# Novel Unobtrusive Approach for Sleep Monitoring Using Fiber Optics in an Ambient Assisted Living Platform

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**Abstract.** Sleep plays a vital role in a person's health and well-being. Unfortunately, most people suffering from sleep disorders remain without diagnosis and treatment since the current sleep assessment systems are cumbersome and expensive. As a result, there is an increasing demand for cheaper and more affordable sleep monitoring systems in real-life environments. In this paper, we propose a novel non-intrusive system for sleep quality monitoring using a microbend fiber optic mat placed under the bed mattress. The sleep quality is assessed based on different parameters. Moreover, the sensor has been integrated into an existing Ambient Assisted Living framework to be validated in real scenarios. Three senior female residents participated in our study and the sleep data was collected over a one-month period in a home-living situation. The proposed system shows accurate and consistent results with a survey collected from each participant showing their sleep patterns and other in-home activities.

## 1 Research Context

Technological progress allows us to take better care of ourselves and our relatives with less effort. Furthermore, we observe an emergence of *Zero-Effort Technologies* (ZET) [1]. They represent technological solutions that provide a service without requiring any form of active participation of the user. Their main paradigm is to leverage on unobtrusive observations of daily activities and on smart use of available information. *Ambient Assisted Living* (AAL) platforms, which is a specific type of ZET, target improving the quality of life – of both the monitored person and their caregivers. Such a platform aims at empowering people who may be at risk without assistance, especially the elderly. It contributes to users' autonomy in their own living space rather than leaving them completely dependent on others (e.g. a nursing home).

In this paper, we focus on sleep monitoring as a substantial vector of quality of life. Sleep is one of the critical physiological human needs. Humans spend a third of their lives sleeping. As advised, amongst others, by the *U.S. National Institutes of Health*, sleep deficiency can lead to fatal health problems. Currently,


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sleep assessments and evaluation tools are burdensome, expensive, and time-consuming. An unobtrusive method, which can provide a sleep monitoring daily is ballistocardiography (BCG). BCG records the mechanical activity of the body generated during each heartbeat. Multiple sensors are commonly used to record the BCG signal such as piezoelectric sensors, electromechanical sensors, fiber optic sensors. In addition to load cells, and pressure pads, these sensors can be integrated with chairs, beds, and cushions or even in weighing scales [2].

This work's contribution consists of a design and integration of a novel sleep quality monitoring model into an Ambient Assisted Living (AAL) platform using a microbend fiber optic sensor. This sensor is a suitable choice for unconstrained sleep monitoring as it is highly sensitive to pressure changes induced by the ballistic forces of the heart, and it does not require close contact with the body. It is also relatively small, lightweight, and affordable. Additionally, it improves sleep activity assessment previously based on motion sensor as presented by Bellmunt *et al.* [3].

The paper is organized in the following way. First, we discuss the technical state of the art of bodily signals processing to extract medical values as well as its inclusion in AAL platforms. Second, we present our methodology; introduce the microbend sensor and its specifications. Next, we introduce our AAL framework and the sensor integration. Fourth, we discuss the process to retrieve the values and the key items in sleep monitoring. Finally, we validate the complete system in real scenarios, and discuss the results.

## 2 Related Work in Sleep Monitoring

Healthcare systems worldwide are struggling with significant challenges, i.e., rapid growth in aging population, increased number of people with chronic and infectious diseases, rising costs, and inefficiencies in health-care systems. As a response to these challenges, the healthcare community is seeking for novel non-invasive solutions that can improve the quality of healthcare for the patient while maintaining the cost of the service provided. To achieve this goal, early diagnosis, prevention, and a more efficient disease management system are highly needed [2]. For example, the sleep disordered breathing (SDB), also known as obstructive sleep apnea (OSA), is one of the most common clinical disorders that can affect elderly people. The patient with OSA will need to stay in a specialist sleep clinic for the whole night to be diagnosed with multiple sensors attached to his/her body to monitor different vital signs besides sleep activates. Therefore, non-intrusive and less-expensive sleep diagnostic modalities are very important for long-term monitoring.

