an explorer tab where the user can navigate through the computer files and select the desired audio file. When having selected the audio file, the filename displays in a text field. The other element present in the window is the '*SLEEP STAGE CLASSIFICATION'* button that when pressed runs the proposed algorithm for sleep stage classification. Also, when pressed the button, different signals are displayed: the audio signal, the envelope of the audio signal with the sleep stages and the final sleep stage classification. Moreover, a sleep report is displayed on the screen. A button has been added in case the user wants to save the sleep stage classification report in a text file. This button, when pressed, opens an explore tab so that the user can navigate through the computer's directories and choose were to store the file.

Screenshots for the Sleep Staging function can be found in Appendix B.3.

4. Results

4.1. Validation of the respiratory signal extraction

In this subsection, the results obtained from the analysis of the audio signals obtained with the proposed method and the respiratory signals as reference are shown.

The audio signal containing respiratory information is the signal acquired with the diadem microphone. As for the ambient audio signal, it did not present respiratory information nor background noise that could corrupt the diadem microphone measure.

Figure 4.1 shows the obtained audio signal, after processing it, and the reference respiratory signal.

As it can be seen, the pre-processed audio signal (inverted envelope of audio signal) presents negative peaks, which correspond to the expirations of a respiratory signal. These peaks are on top of the reference respiratory signal lower peaks, which indicates a high concordance.

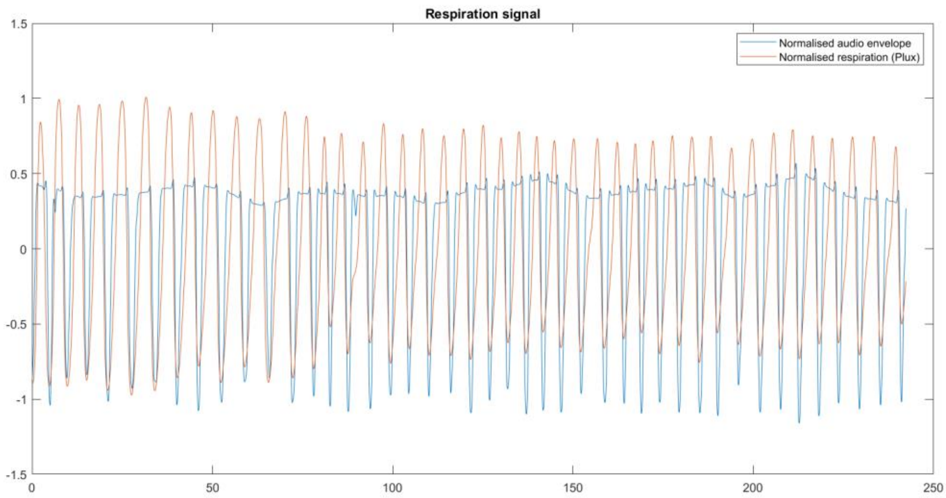

Figure 4.1. Respiration signals

Error assessment

The following table (Table 4.1) presents the results for the comparison of cycles between the proposed method for audio signals and the reference method. The error results are the aggregated error of all eight subjects. Being the number of subjects so small, the distributions were tested to follow a normal distribution, which resulted in MAE and SDE following it and MAPE not following it. As a result, MAE and SDE have been expressed as mean ± SD, and MAPE as median and interquartile range ([0.25 0.75]).

Table 4.1: Mean +- SD of MAE and SDE and median ± interquartile range of MAPE

MAE	0.45 ± 0.23 s
MAPE	5.35 ± [1.33 4.01] %
SDE	0.72± 0.42 s

Discussion of the results

As it can be observed in figure 4.1, the pre-processed audio signal acquired with the proposed method and the reference respiration signal acquired with the inductive respiration (Plux) band are practically superposed which implies higher concordance between them.

Relative to the aggregated error results presented in Table 4.1, all three error measures are relatively low and also imply a high concordance between the audio acquired with the proposed method and reference respiration signals. A low MAE and SDE values indicate a low error between the proposed method and the reference method. Moreover, a relatively low MAPE indicates accuracy and small bias between both methods.

There were several limitations to this study, the first one being the reduced number of recruited subjects for this study. The second limitation is that the subjects are young and close in age.

4.2. Sleep staging results

In this subsection, the results obtained from the analysis of night sleep audio signals acquired with the proposed method are shown.

