Respiratory Rate Estimation via Sensor Pressure Mattress: a single subject evaluation

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Abstract
Respiratory rate monitoring is crucial for many diseases, correlated or not with the lungs, like chronic bronchitis and obstructive apnea, and it is central for the study of sleep stages. Notably for sleep-related diseases, it is important to develop a non-intrusive method to monitor the respiratory rate. This single-subject study investigates the feasibility of using a pressure-sensor mattress to avoid cables and discomfort, for both the patient and the staff, typical of other devices. A pressure-sensor mattress generates a 2D matrix of pressure signals: in this work, those signals are analysed by a processing pipeline to detect the best signal in the matrix. The aim is to find the best signal to exploit for measuring the respiratory rate. Criteria have been identified, resulting in a metric to order the signals. The respiratory rate is then determined by another processing pipeline acting on the stream from this specific sensor. Many complications made the data gathered from all but one subject unusable: nevertheless, the results show that the approach is effective and the respiratory rate can reliably be measured with a commercial pressure-sensor mattress.

Keywords
Respiratory rate measurement, Non-contact sensors, Pressure-sensor mattress

1. Introduction

The main physiological process that our body performs is respiration, namely the output of carbon dioxide (CO_2), and the input of oxygen (O_2). This process can be divided into two main phases: the external phase, which consists of the exchange of gases with the environment, i.e., the transfer of gases across the blood-gas barrier, and the internal phase, which begins from the loading of oxygen onto the haemoglobin molecule and is followed by the transportation, delivery, and transfer of O_2 to the tissues. CO_2 is delivered back to the lung and ventilated out to the environment with the reverse process. Normal tidal breathing occurs with the synchronous movement of the thorax and abdomen, this movement can be automatic or can be controlled voluntarily and it is adjusted based on the activity performed in that moment. In healthy adults the average respiratory rate at rest is between 12 and 15 breaths per minute [1].

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The monitoring of the respiratory rate is also crucial for sleep studies, as breathing affects physical and mental wellness. In fact, people spend about one-third of their lifetime sleeping, and sleeping affects almost every tissue and system in the body, from the brain, heart, and lungs, to metabolism, immune function, mood, and disease resistance. During sleep, two different types of investigation related to respiration can be conducted, based on the objective of the study and/or the illness of the patient: sleep stages and breath-related disorders. 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, heart and breathing rate alterations characterise every phase and stage. REM sleep is characterised by brain activity near to awakeness level, while the body experiences atonia, which is a temporary paralysis of the muscles, with two exceptions: the eyes and the muscles that control breathing. The respiratory rate is quite stable in the NREM phase, and increases during the REM phase, therefore allowing to detect at which sleep stage a person is just by focusing on the respiratory rate [2]. For breath-related disorders, respiratory rate monitoring is also crucial: it is the way to detect sleep apnoea/hypopnoea syndrome (SAS) [3], where the individuals experience a collapse of the airway in deeper sleep states or sleep-related hypoventilation/hypoxia; the ability to monitor respiration rate allows for a faster intervention in severe cases.

Currently, the state-of-the-art in sleep monitoring technology is polysomnography [4], which involves recording sleep stages, respiratory and heart rate, and other parameters. However, this procedure is time-consuming, complicated, expensive, and invasive besides being often unavailable in hospitals. The aim of this study is to investigate a device to monitor the respiratory rate without causing discomfort to the patient and obstructing intervention from the hospital staff. Nowadays, it is possible to achieve this goal using different unobtrusive methods, such as radar technology [5]. The limitation of the radar-based approach lies in the fact that the presence of another person in the room, in a hospital condition, e.g., a nurse or a doctor, or even the presence of fans, could be a source of noise for the radar, which could lead to incorrect predictions; radars can also be disturbed by the movement of the patient [6]. Another possibility is to use video cameras, also equipped with infrared filters [7]; though this approach seems promising, it has strong privacy concerns. It is also possible to rely on smartwatches, like Garmin [8], which can estimate multiple vital signs with good precision [9], 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. Another approach is under-mattress ballistocardiography-based sensors [10], like Emfit [11]; such devices, in case of multiple people in the bed, can cover only half bed and a wrong posture can lead to inaccurate data.

