

# Respiratory Rate Estimation using a Pressure Sensor Mattress

**Relatore:** *Prof. Domenico Sorrenti*

**Correlatore:** *Prof. Cristiano Alessandro*

Tesi di Laurea Magistrale di:  
*Artemisia Sarteschi*  
*Matricola 829677*

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

<b>1</b>	<b>Introduction</b>	<b>3</b>
<b>2</b>	<b>State of Art</b>	<b>10</b>
2.1	Sleep Stages . . . . .	10
2.2	Respiratory System . . . . .	12
2.3	Polysomnography . . . . .	14
2.4	Pressure Sensor Mattress . . . . .	18
2.5	Unobtrusive approaches [DA FINIRE] . . . . .	18
<b>3</b>	<b>Methods</b>	<b>20</b>
3.1	Instruments . . . . .	20
3.1.1	Sensomatique . . . . .	20
3.1.2	SensingTex . . . . .	22
3.1.3	Nox A1, polysomnography . . . . .	25
3.1.4	Somnomat . . . . .	26
3.2	Preliminary Study of different approaches . . . . .	26
3.3	Data Collection . . . . .	26
3.3.1	Normal Bed . . . . .	26
3.3.2	Rocking Bed . . . . .	26
<b>4</b>	<b>Data Analysis</b>	<b>27</b>
4.1	Pipeline . . . . .	27
4.1.1	Weighted and binary method . . . . .	27
4.1.2	Excluding criteria . . . . .	29
4.1.3	Denoised Signals . . . . .	32
4.1.4	Wavelet . . . . .	32

4.1.5	Savitz-Golay filter . . . . .	36
4.1.6	Subsequent analyses of the filtered signal . . . . .	38
4.1.7	Compute the Respiratory Rate . . . . .	40
4.1.8	Result of the Pipeline (visual) . . . . .	40
<b>5</b>	<b>Result</b>	<b>42</b>
5.1	Evaluation Metrics . . . . .	42
5.1.1	Mean absolute error (MAE) . . . . .	42
5.1.2	Mean absolute percentage error (MAPE) . . . . .	42
5.1.3	Root Mean Square Error (RMSE) . . . . .	42
5.2	Result for Wavelet . . . . .	43
5.3	Result for Savitz-Golay filter . . . . .	43
5.4	Bland Altman plot . . . . .	43
5.5	Comparison between the two approaches (wavelet and SG filter) . .	43
5.6	Discussion performance on normal vs rocking bed . . . . .	43
<b>6</b>	<b>Conclusion and future discussin</b>	<b>44</b>

# Chapter 1

## Introduction

This work aims to investigate the possibility of estimating a patient's respiratory rate using a sensor pressure mattress and whether its usage with a rocking bed could hamper reaching this objective. Initially, the possibility of extracting the breath and heart rate from pressure sensors has been investigated using a dataset already available from previous studies. The work, therefore, will focus on respiratory rate. Since the necessary data are not available, data collection has been conducted using an innovative textile pressure sensor mattress and cardiorespiratory polysomnography as ground truth: the primary objective has been to collect data in order to understand the feasibility of determining breath rate from the mattress in case of stationary bed; the second goal has been to understand if the movement of the rocking bed could influence the measurement of the breathing rate. Then a pipeline has been created to analyse the extracted data: from each mattress sensor, the signals are processed to exclude the ones without meaningful information, such as those where the person is not present. Metrics have been designed to assess the confidence that a respiratory pattern could be extracted from a sensor. The selected 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 the number of breaths a person has in a minute could be counted. As a result, the respiration rate per minute of the person has been obtained and compared with the cardiopulmonary polysomnography to assess the error. The influence of the rocking bed on the mattress has been obtained by comparing the mattress's performance with the stationary bed. As a result of the

## *Chapter 1. Introduction*

---

pipeline, a heatmap, has been made available to visualise where the best sensors are positioned with respect to the body and 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 and heart rate, 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 presents 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 at which stage a person is just by focusing 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 data.

In this thesis, it has been 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 has been influenced by the availability, in the lab where this thesis has been 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 very thin and lead to negligible discomfort, but at the same time, can be used to track the respiratory rate and, depending on sensor area density and sampling frequency of the sensors, even heart rate.

In this project, at first, it has been decided to use pressure-sensor textile mattresses from *Sensomatic* [14] that have 14 x 28 sensor elements for a total sensor area of 40cm x 80cm that can cover a 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 have any data. 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 has been 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. The ability to estimate breath and heart rate could be helpful for that 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 or

by its parts on it.

So it has been possible to create a heatmap 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 has been necessary to conduct a data collection with two main objectives: the primary has been to collect data to understand the feasibility of extracting breath rate from the mat; the second goal has been to understand if the movement of the rocking bed could influence the signal. Six people participated in the data collection, 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 has been divided into two phases:

- The setting for the first phase involved 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 has been decided to insert a similar variability in the data. The participant had to perform a set of five jumps and then lie down in a specific position for four minutes. After this period, they had to stand up, repeat the five jumps and lie down again. The positions follow a pattern of supine, left side, prone, right side and with a total of twenty jumps.
- For the second phase, since the data needs to be collected while the Somnomat is moving, the period for the movement of the bed has been fixed at 4 seconds (15 periods in a minute) with an acceleration of  $0.25 \text{ m/s}^2$ . Also, in this phase, the participants were asked to turn around following the specific pattern: supine, left side, prone, right side and remain in that position for 4 minutes.

This resulted 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 where it has been possible to extract valuable information. Many of these channels are stationary on a value; others present just interference from the mattress. It has been 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 has been not excluded and has been 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 has been 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 has been 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 peak finder algorithm 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 has been 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 has been computed as the average of the number of peaks of the signals. A heatmap has also been 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[19].

# **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 [20].

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[21]. 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 comes back to NREM stage 1.

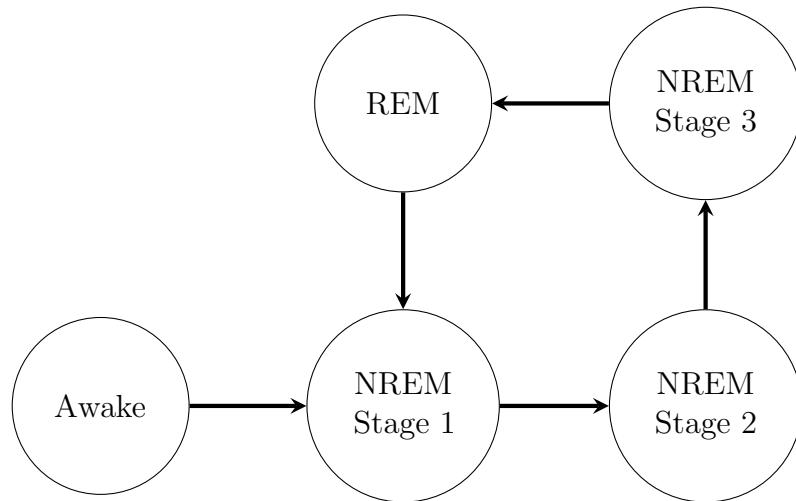


Figure 2.1: Sleep Cycles

NREM sleep is composed of three stages [22]:

- N1: the first stage happens 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 no external events a person can go into stage 2, during the night an uninterrupted sleeper may not spend much more time in stage 1 as they move through further sleep cycles.
- N2: During the second stage the body has a drop in temperature, muscles start to relax, and slowed breathing and heart rate. Simultaneously, brain activity slows, even if they still 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 the sleep time is in N2 sleep.

- N3: The last stage of NREM or deep sleep is when the body is more relaxed: muscle tone, pulse and breathing rate decrease. The brain activity during this period has an identifiable pattern of what is 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 the body to recover and grow. Even though brain activity is reduced, there is evidence that deep sleep contributes to insightful thinking, creativity, and memory[23]. 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 awokeness, 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, creativity and emotions [24]. REM sleep is known for the most vivid dreams, which is explained by the significant uptick in brain activity, this is why the body experiences 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, and 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 System

Respiration is the physiological process[25] of our body to exchange carbon dioxide ( $\text{CO}_2$ ) with oxygen ( $\text{O}_2$ ). This process has an external phase that consists of the exchange of gases with the environment and the transfer of gas across the blood-gas

barrier, and an internal phase that begins with the loading of oxygen onto the haemoglobin molecule and is followed by the transportation, delivery, and transfer of O<sub>2</sub> to the tissue. CO<sub>2</sub> is delivered back to the lung and ventilated out to the environment with the reversed process.

Normal tidal breathing is comprised of inspiratory and expiratory phases and occurs with the synchronous movement of the thorax and abdomen. In particular, during inhalation (Fig.2.2.a ), when we have the loading of O<sub>2</sub> into haemoglobin, the diaphragm moves downward toward the abdomen, and the rib muscles pull the ribs upward and outward making the chest cavity bigger and pulling air through the nose or mouth into the lungs. In exhalation,(Fig.2.2.b), when the CO<sub>2</sub> leave the body, the diaphragm moves upward and the chest wall muscles relax, causing the chest cavity to get smaller and push air out of the respiratory system through the nose or mouth.

This movement can be automatic or can be controlled voluntarily and it is adjusted based on the activity performed at that moment like coughing, sneezing, yawning, or speaking if a person is eating it is coordinated to chew and swallow to avoid choking. It could also increase as a response to physical activity, like running or climbing stairs[26].