The audio signal containing respiratory information is the signal acquired with the head microphone. As for the ambient audio signal, it did not present respiratory information nor background noise that could corrupt the head microphone measure.

Figure 4.2 depicts the first step of the process by which REM and NREM epochs are detected. It shows the detrended RR with its computed thresholds and the first classification of epochs: the epochs with a RR out of range are detected as REM epochs. Moreover, both signals are plotted in different colors, red, blue and green, specifying the final sleeping stage into which they will be classified. Red color indicates that the epochs have been discarded and staged as awake, blue color indicates that the epoch has been classified as NREM state, and green color as REM state.

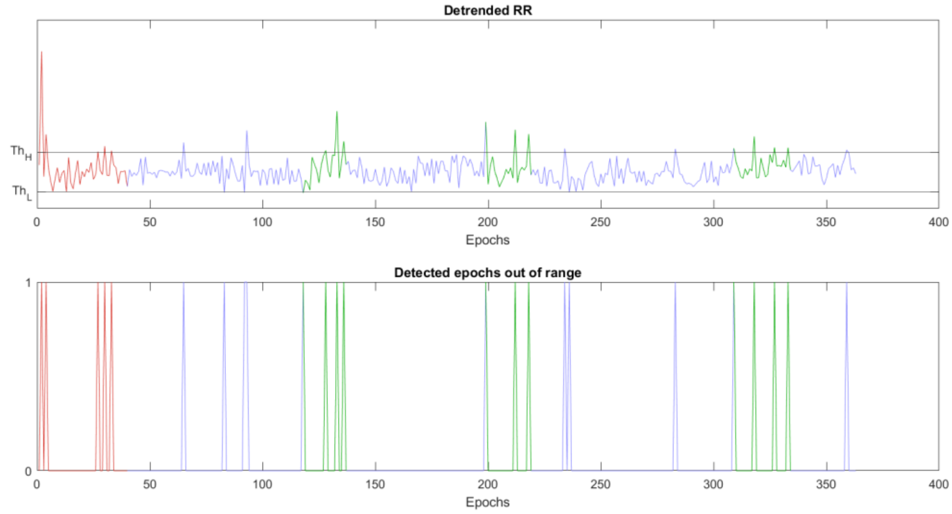

Figure 4.2: Detrended RR with thresholds and detected epochs out our range

Figure 4.3 shows the final classification into NREM and REM sleep stages. It can be observed that the first epochs are not scored either as NREM nor REM. It is assumed that the first forty minutes the subject is awake so the epochs included in that interval of time are discarded for the classification and are automatically scored as wake. If comparing Figure 4.2 (b) and Figure 4.3 it can be observed that some epochs detected as REM initially have finally been classified as NREM. Sleep heuristics have been applied for a better classification.

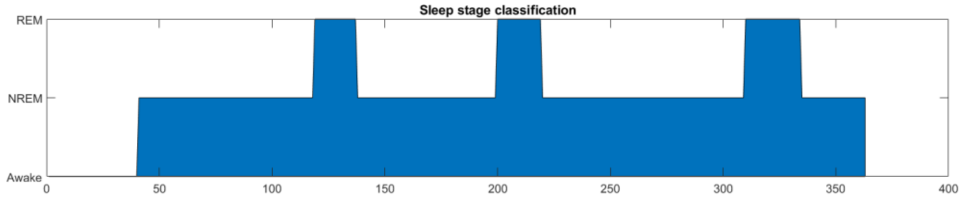

Figure 4.3: Final sleep stage classification for the second subject

The following table (Table 4.2), shows the BPM, power, RC and percentage of total sleep time for the epochs classified in every REM and NREM stage for the first subject. Table 4.3 presents the same results for the second subject. Moreover, the total number of sleep cycles detected and the its average duration for each subject can be found in Table 4.4.