A trend in the field of unobtrusive sensors to track vital signs is the use of bed pressure sensors as a solution to the concerns of the previous solutions. Today there are different pressure sensors, based on different technologies like, e.g., piezo-electric, inductive and capacitive. In the literature we can find pneumatic sensor arrays [12] that can be placed between the mattress and bed base; micro bend optic fibre sensors mattresses [13], that are small, lightweight and affordable and also immune to electromagnetic and radio frequency interference, and can be placed directly under body's person; air-mattress [14], that measure changes in air pressure inside single air comportment of an inflatable mattress. A particular type of pressure mattress available nowadays is the textile pressure sensor mattress, based on piezoelectric sensors. These mattresses appear like thin mats that can be installed over the standard mattress; this means that they lead to negligible discomfort. At the same time, they would allow to monitoring of both physiological and positional data without interfering with the patient's comfort and, depending on the density of the sensors, the sampling, and the signal-to-noise ratio, even the heart rate. In this work, we investigate the use of such sensors.

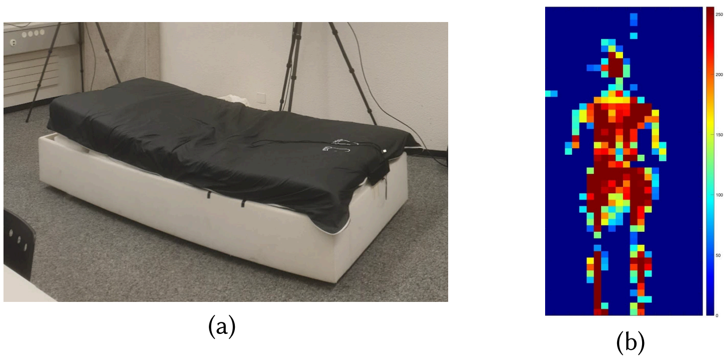
In Section 2 the paper firstly provides an overall view of the instruments involved and the data collection conducted, whose data are then analysed using the pipeline described in Section 3; the results are discussed in Section 4. Finally, conclusions are drawn in Section 5.

2. Instrument and Methods

In this study, we used a sensor-pressure mattress from Sensingtex, in combination with the gold standard for sleep studies, i.e., cardiopulmonary polysomnography, as ground truth. The implementation of the pipeline here described is publicly available as a Matlab package with source code (including simulations), documentation, and a tutorial at https://github.com/Aisimetra/The-Art-e-of-Respiratory-Rate.

2.1. Pressure Sensor Mattress

The SensingTex mattress [15], visible in Figure 1, is a commercially available textile pressure sensor mattress. The mattress covers the entire area of a bed, measuring 192cm x 94cm, with a 48 x 22 sensor elements matrix, and a sampling rate of 10Hz; the output is given in the range [0,256]. This device is already installed in a hospital ward at the University of Bern for studying movement disorders during sleep in patients with Parkinson's disease. It was made available thanks to O. Gnarra [16]. This mattress has already been used in the context of the classification of the posture of the human body during sleep. As shown in Figure 1.b, it is possible to retrieve the posture of the person by analysing the signal produced by the sensors activated by the body weight. Looking in the time domain at the signals of each single channel, it is possible to see a pattern that resembles a breathing rhythm. Furthermore, those signals are similar to the data that can be retrieved from the nasal pressure exerted on the cannula of the cardiorespiratory polysomnography. The exploitation of such similarity is the starting point of our study.



(a) (b)

Figure 1: (a) : The Sensingtex mattress on a bed (b) : The output when a person is lying on it

2.2. Cardiopulmonary polysomnography

Cardiopulmonary polysomnography is an accepted method to monitor physiological data during sleep and to track the breath behaviour of a subject. During this work, we conducted a data collection, as explained later on, and a ground truth was needed, to validate the estimated respiratory rate. We used a Nox A1 by NoxMedical [17], a wireless and portable polysomnography device, to record the following physiological parameters: nasal pressure, and nasal flow via nasal cannula, chest and abdomen movement with Respiratory Inductance Plethysmography (RIP), output as a single value called *RIP Flow*, Heart Rate (ECG), SpO_2 and Pulse with a fingertip sensor. We decided to use the Resp Rate (respiratory rate) value as ground truth, which is based on the RIP Flow data. However, we also used nasal pressure and nasal flow to quickly visually check the output of our pipeline.

