# A smart bed for non-obtrusive sleep analysis in real world context

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**ABSTRACT** Sleep disorders are common health problems in industrialized societies and may be caused by underlying health issues. Current methods to assess the quality of sleep are invasive and not suitable for continuous monitoring in real world contexts. We have developed a smart sensing solution for non invasive sleep monitoring specifically conceived for the early identification of pre-clinical sleep disorders and insomnia in the general population. Our prototype, named the Smart-Bed, is a low-cost solution that gathers and processes data on the movement and position of the subject, physiological signals, and environmental parameters. Our tests on the prototype in controlled lab conditions highlighted that the mattress can reliably detect subject's position/motion, heart rate and breathing activity. It performs well compared to polysomnography and correctly classifies four behavioural conditions (no bed occupancy, wakefulness, non-REM sleep, and REM sleep), which are the basis for creating an objective sleep quality index.

**INDEX TERMS** Accelerometers, piezoresistive devices, physiology, signal analysis, psychology, sleep monitoring, real world data

## I. INTRODUCTION

Sleep disorders including insomnia are among the most common health problems in industrialized societies [1]. Poor sleep quality increases the probability of incidents and accidents at work or during daily activities [2]. Furthermore, insomnia correlates with high rates of absenteeism from work [2]. Compared to people with good sleep quality, insomniacs visit clinical structures more frequently and use drugs much more. A large amount of data [3]–[7] indicates that chronic insomnia increases vulnerability to mental disorders (depression, anxiety, alcoholism), metabolic diseases (diabetes and dyslipidemia), and cardiovascular diseases (myocardial infarction and hypertension), as well as neuro-degenerative disorders (i.e. mild cognitive impairment).

Systematic, preventive, personalized and non-invasive methods for sleep quality assessment are thus of paramount importance. Polysomnography is currently the gold-standard for assessing sleep quality [8], [9], since it estimates the macrostructure of sleep, i.e. the division of sleep into subsequent stereotypical stages [10]. This macrostructure carries

valuable objective information on the quality of sleep, and in fact is corrupted in sleep disorders [11]. Unfortunately, polysomnography is highly invasive. The lack of comfort prevents the subject from sleeping naturally and it does not provide fully reliable measurements of the quality of sleep in real life.

To improve on this situation, within the research project L.A.I.D. (*Linking Automation to artificial Intelligence for revealing sleep Dysfunctions*) [12], we developed a smart sensing solution for non-invasive sleep quality assessment. In the project, we developed a smart mattress (hereinafter called *Smart-Bed*) specifically conceived to assess the quality of sleep to early identify pre-clinical signs of sleep disorders and insomnia in the general population. Our Smart-Bed collects and processes data on the motion and position of the subject, physiological signals (heart rate and breathing rate) and environmental parameters (sound intensity, relative humidity, room temperature and luminosity). The Smart-Bed is based on a single mattress made by *Materassificio Montalese* [13] (the group leader of the L.A.I.D. project) in

which we integrated a pressure mapping system and a set of tri-axial accelerometers.

Several non-invasive sensor technologies have been developed for in-bed monitoring of biomedical parameters, such as sleeping posture/movements and physiological signals [9], [14]–[24]. However, no previous work has focused on the assessment of sleep quality by comparing it with the standard (i.e. polysomnography).

The existing solutions for non invasive sleep monitoring are based on pressure mapping systems that extract an image of the pressure of the subject lying on the mattress. Contact pressures are measured by multiple pressure sensors, generally with high spatial resolution, using piezoresistive [15], capacitive [18]–[20], optical [21] or piezoelectric [23] technologies. The pressure maps are used to detect the subject's presence, sleeping posture or movements or to identify breathing or cardiac activity. Note that the main current solutions are monomodal and are not able to simultaneously detect the position/movement, breathing and heart rate. The *WhizPAD* pressure mapping system developed by Yu-Wei Liu et al. [15] detects user movements and breathing activity. Chang et al. [19], [20] employed a capacitive matrix for movement and breathing monitoring. The solution by Kortelainen et al. [23] records the ballistocardiographic signal and breathing activity during sleep. All the other solutions detect position and movement only. In addition, most current solutions are for hospital locations [15], [18], [21], [25]–[27]. None of the previous works reported the classification of the sleep macrostructure.