Table 4.2: Mean +- SD of BPM, Power, and RC and percentage of total sleep time for NREM and REM intervals for Subject 1

	NREM	REM
BPM	13.63±1.34 s	13.96± 0.88 s
BPM variance	0.7788 s^2	1.8011 s^2
Power	16.92 ± 14.51	21.53 ± 24.08

RC	4.03 ± 0.58 s	4.13 ± 0.79 s
% of total sleep time	70.99%	29.01%

Table 4.3: Mean +- SD of BPM, Power, and RC and percentage of total sleep time for NREM and REM intervals for Subject 2

	NREM	REM
BPM	14.97 ± 1.00 s	14.31 ± 1.20 s
BPM variance	1.01 s^2	1.45 s^2
Power	27.06 ± 24.22	46.03 ± 25.13
RC	3.76± 0.56 s	3.94 ± 0.80 s
% OF TOTAL SLEEP	80.19%	19.81%

Table 4.4: Total complete sleep cycles detected for each subject and their average duration

	Detected complete sleep cycles	Average duration of detected sleep cycles
Subject 1	1 cycle	104 minutes
Subject 2	3 cycles	97 ± 16.04 minutes

An example of the text file generated with the sleep staging is presented in Appendix C.

Discussion

First of all, in figures 4.2 and 4.3 we can observe the different steps for stage classification. The first detection of REM epochs, shown in Figure 4.2, does not provide quality information regarding the overall REM/NREM cycles, for this reason further processing using sleep structure heuristics yields better results.

The acquired and analysed signal for the first subject is three hours and 23 minutes long, being the first forty minutes classified as awake and the resulting signal where the subject was asleep is two hours and forty-five minutes long. During the sleep interval, one full sleep cycle has been detected. The Sleep Foundation [1] defines the average duration of a sleep cycle as ninety minutes, ranging from 70 to 110 minutes. Looking at the results from Table 4.2, for the first subject, the computed average duration of the detected cycle matches the Sleep Foundation statements. Regarding the second subject, the total duration of the acquired audio signal is six hours and three minutes and total sleep time of five hours and 23 minutes. The number of detected sleep cycles makes sense regarding the total sleep time. Also, the average sleep cycle duration is 97 minutes which is within range of the duration of a normal sleep cycle determined by the Sleep Foundation [1].

Comparing the results of BPM of Respiratory rate variability in sleeping adults without obstructive sleep apnoea by Gutiérrez et.al. [15], it can be observed that mean of the BPM for every sleep stage takes similar values while the standard deviation takes higher values for the BPM in REM stages than for NREM stages. Comparing with the results obtained in this study, for both subjects the mean of the BPM has similar values for both sleep stages, and the standard deviation is higher for REM stages.

Looking into the results of Non-Contact Sleep Stage Detection Using Canonical Correlation Analysis of Respiratory Sound by B. Xue et.al. [10], the variance of the respiratory rate or of BPM rate comprises higher values for REM stages than NREM. As for the results of this study, for both subjects, the BPM variance for epochs classified as REM and NREM matches the results of the mentioned literature: it has higher values for REM stages comparing with NREM values.

Relative to power results, looking at the median and interquartile range of the power for both sleep stages, we can observe that median values are lower for REM stages compared to NREM, and that the interquartile range presents increased values for REM stages compared to NREM stages. This results match some of the results presented in Respiration amplitude analysis for REM and NREM sleep classification by X. Long et.al. [16]

Regarding the limitations to this study, are the reduced number of recruited subjects for this study, only two subjects participated in the whole night audio recordings, and that they are young and close in age. This implies that two sleep phenomena have not been observed: snoring and sleep apnoea.

5. Budget

The total budget comprises the cost of the materials used and the salary of the engineer who has been working in the project.

The following table, Table ##, describes the cost of the materials used.

Table 5.1: Materials cost

Materials	Units	Cost per unit	Total
Computer	1	450€	450€
Behringer C2 microphone	1	40€	40€
t.bone HeadmiKe -d microphone	1	58€	58€
Zoom H4n audio recorder	1	202€	202€
RespiBand from BioSignalsPlux™	1	750€	750€
XLR cable	2	15€	30€
MATLAB R2020b Annual License	1	800€	800€
		Total	**2.330€**

A junior engineer has been working on the project for four months. The monthly salary of a junior engineer is 1.900€. So, the total cost for the human resources is **7.600€.**

The total cost of the project is **9.930€**.

6. Conclusions and future development:

In this project, an acquisition system setup has been proposed, alongside with a pre-processing algorithm for the acquired audio signal, a respiratory signal validation method and a sleep stage classification method.