A thin air-filled cushion is introduced by Watanabe *et al.* [4] to detect sleep staging. Sleep data from eight university students were collected over 27 overnight recordings, where the cushion is placed between the bed and the mattress. For validation purposes, the students went to bed at a specific time at night. The proposed system provided heartbeat, respiration, snoring, and body movements.

Kortelainen *et al.* [5] proposed to use an Emfit foil sensor to monitor sleep stages by placing the sensor under the bed mattress. The sleep data was recorded from nine female subjects in a sleep laboratory. The recorded data consisted of heart rate, respiratory rate, and body movements.

Matar *et al.* presented [6] an application for gesture recognition in sleep monitoring. The authors used a pressure mattress covering the whole surface of the bed. The raw data is collected from the pressure sensors. Afterward, the movement is classified through a supervised learning method. Although these systems might be consistent with the gold standard methods, an intermediate training phase is required. Thus, they might not be applicable to real-life deployment. On the other hand, Paalasmaa *et al.* [7] provided a fully automated web application for home-based sleep monitoring using a piezoelectric film sensor, which can be placed under the mattress topper, the sensor can provide heart rate, respiratory rate, and body movements. The proposed approach was validated with 40 patients in a sleep clinic.

Finally, Rosales *et al.* [8] used a hydraulic bed based sensor to monitor sleep quality of four subjects over two to four months in-home living conditions. The hydraulic sensor was placed under the bed mattress, and they estimated the sleep quality based on the heart rate using two different methods. The contribution of this work is superior to other related works in the literature since authors deployed the system in real-life conditions without any constraints of in-lab environments. As we can see above, few approaches in existing literature dedicated to unobtrusive sleep monitoring in-home living situations.

To conclude, we position our research as one of the deployable solutions, which computes some medical parameters during the sleep time of an individual.

## 3 Methodology

We propose to use a microbend fiber optic sensor (FOS) to detect sleep parameters, and its integration into a user-friendly AAL IoT platform that observes and computes activities of daily living of an individual. First, second and third, we explain the principle of the used sensor, we introduce our AAL platform, and we present the integration of the sensor into the platform. Fourth, the algorithm processing the sensor data is provided. Finally, we adjust the key sleep items to the International Classification of Functioning, Disability, and Health (ICF)[1] model presented by the World Health Organization. The mathematical approach homogenizing the aggregated data is provided.

Figure 1 summarizes a deployment of the presented system in user's home.

### 3.1 Unobtrusive Sensor Selection

As described above, the BCG signal is used to analyze the sleep data through a microbend FOS. The fundamental principle is based on the light intensity

[1] http://www.who.int/classifications/icf/en/.

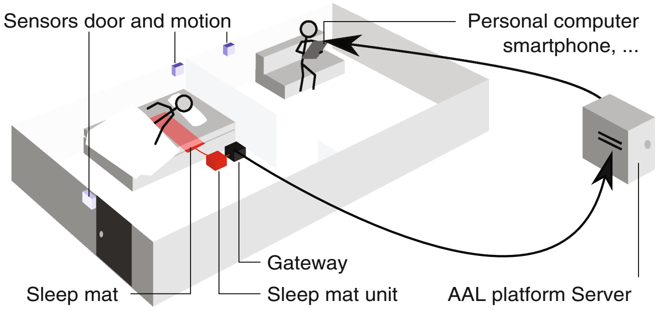



**Fig. 1.** Overview of our unobtrusive monitoring in a living space.

modulation induced by microbending in multimode fibers, which is used as a transduction mechanism for detecting pressure. A 10-meter loop of graded-index multimode fiber is sandwiched between two layers of tuned grating structures that subject the fiber to mechanical perturbation when there is a pressure applied as shown in Fig. 2(a). The pressure causes the transmission modes in the multimode fiber to be coupled into the loss mode, reducing the amount of light received by the photodetector. Hence, the detected light is converted to current by the photodetector, which is, in turn, converted into a voltage using a transimpedance amplifier. The signal is filtered via a 20 Hz low-pass filter and then digitized by a 16-bit analog-to-digital converter with a sampling frequency of 50 Hz [9,10].

