Università degli Studi di Milano - Bicocca
Scuola di Scienze
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Corso di Laurea Magistrale in Informatica

Respiratory Rate Estimation using a Pressure Sensor Mattress

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Anno Accademico 2021-2022

Quando la vita si fa dura sai che devi fare Marlin?
Zitto e nuota, nuota e nuota, zitto e nuota e nuota e nuota?
E noi che si fa?
Nuotiam, nuotiam. . . .
Dory

Contents

Chapter 1

Introduction

This work aims to investigate the possibility of estimating a patient's respiratory rate using a sensor pressure mattress and how a rocking bed could influence its use. Initially, the possibility of extracting the breath and heart rate from pressure sensors is investigated using a dataset already available from previous studies. The work, therefore, goes to focus on respiratory rate. Since the necessary data are not available, data collection is conducted using an innovative pressure textile-sensor mattress and a cardiorespiratory as ground truth: the primary objective is to collect data to understand the feasibility of extracting breath rate from the mat in case of stationary bed; the second goal is to understand if the movement of the rocking bed could influence the signal. Then a pipeline is created to analyse the extracted data: from each mattress sensor, the signals are processed to exclude the ones without meaningful information and designed metrics that assert the confidence that from a sensor could be extracted a respiratory pattern. The remains signals are filtered to eliminate noise using multiresolution analysis of the maximal overlap discrete wavelet transform and Savitz-Golay filter to obtain a clean wave from which could be counted the number of breaths a person in a minute. As a result, the respiration rate per minute of the person is obtained and compared with the cardiopulmonary polysomnography to assert the error. The influence of the rocking bed on the mattress is obtained by comparing the mattress's performance with the stationary bed. As a result of the pipeline is also available a heat-map to visualise where these best channels are positioned in respect of the body and so in the mattress.

Sleep is one of the most important physiological functions. Sleep quality can affect physical and mental wellness; for this reason, it is crucial to monitor vital signs and sleep stages without interfering with natural sleep. The state-of-the-art in sleep monitoring technology for physiological data is polysomnography [1], which involves recording sleep stages, respiratory rate, heart and other parameters. However, this procedure is time-consuming, complicated, expensive, invasive for the patient and often unavailable in hospitals. Even in its simplified version, cardiorespiratory polysomnography [2], where only nose cannulas, chest belts and electrocardiogram (ECG) electrodes are involved and neurophysiological variables are not tracked, the patient is subjected to physical discomfort throughout the night.

Breathing monitoring is also crucial because the population present a higher percentage of sleep-related breathing disorders that can be studied and monitored with this instrument, like sleep apnoea/hypopnoea syndrome (SAS)[3], where the individuals experience a collapse of the airway in deeper sleep states: the ability to monitor it allows for a faster and closer intervention in severe cases.

Also, in the study of sleep stages [4], it is known that different muscle tones, brain wave patterns, eye movements and heart and breathing rate alterations characterise every phase and stage. In particular, the respiratory rate slowly becomes more stable in the Non-Rapid Eye Movement (NREM) phase and increases during the Rapid Eye Movement (REM) phase, giving the possibility to understand in which stage a person is based just on the respiratory signal[5].

Nowadays, it is possible to achieve this goal using different unobtrusive methods, such as radar technology [6]. The limitation of this approach lies in the fact that the presence of another person in the room, in a hospital condition like a nurse or doctor, or even from fans or oxygen concentrators, could be a source of noise for the radar that could lead to an incorrect prediction; it can also be disturbed by the movement of the patient itself [7]. Another possibility is to use video cameras with infrared filters [8]; even if this approach seems promising, it leads to personal privacy concerns.

Currently, it is possible to buy smartwatches, like Garmin[9], that can estimate multiple vital signs with good precision[10], but they need to be worn all night, which could lead to discomfort for some people. Moreover, these devices do not allow raw data extraction, and tracking is lost if the batteries run out. It is also possible to find under-mattress ballistocardiography-based sensors[11], like Emfit [12], that in case of multiple people inside the bed need to be placed in half of it and the wrong position can lead to inaccurate measurement.

In this thesis, it is decided to use unobtrusive methods not to cause discomfort to the user, which could also give us the possibility to track vital signs.