Regarding the acquisition system setup, it involves two condenser microphones: one for recording ambient audio sound and another placed closer to the subject's nose in order to record the breathing. Moreover, a reference respiratory signal has been acquired using an inductive respiration band.

The pre-processing algorithm for the acquired audio signal, consists of filtering, down sampling, normalising and extracting the envelope of the audio signal, in order to obtain a respiratory signal for the sleep stage classification.

Previous to sleep staging, a validation of the respiratory signal is required. This process compares the acquired and pre-processed audio signal with a reference respiratory signal. The results show a high concordance between both acquired audio and reference respiratory signals indicating that the acquired audio signal contains respiratory information.

The sleep stage classification algorithm, analyses the audio signal in 60-second epochs. This method consists on calculating the respiratory rate (RR) of every epoch with thresholds, so that when the RR rate of an epoch is out of range, that epoch is classified as REM. Moreover, the algorithm uses simple sleep structure heuristics for a better classification. The results obtained match the results of other studies from the literature or to know sleep structure data.

In reference to future lines of work, overcoming the limitations of the proposed method in terms of the reduced number of subjects of young age, would be the first step. It would be interesting to have subjects of all ages, so that sleep phenomena such as snoring or sleep apnoea can be observed and studied.

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Appendices:

A. Work Plan packages

Project: Sleep staging using contactless audio-based methods	WP ref: WP1	
WP Title: Research and documentation	Sheet 1 of 5	
Major constituent: Research of information	Planned start date: 17/02/2021 Planned end date: 30/03/2021	
Short description: Research for background and technical information for developing the state of the art of the project.	Start event: 17/02/2021 End event: 31/03/2021	
Internal task T1: Information retrieval about sleep stages Internal task T2: Information retrieval about polysomnography signals and their parameters Internal task T3: Writing state of the art	Deliverables: State of the art description and chapter	Dates: 30/03/2021

Project: Sleep staging using contactless audio-based methods	WP ref: WP2
WP Title: Study of polysomnography and ambient audio signals	Sheet 2 of 5
Major constituent: Polysomnography and ambient audio databases	Planned start date: 17/03/2021 Planned end date: 14/04/2021

Short description: Study of polysomnography and ambient audio signals with the aim to relate the audio signal fragments to sleep stages, and its posterior analysis.	Start event: 22/03/2021 End event: 12/04/2021	
Internal task T1: Study of polysomnography signals. Internal task T2: Study of ambient audio signals and its characteristics. Internal task T3: Comparison of different sleep stages with ambient audio segments	Deliverables:	Dates:

Project: Sleep staging using contactless audio-based methods	WP ref: WP3	
WP Title: Data retrieval	Sheet 3 of 5	
Major constituent: software and measurement setup	Planned start date: 12/04/2021 Planned end date: 5/05/2021	
Short description: A measurement setup definition will be proposed for signal acquisition from subjects and data will be retrieved.	Start event: 12/04/2021 End event: 5/05/2021	
Internal task T1: Definition of a measurement setup. Internal task T2: Data retrieval and acquisition from various subjects. Internal task T3: Respiratory signal validation	Deliverables: Definition of the measurement setup	Dates: Fourth week of April

Project: Sleep staging using contactless audio-based methods	WP ref: WP4
WP Title: Signal processing and algorithm development	Sheet 4 of 5
Major constituent: Software	Planned start date: 21/04/2021 Planned end date: 21/05/2021

Short description: Signal processing and development of an algorithm to obtain the different sleep stages from acquired ambient audio signals.	Start event: 20/04/2021 End event: 23/05/2021	
Internal task T1: Enhancement of the ambient audio signals. Internal task T2: Feature extraction to identify different sleep stages	Deliverables: Developed Algorithm	Dates: Last week of May

Project: Sleep staging using contactless audio-based methods	WP ref: WP5	
WP Title: Results and conclusions	Sheet 5 of 5	
Major constituent: Documentation	Planned start date: 24/05/2021 Planned end date: 24/06/2021	
Short description: Final extraction of the conclusions and final report writing.	Start event: 24/05/2021 End event:	
Internal task T1: Writing the final report Internal task T2: Preparing the final presentation	Deliverables: - Final report - Final presentation slides	Dates: - 17/06/2021 - 24/06/2021