In this work, we developed a multimodal sensing system by combining textile-based pressure mapping and tri-axial accelerometers to detect position/movement, breathing activity and heart rate in a non-obtrusive way. As previously noted, the main current solutions are monomodal and, to the best of our knowledge, our Smart-Bed is the only prototype that can simultaneously detect position/movement, breathing and heart rate. In addition, our Smart-Bed is specifically designed as a consumer product for the general population. In fact, we have designed a low cost solution that is still able to detect key clinical parameters. More importantly, our machine learning analysis identifies four behavioural conditions, and differentiates between non-REM and REM phases. We have thus demonstrated the possibility of identifying the main sleep macrostructures. To the best of our knowledge, our mattress is the first of its kind.

We developed the pressure mapping system by using piezoresistive textile technology inspired by [28], with modifications to reduce the cross-talk between pressure sensors. We tested the prototype in controlled lab settings on several groups of subjects. The results demonstrated that the Smart-Bed gives a reliable detection of the subject's position and movements as well as heart rate and breathing activity. In addition, the preliminary assessment performed very promisingly in comparison to polysomnography. In fact, the mattress signals enabled us to classify four behavioural conditions that represent the sleep macrostructure.

The results obtained are encouraging and highlight the technical validity of the Smart-Bed. However, an extensive validation phase on a high number of heterogeneous subjects is needed. In fact, we are currently testing a high number of subjects in order to validate the Smart-Bed as a tool for reducing socio-economic costs due to sleep disorders and for increasing individual well-being.

## II. MATERIALS AND METHODS
### A. OVERALL ARCHITECTURE
The architecture of the Smart-Bed prototype comprises the following functional blocks (see Figure 1):
- Docking station (DS)
- Physiological data collector (PDC)
- Environmental data collector (EDC)

Both the PDC and EDC are wired to DS via USB serial communication interface. The DS is a Microsoft Windows 10 based system with a touchscreen interface. The DS is equipped with tailored software for: i) managing PDC and EDC, ii) processing the signals and parameters from PDC/EDC, iii) storing the collected data, and iv) extracting the sleep and environmental quality indices. The PDC is a
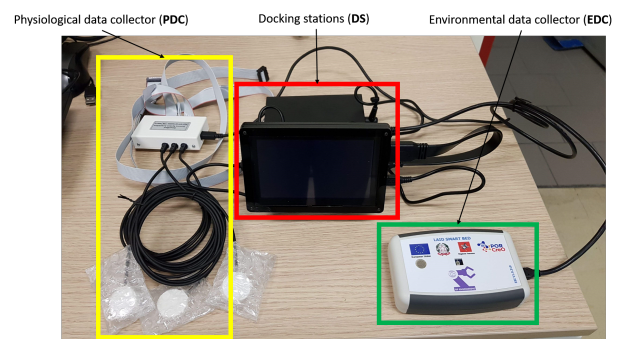


**FIGURE 1.** Hardware of functional blocks of the Smart-Bed prototype. Docking station (DS) is in the red frame, Physiological data collector (PDC) in the yellow frame and Environmental data collector (EDC) in the green frame.

custom-designed acquisition unit with two different kinds of sensors: pressure mapping system and three tri-axial accelerometers. The architecture of the sensing components, the PDC and the EDC were designed by IFC-CNR and University of Pisa. The mattress is made of memory foam and is produced by Materassificio Montalese S.P.A. (Pistoia, Italy). The PDC was developed by EB Neuro S.P.A. (Firenze, Italy), and the EDC and DS by BP Engineering S.P.A. (Carrara, Italy).

### B. PRESSURE MAPPING SYSTEM
The PDC is equipped with a pressure mapping system based on a piezoresistive textile applied onto the foam layer below the mattress top cover. We designed the pressure mapping system to detect the distribution of pressures when a subject is lying on the bed. The pressure signals obtained can be used to detect the subject's position and movements and to extract the subject's breathing rate. On the basis of an analysis of the

literature and prioritizing low complexity, low cost and good tolerance to external disturbances, we developed a resistive sensor matrix configuration, similar to the one reported in [28]. In the design phase, as a compromise between reducing the overall cost and complexity, we used a relative low number of sensing areas yet still maintained an acceptable quality of signals. Considering a single mattress measuring 190x90 cm, we built a pressure sensing textile based on a resistive matrix of 15x13 uniformly-spaced sensing areas that cover a surface of 125x75 cm (head and feet are not considered). Note that most solutions in the literature have a much higher number of sensors (typically by a factor greater than 10). Figure 2 shows our solution: the central layer is a pressure sensing piezoresitive fabric, while the additional two layers are fabrics with integrated row and column conductors. Row and column conductors are perpendicular. Two analog mul-
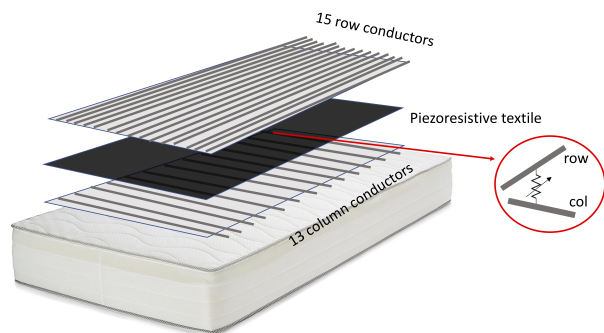