2.3. Data Collection

The data collection has been conducted due to the lack of Sensingtex raw data at the time this work was conducted. The objective was to collect data in order to understand the feasibility of extracting the breath rate from the mattress, and to study the limits of this instrument. Since the laboratory had available a rocking bed, used for other studies concerning sleep, this bed has also been used in the data collection, with the aim of understanding if its movement could influence the quality of the estimated respiratory rate.

On the basis of the habits of the hosting laboratory, this data collection has been classified as not requiring the approval of an ethical committee.

The participants involved were 6, half of whom female, between 20-30 years old, students of the laboratory. Since the data collection has been performed in a laboratory condition, it has been necessary to force some variations in the respiratory rate, in analogy to the natural increases and decreases taking place during the night and through the different sleep stages. Consequently, the participants has been asked to perform some jumps in order to obtain an increase in breath rate.

The data collection has been conducted as follows: each participant has been asked to perform 5 jumps, and then lie down on a standard mattress covered with the Sensingtex mattress for 4 minutes. They were then asked to stand up, perform other 5 jumps and lie down again on a different body posture. This has been done for each of the considered postures (supine, left side, prone, and right side) with 20 total jumps performed and a total recording time of 18 minutes, including the time required for getting in and out of the bed and jumping. The recording performed on the moving bed didn't involve the jumps, in order to have less variability in the breath patterns and to check for possible interferences due to the movement of the bed. The total length of the data collection for each participant is therefore 36 minutes, divided into 4 minutes intervals for each of the 4 positions with the normal and the rocking bed.

After the data collection, it was necessary to clean the data in order to remove the moment when the participant was getting in and out of bed. For each recording, based on different data extracted from the polysomnography and the pressure mattress, it has been possible to retrieve when the person stands up to perform the jumps or to turn around in another position. In the end, for each participant, there are eight different 4-minute long recordings, one for each position of the different postures.

However, only the data from a single subject turned out to be usable, due to different problems that occurred during the data collection. Examples of such problems are: the disconnection of a whole line of the sensing elements matrix, the breaking of a connector, the absence of a power supply, the corruption of the software executable on the disk of the computer handling the collection, the stop of the polysomnography because of defects with its batteries, interruption of the electrical contact with the body of the cardio-electrodes of the polysomnography device, etc.

3. Processing pipeline

Each sensing element of the mattress is positioned under a different point of the body, therefore their perception of the pressure variations exerted by the body during breathing is different. We then need a metric to discriminate the one(s) from which it is possible to estimate the respiratory rate. Our objective with this metric is to use it as a confidence about the quality of the signal in order to use it for the task.

This metric will rely on a few criteria, which each signal has to satisfy to a certain degree, in order to give out a large confidence. Each criterion, which will be explained in the next paragraphs, has been implemented in two variants: "binary", i.e., it can be passed or not passed (1 passed, 0 not passed), and "weighted", where the percentage of the duration of the recording that could contain valuable information is given out. Those versions have been designed to take into account the possible presence of phenomena deteriorating the signal, which on one hand could make it completely unusable or might just make unusable some parts of the recording. The choice between the two versions can be taken at the beginning of the pipeline. In both cases, the final metric is simply the mean of the values of each criterion.

In order to have a quasi-realtime analysis of the data we take in input a sliding window of 60 seconds, moving it through the 4mins recording in steps of 10s. Each 60s window for each signal is analysed and is given a certain confidence, or even discarded by the Excluding Criteria (described in the following paragraph 3.1), at the subsequent iteration all the signals are again taken into account. Figure 2 shows a 4mins recording, highlighted is the first 60s window.

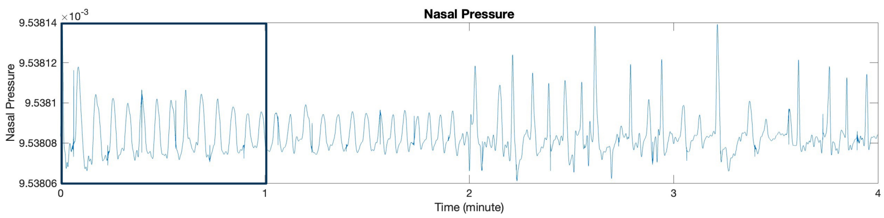


Figure 2: A 4mins nasal pressure record, the black box is the first 60s moving window.