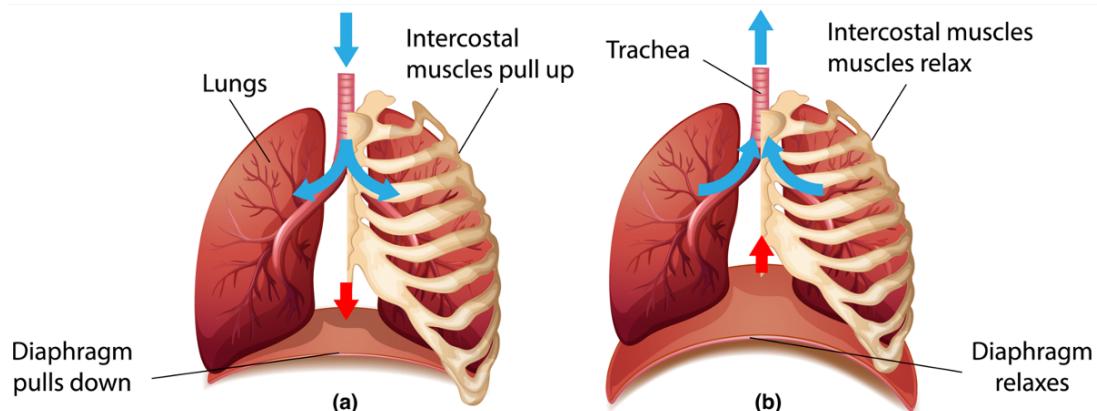


Figure 2.2: Respiratory sistem

The respiration and the tidal volume vary in response to metabolic demand or diseases such as infection. Patients with elevated respiratory rates, reflected by the magnitude of the metabolic demand, often have a more serious illness.

The respiratory rate per minute (rpm) varies by age, focusing on healthy adults the average respiratory rate at rest is between 12 and 15 breaths per minute[27].

Some studies found that a respiratory rate greater than 20 breaths per min was predictive of cardiopulmonary arrest within 72 hours and death within 30 days[28]; greater than 27 breaths per minute was predictive of cardiopulmonary arrest within 72 hours [29]; also a prospective observational study of acute medical admissions, patients with a composite outcome of cardiopulmonary arrest, intensive care admission, or death within 24 hours had a mean respiratory rate of 27[30].

## **2.3 Polysomnography**

Polysomnography (PSG) is the state-of-art to monitor physiological data during sleep and is used to diagnose sleep disorders [1, 31], such as obstructive sleep apnea (OSA), sleep-related hypoventilation/hypoxia, nocturnal seizure, or periodic limb movement disorder. PSG require a complex monitor system because it consists of several instruments that the patient has to wear, visible in Fig 2.3.

This procedure involves:

- electroencephalogram(EEG)[32]: this test measures electrical activity in the brain using electrodes, small metal discs with wires pasted on the scalp.
- electrooculogram(EOG)[33]: this test measures the corne-positive stain potential relative to the back of the eye, it is performed using skin electrodes outside the eye.
- electromyogram(EMG)[34]: this diagnostic procedure can reveal nerve dysfunction, muscle dysfunction or problem with nerve-to-muscle signal transmission since is used to assess the health of muscles and the nerve cells that control them.

- electrocardiogram(ECG)[35]: this test can be used to check the heart's rhythm and electrical activity.
- pulse oximetry[36]: this electronic device measures the saturation of oxygen carried in red blood cells, it is used to understand how well the oxygen is being sent to the part of the body furthest from the heart.
- cannula: this instrument via nasal pressure monitor the airflow and respiratory effort[37].
- respiratory inductance plethysmography(RIP)[38]: which is a method of evaluating pulmonary ventilation by measuring the movement of the chest and abdominal wall.

As part of PSG are also monitored limb movement, body position and as derived data sleep stages. After the test is completed a “score” analyzes the data by 30-second “epochs”

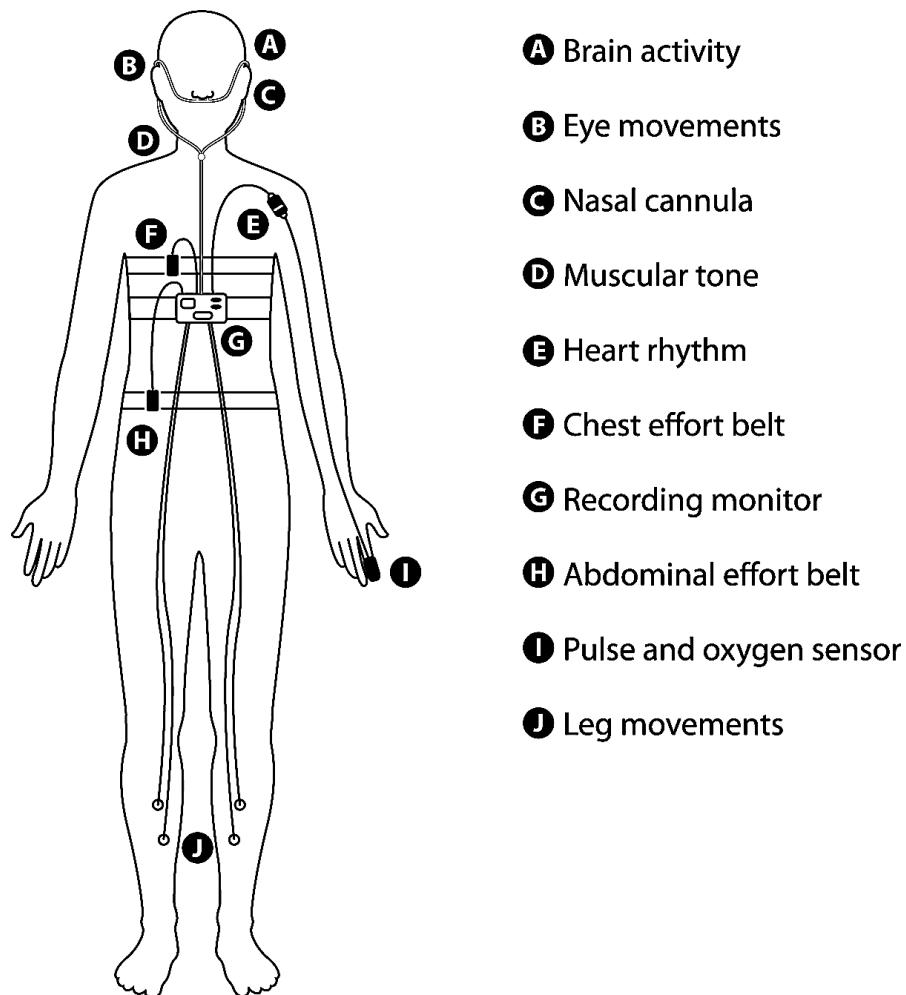


Figure 2.3: Polysomnography

## Cardiorespiratory 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.

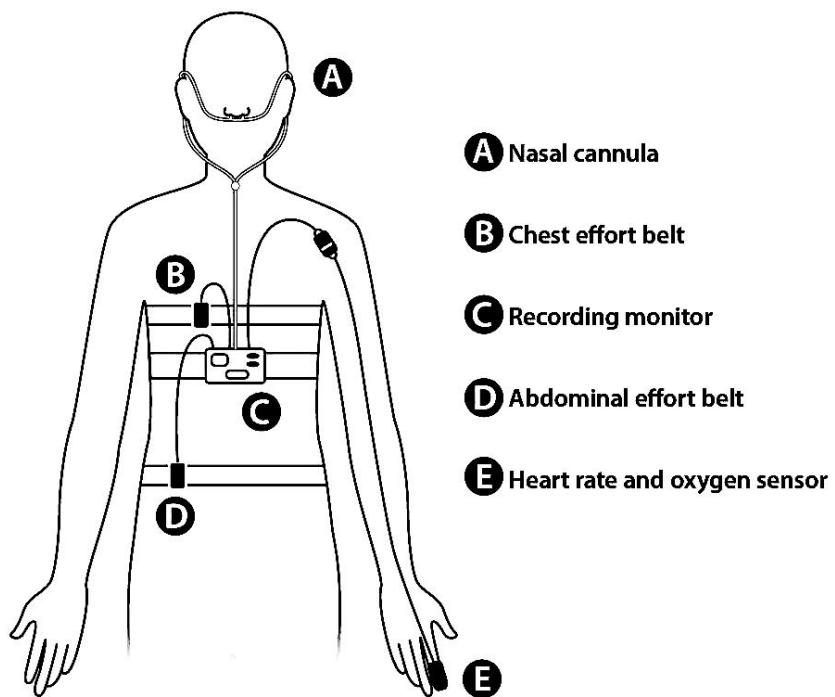


Figure 2.4: Cardiorespiratory Polysomnography

## 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 ]

Unobtrusive approaches [DA FINIRE] This section first explains the different sensor systems that can be used for classifying lying position. Then three different sensors and their characteristics are compared and the most suitable model is selected.