However, the decision of which type of method to use is influenced by the availability, in the lab where this thesis is carried out, of a rocking bed part of the *Somnomat*[13] project. This rocking bed aims to interact with the person and study how to improve sleep quality via vestibular stimulation. Also, in this case, the possibility of tracking vital signs could be significant, so the possibility of integrating unobtrusive methods with the Somnomat is part of this thesis. Given all those considerations, the choice fell to pressure sensor mattresses (hereafter referred to as "pressure mattresses"). They can be installed over the standard mattress and are now available as textile-sensor, which means that they can be as thin as possible and lead to less possible discomfort, but at the same time, can be used to track the respiratory rate and, depending on area density and sampling frequency, even heart rate.

In this project, at first, it is decided to use pressure-sensor textile mattresses from *Sensomative* [14] that have 14 x 28 sensor elements for a total sensor area of 40cm x 80cm that can cover the width of a regular bed with a sampling rate of 50Hz. Due to the small area of this pressure mattress, it needs to be placed in a specific position and in case the patient moves, it is not possible to retrieve information. Previous studies have brought out the possibility of estimating breathing patterns and heart rates; since the data from this mattress and the ground truth data from polysomnography are available, both possibilities are explored.

After evaluating a possible valid approach to this data, it is decided to use it on a second mattress, from *SensingTex* [15] that is already installed in a hospital ward of the *University of Bern* for the study research on movement disorders during sleep in patients with Parkinson's disease. Therefore the ability to estimate breath and heart rate could be helpful in this study. This mattress has a sampling frequency of 10Hz and 40 x 22 sensor elements for a total area of 192cm x 94cm that can cover a standard bed's area.

Raw data extracted from the mattress can be visualized to determine the person's position and movement, and it is shown as a heatmap since pressure sensors record the different pressures exerted by the presence/absence of a body on it or by its parts.

So it is possible to create a heat map to show the variation in colour of the intensity of the pressure, which can produce the shape of a person on the mattress. Looking closer into signals of single channels is possible to see a pattern that resembles a breathing rhythm, similar to the data that can be retrieved from the nasal pressure exerted on the cannula of cardiorespiratory polysomnography. This pattern was the key factor in deciding to use this pressure mattress.

Since there is no data on the rocking bed recorded before this project, it is necessary to conduct a data collection with two main objectives: the primary is to collect data to understand the feasibility of extracting breath rate from the mat; the second goal is to understand if the movement of the rocking bed could influence the signal. The participants are six, half male and half female, between 20 and 30 years old. Each participant wears a cardiorespiratory wireless and portable polysomnography device (Nox A1 PSG by Nox Medical[16]) that monitors nasal pressure, pulse, and heart rate with ECG and respiratory inductance plethysmography (RIP), which is a method of evaluating pulmonary ventilation by measuring the movement of the chest and abdominal wall.

The protocol is divided into two phases:

- The setting for the first phase involves placing the pressure mat over a standard bed. During the night and through the different sleep stages, the breath rate increases or decreases, so it is decided to insert a similar variability in the data. The participant has to perform a set of five jumps and then lie down in a specific position for four minutes. After this period, they have to stand up, repeat the five jumps and lied down again. The positions follow a pattern of supine, left side, prone, right side and with a total of twenty jumps.

- The setting for the second phase, since the data needs to be collected while the Somnomat is moving, the period for the movement of the bed is fixed at 4 seconds (15 periods in a minute) with an acceleration of 0.25 m/s^2. Also, in this phase, the participants are asked to turn around following the specific pattern: supine, left side, prone, right side and remain in that position for 4 minutes.

This results in a recording of 32 minutes for each participant divided into 4 minutes in each of the four positions with a standard bed and with Somnomat.

The SensingTex has a total of 1056 sensors, but they are never all significant at the same time. A person's body can not cover the entire mattress and activate all the sensors (hereafter referred to as "Channels") simultaneously. Consequently, this leads to the necessity of an algorithm to discriminate the ones from whom it is possible to extract valuable information. Many of these channels are stationary on a value; others present just interference from the mattress. It is possible to retrieve a respiratory pattern from just a few sensors and then extract the respiratory rate per minute (rpm). Therefore becomes necessary to design a metric that underlines these channels. This metric must be interpreted as confidence expressed in percentual of the goodness of the signal; at the same time, it is necessary to have a workflow that can estimate a person's respiratory rate from mattress data. This led to the creation of a pipeline that estimates the rpm based on the previous minute. The objective is to create a real-time pipeline in which the streaming of the sensors is simulated with a 60-second long moving window that slides with an interval of 10 seconds on the data collected in the project.