3.1. Excluding criteria

The first set of criteria, explained in this paragraph, is referred to as “Excluding Criteria”. Those criteria aim to exclude all the mattress signals that cannot contain valuable information. When the signals are stationary in value, have a small amplitude, or present only interference from the other sensors of the mattress, for the entire window length, there are excluded. Since these problems could take place only in part of the window, the value of the metric is different for the binary and the weighted approach.

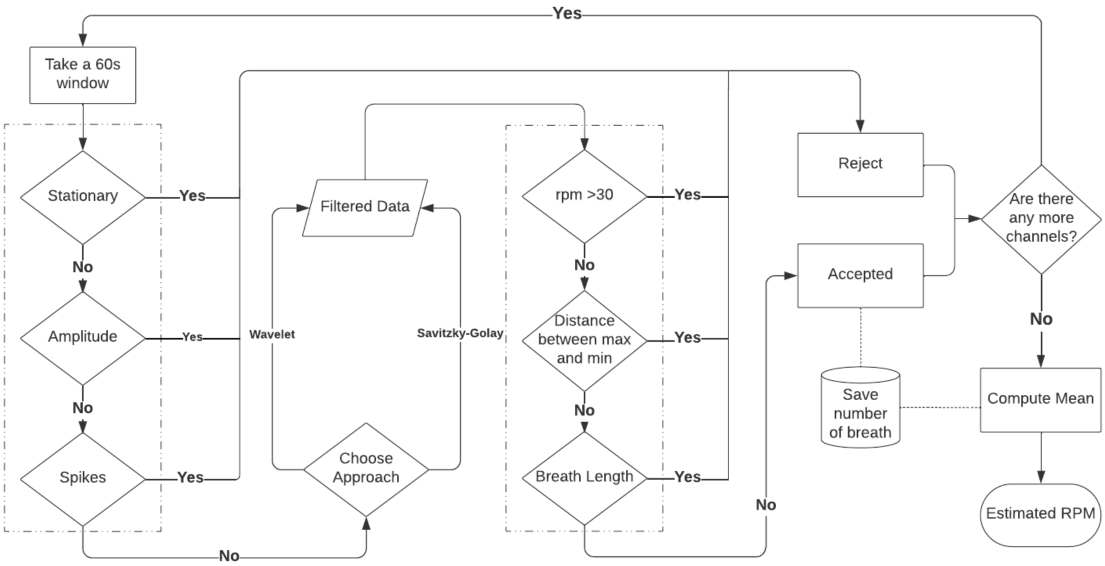


Figure 3: Pipeline scheme.

Stationary window

As a person’s body cannot cover the entire mattress, not all sensing elements (hereafter referred to as ”channels“) are active. Such channels are most of the time stationary. Stationary signals are those that keep the same value for the entire length of the window. If the window shows only a part being stationary, the length of this part is used for the criterion, i.e., the percentage of the window taken by the part. For the weighted approach, the metric value will be the percentage of the non-stationary portion. For the binary approach, the criterion will take the 1 value (passed) if the non-stationary part is longer than 20% of the window duration.

Window with small amplitude

Several channels present a signal with a small amplitude. Those channels were likely detecting interference from the nearby channels or just detecting partially the body movement. Since they cannot help in estimating the respiratory rate, they are excluded. If the window shows only a part being a small amplitude, we will assign a percentage to the criterion, For the weighted approach it will be the percentage with a non-small amplitude. For the binary approach, it will take the 1 value if the small amplitude duration is less than 20% of the window duration.

Window with spikes

The mattress can produce spike artefacts, which could also be present in channels that would allow the detection of the respiratory pattern, as highlighted in Figure 4. After evaluating different thresholds for the spike detection, both in intensity and duration, we decided to accept channels where the overall duration of the spikes in the window is below 30%. In such cases, both the binary and the weighted approach take the same output: 100% or 1 when the criterion is passed, 0% or 0 otherwise.