B. Graphical interface

B.1 Main menu

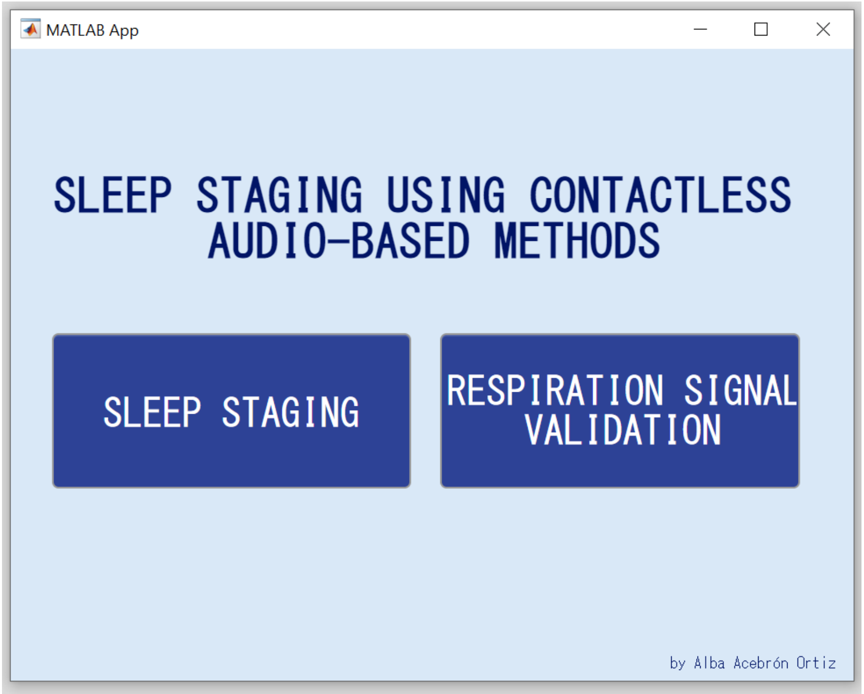

Figure B.1: Main menu

B.2 Respiratory signal verification

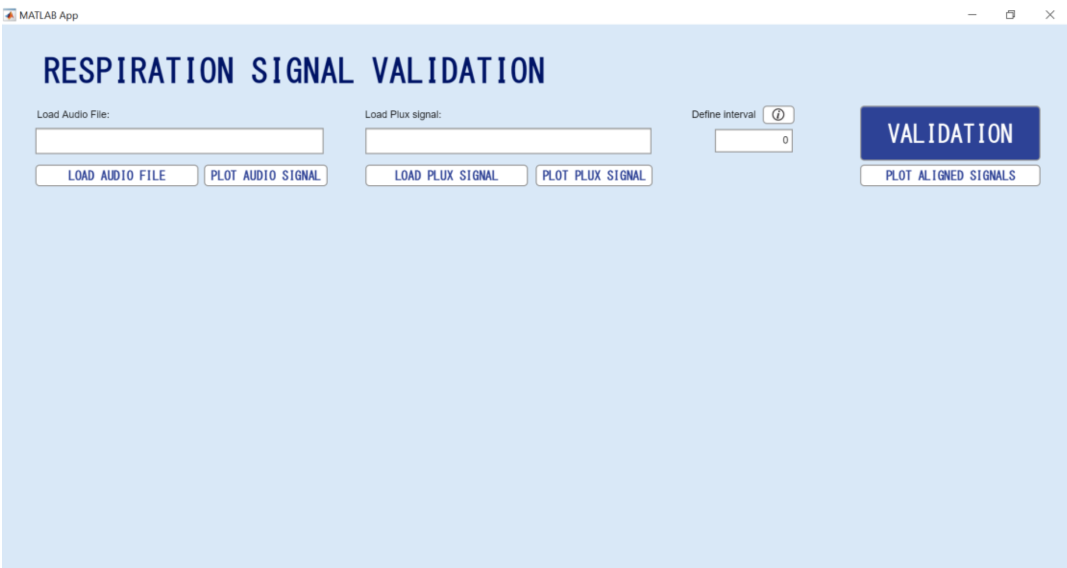

Figure B.2: Respiration signal validation initial view

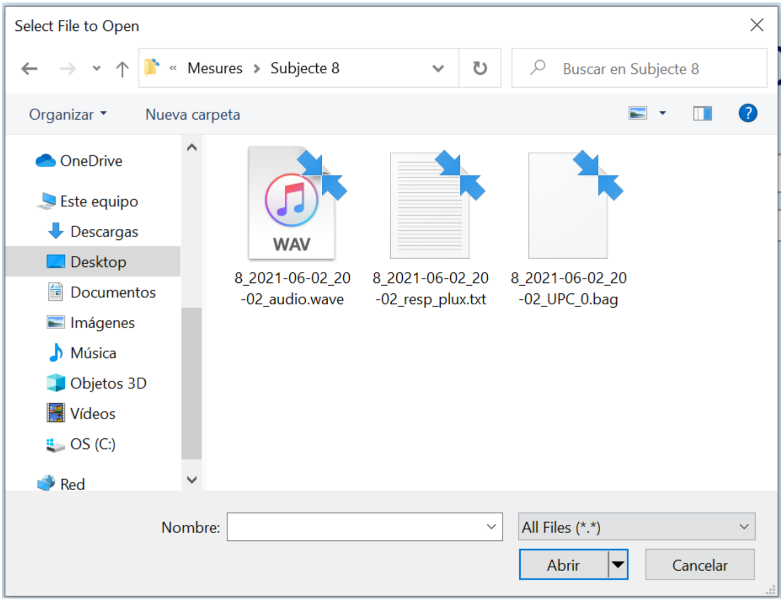

Figure B.3: Load audio or Plux signal explorer window

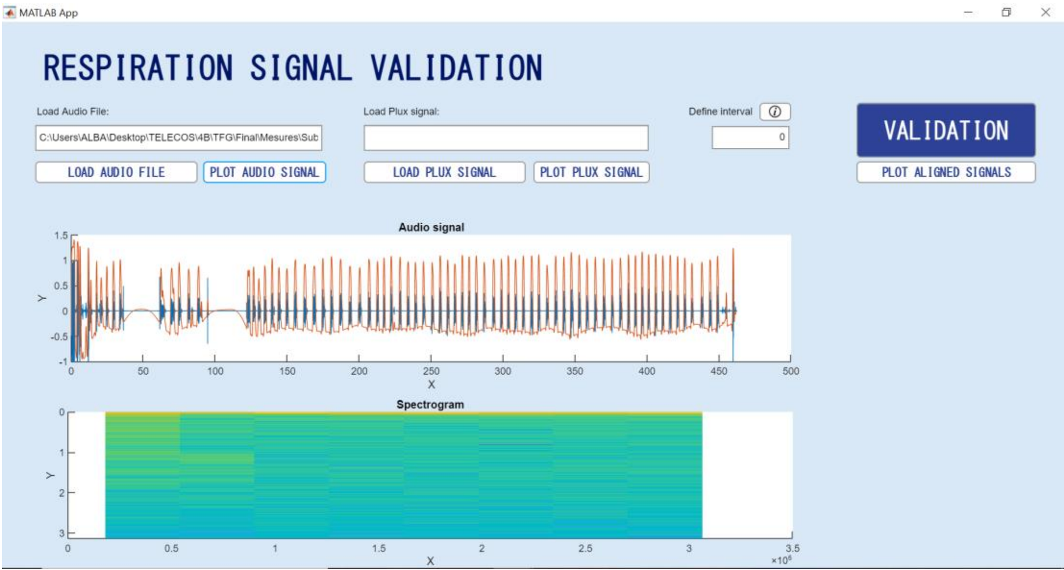

Figure B.4: Audio signal load and plot functions