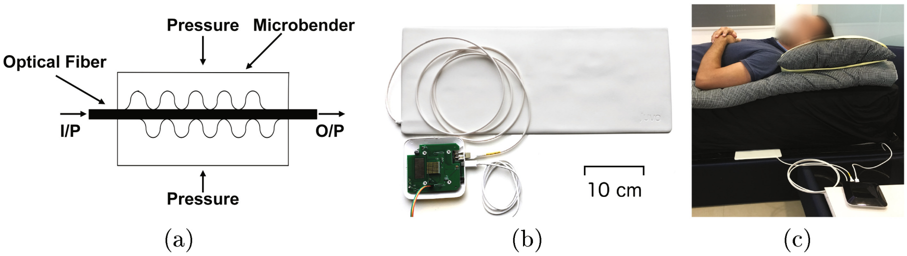



**Fig. 2.** (a) Longitudinal section of the microbend fiber optic sensor, (b) Sleep mat and processing box. (Mat dimensions: 20 cm × 50 cm × 0.5 cm) (c) Sleep mat positioned under the mattress.

### 3.2 UbiSmart Design

UbiSmart is a web-enabled AAL platform intended for large-scale deployments following the approach presented by Bellmunt *et al.* [11]. Key features [12] are *plug & play* ability, privacy protection as there is no sound and no image recording, easy interaction for end-users, and generic architecture. This AAL platform is able to transform any environment into a smart space in five minutes, enabling an unobtrusive assessment of indoor as well as outdoor activities of dependent people in their home environment. The purpose of UbiSmart is to detect the *Activities of Daily Living* (ADL), and to provide rich services in the right context through appropriate channels.

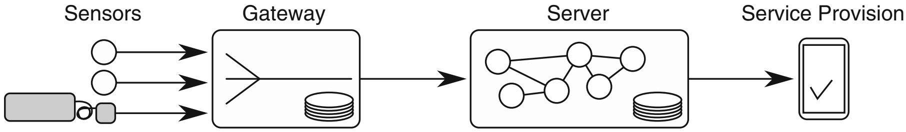



**Fig. 3.** Simplified view of UbiSmart AAL platform with sleep mat and its processing unit as a sensor.

The framework is composed of three main parts (Fig. 3), in data flow order: (1) **Gateway**, "smart home in a box" – sensors (motion sensors, contact sensors and the newly integrated bed sensor for sleep monitoring) and a gateway (Raspberry Pi); (2) **Server** – receives formatted inputs from the gateway, and processes them using semantic reasoning following the approach presented by Aloulou and Bellmunt *et al.* [3,13]; (3) **Service Provisioning** – responsive user interfaces on the web or on hand-held devices that allow users to receive notifications or interact with the platform.

### 3.3 Integration of Microbend Fiber Optic Sensor

The sleep mat equipment is considered as another sensor that contributes to the knowledge base of the AAL platform. We explain its integration into the existing system following the data flow from the source to the presentation.

**Collection.** The bed sensor-processing unit is wired to our *Gateway* (Raspberry Pi). Voluminous raw data is read and stored on a micro SD-card for a deeper off-line analysis. Simultaneously, the data is preprocessed to generate high level events, such as *bed empty*, *bed motion*, *sleep*. Currently, it operates on a time window of 10 s. For each time window an event is produced. The events are then sent to the *Server* as a structured sensor data using MQTT protocol over an Internet connection [3].

**Reasoning.** *Server* handles the received structured information (event). The bed sensor will appear in the *home description* interface as available for association to a house. If confirmed, this association is stored in the knowledge base (KB). Any subsequent events are then inserted into the KB of the associated house, allowing to the reasoning engine to be aware of bed occupancy with respect to our ontology (Listing 1.1). Coupled with the information from other sensors and sources, it provides an accurate contextual information. In parallel, the raw data is processed every 5 min to extract information about the occupant's respiratory effort and heart rate. This information is also inserted into the KB.