**FIGURE 3.** Prototype of the pressure mapping system.

system provides a 800x600 image in which each pixel value is related to the pressure applied on the specific point of the mattress. The pressure image is constructed by a linear spatial interpolation of the raw output values obtained by the 195 sensing areas to obtain the 800x600 image.

### C. ACCELEROMETERS
The accelerometers of the PDC were used to extract the ballistocardiograph (BCG) signal [30] for the unobtrusive recording of cardiac activity (i.e. heart rate) of the subject lying on the mattress. For the extraction of the BCG signals, we selected the micropower digital accelerometer ADXL362 (Analog Device Inc, MA, US). The main specifications of the ADXL362 are reported in Table 1. The Smart-Bed simultaneously collects the signals of the three accelerometers (a1, a2 and a3) placed in different positions over the pressure mapping system. As shown in Figure 4, an accelerometer (a1) was placed in a central area, the others (a2 and a3) in lateral and contro-lateral sites. We used multiple accelerometers for two main reasons. Firstly, averaging the signals from different accelerometers reduces the noise and robustly detects artifacts. Secondly, the multi-site configuration ensures that at least one of the accelerometers lies below the subject, even if the subject is not in a central position on the mattress.

### D. ENVIRONMENTAL DATA COLLECTOR AND ENVIRONMENT QUALITY INDEX
The EDC module is based on a Seeeduino V4.2 board, and is equipped with four sensors that collect the following environmental signals: i) sound intensity, ii) temperature, iii) relative humidity, and iv) luminosity. All the signals are collected with a sampling frequency of 1 Hz, except for the sound intensity which is sampled at 20 Hz (due to the fast dynamics of environmental noise and snoring events). The collection



**FIGURE 2.** Pressure mapping system based on a textile resistive matrix with 13 column conductors and 15 row conductors for a total of 195 sensing areas. A single sensing area is highlighted in the inset.

tiplexers are used to scan rows (row mux) and columns (col mux) in order to select all the sensing areas of the resistive matrix. The row mux sequentially connects each row conductor to Vcc (3.3V) through a pull-up resistor R1 (2 K$\Omega$). When a row is selected (i.e. powered), the col mux sequentially connects each column conductor to a voltage divider stage (pull down resistor R2, 10K$\Omega$). Each crossing between a row and a column thus represents a sensing area whose electrical resistance decreases as the applied pressure increases. For the pressure-sensing layer, we used the piezoresistive fabric CARBOTEX 03-82 manufactured by SEFAR AG (Heiden, Switzerland). The top and bottom layers are made of a PET fabric (from SEFAR AG) with integrated evenly-spaced metallic stripes. In our design, the metallic stripes have a 2 cm width and are separated by 3 cm in the top layer (rows) and 8 cm in the bottom (columns) layer. As described in [29], this sensing architecture has parasitic resistivity in the transversal directions due to the surface conductivity of the pressure-sensing layer. To reduce the cross-talk due to the parasitic resistivity, we built our prototype by cutting the piezoresistive layer into strips parallel to the row direction (around 3.5 cm width). The strips were then sewn onto the top layer centered on the row conductors. Figure 3 shows the pressure-sensing matrix prototype. The pressure mapping
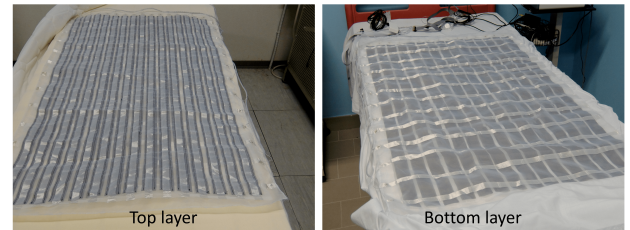
**TABLE 1.** PDC-equipped accelerometer specifications

