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Dipartimento di Informatica, Sistemistica e Comunicazione

Corso di Laurea Magistrale in Informatica

Respiratory Rate Estimation using a Pressure Sensor Mattress

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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

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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. At first, it is focused on studying approaches to extract the breath and heart rate from pressure sensors using a dataset already available from previous studies. Then the work is focused on respiratory rate, and for this reason, it is conducted data collection 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. In the second part, a pipeline to analyse the extracted data is created: from each mattress sensor, the signals are processed to exclude the ones without meaningful information and designed metrics that asset 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-Golav 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 asset the error. The influence of the rocking bed on the mattress is obtained via the comparison of the mattress performance on 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.

Parte succosa

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 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. Even in its simplified version, cardiorespiratory polysomnography [2], where are involved just nose cannulas, chest belts and electrodes for an electrocardiogram (ECG) and does not track neurophysiological variables, the patient is subjected to physical discomfort throughout the night.

Breathing monitoring is also crucial because inside the population it is present higher percentage of sleep-related breathing disorders that can be studied and monitored with this instrument, like sleep apnoea/hypopnoea syndrome (SAS), 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, it is known that every phase and stage is characterised by different muscle tones, brain wave patterns, eye movements and heart and breathing rate alterations. So if focused on one of the vital signs that characterise the different sleep stages like respiratory rate which in particular slowly becomes more stable in the Non-Rapid Eye Movement (NREM) phase and increases during the Rapid Eye Movement (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.

Nowadays, it is possible to achieve this goal using different unobtrusive methods, like pressure sensor 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 hearth rate. For this reason, this thesis used two different kinds of pressure-sensor textiles mattresses:

The first, from *Sensomative* [3], with a higher sampling frequency and can cover a smaller area of a mattress, means that it needs to be positioned in a specific position and case the patient moves; it is possible not to have any more information. Previous studies have brought out the possibility of estimating breathing patterns and heart rates, so this thesis will explore this possibility.

The second, from SensingTex [4], with a lower sampling frequency, is less expensive and with a total area that covers all mattresses; in addition, it 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.

In the lab where this thesis is carried out is available a rocking bed (Somnomat) 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 the second mattress with the Somnomat is addressed.

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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.

State of Art

2.1 Sleep Stages

For this reason, it is nowadays acceptable to use cardiorespiratory polysomnography that does not track neurophysiological variables. This type of polysomnography involves a cannula, chest belts and electrodes for an electrocardiogram (ECG) but does not involve an electroencephalogram (EEG). Another reason why this kind of instrument is widely used is that inside the population, we have a higher percentage of sleep-related breathing disorders that can be studied and monitored with this instrument, like sleep apnoea/hypopnoea syndrome (SAS), 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. 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.

2.2 Respiratory Rate

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.

2.3 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.

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 without interfering with natural sleep. 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. For this reason, it is nowadays acceptable to use cardiorespiratory polysomnography that does not track neurophysiological variables. This type of polysomnography involves a cannula, chest belts and electrodes for an electrocardiogram (ECG) but does not involve an electroencephalogram (EEG).

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Instruments

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 SensingTex(R); in our case, was used the Pressure Mat Dev Kit, that has a sensor area of 192×94 cm filled with 1056 sensors (hereafter also referred to as "Channels") sampled at 250hz with a total sensor area density of 4 sensors for 10cm². 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.

Data Collection

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.

Data Analysis 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 $\pm 20\%$ 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.

Result

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Methods

3.1 Instruments

3.1.1 SensingTex

3.2 Nox A1, polysomnography

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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.