### 2.1 Sensors for Position Detection

There are many different approaches to determine the sleep position. It is of great interest that the measurement is non-intrusive. The gold standard for sleep monitoring is by using Polysomnography most often in combination with a camera setup. Polysomnography offers the possibility to detect the angular position of the test person by means of acceleration sensors. However, this is an intrusive measurement method. Sensor systems with a non-intrusive measurement approach used in research to date are based on the following sensor principles:

- Optical:** Using an infrared camera, high-contrast images can be generated even in darkness. As shown by [3], machine learning approaches are mostly used to classify the sleep position based on the camera images. However, the use of cameras in private areas such as the bed is often perceived as uncomfortable and thus the compliance of such systems may decrease.
- Radar:** By using the doppler effect, the breathing rate of a person lying still can be determined. [15] has shown that the sleep position can also be detected using radar technology. However, such systems reach their limits when there is more than one person in the room.
- Force Sensors:** Although force sensors are not contact-free, they are not noticed by the user due to their soft material properties and therefore also belong to the non-intrusive measurement methods. The resolution of such force sensors can vary greatly, ranging from a few pressure-sensing elements to over 1000 sensor elements distributed over an entire bed surface. In this work we only focus on classifying

the user's lying position by using force sensors. 3 2

# **Chapter 3**

## **Methods**

### **3.1 Instruments**

The project involved two textile sensor mattress: Sensomative 3.1.1 and SensingTex 3.1.2. The chosen instrument to collect the ground truth, cardiopulmonary polysomnography, is Nox A1, discuss in subsection 3.1.3.

#### **3.1.1 Sensomative**

Sensomative (Rothenburg, Switzerland)[14] is a start-up company, founded in 2015 in Switzerland, which produces textile pressure-measuring mats. These are based on the same principle as resistive touchpads. The sensor mass consists of two layers of conductive textile which are separated from each other by a spacer grid.

The sensor seen in Fig.3.1 is composed of 14 x 28 sensor elements with a sampling frequency of 50Hz. The sensing area is 40 cm x 80 cm and thus stretches almost over the entire width of a standard sized bed. Each sensor element is round and has a diameter of 2 cm. This mattress is commonly used to investigate position, since it is possible to have the pressure distribution (example visible in Fig.3.2). This mattress is used, for example, to control the sitting posture of office chairs and wheelchairs, analysing the pressure distribution is possible to discover posture errors and uneven loads.



Figure 3.1: Sensomative over a bed

However, its dimension of 40 cm x 80 cm does not allow to cover the entire mattress so it is crucial to find the correct position to detect the desirable data. In this project the aim is to estimate the respiration rate so the position chosen is under the lungs, so from just above shoulder to middle of abdomen.

This is to be able to track the movement of the thorax during respiration. The movement is extracted and evaluated from the single sensor channel of the mattress, for the inhalation phase it has been seen an increase of pressure and during exhalation phase a decreasing. Following a pattern [DATA] similar to nasal pressure or RIP Flow, recorder by the cardiopulmonary polysomnography 3.1.3.

The data for this mattress are a subsection of the entire data and come from a previous data collection of one of the supervisor of this thesis, Manu Fujis [19], that kindly made them available to inspect further the possibility to estimate respiratory and heart rate from this mattress and also to have the data to do a preliminary study of the general feasibility to extract this physiological data.

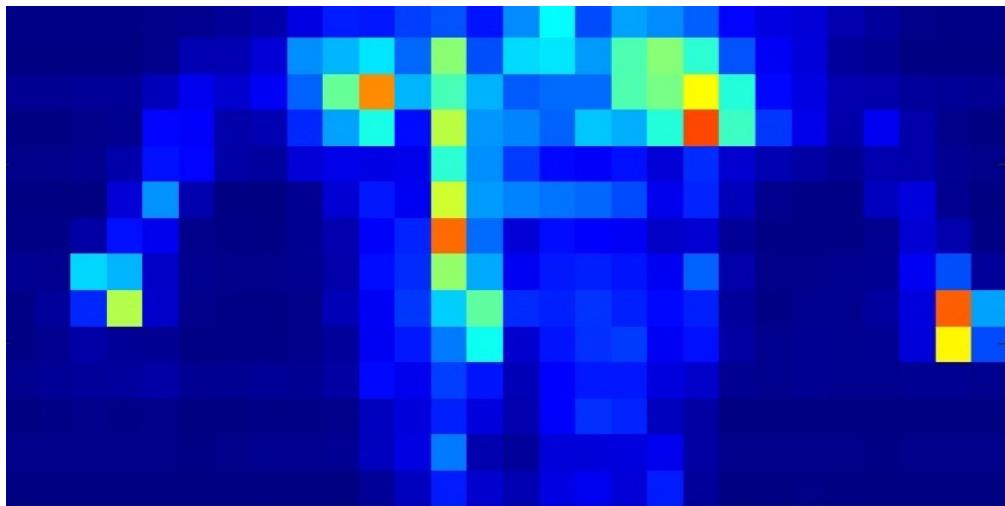


Figure 3.2: Sensomative data

### 3.1.2 SensingTex

The instrument on which this thesis is focalised then is SensigTex [15], visible in Fig 3.3 this is a commercially available textile pressure sensor mattress. The Mattress Mat Dev Kit that is capable to cover the entire area of a bed measuring 192cm x 94cm, with 48 x 22 sensor element and a sampling rate of 10Hz. This means that is five times slower than Sensomative (Chapter 3.1.1), but 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. The ability to estimate breath and heart rate could be helpful for that study and then this project focused on this possibility.



Figure 3.3: SensigTex over a bed

dati e cose

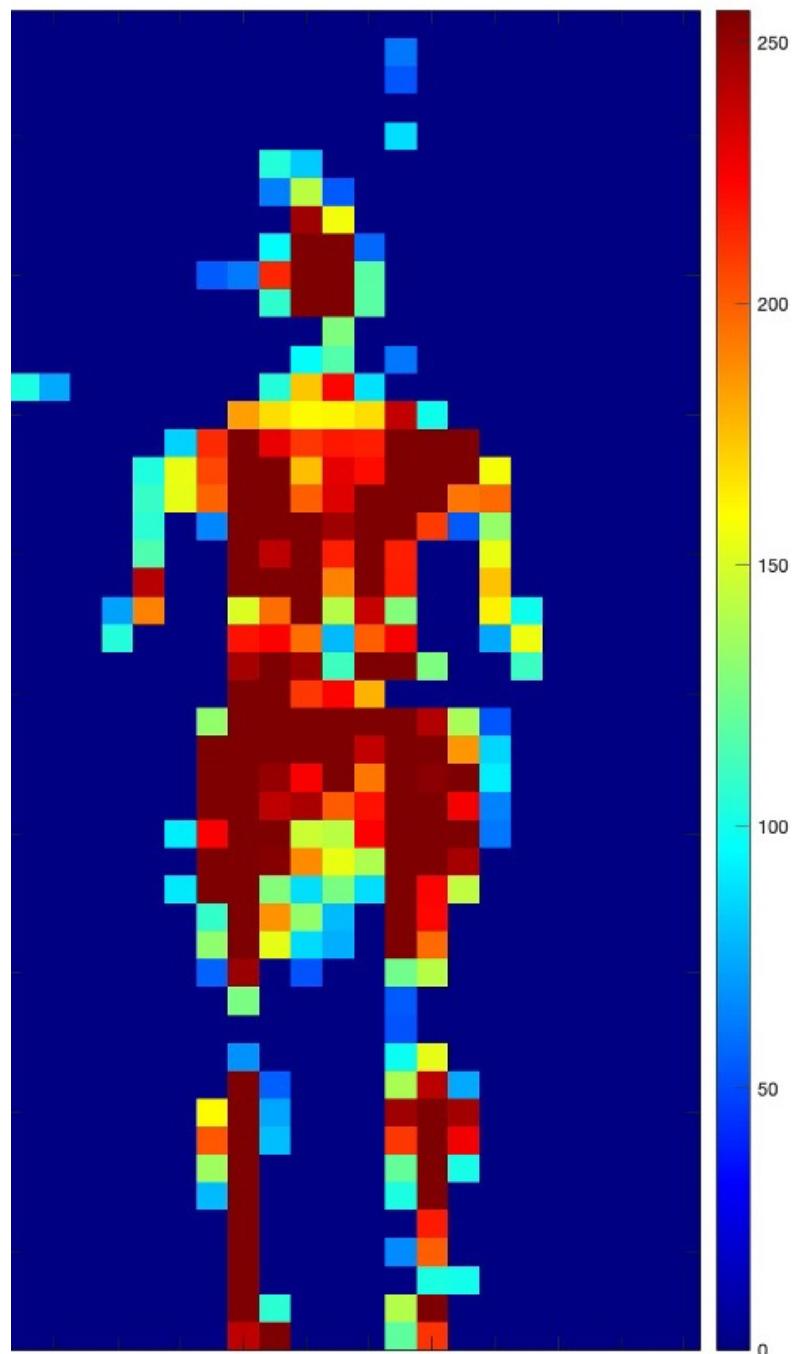


Figure 3.4: SensigTex Data

### 3.1.3 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.

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 *Sensing Tex®*; 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<sup>2</sup>. 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.

### 3.1.4 Somnomat

## 3.2 Preliminary Study of different approaches

## 3.3 Data Collection

### 3.3.1 Normal Bed

### 3.3.2 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  $0.25 \text{ m/s}^2$ . 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 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. A person's body can not cover the entire mattress and activate all sensors (hereafter referred to as "Channels") simultaneously. Many of these channels present a signal that is 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. In Figure 4.1 it is possible to visualize a scheme of the entire pipeline.

#### 4.1.1 Weighted and binary method

The metric has been designed as a confidence expressed as the goodness of the signal in percentual. To create this percentual has been decided to use create a series of criteria that each signal has to follow.