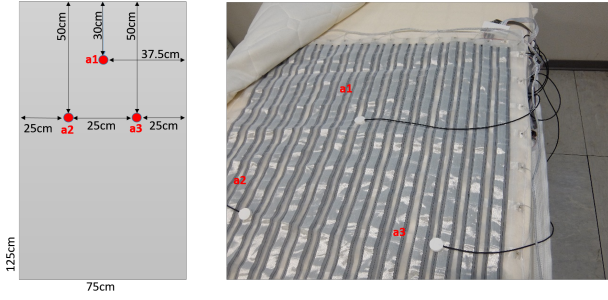| Specification | Value |
|---|---|
| Number of axes | 3 |
| Range | $\pm 2$ g |
| Supply voltage | 3.3 V |
| Sensitivity | 1mg/LSB |
| Raw data noise level | $175 \mu g / \sqrt{Hz}$ (ultralow noise mode) |
| Bit resolution | 12 bits |
| Sampling frequency | 128 Hz |
| Shape and dimension | Circular, diameter 2.2 cm |

**FIGURE 4.** Position and topological configuration of the three accelerometers (a1, a2 and a3) over the pressure mapping layer.

of all the ECD signals and parameters is synchronized with respect to the data from the PDC.

We used the collected signals to estimate a binary index regarding the best environmental conditions for sleep (environment quality index, EQI), based on data from the literature. For each environmental parameter, we therefore assigned optimal sleep value ranges in order to obtain four environmental criteria:

- sound intensity: continuous noise level lower than 35 dB, no more than 45 dB for single noisy events [31], [32];
- temperature: minimum temperature of $17°C$ and maximum temperature of $28°C$ [33].
- relative humidity: between 40% and 60% [33];
- luminosity: less than 10 lux [34];

The EQI is evaluated for each night's sleep and it is set to 1 if all four environmental criteria are satisfied, otherwise to 0 (not optimal environmental conditions).

In addition to the EQI extraction, we hypothesized that information on sounds such as snoring, environmental noise due to the subject's activity, and voices could contain relevant information on the subject's state during sleep. We thus used the recorded sound information as one of the inputs to classify the behavioural conditions that will be described in Section II-E. For each 30-second epoch, we therefore calculated the mean values and variances of the sound intensity ($SI_e$, $SI_v$).

### E. SLEEP QUALITY ALGORITHM
The analysis of the PDC data acquired by the Smart-Bed consists of three main post-processing steps: 1) analysis of the PDC signals and extraction of physiological (heart rate and breathing rate) and activity (movement and sleeping posture) data; 2) automatic classification of the subject's behavioural conditions based on the physiological and activity data extracted including the sound information extracted from the EDC as described in Section II-D; 3) exploitation of the classified behavioural conditions to estimate standard sleep evaluation parameters, which are then condensed into a global Sleep Quality Index (SQI).

All the algorithms and analysis were performed in Matlab (R2018b, Natick, Massachusetts: The MathWorks Inc.).

### 1) Physiological and activity data
To estimate the breathing rate, we employed a frequency spectrum-based approach. Firstly, we derived the signal averaged over the sensing areas of the pressure matrix (below the lying subject). Then, we evaluated the average signal spectrum (Welch periodogram) to detect the maximum peak of the spectrum in the frequency range 0.1 Hz to 0.35 Hz. In our hypothesis, the maximum peak is likely to correspond to respiratory activity.

We estimated the heart rate from the squared modulus of the grand average raw signal of the three accelerometers. To remove possible components due to respiratory activity or movements, the grand average signal was band-passed in the frequency range of 0.3–20 Hz. We then extracted the heart rate using a method based on an autocorrelation function similar to the ones described in [30], [35], [36].

To evaluate the activity data consisting in the position and motion of the subject on the mattress, we reduced the sensing area density from 15x13 to 3x3 by topological averaging. The position feature vector obtained (9 elements) is assigned by an artificial neural network (ANN) [37] according to six putative classes: i) not on bed, ii) supine position, iii) lying on the left side, iv) lying on the right side, v) prone position and vi) movement. We used a two-layer ANN, the size of hidden layer was set to 10. For the training process, we applied a backward propagation algorithm with scaled conjugate gradient method [38].

Each estimated data sequence (heart rate, breathing rate, position and movements) is temporally divided into 30-second epochs in accordance with the clinical standard in polysomnographic evaluation. For each 30-second epoch, the mean values and variances of heart rate ($HR_e$, $HR_v$), breathing rate ($BR_e$, $BR_v$), movements ($MV_e$, $MV_v$), and position ($PS_e$, $PS_v$) were calculated.