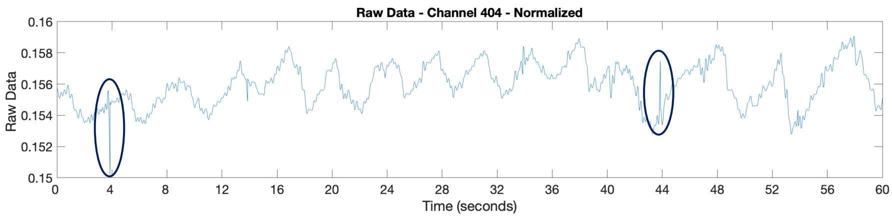


Figure 4: Raw Data - Channel 404 - Low presence of spikes

Denoising

To estimate the number of breaths we have tried to detect the moment between inhalation and exhalation, which turns in a peak in the pressure signal. After the aforementioned analysis, the number of usable channels/windows decreases drastically, and those that could contain valuable information, altogether with the confidence measure, are obtained. Nevertheless, most of the signals are still noisy. Given the frequency of breathing w.r.t. the sampling of the pressure, we can increase the signal-to-noise ratio by low-passing the signals. An analysis of the literature showed that the most used filtering approaches are “multiresolution analysis of the maximal overlap discrete wavelet transform”, and the “Savitzky-Golay filter” [18, 13, 19, 20, 21].

Multiresolution Overlap Discrete Wavelet Transform and Savitzky-Golay filter

The Multiresolution Overlap Discrete Wavelet Transform (hereafter also referred to as "MODWTMRA") is a technique based on wavelet analysis that transforms the original signal into a time-frequency domain to analyse it. The transform decomposes the signal in components that produce the original signal when added back together. We chose the Daubechies wavelet with two vanishing moments to represent the breath signal, as done in the literature. The raw data is decomposed into 13 levels, and to obtain the denoised signal we sum only a subset of these (the best results were obtained using the 9^{th} and 10^{th} levels), where the peaks could be easily counted.

Another approach frequently used in the literature is the Savitzky-Golay filter. It is used to smooth a noisy signal whose frequency span (without noise) is significant. The filters in this family are called digital smoothing polynomial or least-squares smoothing filters. Savitzky-Golay filters based on least-square fitting an n^{th}-order polynomial through the values in the window and taking the central point of the fitted polynomial as the new smoothed data point. For the filter, we choose a 9^{th} order polynomial, which gives an outcome similar to the one from the MODWTMRA filter.

3.2. Subsequent analyses of the filtered signal

The signals resulting from the application of the MODWTMRA or the Savitzky–Golay filters are then analysed, based on physiological information. The following criteria have been considered, as pass / no-pass. Therefore, for the weighted approach, a 100% was considered in case of a pass, and a 0% otherwise.

Respiratory rate lower than a threshold

A maximum value for the respiratory rate has been imposed, given the human physiology. The threshold is set at 30rpm because a larger than 20 value is predictive of cardiopulmonary arrest within 72 hours and death within 30 days [22], while a value greater than 27 is predictive of cardiopulmonary arrest within 72 hours [23]. The threshold is slightly larger to account for the errors in the reconstruction of the signal. The windows with a value larger than 30 are given a confidence of 0%.

Distance between maxima and minima

The resulting signals are given in input to a peak finder, to determine the moment between inhaling and exhaling, which is a maximum and is counted as a breath. Since the window is 60s long, the number of maxima in a window is the respiration rate, i.e., the breathing acts per minute.

Also, the minima are detected and used for computing the distance in the $x - y$ plane, see Figure 5, between the minimum and the subsequent maximum value of the pressure during the inhaling act. A similar distance is computed between the maximum and the subsequent minimum, corresponding to the reduction in pressure during the consecutive exhaling act. For each breathing act, these two distances have to differ by less than the ±20%. In such a case the signal is considered meaningful and given a 100% confidence if all breathing acts satisfy this constraint.

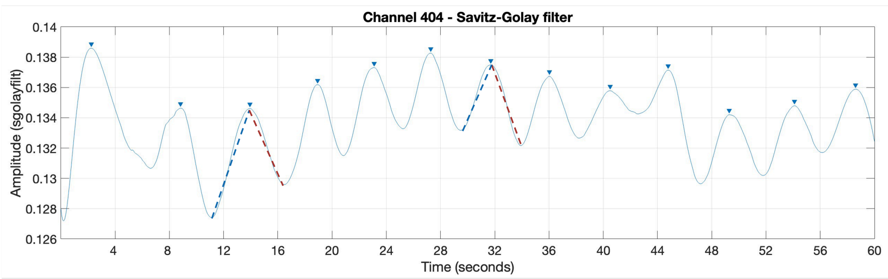


Figure 5: The distances minimum-maximum in inhaling, in dashed blu lines; dashed red lines are the distances maximum-minimum in exhaling.