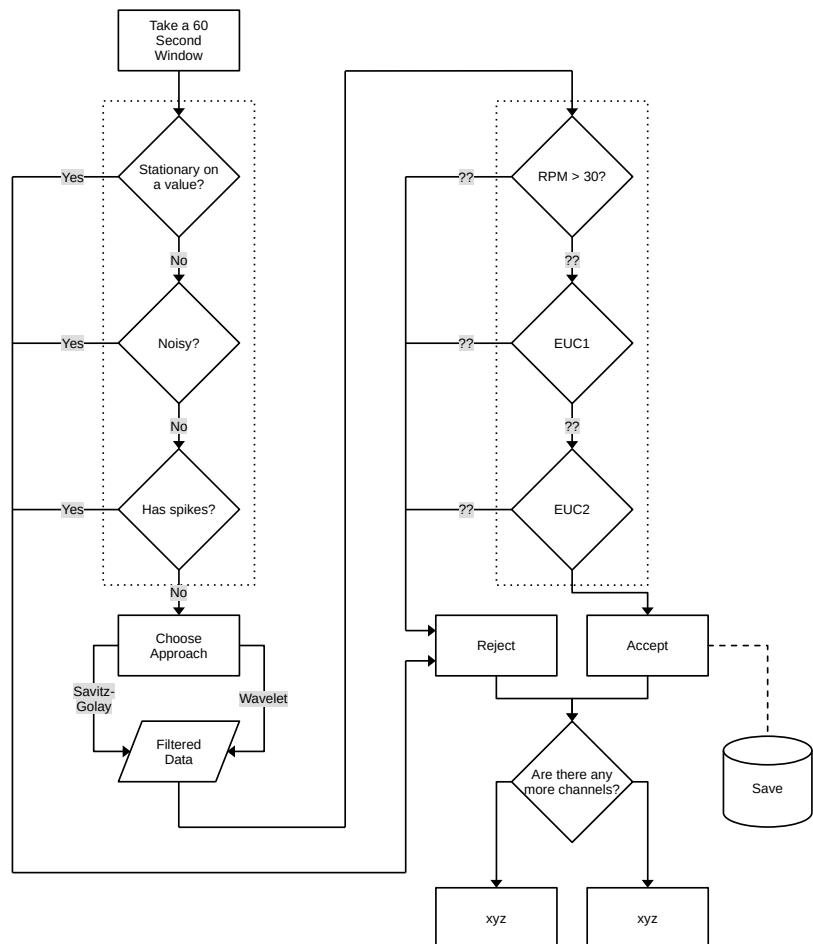


Figure 4.1: Pipeline

Some of these criteria, such as in Chapter 4.1.2, are excluding criteria, that are referred to particular phenomena that if present for the entire length lead to having an unusable signal. If one of these criteria is not passed the signal is not further analysed, but if they present the phenomena but not for the entire length, it has been decided to keep them and understand if in another part they could be meaningful. So they can express the percentage of the signal that follow those criteria or just that they present a possible meaningful part.

For this reason, it has been implemented a version of the pipeline where the criteria are binary, they can be passed or not (1 passed, 0 not passed), and a version where some criteria give as an answer the percentage of the channel that could contain valuable information (hereafter also referred to as "weighted method"). For each criterion, the following section will explain the different outputs of the metrics, in the case of binary or weighted approach. In both cases, the final confidence is the mean of percentages of each criterion.

### 4.1.2 Excluding criteria

The first step of this pipeline excludes those signals for the entire window length that is stationary on value, with small amplitude, or present only interference from the mattress. So channels do not have meaningful information, in case this behaviour is present in a part of the signal the output for the metric is different based on the binary or weighted approach. Only artefacts are an excluding only criterion.

#### Stationary signals on a value

A stationary signal on a value is defined as a signal that remains on the same value for the entire length of the window.

An example of the stationary signal on a value is shown in Figure4.2, in this case, the channel, for this window, is excluded and not further analysed. However, since it is used as a moving window it will take again into account in the next window and, if it presents a different behaviour, it maybe is considered. Nevertheless, If the channel presents only a part of the signal stationary on a value as in Figure4.3, the channel is given as a percentage of confidence, the percentage of the non-stationary on a value signal for weighted approach or 1 for binary if the non-stationary value

is more than 20%.

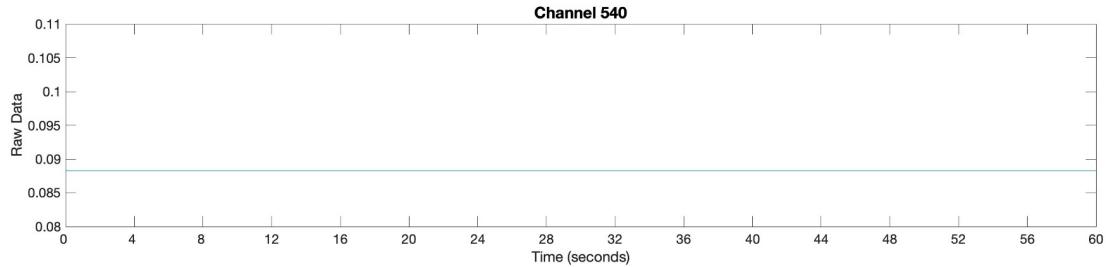


Figure 4.2: Stationary Signal

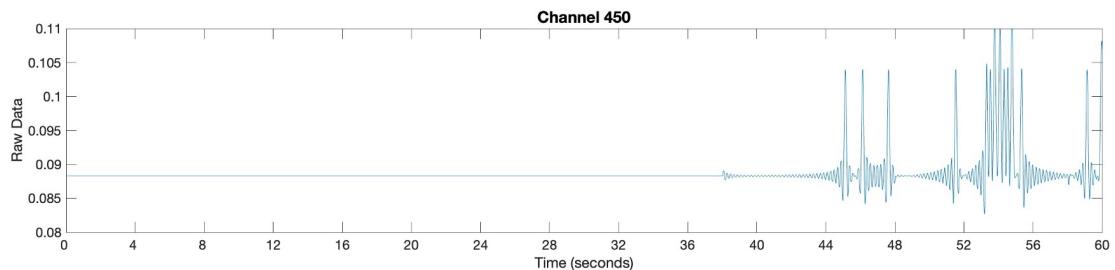


Figure 4.3: Spike Signal

### Signal with small amplitude

Several channels present a signal with a small amplitude, between [intervall], an example is visible in Figure 4.4, so after verifying if they are not stationary on a value case (Chapter 4.1.2), if the signal presents a small amplitude for the entire length of the window that could not represent a respiratory pattern is excluded. Otherwise, if part of the signal does not have a small amplitude: for the weighted approach, the percentage of confidence in output is equal to the percentage of a signal without a small amplitude.; for the binary approach, the criteria is passed if the small amplitude is present in less than 20% of the signal. As in the previous case, due to the moving window nature of the pipeline after the shift of 10 seconds, the channel could have a different behaviour and be further analysed.

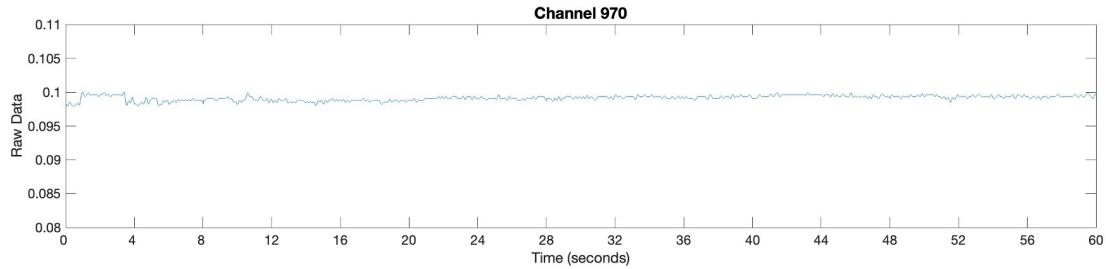


Figure 4.4: Noisy Signal

### Spikes Signals

The mattress can produce artefacts, that are visible in the channels as spikes as in Figure 4.5. Since these artefacts are visible also in channels that present a good respiratory pattern (Figure 4.6), after evaluating different thresholds it has been decided to accept the channel that has a percentage of spikes under 30%. In this case, both methods (binary and weighted), has the same output 100% or 1 in case of passed criteria, 0 otherwise.