### 2) Behavioural conditions classification
We classified the subjects' behavioural conditions in 30-second epochs using the input parameters described in Section II-E1 and II-D: $HR_e$, $HR_v$, $BR_e$, $BR_v$, $MV_e$, $MV_v$, $PS_e$, $PS_v$, $SI_e$ and $SI_v$. We trained a decision tree algorithm with bootstrap aggregation [39] to assign to each 30-second epoch one of the following classes: no bed occupancy, wakefulness, non-REM sleep and REM sleep. We co-recorded the Smart-Bed signals and standard polysomnography with a clinical polysomnographic system in order to estimate the real behavioural conditions and sleep staging following the clinical criteria. The following signals were collected using the standard polysomnographic recordings: electroencephalography, electrocardiography, respiratory airflow, snoring, electromyography, and oxygen saturation. Based on polysomnographic data, each sleep recording is staged in 30-second epochs according to standard clinical criteria [10], then the sleep staging is used as a reference to train the decision tree algorithm.

### 3) Global Sleep Quality Index

The final step of the sleep quality algorithm was based on the sleep macro-structure estimated previously. Firstly, the sleep macro-structure was used to extrapolate the main sleep time-domain parameters [9], [40], [41] related to each night's sleep, such as: sleep efficiency, sleep latency, REM latency, total sleep time, and wake after sleep onset (WASO). The SQI was then estimated based on the following partial criteria (pc):

- $pc_1 = 1$ if sleep efficiency > 85%, otherwise it is set to 0
- $pc_2 = 1$ if sleep latency < 15 min, otherwise it is set to 0
- $pc_3 = 1$ if 60 min > REM latency < 120 min, otherwise it is set to 0
- $pc_4 = 1$ if total sleep time > 7 hours, otherwise it is set to 0
- $pc_5 = 1$ if 70 % < ratio between non-REM sleep and total sleep time < 95%, otherwise it is set to 0
- $pc_6 = 1$ if WASO < 45 min, otherwise it is set to 0

Finally, the SQI is assessed for each night and defined as:

$$SQI = \sum_i pc_i$$

SQI ranges from 0 (bad sleep) to 6 (good sleep), with an ordinal scale of seven discrete levels.

### F. EXPERIMENTAL PROCEDURES

To evaluate the estimation of position/movement, breathing activity and heart rate, we tested the Smart-Bed prototypes on a group of 15 volunteers (29 to 72 years old, mean=48,4; 8 female/7 male) during wakefulness (signal-testing group). In these wakefulness tests, during experimental sessions the subjects were asked to voluntarily modulate their respiratory activity and change their body position, thus enabling us to collect different respiratory and postural patterns.

The ANN for the classification of the activity data (Section II-E1) was trained with a dataset of 30-second epochs obtained from six subjects (29 to 59 years old, mean=47,3; 3 female/3 male) during wakefulness (ANN-training group, with different subjects from the signal-testing group).

The decision tree used to classify the behavioural conditions (Section II-E2) was trained with a dataset acquired from an additional group (condition-training group) of eight subjects (26 to 71 years old, mean=54,3;1 female/7 male) sleeping on the Smart-Bed prototype whilst being recorded by standard polysomnography (BE LTM, EB Neuro S.p.A., Florence Italy). We used the 75% of the epochs for training and 25% for testing.

To test the durability and robustness of the Smart-Bed and to evaluate the SQI and EQI as a function of time, we collected the Smart-Bed signals from a group (long-testing group with different subjects from the signal-testing, ANN-training and condition-training groups) of five subjects (27 to 45 years old, mean=35,2;2 female/3 male) over multiple continuous days (from 12 to 231 days).

## III. RESULTS

To date, we have developed seven Smart-Bed prototypes to test the modules' (DS, PDC and EDC) functionality, sensing solutions and algorithms. Our estimated cost for our Smart-Bed prototype is around 1000 euros of which approximately 150 euros is for the pressure-sensing matrix. This cost is low for a research prototype and could be lowered even further with a series production.

Figure 5 shows four examples of sleeping postures detected by the pressure mapping system when a subject is lying on the Smart-Bed (prone, supine, left side, and right side ). The chest, upper arms and legs are easily recognizable. In static conditions, the pressure image detects the presence of the subject on the mattress and his/her sleeping posture. In dynamic conditions, when the subject moves while lying on the mattress, the pressure image changes continuously and this variation can be used to determine the subject's movement during sleep.