**Listing 1.1.** Simplified sample of our knowledge base in *Notation3* – sleep monitoring model featuring basic ontology, rule, instantiation and conclusions. (Note that not all the objects have been declared in the code sample.)

```
## Workspace definition ##
@prefix rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>.
@prefix qol: <http://www.ubismart.org/n3/qol-model#>.
@prefix hom: <http://www.ubismart.org/n3/home#>.

## INFERENCE RULE ##
{?se qol:hasLastUpdate true. ?se qol:indicateSleep true. ?se qol:attachedTo ?b. ?b a qol:Bed.}
=> {hom:user qol:believedToDo hom:sleepOnBed}.

## EXCERPT FORM KNOWLEDGE BASE ##
hom:bed rdf:type qol:Object.
hom:sleep rdf:type qol:Activity.
hom:bed qol:locatedIn hom:house.
hom:sensor_sleepmac_b8_27_eb_10_1c_79 rdf:type qol:Sensor.
hom:sensor_sleepmac_b8_27_eb_10_1c_79 rdf:type hom:SleepMatSensor.
hom:sensor_sleepmac_b8_27_eb_10_1c_79 qol:id "sleepMac_b8_27_eb_10_1c_79".
hom:sensor_sleepmac_b8_27_eb_10_1c_79 qol:attachedTo hom:bed.
hom:SleepMatSensor qol:hasPossibleState _:b1.
hom:SleepMatSensor qol:hasPossibleState _:b2.
_:b1 qol:hasValue "bed_empty".
_:b2 qol:hasValue "bed_motion".
_:b2 qol:hasValue "sleep";
      qol:indicateSleep "true"^^xsd:boolean.

## CONCLUSIONS ##
hom:sensor_sleepmac_b8_27_eb_10_1c_79 qol:hasValue "sleep".
hom:user qol:believedToDo hom:sleepOnBed.
```

**Presentation.** *Service provisioning* through our simple responsive web interface *Life Tiles* Fig. 4 allows us to give the user an instant feedback about bed occupancy and continuously updated information about the occupant's respiratory effort and heartbeat. Other indicators show aggregated information about activities out of the scope of this paper.

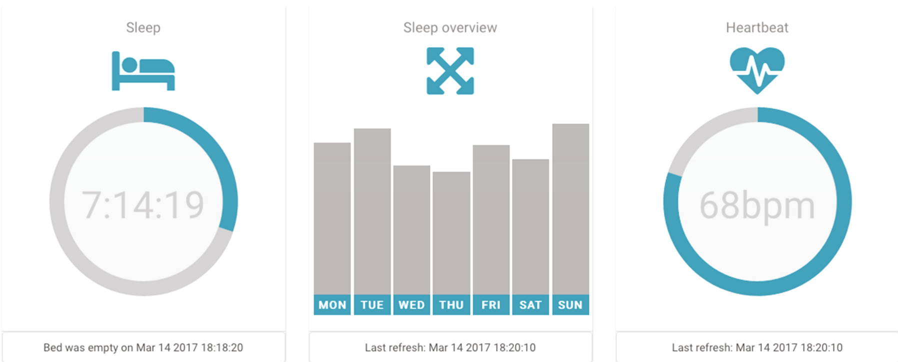



**Fig. 4.** UbiSmart user interface is organized in tiles and it provides following information: daily quantity of sleep (selected day) with updated bed occupancy status that changes the color of the icon and status line; aggregated week overview of sleep quantity; and heartbeat information.

### 3.4 Fiber Optic Data Processing

The sleep data is stored in 5-minutes chunks on a Micro SD-Card embedded in the processing unit. Then it is sent to a cloud-based server for data processing. Subsequently, the resident bed state is determined using a sliding window $w$ with a size of 1500 samples, i.e., 30 s. Thereafter, three-bed states are recognized, as illustrated in Fig. 5. First, if the standard deviation (SD) of the window is greater than 0.7 of the mean SD of all windows, the status is considered as a *bed motion* (Fig. 5). Second, if the SD of the window is smaller than a predetermined threshold, the status is regarded as a *bed empty* (Fig. 5). Finally, in other cases, the state is identified as a *sleep* (Fig. 5). Algorithm 1 summarizes the bed state data processing.