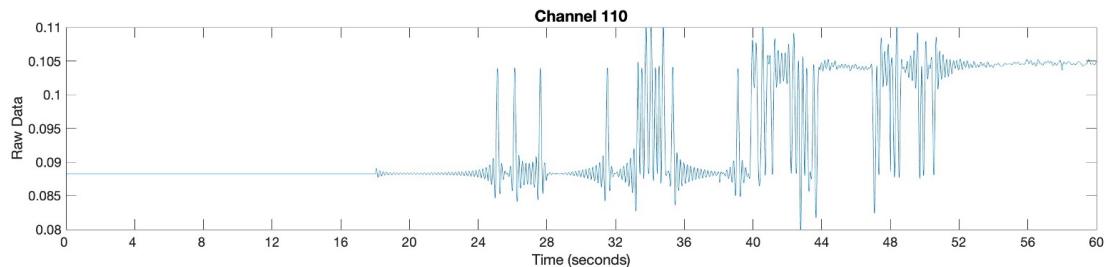


Figure 4.5: Stationary Signal

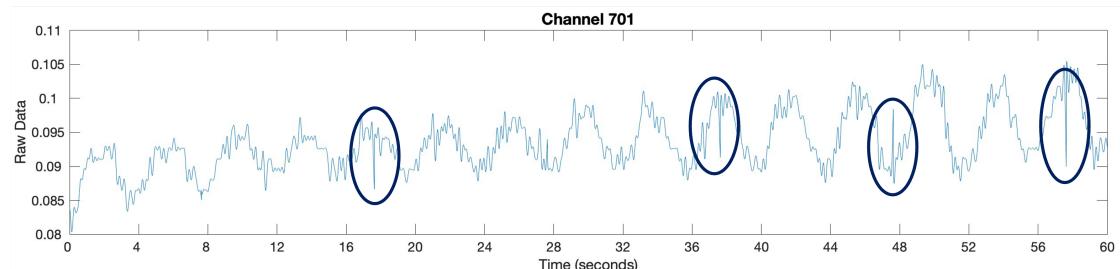


Figure 4.6: Good signal

### 4.1.3 Denoised Signals

After these preliminary analyses, the number of signals decreases drastically; as a result, has been obtained signals that could contain valuable information and the relative percentage of confidence. To be able to estimate the number of breaths it has been assumed 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 has been decided to filter them. In general, filtering consists of replacing each point of a signal with some combination of the signal values contained in a moving window centred at the point, on the assumption that nearby points measure nearly the same underlying value.

In this pipeline two different kinds of approaches are involved: Multiresolution analysis of the maximal overlap discrete wavelet transform (Chapter 4.1.4), and Savitz-Golay filter (Chapter 4.1.5). It is possible to choose which approach to use in the context of the data, in this project are both used rather than compare them.

### 4.1.4 Wavelet

The Multiresolution Overlap Discrete Wavelet Transform (hereafter also referred to as "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.

The input data of MOWDT are samples of a function  $f(x)$  evaluated at  $N$  time points, this function can be expressed as the linear combination of the scaling function  $\phi(x)$  and wavelet  $\psi(x)$  at varying scales and translations:

$$f(x) = \sum_{k=0}^{N-1} c_k 2^{-J_0/2} \phi(2^{-J_0}x - k) + \sum_{j=1}^{J_0} f_j(x)$$

where

$$f_j(x) = \sum_{k=0}^{N-1} d_{j,k} 2^{-J/2} \phi(2^{-J}x - k)$$

and  $J_0$  is the number of levels of wavelet decomposition calculated as  $\text{floor}(\log_2(N))$ . The first sum represents the first approximation of the signal and then the

successive scales. MODWT returns the  $N$  coefficients  $\{c_k\}$  and the  $(J_0 \times N)$  detail coefficients  $\{d_{j,k}\}$  of the expansion.

Since it has been used the MODWTMRA, instead of just MODWT, the returns are the projections of the function  $f(x)$  onto the various wavelet subspaces and final scaling space. That is, MODWTMRA returns

$$\sum_{k=0}^{N-1} c_k 2^{-J_0/2} \phi(2^{-J_0} x - k)$$

and the  $J_0$ -many  $\{f_j(x)\}$  evaluated at  $N$  time points. It is then obtained a projection of  $f(x)$  onto a different subspace, the original signal can be recovered by adding all the projections.

For our approach, we choose the Daubechies wavelet with two vanishing moments (Figure 4.7) that better represent the breath signal present in our data.

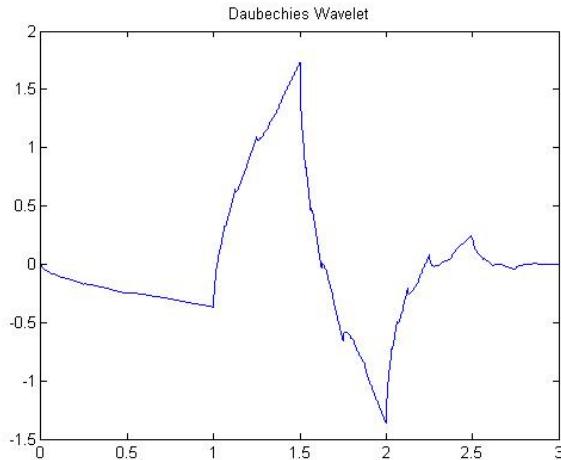


Figure 4.7: Daubechies wavelet with two vanishing moments

The decomposition of the signal of channel 404 (Figure 4.9), is shown in Figure 4.8. The raw data has been decomposed into 13 levels to obtain our denoised signal, it has been decided to sum only a subset of this scale, which allowed us to reconstruct a clear signal where the peaks could be underlined and counted.

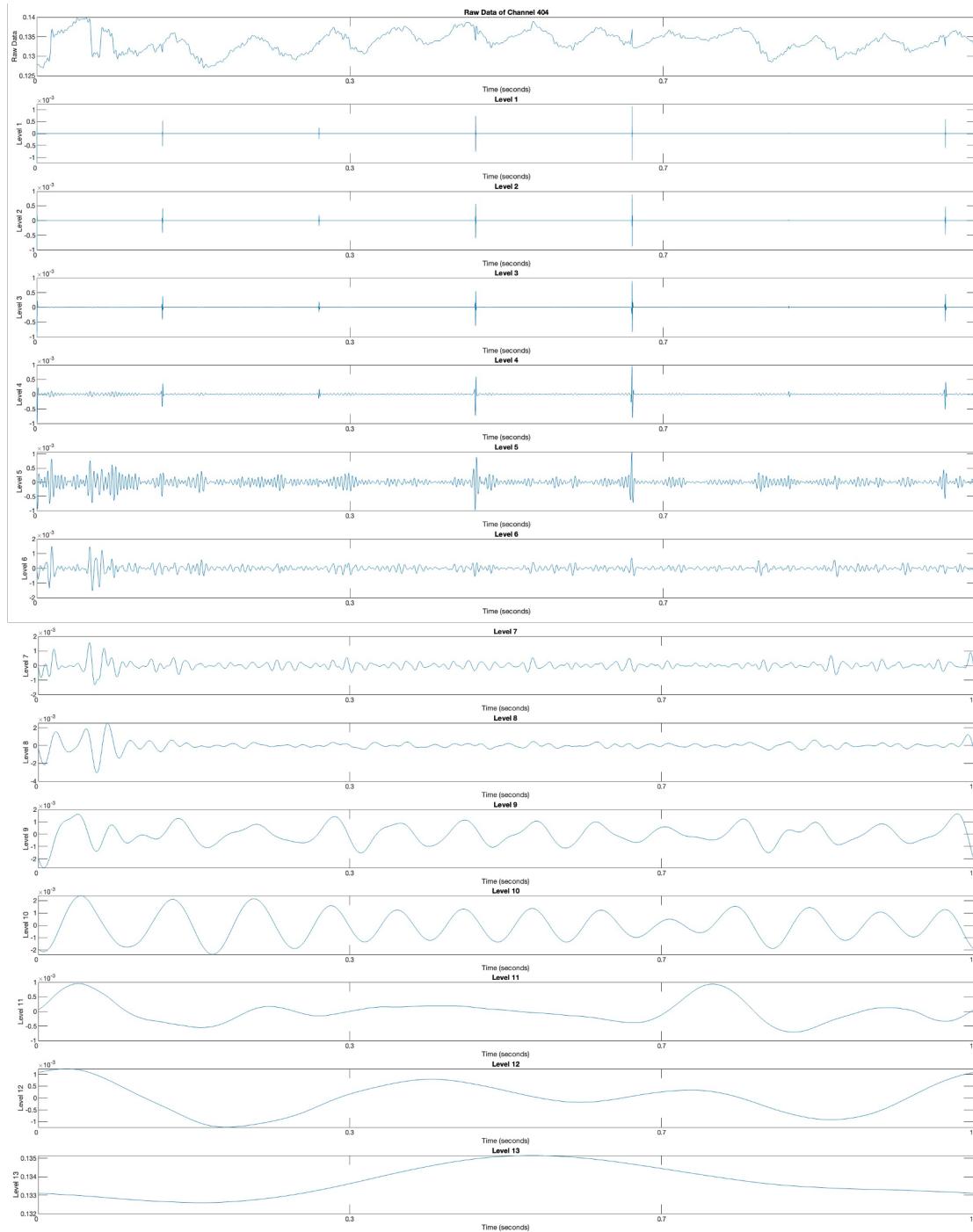


Figure 4.8: Stationary Signal

## Application in the Pipeline

To show the application of the MOWDTMRA in the pipeline, the signal in Figure 4.9, which has not been excluded by the criteria explained in Chapter 4.1.2 is taken as an example.

The signal is decomposed in 13 levels, as shown in Figure 4.8, and choose the levels that are added together to reconstruct the signal of breath rate, in the context of this project the 9<sup>th</sup> and 10<sup>th</sup> level. The levels are chosen to recreate a wave that best fits the original wave of the signal but excludes the noise. The resulting wave is given as input to a peak finder to point out the moment between inhaling and exhaling, visible as a peak in the wave and counted as a breath. Since the window is 60 seconds long, these peaks are interpreted as rpm. The resulting plot is shown in Figure 4.10.