Figure 6 shows an example of breathing activity estimated by the Smart-Bed and compared with a ground truth obtained using a thermistor inserted in a nasal cannula. The reference signal is based on measuring the temperature during expiration and inspiration and of the air passing in the nasal cannula. The subjects of the test (signal-testing group) voluntarily controlled and modulated their breathing in order to verify the ability of the Smart-Bed to replay different breathing rates without a significant delay. As shown in Figure 6, the estimation of breathing rate extracted from the Smart-Bed reproduces the reference data well with only a small delay. The same accuracy was observed in all the experimental sessions with different subjects and different voluntarily-modulated respiratory rates.

Figure 7 shows three traces of heart rate estimation compared with the heart rate obtained with reference ECG signals. The heart rate obtained by our mattress proved to be very efficient and accurate. The evaluation of the mean heart rate over the 30-second epoch was very stable and close to real values. Considering the estimation over one-second epochs , the estimated heart rate shows a low pass filtering behavior, with a loss of high frequency components. However, the low-pass filtering showed no particular effects using the 30-second epochs for sleep staging and behavioural condition classification. The estimation of heart rate via Smart-Bed-BCG was accurate and robust when the subject was not moving, as during sleep or in relaxed wakefulness before sleep.

Figure 8 shows the results of the classification of the position and motion of the subject on the mattress using the ANN classifier on the ANN-training group. We obtained an overall accuracy of about 91.8% and more specifically: 83.9% for not on bed, 83.8% for supine position, 96.4% for lying on the left side, 94.5% for lying on the right side, 89.3% for prone position, and 93.1% for movement.

We performed the training and testing of the automatic classifier (decision tree algorithm) of behavioural conditions on the condition-training group. From the eight nights of
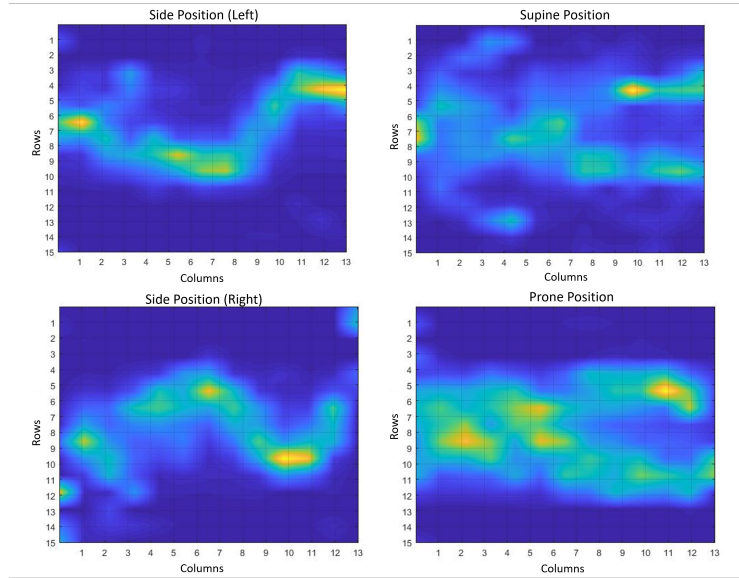
**FIGURE 5.** Pressure maps measured in four typical sleeping postures: left side, supine, right side and prone.
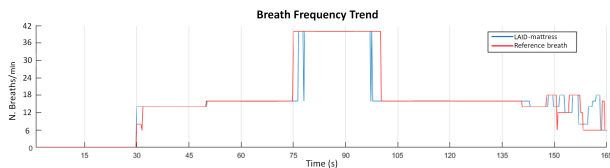


**FIGURE 6.** Analysis of respiratory signals related to a subject in a supine position: time course of breathing rate (Hz) obtained with Smart-Bed (blue line) and with an estimation of the air-flow in the nasal cannula (reference breath, red line). The respiratory frequency extracted from the Smart-Bed accurately reflects the ground truth data.
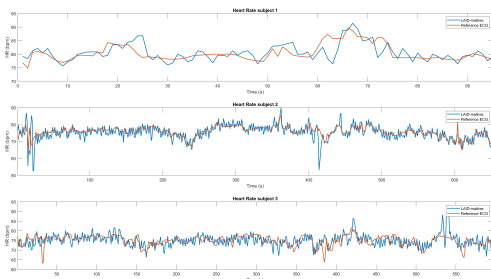


**FIGURE 7.** Analysis related to three different subjects: heart rate time course (with different time lengths) detected by BGC with the Smart-Bed (blue lines) and simultaneous heart rate signals collected by reference ECG system (red lines). The estimation is performed with a 1 second time resolution.