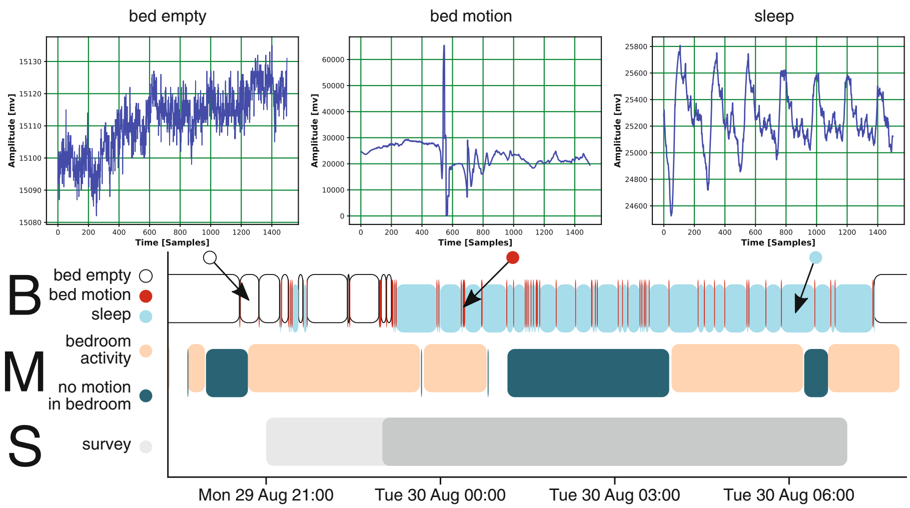



**Fig. 5.** Representation of a participant's night from our real life deployment. Three typical signal shapes are labeled according to recognized conditions: *bed empty*, *bed motion*, *sleep*. Gantt diagram: **Row "B"** is the result of the signal processing from the bed sensor. **Row "M"** shows a very inaccurate detection using motion sensors (blank space indicates activity detection in other rooms out of scope). **Row "S"** indicates the participant's answer in the survey Table 2 about their waking and sleeping habits.

The heart rate is computed in beats per minute as introduced in [9,10]. The idea is to use the *Complete Ensemble Empirical Mode Decomposition with Adaptive Noise* (CEEMDAN) algorithm to decompose the raw FOS data into what is called intrinsic mode functions (IMFs). Consequently, we select the IMF that matches the heart beats.

We employed the CEEMDAN algorithm as implemented in the *libeemd* package [14]. The algorithm is applied with a noise standard deviation of 0.25, an ensemble size of 250, $S$ number of 4, while the number of siftings is 50.

The 5$^{\text{th}}$ IMF is selected for heart rate estimation because each local maximum shows an agreement with heart beats. Heart rate is computed using a sliding time window of a size 10 s.

The respiratory rate is computed in breaths per minute using a sliding time window of a size 20 s, where the raw FOS data is filtered using Chebyshev type I bandpass filter with frequency limits of 0.03 and 0.4 Hz. Then, a simple peak detector is utilized for respiratory peak detection.

**Algorithm 1.** Sleep mat data processing

**Input:** $W = \{w_1, w_2, \ldots, w_N\}$, $\mathtt{T} = 10$
**Output:** state
**for** $i = 1, \ldots, N$ **do**
    Compute $\mathtt{S}(i) = \mathtt{SD}(w_i)$
**end for**
Compute $\mathtt{M} = \mathtt{mean}(\mathtt{S})$
**for** $j = 1, \ldots, N$ **do**
    **if** $SD(w_j) > 0.7 * \mathtt{M}$ **then**
        state = *bed motion*
    **else if** $SD(w_j) < \mathtt{T}$ **then**
        state = *bed empty*
    **else**
        state = *sleep*
    **end if**
**end for**

### 3.5 Sleep Monitoring Parameters Computation

In this paper, we focus on the sleep performance using a single fiber optic sensor placed under the mattress. To make sense of the collected data, we have conceived a sleep model based on the current literature. As mentioned in Sect. 3, we have identified six key sleep parameters following the ICF model, which can be computed using the collected data. Table 1 presents these six items with its description and its correspondence within the ICF model.