Length of breath

The maxima and minima are used also for computing the duration of the inhaling and exhaling phases. The difference between the two should not vary, for each breathing act more than ±20% w.r.t. the previous breath. In such a case the signal is considered meaningful and given a 100% confidence.

3.3. Computation of the respiratory rate

In order to compute the respiratory rate, we consider the channels with a confidence higher than a threshold, e.g., 80%. The respiratory rate is computed as the average of the respiratory rates from all these channels. As our analysis is repeated on every window, we can give out an estimate of the respiratory rate at 0.1Hz.

4. Results

The respiratory rate has been computed for each posture (supine, left side, prone, right side) with both approaches (binary and weighted) on the available data. The results are evaluated w.r.t. the number of breaths per minute given by the ground truth. The evaluation metrics are: Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). The results have also been evaluated visually, with Bland-Altman plots, Figure 6, typically used to visualize the difference in measurements between two different instruments or two different measurement techniques. The *x-axis* of the plot displays the average measurement of the two instruments and the *y-axis* displays the difference between the two instruments. In the plot also 3 lines are shown, the central black one represents the average difference in measurements between the two instruments, also known as "bias" between the two measurements. The red dotted lines are the limits of the agreement (confidence interval), defined as the mean difference ± 1.96 standard deviation of the difference.

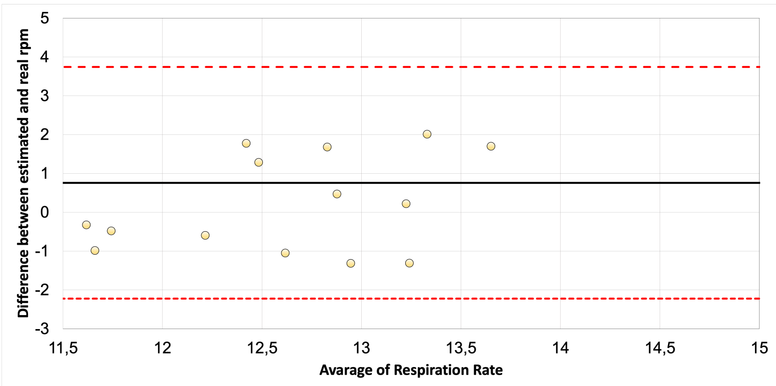


Figure 6: Bland-Altman plot of the estimated respiratory rate w.r.t. to the ground truth, Normal bed, supine posture, Savitzky–Golay filter

The output of the pipeline is shown in the heatmap in Figure 7, where the channels with the highest confidence value are coloured red and those with the lower values are coloured green up to blue when the channels have the 0% of confidence in representing a respiratory pattern.

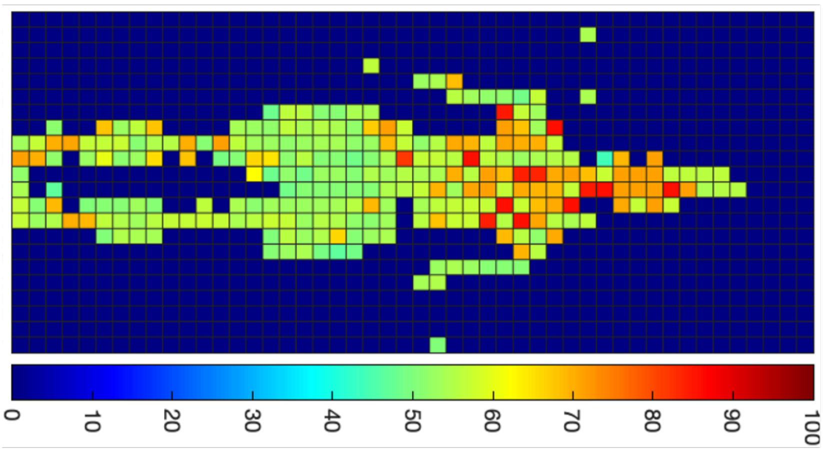


Figure 7: Heatmap of the channels with the highest confidence.

The results for the Savitzky–Golay filter are reported in Table 1 and for MODWTMRA in Table 2. The denoise method has been applied for the binary and the weighted approaches, and for each posture of the participant. The table also shows the results for the same user on the rocking bed, to test whether the motion of the rocking bed could influence the signals from the mattress. Even if the bed is designed to have an inaudible rocking mechanism, it is reasonable to expect that the movement could influence the data acquisition. The raw data visually present noise, but not significantly more than the signals from the normal bed.