3.3 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:

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Data Analysis

4.1 Weighted and binary method

4.2 Pipeline

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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 Wavelet

theory

using in the thesis

4.2.3 Savitz-Golay filter

theory

using in the thesis

- 4.2.4 Subsequent analyses of the filtered signal
- 4.2.5 Result of the Pipeline (visual)

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

 \bullet toolbox = toolbox for analyzing respiratory recordings

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

Binary SGf	binary Waveleft	weighed SGf	weighed Waveleft	resp rate	toolbox
12.8529	14.8438	12.8333	14.7353	13.485	14
12.0909	14	12.0909	14	13.1443	13
11.9167	15.125	11.9167	15.125	12.5154	13
13.3333	13.8333	13.4	13.8333	13.117	13
12.2857	14.4286	12.2857	14.4286	13.6077	14
12.5833	15.5	12.3077	15.5	13.8993	15
11.6	15	11.6	15	12.0681	15
9	11	9	11	11.4768	15
11.1667	14.3333	10.625	14.3333	12.1549	14
14.5	17	14.5	17	12.8028	13
14.3333	15	14.3333	15	12.3275	14
11.625	14.1667	11.625	14.1667	10.9785	11
13.125	15.125	13.125	15.125	11.8441	11
13.1111	14.7778	13.1111	14.7778	12.6438	10
13.3077	15	13.3077	15	11.5351	11
13.6667	14	13.6667	14	11.99	10
11.5	14.2222	11.5	14.2222	11.9868	10
11.4545	14.1667	11.2308	13.8571	11.7824	10

Table 5.1: Breath per minutes for each approach, result from Noxtural and toolbox - Back position still mattress

- 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

	Binary SGf	binary Waveleft	weighed SGf	weighed Waveleft
RMSE resp	1.2517	2.4000	1.3043	2.3806
RMSE tool	2.4481	2.9583	2.4960	2.9332
MAE resp	1.0796	2.1731	1.1422	2.1499
MAE tool	2.0256	2.4179	2.0633	2.3947
MAPE resp	8.7793	17.8104	9.2789	17.6198
MAPE tool	16.3648	21.3416	16.5938	21.1266

Table 5.2: Metrics to evaluate the participant in back position with still mattress

binary Waveleft	weighed SGf	weighed Waveleft	resp rate	toolbox
15.5	14.1667	15.5	10.7609	8
16.1333	14.0667	16.1333	11.3077	6
15.3333	13.5	15.3333	13.1449	8
14.9474	13.75	14.9474	11.3366	8
15.1	12.9474	15.1	12.7314	6
15.6364	12.4615	15.6364	11.8892	9
14.6923	12.6875	14.6923	11.42	9
15.2222	13.6364	15.2222	13.0092	10
15.1667	14.6154	15.1667	13.2539	12
14.6667	13.1429	14.6667	11.6391	11
15	14.375	15	12.2165	11
14.75	15.4286	14.75	11.9216	12
15	14.6667	15	11.3091	13
14.625	14.8182	14.625	13.8905	12
15.6154	14.5385	15.6154	11.3344	13
15	13.9167	14.8182	11.4474	11
15.1765	13.8824	15.1765	11.6675	11
14.6154	13.8667	14.6154	13.4799	12
	15.5 16.1333 15.3333 14.9474 15.1 15.6364 14.6923 15.2222 15.1667 14.6667 15 14.75 15 14.625 15.6154 15 15.1765	15.5 14.1667 16.1333 14.0667 15.3333 13.5 14.9474 13.75 15.1 12.9474 15.6364 12.4615 14.6923 12.6875 15.2222 13.6364 15.1667 14.6154 14.6667 13.1429 15 14.375 14.75 15.4286 15 14.6667 14.625 14.8182 15.6154 14.5385 15 13.9167 15.1765 13.8824	15.5 14.1667 15.5 16.1333 14.0667 16.1333 15.3333 13.5 15.3333 14.9474 13.75 14.9474 15.1 12.9474 15.1 15.6364 12.4615 15.6364 14.6923 12.6875 14.6923 15.2222 13.6364 15.2222 15.1667 14.6154 15.1667 14.6667 13.1429 14.6667 15 14.375 15 14.75 15.4286 14.75 15 14.6667 15 14.625 14.8182 14.625 15.6154 14.5385 15.6154 15 13.9167 14.8182 15.1765 13.8824 15.1765	$\begin{array}{cccccccccccccccccccccccccccccccccccc$