The generated dataset per user results to be very heterogeneous. While items as **Bed Time** or **Wake Up Time** are computed in time scale, others as **Heart rate** are expressed as a natural number. Moreover, some items are represented on a much smaller scale than the sleep time. Therefore, the system processes these values to reduce its range and homogenizes them into the same scale. Consequently, the collected datasets have been normalized using the zero normalization ($Z_{\text{Norm}}$), or standardization, to reduce the large trend of the data.

Let $x_{id}$ be the observation for an item $i$ in a day $d$. This value $x_{id}$ is then standardized using a $Z_{\text{Norm}}$ with the previous days' observations. The values will be in the range of $-1$ *to* 1,

**Table 1.** Sleep items computed during our study. Each item is represented by its code in the IFC model and its description.

| Sleep parameter | ICF code | Unit | Daily computation |
|---|---|---|---|
| Sleep time | b1340 | Time | Amount of deep sleep time |
| Night movement | b1342 | Time | Movement during sleep time |
| Wake up time | b1343 | Time | Time when the user wakes up |
| Bed time | b1343 | Time | Time when the user goes the bed |
| Respiration functions | b440 | Breaths/Min | respiratory effort during sleep time |
| Heart rate | b4100 | Beats/Min | Heart rate during sleep time |

$$\widehat{x_{id}} = Z_{\text{Norm}} = \frac{x_{id} - \mu_{id}}{\sigma_{id}} \qquad (1)$$
$$-1 \leq \widehat{x_{id}} \leq 1$$
$$\text{where: } \mu_{id} = mean(\mathbf{x_i}), \quad \sigma_{id} = SD(\mathbf{x_i}) \quad \text{and} \quad \mathbf{x_i} = \{x_{ij} \mid 0 \leq j \leq d\}$$

The standardization highlights the outliers within a dataset. On daily basis, the system produces reference items' values for each user. The proposed solution aims to detect spontaneous and unexpected abnormalities. For this purpose, the system applies the Bland-Altman analysis, which is employed to find unpredictable or aberrant values. As a person might change his behavior in a long-term deployment, the system computes the average value $\mu$, and the standard deviation $\sigma$, for a given day $d$ based on all previous observations. This procedure helps to evolve the boundaries of normality for each parameter adding dynamism to the Bland-Altman analysis.

## 4 Results and Discussion

The proposed solution was deployed in real conditions for 30 days in order to validate our approach. During the deployment in participants' homes, our system recorded data, and they were post-processed and evaluated. The objective of this validation was to study the reliability of the sleep monitoring and the performance of the entire system in a distant real deployment. At the same time, this deployment allows us to validate the interconnectivity of different sensors, the communication between the gateway and the server, and presentation of results in real time.

The sleep data is continuously acquired from three HDB[2] flats with elderly female residents, where the FOS sleep mat shown in Figs. 2(b) and (c) is placed under the bed mattress. However, one of the residents prefers to sleep on the

[2] http://www.hdb.gov.sg *Housing & Development Board* is a Singaporean governmental organization responsible for public housing, on their website, HDB claims: "HDB flats are home to over 80% of Singapore's resident population".


(a) (b) (c)

**Fig. 6.** Sleep mat integration at the three HDB apartments; (a) 1st home with mat under bed mattress, (b) 2nd home with mat under sleeping rug, (c) 3rd home with mat under bed mattress.

floor thus the sleep mat is placed under the sleeping rug. Before data collection, a survey is collected from the residents to indicate their sleep habits and other social activities as presented in Table 2. Figure 6 (a), (b), and (c) show sleep mat deployment in the three HDB apartments.