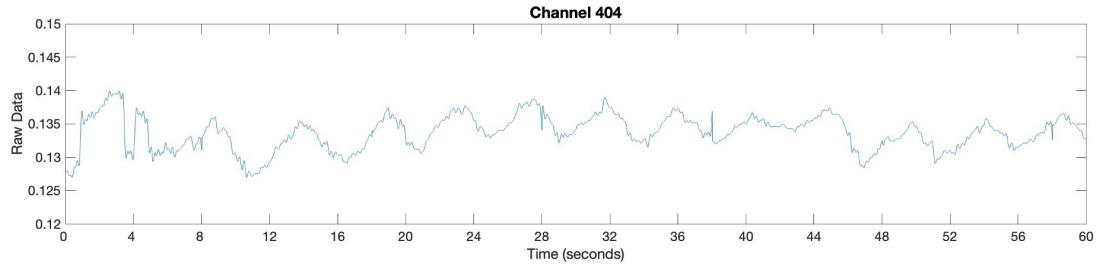


Figure 4.9: Raw Data of Channel 404

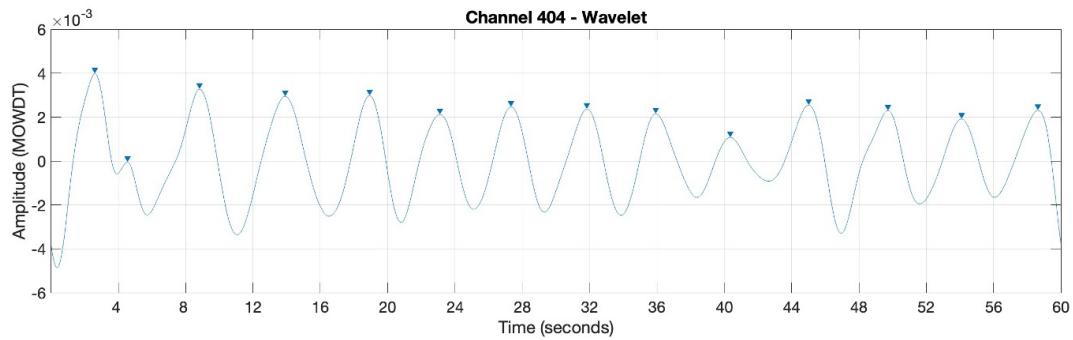


Figure 4.10: Channel 404 Filtered - with Wavelet

### 4.1.5 Savitz-Golay filter

The Savitz-Golay 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. Savitzky-Golay filters generalize the idea of filtering by replacing each point of a signal with a combination of the signal values contained in a moving window centred at the point, on the assumption that nearby points measure nearly the same underlying value, by least-squares fitting an  $n$ th-order polynomial through the signal values in the window and taking the calculated central point of the fitted polynomial curve as the new smoothed data point.

For a given point  $\mathbf{x}$  that has  $k$  points to the left and  $k$  points to the right, for a total window length of  $L = 2k + 1$ :

$$\mathbf{x} = \begin{bmatrix} 1 & -k & (-k)^2 & \cdots & (-k)^n \\ 1 & \vdots & \vdots & \ddots & \vdots \\ 1 & -2 & (-2)^2 & \cdots & (-2)^n \\ 1 & -2 & (-1)^2 & \cdots & (-1)^n \\ 1 & 0 & 0 & \cdots & 0 \\ 1 & 1 & 1^2 & \cdots & 1^n \\ 1 & 2 & 2^2 & \cdots & 2^n \\ 1 & \vdots & \vdots & \ddots & \vdots \\ 1 & k & k^2 & \cdots & k^n \end{bmatrix} \begin{bmatrix} a_0 \\ \vdots \\ a_n \end{bmatrix} \equiv \mathbf{H}\mathbf{a}$$

To find the Savitzky-Golay estimates, use the pseudoinverse of  $\mathbf{H}$  to compute  $\mathbf{a}$  and then premultiply by  $\mathbf{H}$

$$\hat{\mathbf{x}} = \mathbf{H}(\mathbf{H}^T\mathbf{H})^{-1}\mathbf{H}^T\mathbf{x} = \mathbf{B}\mathbf{x}$$

An example of how the Savitzky-Golay filter works is shown in Figure 4.11.

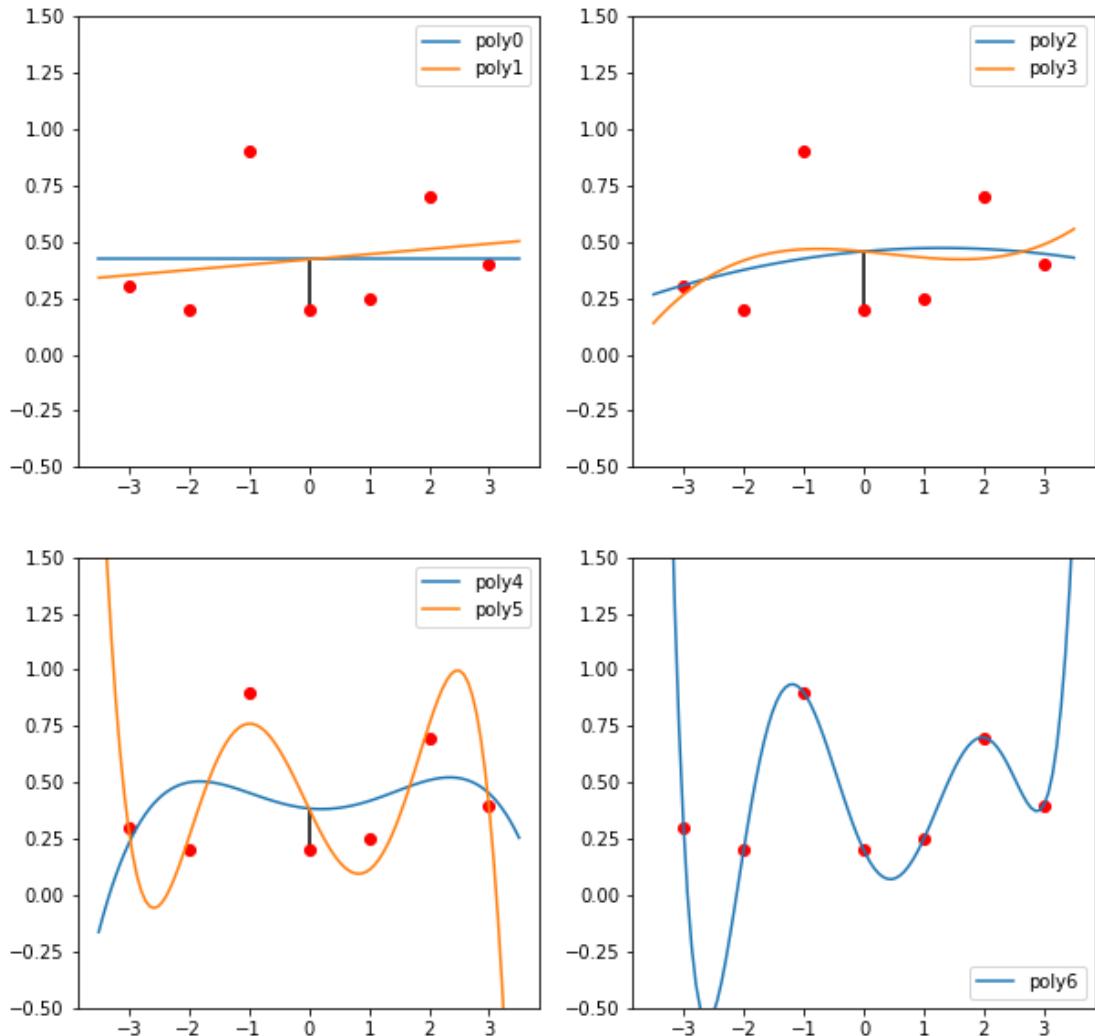


Figure 4.11: Savitzky-Golay filter

## Application in the Pipeline

To show the application of the Savitz-Golay filter in the pipeline, the signal in Figure 4.9, which has not been excluded by the criteria explained in Chapter 4.1.2 is taken as an example.

For the filter is chosen a 9th order polynomial, that allows for obtaining a wave similar to the one in MODWTMRA form. The resulting wave is given as input to a peak finder to point out the moment between inhaling and exhaling, visible as a peak in the wave and counted as a breath and since the window is 60 seconds long, these peaks are interpreted as rpm. The resulting plot is shown in Figure 4.12.

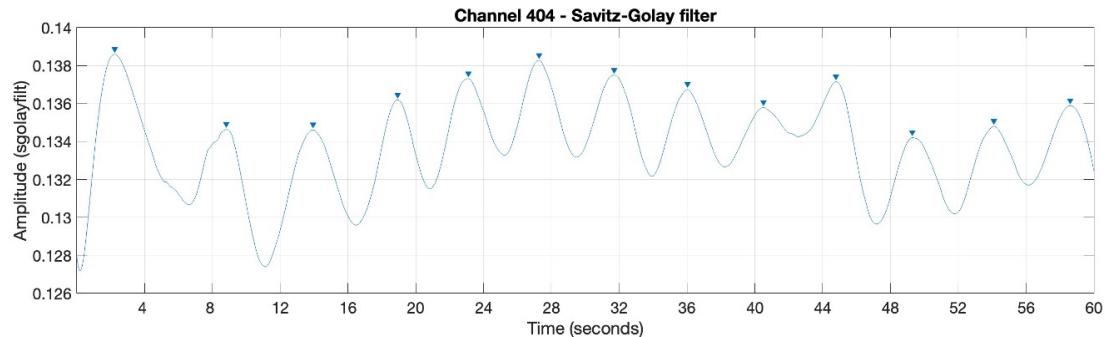


Figure 4.12: Channel 404 Filtered - with Savitz-Golay filter

### 4.1.6 Subsequent analyses of the filtered signal

The reconstructed signal with MODWTMRA or Savitzky–Golay filter is then further analysed, based on physiological information. This criterion is considered binary, so the weighted approach follows the scheme 1000% in case of passed and 0% otherwise.