It appears that the binary and the weighted methods perform similarly. We believe that this is due to the percentage of confidence set, which did not result restrictive enough. The posture of the participant appears decisive, as in the prone posture the error increases particularly, and the supine results in the minimum error. It might depend on the motion of the chest, which may be less intense in the prone posture. Furthermore, the results show that the error is influenced mostly by the chosen filtering approach rather than the bed. Actually, the Savitzky–Golay filter shows a lower error, compared to the wavelet approach. Focusing on the MAPE metric, it is 10% lower in most of the postures and both beds. The average error for the Savitzky–Golay filter is 1.6 breaths with the exception of the prone posture for the stationary bed, which shows an error of 3.3 breaths. MODWTMRA, instead, shows up to 4.2 breaths of error in the case of a prone posture with the rocking bed and has an average error of 2.6 breaths.

5. Conclusions

In this work, we investigated the possibility of estimating a patient's respiratory rate using a commercial sensor pressure mattress. The signals from the mattress show that it could be possible to compute the respiratory pattern. In the course of the data collection we, unfortunately, suffered various problems with the instruments and most of the data had to be discarded resulting in the possibility of analysing and testing the pipeline on just a single subject. The pipeline has

	Supine St.		Supine Rk.		Prone St.		Prone Rk.	
Metric	Binary	Weighed	Binary	Weighed	Binary	Weighed	Binary	Weighed
rpm mean	12.389	12.360	13.907	13.915	14.1734	12.1734	14.1829	14.1820
MAE rpm	1.0796	1.1422	1.8091	1.8171	3.3532	3.3532	1.9835	1.9825
MAPE (%)	9.779%	9.279%	15.538%	15.601%	31.914%	31.914%	17.895%	17.888%

	Left St.		Left Rk.		Right St.		Right Rk.	
Metric	Binary	Weighed	Binary	Weighed	Binary	Weighed	Binary	Weighed
rpm mean	13.503	13.401	13.907	13.915	14.523	14.433	14.645	14.613
MAE rpm	1.392	1.359	1.423	1.459	1.821	1.759	2.237	2.2046
MAPE (%)	11.83%	11.56%	11.675%	11.944%	14.934%	14.407%	18.544%	18.281%

Table 1
Results for Savitzky–Golay filter in: supine and prone (top table) left and right (bottom table) in the two different settings: Normal bed (St.) and Rocking bed (Rk.)

	Supine St.		Supine Rk.		Prone St.		Prone Rk.	
Metric	Binary	Weighed	Binary	Weighed	Binary	Weighed	Binary	Weighed
rpm mean	14.529	14.506	15.121	15.111	15.029	15.029	15.466	15.461
MAE rpm	2.173	2.150	3.023	3.0133	4.210	4.210	3.233	3.229
MAPE (%)	17.810%	17.619%	25.732%	25.644%	36.598%	36.598%	28.550%	28.522%

	Left St.		Left Rk.		Right St.		Right Rk.	
Metric	Binary	Weighed	Binary	Weighed	Binary	Weighed	Binary	Weighed
rpm mean	15.441	15.360	15.2342	15.2393	15.015	15.020	15.3536	15.3291
MAE rpm	2.4545	2.8934	2.4545	2.4597	2.4638	2.4691	2.9452	2.9208
MAPE (%)	24.620%	24.004%	19.961%	19.996%	19.915%	19.969%	24.401%	24.199%

Table 2
Results for MODWTMRA in: supine and prone (top table) left and right (bottom table) in the two different settings: Normal bed (St.) and Rocking bed (Rk.)

been tested and showed an error of 2 breaths on average, mostly determined by the denoise method used (Savitzy-Golay or MODWTMRA), and the posture of the person on the mattress.

However, this study had to be conducted on few raw data, due to the necessity of discarding many recordings. The result suggests the possibility of using this kind of instrument to track the respiratory rate of a person and also that the design pipeline could be a useful instrument, but this requires a more extended data collection. This could lead the designed pipeline to be more tuned, and incorporate new parameters and factors to reduce the number of misinterpreted breathings. Otherwise, if larger trials confirm the magnitude of the error on the number of breaths, this would imply the approach is not good enough in medical contexts, as the average error is too high for, e.g., the study of sleep stages, which requires more accurate estimates. Nevertheless, in domestic usage, this error would not be an issue.

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