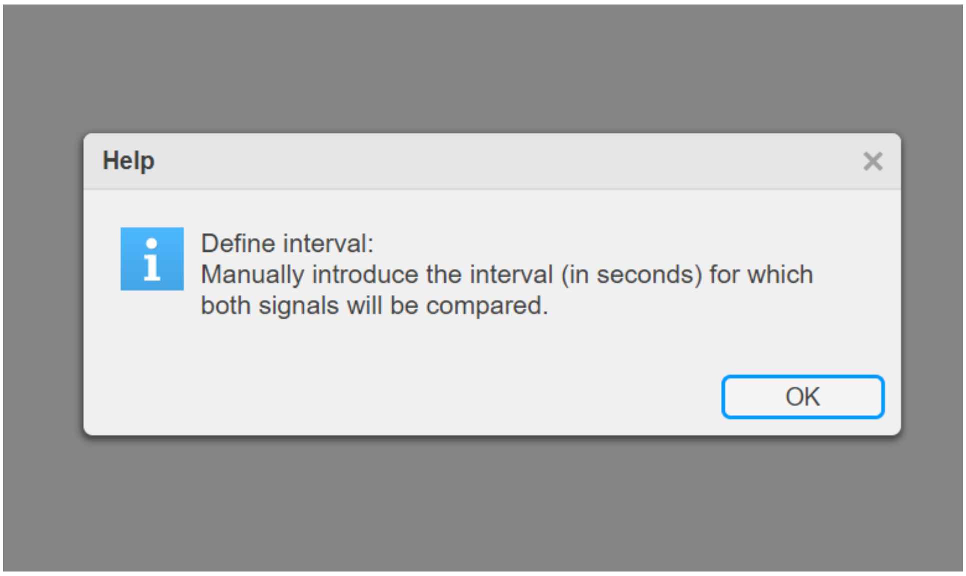

Figure B.5: Define interval help window

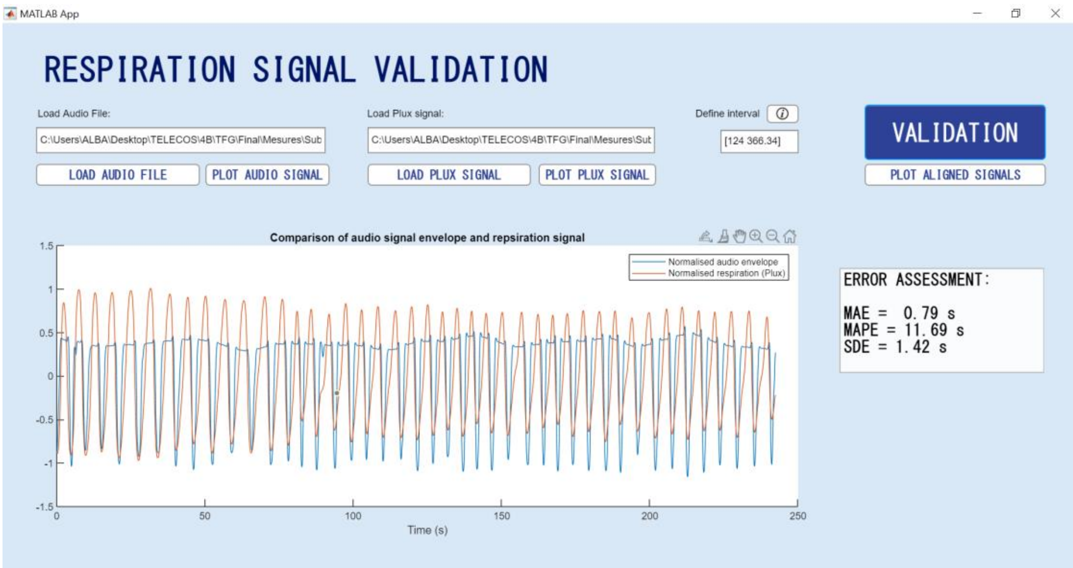

Figure B.6: Validation of respiratory signal results

B.3 Sleep staging

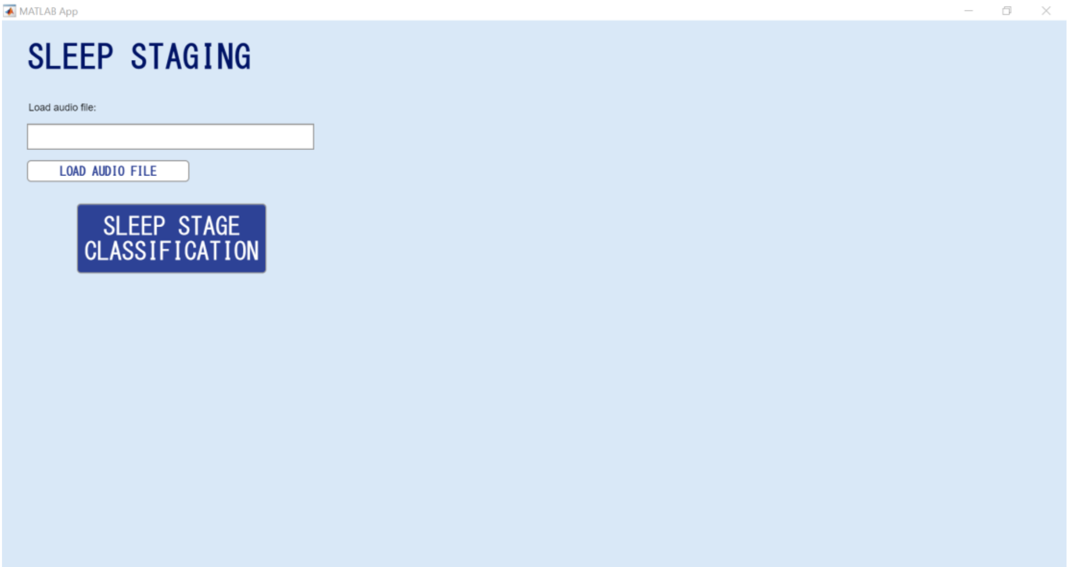

Figure B.7: Sleep staging initial window

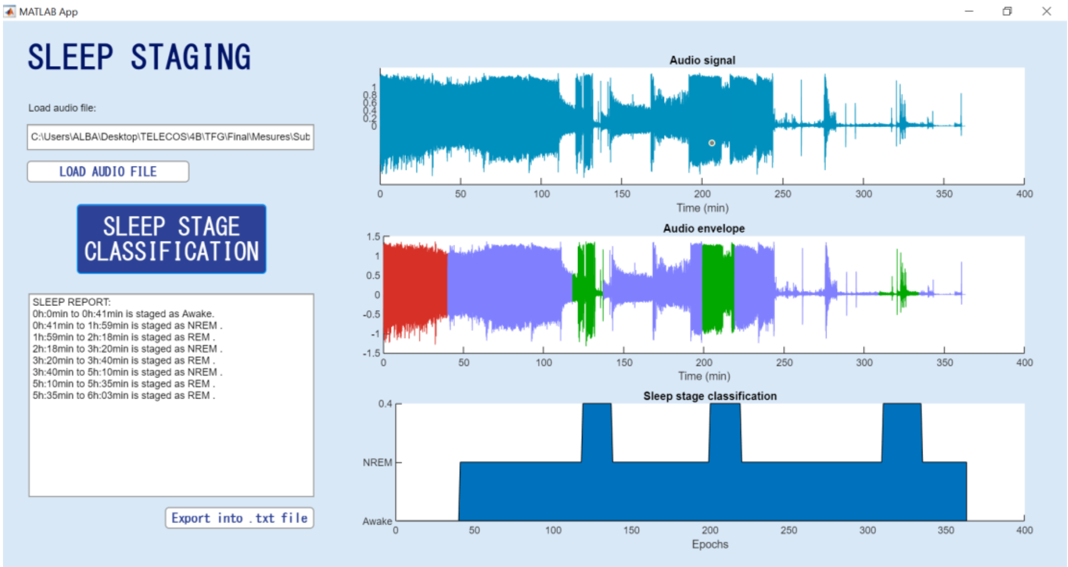

Figure B.8: Sleep staging results

C. Sleep stage classification results .txt file

0h:0min to 0h:41min is staged as Awake.

0h:41min to 1h:59min is staged as NREM.

1h:59min to 2h:18min is staged as REM.

2h:18min to 3h:20min is staged as NREM.

3h:20min to 3h:40min is staged as REM.

3h:40min to 5h:10min is staged as NREM.

5h:10min to 5h:35min is staged as REM.

5h:35min to 6h:03min is staged as REM.

Glossary

BMP	Breaths per Minute
ECG	Electrocardiogram
EEG	Electroencephalogram
EOG	Electrooculography
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MFCC	Mel-Frequency Cepstral Coefficients
NREM	Non-Rapid Eye Movement
OSA	Obstructive Sleep Apnoea
PCM	Pulse Code Modulation
PSG	Polysomnography
RC	Respiratory Cycle
REM	Rapid-Eye Movement
RFCOMM	Radiofrequency Communication
ROS	Robotic Operative System
RR	Respiratory Rate
SD	Standard Deviation
SDE	Standard Deviation of the Error
SWS	Slow Wave Sleep
XLR	External Line Return