#### Respiratory Rate over a Threshold

Since this project is a preliminary analysis of the feasibility to use pressure sensor mattresses to estimate a respiratory rate per minute (rpm). It has been decided to choose a threshold over which a respiratory rate of a person should not go , threshold is 30rpm because as discussed in Chapter 2.2 an rpm greater than 20

breaths per min was predictive of cardiopulmonary arrest within 72 hours and death within 30 days[28]; greater than 27 breaths per minute were predictive of cardiopulmonary arrest within 72 hours [29]. So the channels with a signal with more than 30 rpm, to admit a part of the error in our reconstruction and arrive at the limit given by literature between healthy and problematic and lead to a 0% percentage of confidence.

### Distance peaks valley

The signal is then given as input to an algorithm that points out the valley of the filtered signal and not only the peaks. The distance between valley and peaks is calculated with Euclidean distance, if the value between the signal's valley and peaks should differ inside the interval of  $\pm 20\%$  from the preceding breath the signal is considered to be meaningful and lead to a 100% percentage of confidence.

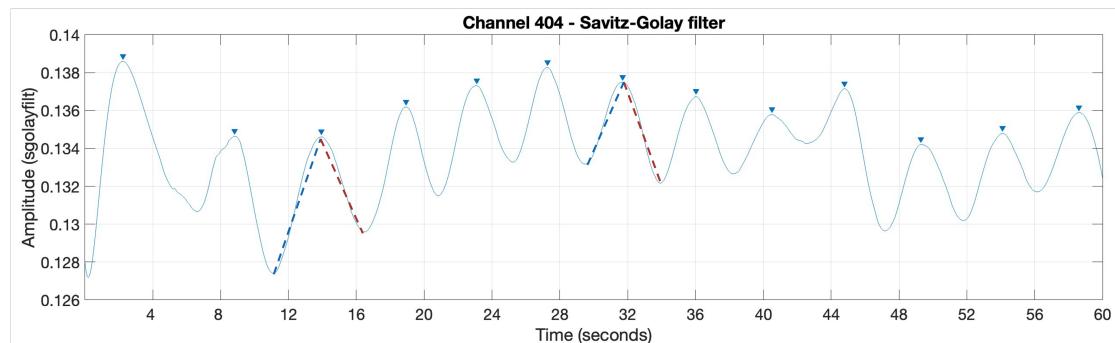


Figure 4.13: Euclidean

### Lenght of breath

The valley calculated in Chapter 4.1.6 are taken into account to calculate the distance between peaks and valleys on the time axis, to check the length of inspiration and expiratory phase. The difference should not vary between  $\pm 20\%$  from the previous breath. If the signal is in this range the channel is considered meaningful and leads to a 100% percentage of confidence.

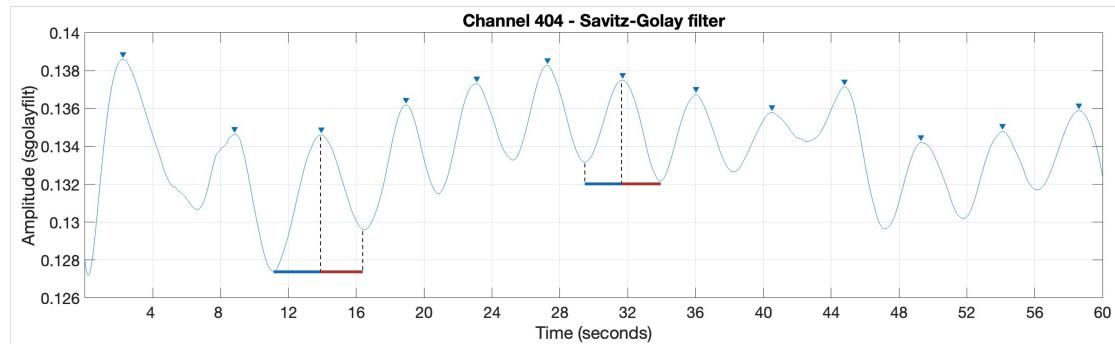


Figure 4.14: Length

### 4.1.7 Compute the Respiratory Rate

At the end of the pipeline, for each method: binary or weighted; for each approach: MODWTMRA and Savitzky–Golay filter, it has been saved the result of each of them. In case it is been decided to perform the approach and methods, there are a total of four combinations:

- MODWTMRA filter with a binary approach
- MODWTMRA filter with MODWTMRA approach
- Savitzky–Golay filter with a binary approach
- Savitzky–Golay filter with MODWTMRA approach

In the end, to calculate the rpm, the channels with the highest accuracy, which can be chosen at the beginning of the pipeline, are taken into account, and the rpm is computed as the average of the number of peaks of the signals.

### 4.1.8 Result of the Pipeline (visual)

As a result, the pipeline is also available a heatmap that allows visualizing where the channels with the highest percentage of confidence, understand where are in

respect of the body. Figure 4.15, is an example of the resulting heatmap, where the channels with the highest value are red and with lower are green up to blue when the channels have the 0% of representing a respiratory pattern.

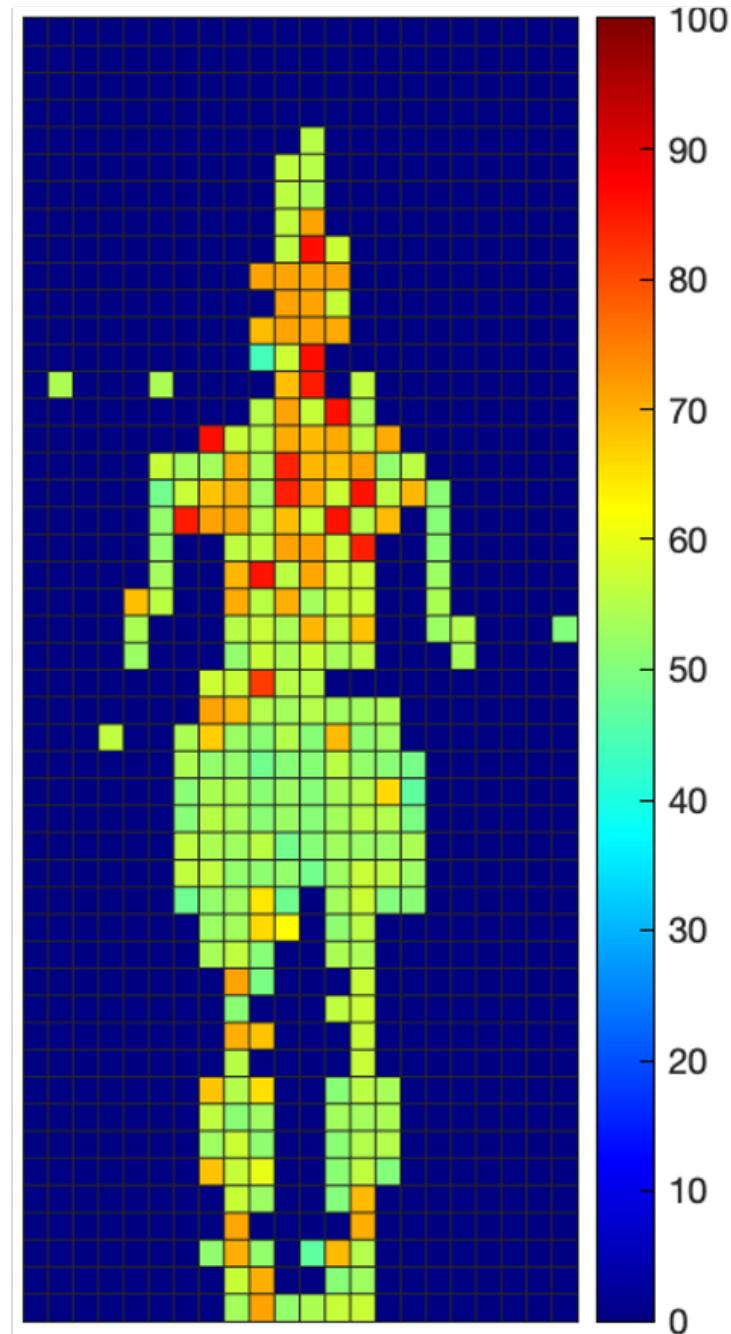


Figure 4.15: Heatmap of channels with the highest confidence

# 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**

# List of Tables

# List of Figures

2.1	Sleep Cycles . . . . .	11
2.2	Respiratory sistem . . . . .	13
2.3	Polysomnography . . . . .	16
2.4	Cardiorespiratory Polysomnography . . . . .	17
3.1	Sensomatic over a bed . . . . .	21
3.2	Sensomatic data . . . . .	22
3.3	SensigTex over a bed . . . . .	23
3.4	SensigTex Data . . . . .	24
4.1	Pipeline . . . . .	28
4.2	Stationary Signal . . . . .	30
4.3	Spike Signal . . . . .	30
4.4	Noisy Signal . . . . .	31
4.5	Stationary Signal . . . . .	31
4.6	Good signal . . . . .	31
4.7	Daubechies wavelet with two vanishing moments . . . . .	33
4.8	Stationary Signal . . . . .	34
4.9	Raw Data of Channel 404 . . . . .	35
4.10	Channel 404 Filtered - with Wavelet . . . . .	35
4.11	Savitzky-Golay filter . . . . .	37
4.12	Channel 404 Filtered - with Savitz-Golay filter . . . . .	38
4.13	Euclidean . . . . .	39
4.14	Length . . . . .	40
4.15	Heatmap of channels with the highest confidence . . . . .	41