The first step of the pipeline excludes those signals for the entire window length that are: either stationary or present only interference from the mattress. That interference appears as spikes but sometimes is present just in a percentage of the signal; the same could happen for stationarities that can be focused in just a subpart of the windows. In this case, the signal is not excluded and is assigned with confidence equal to the percentage of the signal that could have meaningful information. Another possibility is a noisy signal, excluded or weighted with a percentage of confidence with the same approach as the previous two.

After these preliminary analyses, the number of signals decreases drastically. It is assumed to count as one breath the moment between inhaling and exhaling, which can also be considered a peak in the signal wave. At this point, most of the signals are still noisy. To be better analysed, it is decided to filter them using two different approaches: Multiresolution analysis of the maximal overlap discrete wavelet transform and Savitz-Golay filter.

The reconstructed signals are given as input to a pick finder to select both peaks and valleys of the signal. The channels with peaks greater than 30 rpm are excluded because the normal rpm during sleep is between 8-25rpm [17], but since a rate over 25rpm is predictive of cardiopulmonary arrest [18], it is decided to keep only signals under 30rpm. The remaining signals are further analyzed in their structure to understand whether they represent a breath pattern.

In the end, to calculate the rpm, the channels with the highest confidence percentage are taken into account, and the rpm is computed as the average of the number of peaks of the signals. A heatmap is also visualized in the different moments to understand where the best channels are in respect of the body depending on the position.

indice in forma discorsiva
lo compilo come ultime cosa

Acknowledgement

The project is carried out in collaboration with *Sensory-Motor System Lab* of Prof. Robert Riener at *Eidgenössische Technische Hochschule (ETH) Zürich* and supervised by Dr. Alexander Breuss, Dr. Oriella Gnarra and Dr. Manuel Fujis.

Chapter 2

State of Art

2.1 Sleep Stages

Sleep is a fundamental physiological function that occupies one-third of everyday life and affects almost every type of tissue and system in the body from the brain, heart, and lungs to metabolism, immune function, mood, and disease resistance. The quality and the quantity also can affect mental wellness, for example, lack of sleep affects our memory and ability to think clearly or sleep deprivation can lead to neurological dysfunction such as hallucinations. Moreover, those who do not get enough sleep are at higher risk of developing high blood pressure, cardiovascular disease, diabetes, depression, and obesity [19].

The sleep cycle of a person is divided into two phases Non-Rapid Eye Movement (NREM) and Rapid Eye Movement (REM); this second phase is further divided into three other stages (N1-N3). Different muscle tones, brain wave patterns, eye movements, and heart and breathing rate alterations characterise every phase and stage. Each cycle is approximately 90 minutes long, over the course of the night a person goes through four to six sleep cycles[20]. The composition of each cycle, so time spent in each sleep stage, changes as the night goes along and depending on other factors such as age, recent sleep patterns, and alcohol consumption. During an interrupted sleep, the stages progress as follows, also visible in Fig 2.1:

- Awake to NREM stage 1 sleep.
- NREM stage 1 progresses into NREM stage 2.
- NREM stage 2 is followed by NREM stage 3.
- NREM stage 3 to REM sleep.

Then the cycle come back to NREM stage 1.

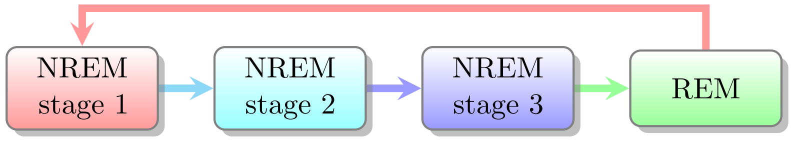

Figure 2.1: Sleep Cycles

NREM sleep is composed of three stages [21]:

- N1: the first stage happend when a person first falls asleep, it last between one and seven minutes. The body has not fully relaxed and body and brain activities start to slow with periods of brief movements. If there are not external events a person can go into stage 2, during the nights an uninterrupted sleeper may not spend much more time in stage 1 as they move through further sleep cycles.

- N2: During second stage the body has a drop in temperature, muscles start to relax, and slowed breathing and heart rate. Simultaneously, brain activity slows, even they stil present some short bursts of activity and eye movement stops. This stage can last for 10 to 25 minutes during the first sleep cycle, and each N2 stage can become longer during the night. Jointly, half of sleep time is in N2 sleep.