Table 5.3: Breath per minutes for each approach, result from Noxtural and toolbox - Back position moving mattress

	Binary SGf	binary Waveleft	weighed SGf	weighed Waveleft
RMSE resp	2.1340	3.2155	2.1365	3.2047
RMSE tool	4.2192	5.5405	4.2259	5.5334
MAE resp	1.8091	3.0234	1.8171	3.0133
MAE tool	3.7957	5.0100	3.8037	4.9999
MAPE resp	15.5385	25.7324	15.6004	25.6442
MAPE tool	44.4027	58.5849	44.4823	58.4931

Table 5.4: Metrics to evaluate the participant in back position with moving mattress

Binary SGf	binary Waveleft	weighed SGf	weighed Waveleft	resp rate	toolbox
13.375	14.6364	13.375	14.6364	11.2045	10
13.6667	15	13.6667	15	12.7397	11
14	16	13.5	15.25	13.0613	12
14.3571	14.2	14.3571	14.2	12.2669	12
14	19	14	19	12.1628	13
12.8	15	12.6667	14.5	13.6039	13
11.8	14.2222	11.8	14.2222	13.1398	13
14	15.6667	14	15.6667	11.5445	14
13.8333	14.7	13.8333	14.7	10.77	11
13.8889	15.8571	13.8889	15.8571	14.2216	12
13.0833	15.5556	13.0833	15.5556	13.1656	12
14.1111	16.5714	13.7	16.5714	12.9764	12
14.2	15	14.2	15	10.9055	13
13.25	15.125	13.25	15.125	13.2294	11
12.7692	15.7143	12.2857	15.5	12.8524	11
13.9167	15.2	13.6154	15.2	11.3824	13
13	14.6	13	14.6	13.5579	11
13	15.8889	13	15.8889	11.6069	12

Table 5.5: Breath per minutes for each approach, result from Noxtural and toolbox - Left position still mattress

	Binary SGf	binary Waveleft	weighed SGf	weighed Waveleft
RMSE resp	1.7158	3.2950	1.6774	3.2425
RMSE tool	1.8743	3.6582	1.7959	3.5879
MAE resp	1.3922	2.4545	1.3591	2.8934
MAE tool	1.6584	2.9748	1.5716	3.3596
MAPE resp	11.8278	24.62	11.5556	24.0041
MAPE tool	14.4565	29.3635	13.7188	28.6943

Table 5.6: Metrics to evaluate the participant in left position with still mattress

Binary SGf	binary Waveleft	weighed SGf	weighed Waveleft	resp rate	toolbox
13.6875	15.0625	13.6875	15.0625	13.6613	11
14.5294	15.5556	14.5294	15.5556	11.4545	8
14.5	15.8824	14.5	15.8824	12.3288	6
13.9444	16.1176	13.9444	16.1176	10.8865	7
14.0455	15.2083	14.0455	15.2083	11.4082	9
13.44	15.3214	13.4231	15.3103	12.2589	6
13.9091	15.4583	13.9091	15.4583	13.7093	8
14	15.4375	14	15.4375	12.7019	10
14.4	15.2353	14.4	15.2353	13.3305	12
14.5769	15.5556	14.5769	15.5556	13.7078	13
14.7	15.2143	14.7	15.2143	13.5674	14
14.8421	15.2	14.8421	15.1538	11.8694	15
14.85	15.5556	14.85	15.5556	13.4086	15
15.5	14.75	15.5	14.75	13.9781	15
13.6667	14.5	13.6667	14.5	12.4749	13
13.8571	15.25	13.8571	15.25	12.4049	13
13.375	14.625	13.7	14.7273	13.4108	12
13.75	14.2857	14.1667	14.3333	13.4716	14

Table 5.7: Breath per minutes for each approach, result from Noxtural and toolbox - Left position moving mattress