# Bibliography

- [1] T. Penzel, J. W. Kantelhardt, R. P. Bartsch, M. Riedl, J. F. Kraemer, N. Wessel, C. Garcia, M. Glos, I. Fietze, and C. Schöbel, “Modulations of Heart Rate, ECG, and Cardio-Respiratory Coupling Observed in Polysomnography,” *Frontiers in physiology*, vol. 7, 10 2016.
- [2] J. M. Calleja, S. Esnaola, R. Rubio, and J. Durá, “Comparison of a cardiorespiratory device versus polysomnography for diagnosis of sleep apnoea,”
- [3] Z. Wang, Z. Sui, A. Zhang, R. Wang, Z. Zhang, F. Lin, J. Chen, and S. Gao, “A piezoresistive array based force sensing technique for sleeping posture and respiratory rate detection for sas patients,” *IEEE Sensors Journal*, pp. 1–1, 2021.
- [4] A. Gasmi, V. Augusto, P. A. Beaudet, J. Faucheu, C. Morin, X. Serpaggi, and F. Vassel, “Sleep stages classification using cardio-respiratory variables,” *IEEE International Conference on Automation Science and Engineering*, vol. 2020-August, pp. 1031–1036, 8 2020.
- [5] A. Pal, F. Martinez, M. A. Akey, R. S. Aysola, L. A. Henderson, A. Malhotra, and P. M. Macey, “Breathing rate variability in obstructive sleep apnea during wakefulness,” *Journal of clinical sleep medicine : JCSM : official publication of the American Academy of Sleep Medicine*, vol. 18, pp. 825–833, 3 2022.
- [6] D. Zito, D. Pepe, M. Mincica, F. Zito, A. Tognetti, A. Lanata, and D. De Rossi, “Soc cmos uwb pulse radar sensor for contactless respiratory rate monitoring,” *IEEE Transactions on Biomedical Circuits and Systems*, vol. 5, no. 6, pp. 503–510, 2011.

- [7] T. Lauteslager, M. Maslik, F. Siddiqui, S. Marfani, G. D. Leschziner, and A. J. Williams, “Validation of a new contactless and continuous respiratory rate monitoring device based on ultra-wideband radar technology,” *Sensors*, vol. 21, p. 4027, Jun 2021.
- [8] M. van Gastel, S. Stuijk, S. Overeem, J. P. van Dijk, M. M. van Gilst, and G. de Haan, “Camera-based vital signs monitoring during sleep – a proof of concept study,” *IEEE Journal of Biomedical and Health Informatics*, vol. 25, no. 5, pp. 1409–1418, 2021.
- [9] “Garmin.” <https://www.garmin.com>. visited on 20.02.2023.
- [10] E. D. Chinoy, J. A. Cuellar, K. E. Huwa, J. T. Jameson, C. H. Watson, S. C. Bessman, D. A. Hirsch, A. D. Cooper, S. P. A. Drummond, and R. R. Markwald, “Performance of seven consumer sleep-tracking devices compared with polysomnography,” *Sleep*, vol. 44, 12 2020.
- [11] M. Tenhunen, E. Elomaa, H. Sistonen, E. Rauhala, and S. L. Himanen, “Emfit movement sensor in evaluating nocturnal breathing,” *Respiratory Physiology & Neurobiology*, vol. 187, pp. 183–189, 6 2013.
- [12] “Emfit.” <https://www.emfit.com>. visited on 19.02.2023.
- [13] “Developing a robotic platform to improve the quality of sleep.” <https://www.news-medical.net/news/20220318/Developing-an-autonomous-robotic-platform-to-improve-the-quality-of-sleep.aspx>. visited on 12.02.2023.
- [14] “Sensomatique.” <https://sensomatique.com/en/>. visited on 13.10.2022.
- [15] “Sensing Tex.” <https://sensingtex.com/>. visited on 13.10.2022.
- [16] “Wireless and Portable Polysomnography Device: Nox A1 PSG System.” <https://noxmedical.com/products/nox-a1-psg-system/>. visited on 13.02.2023.
- [17] C. Chourpiliadis and A. Bhardwaj, “Physiology, Respiratory Rate,” *StatPearls*, 9 2022.

- [18] G. Yuan, N. A. Drost, and R. A. McIvor, “Respiratory rate and breathing pattern,” *McMaster Univ. Med. J.*, vol. 10, no. 1, pp. 23–25, 2013.
- [19] “Manuel Fujs – Sensory-Motor Systems Lab — ETH Zurich.” [https://sms.hest.ethz.ch/the-group/team/manuel\\_fujs.html](https://sms.hest.ethz.ch/the-group/team/manuel_fujs.html).
- [20] H. R. Colten and B. M. Altevogt, “Sleep Disorders and Sleep Deprivation: An Unmet Public Health Problem,” *Sleep Disorders and Sleep Deprivation: An Unmet Public Health Problem*, pp. 1–404, 10 2006.
- [21] A. K. Patel, V. Reddy, K. R. Shumway, and J. F. Araujo, “Physiology, Sleep Stages,” *StatPearls*, 9 2022.
- [22] “Stages of Sleep: What Happens in a Sleep Cycle — Sleep Foundation.” <https://www.sleepfoundation.org/stages-of-sleep#references-175856>. visited on 10.03.2023.
- [23] J. Yordanova, V. Kolev, U. Wagner, and R. Verleger, “Differential associations of early- and late-night sleep with functional brain states promoting insight to abstract task regularity,” *PloS one*, vol. 5, 2 2010.
- [24] B. Baran, E. F. Pace-Schott, C. Ericson, and R. M. Spencer, “Processing of Emotional Reactivity and Emotional Memory over Sleep,” *Journal of Neuroscience*, vol. 32, pp. 1035–1042, 1 2012.
- [25] C. J. Fisher, “Physiology of respiration,” *Emergency Medicine Clinics of North America*, vol. 1, no. 2, pp. 223–239, 1983.
- [26] C. A. Del Negro, G. D. Funk, and J. L. Feldman, “Breathing matters,” *Nature Reviews Neuroscience 2018 19:6*, vol. 19, pp. 351–367, 5 2018.
- [27] K. E. Barrett, S. Boitano, S. M. Barman, and H. L. Brooks, “Ganong’s review of medical physiology twenty,” p. 588, 2010.
- [28] W. Hong, A. Earnest, P. Sultana, Z. Koh, N. Shahidah, and M. E. H. Ong, “How accurate are vital signs in predicting clinical outcomes in critically ill emergency department patients,” *European Journal of Emergency Medicine*, vol. 20, pp. 27–32, 2 2013.

## BIBLIOGRAPHY

---

- [29] J. F. Fieselmann, M. S. Hendryx, C. M. Helms, and D. S. Wakefield, “Respiratory rate predicts cardiopulmonary arrest for internal medicine inpatients,” *Journal of General Internal Medicine*, vol. 8, pp. 354–360, 7 1993.
- [30] C. P. Subbe, R. G. Davies, E. Williams, P. Rutherford, and L. Gemmell, “Effect of introducing the Modified Early Warning score on clinical outcomes, cardiopulmonary arrests and intensive care utilisation in acute medical admissions\*,” *Anaesthesia*, vol. 58, pp. 797–802, 8 2003.
- [31] J. V. Rundo and R. Downey, “Chapter 25 - polysomnography,” in *Clinical Neurophysiology: Basis and Technical Aspects* (K. H. Levin and P. Chauvel, eds.), vol. 160 of *Handbook of Clinical Neurology*, pp. 381–392, Elsevier, 2019.
- [32] “Electroencephalogram (EEG) — Johns Hopkins Medicine.” <https://www.hopkinsmedicine.org/health/treatment-tests-and-therapies/electroencephalogram-eeg>. visited on 14.03.2023.
- [33] D. J. Creel, “Chapter 33 - the electrooculogram,” in *Clinical Neurophysiology: Basis and Technical Aspects* (K. H. Levin and P. Chauvel, eds.), vol. 160 of *Handbook of Clinical Neurology*, pp. 495–499, Elsevier, 2019.
- [34] “Electromyography (EMG) — Mayo Clinic.” <https://www.mayoclinic.org/tests-procedures/emg/about/pac-20393913>. visited on 13.03.2023.
- [35] “Electrocardiogram (ECG) - NHS.” visited on 17.03.2023.
- [36] “Pulse Oximetry — Johns Hopkins Medicine.” visited on 17.03.2023.
- [37] S. J. Heitman, R. S. Atkar, E. A. Hajduk, R. A. Wanner, and W. W. Flemons, “Validation of nasal pressure for the identification of apneas/hypopneas during sleep,” *American journal of respiratory and critical care medicine*, vol. 166, no. 3, pp. 386–391, 2002.
- [38] G. Brüllmann, K. Fritsch, R. Thurnheer, and K. E. Bloch, “Respiratory Monitoring by Inductive Plethysmography in Unrestrained Subjects Using Position Sensor-Adjusted Calibration,” *Respiration*, vol. 79, pp. 112–120, 12 2010.