- N3: The last stage of NREM or deep sleep is when the body is more relaxe: muscole tone, pulse and breathing rate decress. The brain activity during this period has an identifiable pattern of what are known as delta waves. For this reason, stage 3 may also be called delta sleep or slow-wave sleep (SWS). This stage is critical for restorative sleep, allowing for body to recovery and growth. Even though brain activity is reduced, there is evidence that deep sleep contributes to insightful thinking, creativity, and memory[22]. The duration of this stage is 20 to 40 minutes, overnight the other stages became shorter and more time gets spent in REM sleep instead.

REM sleep is characterised by brain activity near levels of awakeness, due to this at the same time the body experience atonia, which is a temporary paralysis of the muscles, with two exceptions: the eyes and the muscles that control breathing. Even though the eyes are closed, they can be seen moving quickly, which is how this stage gets its name. This sleep phase is essential to cognitive functions like memory, learning, and creativity and emotions [23]. REM sleep is known for the most vivid dreams, which is explained by the significant uptick in brain activity, this is why the body experience a temporary atonia as it prevents from acting out inside dreams. Dreams can occur in any sleep stage, but they are less common and intense in the NREM periods. The first REM stage could last only a few minutes, later stages can last for around an hour.

Both NREM and REM are important because they allow the brain and body to recuperate and develop. Sleepers who are frequently awoken during earlier stages, such as people with sleep apnea, may struggle to properly cycle into these deeper sleep stages. People with insomnia may not get enough total sleep to accumulate the needed time in each stage.

2.2 Respiratory Rate

2.3 Caridiorespiratory Polysomnography

The state-of-the-art to monitor physiological data during sleep is polysomnography [1] , which involves recording sleep stages, respiratory rate, heart and other parameters. However, this procedure is time-consuming, complicated, expensive, invasive for the patient and only sometimes available in hospitals. Focusing on one of the vital signs that characterise the different sleep stages is the respiratory rate which slowly becomes more stable going from the awake to the REM phase; this characterisation of the different stages gives the possibility to understand in which stage a person is based just on the respiratory signal.

2.4 Pressure Sensor Mattress

As said before, the state-of-art is a cumbersome device that requires cables attached to the users' bodies and often interferes with natural sleep. To avoid it, in literature is possible to find new instruments like video cameras which lead to privacy concerns, radar technology that could have problems in case there are more than one person inside the room or smartwatches that are also able to track respiratory rate but involve to have something on the arm that still can lead to discomfort.

2.5 Unobstrusive approaches

Chapter 3

Methods

3.1 Instruments

3.1.1 Sensomative

Figure 3.1: Sensomative over a bed

3.1.2 SensingTex

3.2 Nox A1, polysomnography

For this reason, this thesis aims to study the possibility to use an unobtrusive sensor placed over the usual mattress to retrieve respiratory rate without discomfort for the person lying down on it.

Figure 3.2: Sensomative over a bed

The sensors in this project appear like a thin mattress similar in size to a common one that can be easily installed with adjustable straps. In particular, the sensors are pressure-sensor textiles from *SensingTex®*; in our case, was used the Pressure Mat Dev Kit, that has a sensor area of 192 x 94 cm filled with 1056 sensors (hereafter also referred to as "Channels") sampled at 250hz with a total sensor area density of 4 sensors for $10cm^2$. The raw data extracted from the mattress can be viewed together to visually see the position of the person since the sensors are pressure sensors the different pressures exerted by the presence/absence of a body on it or by its parts are given as a number inside an interval. So it is possible to create a heat map (or heatmap) to show the variation in colour of the intensity of the pressure, which can create the shape of a person on the mattress.

Looking closer into signals of singles channels is possible to see a pattern that resembles a breathing rhythm, similar to the data that can be retrieved from the nasal pressure exerted on the cannula of cardiorespiratory polysomnography. This pattern was the key factor in deciding to use this sensor mattress (hereafter also referred to as "Sensor Mat" or "Mat"). In the laboratory where this project was carried on, was available a rocking bed (Somnomat) involved in a study of an intervention for sleep apnea, it was decided to address another question or if it is possible to retrieve the respiratory rate while the rocking bed is moving. The possibility of integrating SensingTex® with Somnomat could be significant to have a closer and faster intervention on sleep apnea.