	Binary SGf	binary Waveleft	weighed SGf	weighed Waveleft
RMSE resp	1.7259	2.7236	1.7331	2.7232
RMSE tool	4.1782	5.2608	4.1829	5.2627
MAE resp	1.4229	2.4545	1.4592	2.4597
MAE tool	3.0939	4.0953	3.1063	4.1004
MAPE resp	11.6751	19.9605	11.9443	19.9959
MAPE tool	39.3516	50.7242	39.4533	50.7631

Table 5.8: Metrics to evaluate the participant in left position with moving mattress

Binary SGf	binary Waveleft	weighed SGf	weighed Waveleft	resp rate	toolbox
15.3	15.7	15.3	15.7	11.5949	14
14.8125	15.7333	14.8125	15.7333	11.1628	16
14.2	16.1	14.2	16.1	11.0005	16
14.8889	15.6667	14.8889	15.6667	10.4762	15
13.5	15.25	13.5	15.25	10.4723	15
13.8571	14.5714	13.8571	14.5714	9.5345	14
13.8571	15.5714	13.8571	15.5714	9.5467	13
14.3	15.875	14.3	15.875	13.5758	14
15	14	15	14	11.1779	14
13.9	14.375	13.9	14.375	9.5345	14
13.8667	14.4667	13.8667	14.4667	9.5841	15
13.8235	14.5	13.8235	14.5	11.8196	14
14.0714	14.2143	14.0714	14.2143	11.8153	10
13	13.9474	13	13.9474	9.5223	8
14.4828	15.037	14.4828	15.037	10.8508	8
14.3793	14.931	14.3793	14.931	10.8876	7
13.7	15.25	13.7	15.25	10.9705	7
14.1818	15.3333	14.1818	15.3333	11.237	6

Table 5.9: Breath per minutes for each approach, result from Noxtural and toolbox - Belly position still mattress

	Binary SGf	binary Waveleft	weighed SGf	weighed Waveleft
RMSE resp	3.4835	4.3281	3.4835	4.3281
RMSE tool	3.8127	4.3162	3.8127	4.3162
MAE resp	3.3532	4.2088	3.3532	4.2088
MAE tool	2.6347	2.8957	2.6347	2.8957
MAPE resp	31.914	39.9076	31.914	39.9076
MAPE tool	32.6041	36.5982	32.6041	36.5982

Table 5.10: Metrics to evaluate the participant in belly position with moving mattress $\frac{1}{2}$

Binary SGf	binary Waveleft	weighed SGf	weighed Waveleft	resp rate	toolbox
14.6667	16	14.6667	16	12.6296	9
14.0455	15.3684	14.0455	15.3684	14.168	12
14.3478	15.6818	14.3478	15.6818	13.2588	13
14.381	15.5	14.3636	15.4286	13.8107	13
13.7143	15.8333	13.7143	15.8333	13.485	13
14	16	14	16	12.6052	14
16.1	16	16.1	16	11.0417	17
15.7647	15.7059	15.7647	15.7059	12.9088	17
14.7333	15.5333	14.7333	15.5333	13.0502	16
14.6	16.3333	14.6	16.3333	11.1723	17
14.3846	14.5625	14.3846	14.5625	14.6869	16
13.8889	15.5294	13.8889	15.5294	11.3484	13
13.7273	14.7273	13.7273	14.7273	13.0399	11
13.8235	14.7778	13.8235	14.7778	9.5487	10
13.6111	15.4444	13.6111	15.4444	11.7918	11
13.2667	14.9286	13.2667	14.9286	12.8182	8
12.9375	15.8333	12.9375	15.8333	9.5345	8
13.3	14.619	13.3	14.619	9.5416	13

Table 5.11: Breath per minutes for each approach, result from Noxtural and toolbox - Belly position moving mattress

	Binary SGf	binary Waveleft	weighed SGf	weighed Waveleft
RMSE resp	2.4778	3.6110	2.4775	3.6092
RMSE tool	2.7357	3.8447	2.7352	3.8422
MAE resp	1.9835	3.2326	1.9825	3.2286
MAE tool	2.1737	3.2326	2.1728	3.1687
MAPE resp	17.8949	28.5509	17.8879	28.5221
MAPE tool	20.8138	30.5337	20.8064	30.5032