**FIGURE 8.** Confusion matrix related to the performance of the position and motion classification (ANN algorithm) regarding the ANN-training group, with six classes: i) not on bed, ii) supine position, iii) lying on the left side, iv) lying on the right side, v) prone position and vi) movement. The positive predictive values and false discovery rate are reported.

recordings of the condition-training group, we collected a total of 4761 epochs (i.e. about 40 hours). We removed 1280 artifactual epochs due to the poor EEG signal quality of the polysomnography. We extracted 581 epochs of no bed occupancy, 554 epochs of wakefulness, 2193 epochs of non-REM sleep, and 153 epochs of REM sleep. The classification

performance obtained with the decision tree algorithm was satisfactory in terms of aim f the classification. The overall accuracy was about 86%, and specifically (see the confusion matrix in Figure 9): 99% for "no bed occupancy", 83% for "wakefulness", 83% for "non-REM sleep", and 79% for "REM sleep".

Figure 10 reports the variation in estimated heart rate,

**FIGURE 9.** Confusion matrix related to the performance of the behavioural conditions classification (decision tree algorithm) regarding the condition-training group, with four classes: no bed occupancy, wakefulness, non-REM sleep, and REM sleep. The positive predictive values and false discovery rate are reported.



**FIGURE 10.** Physiological signals and behavioural conditions estimated from the data collected by Smart-Bed for a subject (condition-training group) during sleep. The estimated data are heart rate (beats per minute, bmp), breathing rate (bpm) and motion (movement detected or not). The time unit is the epoch (30 seconds).



**FIGURE 11.** Single subject continuously monitored for 60 sleep nights. The time course of the Sleep Quality Index (SQI, seven-level index) and the Environmental Quality Index (EQI, dichotomic index) are shown in the upper and lower panels, respectively. In the lower panel, for each parameter contributing to EQI, up-pointing red triangles and down-pointing blue triangles for each day indicate whether the corresponding parameter exceeded or losing to the optimal range, respectively.

breathing rate, motion and behavioural conditions as a function of time (in epochs) for one subject in the condition-training group. Within each epoch, the estimated physiological and environmental information (see II-E2 section) is used as input in the automatic classifier to evaluate the related behavioural condition. The behavioural condition pattern assesses the sleep macrostructure (sleep staging) of the subject and can reproduce the hypnogram.

Figure 11 reports the time course of the SQI and EQI for a subject in the long-testing group, monitored with the Smart-Bed for 60 days continuously. As regards the environmental quality, the deviations in environmental parameters from the optimal ranges are also reported. A comparison of the time courses suggests that sub-optimal environmental conditions have contributed to non- fully restorative sleep. However, it seems that the subject adapted to the environmental conditions (from day 27), demonstrating an improvement in sleep quality . During the durability tests, no functional issues, data losses or hardware faults were reported.

## IV. DISCUSSION

The results of Section III show that our mattress is a valid unobtrusive solution for detecting physical, physiological, and environmental parameters.

To the best of the authors' knowledge, our mattress is the only in-bed solution that can simultaneously detect position and motion as well as breathing and heart activity. The Whiz-
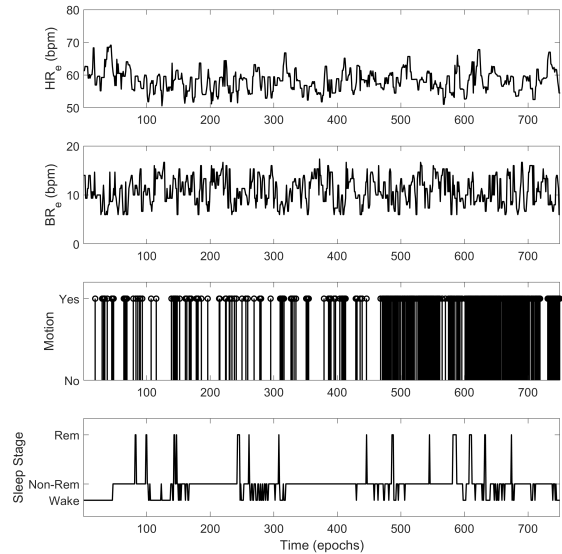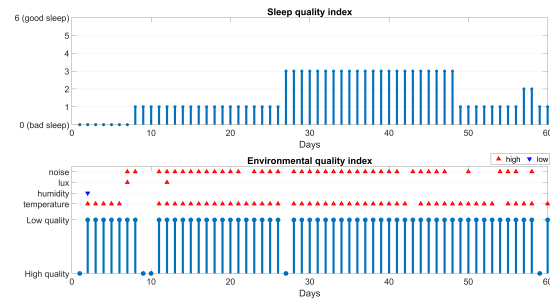
Pad [15] and the Kinotex [22] were tested for posture/motion and breathing detection, while the solution developed by Kortelainen [23] was assessed for breathing and cardiac activity detection (i.e. no static postures due to the piezoelectric technology). The other examples cited in Section I ( [18]–[20], [24]) focus on the measurement of a single parameter (position/movement or a single physiological parameter).