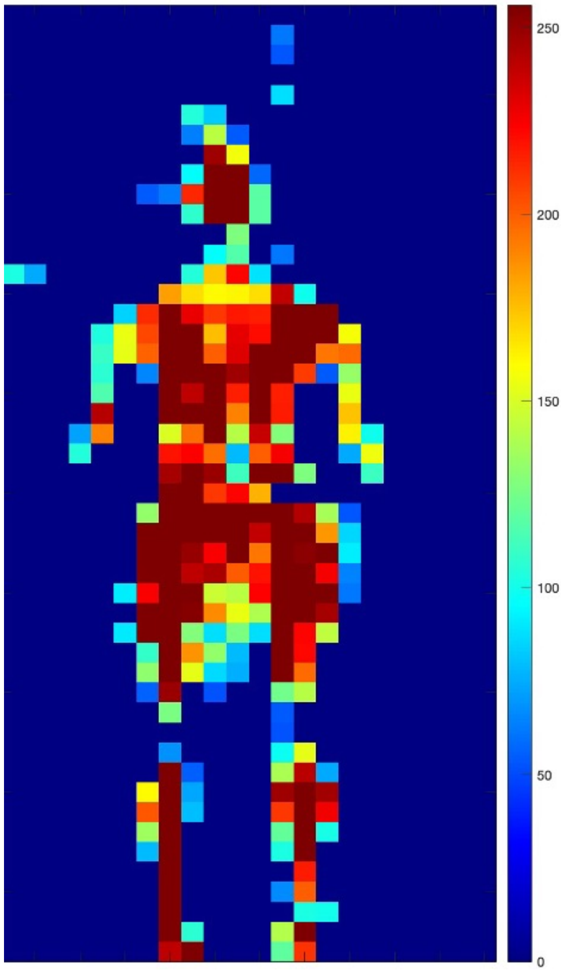

Figure 3.3: Sensomative over a bed

3.2.1 Somnomat

3.3 Preliminary Study of different approaches

3.4 Data Collection

3.4.1 Normal Bed

3.4.2 Rocking Bed

The primary objective of this study is to collect data to understand the feasibility of extracting breath rate from the mat; the second goal is to understand if the movement of the rocking bed could influence the signal. The participant involved was 6, half male and half female, between 20-30 years old, who were asked to lie on a standard mattress covered with the sensor mattresses in a specific position. After the 4 minutes, they were asked to turn around in another position following a specific pattern: supine, left side, prone, right side. Each participant wore a cardiorespiratory wireless and portable polysomnography device (Nox A1 PSG of Nox Medical) that was monitoring respiratory inductance plethysmography (RIP) which is a method of evaluating pulmonary ventilation by measuring the movement of the chest and abdominal wall, nasal pressure, pulse and heart rate with ECG. The study was divided into two phases:

The setting for the first phase involves the pressure mat over a standard bed. During the night and through the different sleep stages, the breath rate increase or decreases, so we decide to insert a similar variability in our data. We asked the participant to perform a set of five jumps before lying down, so they performed a total of 20 jumps. The setting for the second phase, since in this part we want to collect the data while the Somnomat is moving, we fixed the period for the movement of the bed at 4 seconds (15 periods in a minute) with an acceleration of 0.25 m/s^2. Also, for this phase, they have been asked to turn around following the specific pattern: supine, left side, prone, right side. This results in a recording of 32 minutes long for each participant divided into 4 minutes in each of the 4 positions with normal bed and with Somnomat.

Chapter 4

Data Analysis

4.1 Weighted and binary method

4.2 Pipeline

The total number of sensors is 1056, and consequently, the same number of signals from the mattress; this leads to the necessity of an algorithm to discriminate the ones from whom it is possible to extract valuable information about the respiratory rate of the person on the mattress. Many of these channels are stationary on a value; others present just interference from the mattress. From just a few sensors, it is possible to retrieve a respiratory pattern and extract the respiratory rate per minute (rpm). Therefore becomes necessary to design a metric that underlines these channels. The meaning of this metric must be interpreted as confidence expressed as the goodness of the signal in percentual.

The designed pipeline aims to replicate a semi-realtime analysis using the data obtained during the data collection. For this reason, it takes in input a sliding window of 60 seconds that is moving, for each position, through the 4-minute recording. The first step excludes those signals for the entire window length that are stationary or present only interference from the mattress. That interference appears as spikes but sometimes is present just in a percentage of the signal; the same could happen for stationarities that can be focused in just a subpart of the windows. In this case, the signal is not excluded and is assigned with confidence equal to the percentage of the signal that could have meaningful information. Another type is a noisy signal, excluded or weighted with a percentage of confidence with the same approach as the previous two.