Table 5.12: Metrics to evaluate the participant in belly position with moving mattress

Binary SGf	binary Waveleft	weighed SGf	weighed Waveleft	resp rate	toolbox
14.5714	16.1667	14.5714	16.1667	12.4771	17
14	17.75	14	17.75	13.0835	17
16.5	16.5	16.5	16.5	14.3858	17
14.7778	15.25	14.7778	15.25	12.7261	17
14.5	15.8333	14.5	15.8333	13.4867	17
13.9333	15	13.9333	15	12.9816	16
15	15.2353	15	15.2353	14.0566	15
13.7692	15.1667	13.7692	15.1667	12.038	16
14	15.5	14	15.5	11.4923	12
14.6	13	14.6	13	11.9625	10
15	13.3333	14.3333	13.5	11.0151	9
16.5	15.5	16.5	15.5	11.9016	10
14.5	14.3333	14.5	14.3333	11.4255	10
12.2857	13.8333	12.2857	13.8333	12.5227	7
12.8333	15.2	12.8333	15.2	11.5945	10
12.3333	14.0909	12.3333	14.0909	13.4141	8
12.3636	14.5	12.4783	14.4286	13.5282	11
13.4286	15.2308	12.875	15.2308	12.9839	11

Table 5.13: Breath per minutes for each approach, result from Noxtural and toolbox - Right position still mattress

	Binary SGf	binary Waveleft	weighed SGf	weighed Waveleft
RMSE resp	2.1572	2.7087	2.0877	2.7156
RMSE tool	3.5099	3.6341	3.4330	3.6416
MAE resp	1.8214	2.4638	1.7593	2.4691
MAE tool	3.0440	2.9772	2.9826	2.9825
MAPE resp	14.9336	19.9146	14.4066	19.9693
MAPE tool	28.9627	30.229	28.3295	30.2958

Table 5.14: Metrics to evaluate the participant in right position with still mattress

Binary SGf	binary Waveleft	weighed SGf	weighed Waveleft	resp rate	toolbox
14.2273	15.8095	14.2273	15.8095	11.7955	10
13.625	15.2105	13.5294	15.1	11.9185	9
13.9524	15.5652	13.9524	15.5652	11.8639	8
15	15.8261	14.7826	15.8261	12.28	10
14.5652	15.6667	14.375	15.6667	12.0136	10
13.625	15.1176	13.625	15.1176	12.8838	10
14.4118	15.3571	14.4118	15.3571	11.5695	12
14.72	15	14.72	14.8696	12.8922	13
14.85	15.1176	14.85	15.1176	11.587	14
15	15.2857	15	15.2857	11.2449	14
15.2917	15.3333	15.28	15.3333	11.7082	15
15.5294	15.3684	15.5	15.35	13.9497	15
14.5625	15.6154	14.5294	15.4286	11.6145	16
14.8182	15.4286	14.8182	15.4286	13.9913	16
14.7333	15.2727	14.7333	15.2727	11.6172	16
14.8824	15.3	14.8824	15.3	13.3257	16
14.75	15.1667	14.75	15.1667	13.5179	16
15.0667	14.9231	15.0667	14.9286	13.5767	16

Table 5.15: Breath per minutes for each approach, result from Noxtural and toolbox - Right position moving mattress

	Binary SGf	binary Waveleft	weighed SGf	weighed Waveleft
RMSE resp	2.4083	3.1106	2.3763	3.0860
RMSE tool	2.9182	3.6785	2.8737	3.6656
MAE resp	2.2367	2.9452	2.2046	2.9208
MAE tool	2.3325	2.7195	2.3041	2.7152
MAPE resp	18.5442	24.4008	18.2803	24.1986
MAPE tool	22.0502	26.6562	21.761	26.5883

Table 5.16: Metrics to evaluate the participant in right position with moving mattress

Conclusion and future discussin

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