It should also be emphasized that some of the examples in the literature show a much higher performance with regard to the spatial resolution of the pressure mapping system. For example, the XSENSOR pressure mapping system [25], tested in [18] to prevent ulcers, has 6136 sensing areas (52 rows x 118 columns) that can be scanned at a rate of 1

Hertz. The Smart-Bed pressure mapping system has a smaller number of sensors by a factor of about 30 (195 vs 6136). If the objective was to monitor and prevent pressure ulcers, the lower spatial resolution could be a limitation. However, for a low-cost prototype suitable for future exploitation as a consumer product that monitors sleep quality in the general population, the lower spatial resolution is not a limitation. In fact, we have demonstrated that the pressure mapping system with a lower number of elements still leads to a good evaluation of postural and motion parameters. Many of the prototypes presented in the literature discussion in Section I have a higher number of pressure sensing areas by a factor greater than 10.

In addition, the Smart-Bed, unlike other solutions, is able to monitor a set of basic environmental parameters (sound intensity, relative humidity, temperature and luminosity) that are known to be correlated with sleep quality.

From a technical point of view, we have demonstrated the robustness of the Smart-Bed prototype which continuously monitored five subjects for up to 231 days without significant data losses (data collection and extraction of the SQI and EQI indexes).

The most important result obtained with the Smart-Bed is the classification of the main behavioural conditions characterizing sleep, which is the basis for a robust extraction of an index used to quantitatively assess sleep quality. To the best of the authors' knowledge, the existing smart bed solutions have not been demonstrated as being capable of classifying the different behavioural conditions that characterise sleep. An approach to behavioural assessment based on machine learning was developed and assessed by Wang et al. in [17] with the WhizPad prototype [15]. However, in their work the authors classified only two classes: sleep vs awake. In fact, the ability to classify four conditions, in particular REM vs non-REM, is a key feature of the design of our prototype. In fact, despite the relative low number of sensors, the Smart-Bed can detect relevant physiological and activity parameters that are integrated through our machine-learning approach.

Monitoring environmental conditions together with physiological parameters could lead to the development of specific applications aimed at identifying causes and thus suggesting solutions to the poor sleep quality. In addition, an integrated environmental-subjective index of sleep quality is advisable.

## V. CONCLUSIONS

In this work, we have described the architecture and preliminary results of an innovative system for non-invasive sleep monitoring in real world contexts. The proposed system, developed within the L.A.I.D. research project, is a low-cost smart mattress (Smart-Bed) capable of recording the signals related to the physiological (cardio-respiratory activity), postural (body position and movements) and environmental (temperature, noise, humidity and luminosity) aspects used to identify the main stages of wakefulness and sleep and to estimate a global sleep quality index and environmental quality index.

Our preliminary tests with the Smart-Bed prototypes verified the full functionality and robustness of the proposed architecture, both considering the hardware and data-processing solutions. However, the results presented herein were obtained from a relatively small number of subjects.

In fact, we are in the process of performing additional in-depth tests on a higher number of subjects to validate and improve the prototypes. This will lead to the final version of the Smart-Bed for the easy and low-cost monitoring of sleep quality for large populations. Sleep investigations based on a validated Smart-Bed solution would enable the sleep macrostructure to be studied in real life. We are also designing a second version of the prototype to improve various engineering aspects. This includes a wireless connection between the sensors and a remote data collection hub in which the data are transmitted when the Smart-Bed detects that the subject is not present.

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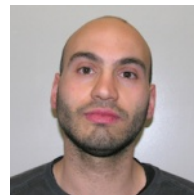
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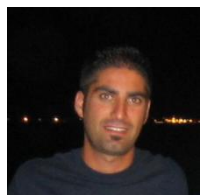
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