After these preliminary analyses, the number of signals decreases drastically; as a result, we obtain signals that could contain valuable information. We assume to count as one breath the moment between inhale and exhale, which can also be considered a peak in the signal. At this point, most of the signals are still noisy. To be better analysed, we decide to denoise it (NON SO CHE TERMINE USARE) using two different kinds of approaches: Multiresolution analysis of the maximal overlap discrete wavelet transform (hereafter also referred to as "MODWTMRA"), and Savitz-Golay filter.

The MODWTMRA is based on wavelet analysis(MOWDT) that transforms the original signal into a time-frequency domain to be analysed and processed, the multiresolution analysis (MRA), which cuts the signal into components, can produce the original signal exactly when added back together. For our approach, we choose the Daubechies wavelet with two vanishing moments that better represent the breath signal present in our data, so we slide it across the entire signal to vary its location, where we multiply the wavelet and signal at each time step. The product of this multiplication gives us a coefficient for that wavelet scale at that time step. We then increase the wavelet scale and repeat the process to obtain the signal divided into different scales that combine to recreate the original signal. To obtain our denoised signal, we decided to extract and sum only a subset of this scale, which allowed us to reconstruct a clear signal where the peaks could be underlined and counted.

The Savitz-Golay filter, hereafter also referred to as "SG filter", is a filter used to "smooth out" a noisy signal whose frequency span (without noise) is significant. They are also called digital smoothing polynomial filters or least-squares smoothing filters. The idea of Savitzky-Golay filters is that each sample in the filtered sequence takes its direct neighbourhood of N neighbours and fits a polynomial to it. So, in the end, is possible to obtain a wave similar to the one in MODWTMRA form, which is likely to count the peaks, interpreted as the rpm.

The so reconstructed signals were given as input to a pick finder to select both peaks and valleys of the signal. We then exclude the channels with a signal with more than 30 rpm because the normal rpm during sleep is between 8-25 rpm, but since over 20 is predictive of cardiopulmonary arrest, we decide to keep only signals under 30 rpm.

The remaining signals are further analyzed in their structure: via Euclidean distance between the signal's valley and peaks should differ by up to $\pm 20\%$ from the preceding breath, and also via the distance between peaks and valleys on the time axis that should vary between ± 20 % from the previous breath. These two last analysis also gives a percentage of confidence that the signal recreates a breath pattern.

In the end, to calculate the rpm, the channels with the highest accuracy are taken into account, and the rpm is computed as the average of the number of peaks of the signals. It is also possible to visualize a heatmap to understand where the best channel is in respect of the body.

4.2.1 Excluding criteria

4.2.2 SNR ratio

4.2.3 Wavelet

theory

using in the thesis

4.2.4 Savitz-Golay filter

theory

using in the thesis

4.2.5 Subsequent analyses of the filtered signal

4.2.6 Result of the Pipeline (visual)

Chapter 5

Result

5.1 Evaluation Metrics

5.1.1 Mean absolute error (MAE)

Mean Absolute Error MAE is the average absolute error between actual and predicted values. It is a measure of model accuracy given on the same scale as the prediction target, it can be seen as the average error that the model's prediction has in comparison with their corresponding actual targets.

5.1.2 Mean absolute percentage error (MAPE)

Mean Absolute Percentage Error (MAPE) is the mean of all absolute percentage errors between the predicted and actual values. MAPE can be interpreted as the inverse of model accuracy, but more specifically as the average percentage difference between predictions and their intended targets in the database.

5.1.3 Root Mean Square Error (RMSE)

Root Mean Squared Error (RMSE) is the square root of the mean squared error between the predicted and actual values. RMSE is a weighted measure of model accuracy given on the same scale as the prediction target. It can be interpreted as the average error that the model's predictions have in comparison with the actual, with extra weight added to larger prediction errors.

Abbreviations:

- SGf = Savitzky–Golay filter
- resp rate = data extracted from Noxtural

- toolbox = toolbox for analyzing respiratory recordings

The study of the following papers was fundamental for the choice of metrics:

5.2 Result for Wavelet

5.3 Result for Savitz-Golay filter

5.4 Bland–Altman plot

5.5 Comparison between the two approaches (wavelet and SG filter)

5.6 Discussion performance on normal vs rocking bed

Chapter 6

Conclusion and future discussin

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