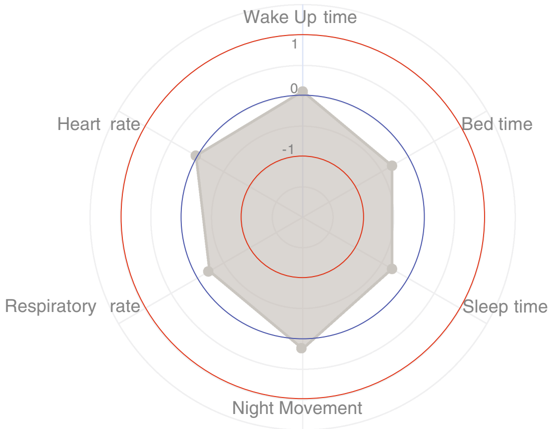
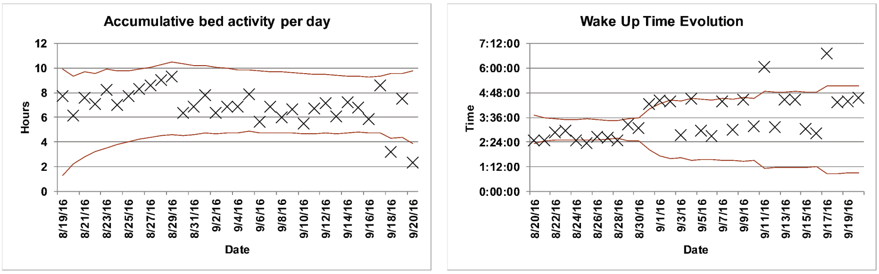



**Fig. 7.** Sleep chart model for 1st resident.

We observed a notable improvement in terms of detection of bed activity compared to the previous approach using motion sensors. Figure 5 presents a sample of the processed data. In Fig. 7 the user is characterized in a multidimensional spider graph. The values are computed on daily basis, normalized and compared to its statistical components, arithmetic mean and standard deviation following Bland-Altman analysis to detect outliers. This graph allows us to observe whether sleep performance has remained within a range of normality. The heart rate and the respiratory rate are computed and updated each hour. Figure 8(a) represents the result of the evolution of the *bed activity* along our




(a) (b)

**Fig. 8.** Sleep data analysis for $1^{st}$ resident; (a) Bed activity, (b) Wake up time.

deployment. Each day is represented by its value and the range of normality represented by $\mu \pm \sigma$.

**Table 2.** Age and sleep profile of each independent resident (no chronic diseases or disabilities are reported).

| | Age | Living situation | Sleep time (approx) | Wake up time (approx) | Nap |
|---|---|---|---|---|---|
| Resident#1 | 68 | Family | 18:30–19:30 Sometimes at 22:00 | 02:30 | 2–3 times 14:00–15:00 pm 30 min |
| Resident#2 | 69 | Alone | 23:00–00:00 | 07:00 weekends 05:30 | 1–2 times 14:00–15:00 30–60 min |
| Resident#3 | 65 | Family | 21:00–23:00 | 07:00 wednesday 04:00 | Not reported |

In order to validate our aggregated values, we performed individual interviews to understand the individual lifestyle of each participant. Table 2 presents an abstract of the results of the personal interviews. For instance, we detected that resident 1 started his bed activity very soon in the evening, and they woke up around 2.30 am. At first, it seemed to be an aberration in our measurement. However, in the survey, the resident confirmed her sleeping time matched our results. Thus, we could validate our inferred values.

## 5 Conclusion

In this paper, we presented a novel unobtrusive method for sleep monitoring using fiber optics in an Ambient Assisted Living platform, featuring a concise user interface. Our system was tested for 30 days in a real deployment in three flats in Singapore. Personal interviews confirmed the results of our post-processing.

Subsequently, the signal processing was implemented to be performed in real-time. The sleep mat was wired to our gateway in the user's place. The gateway processes the raw data, extracts bed events, and sends them to the server. At the same time, it stores the raw data and sends them to a dedicated cloud API for a deeper processing in order to extract the proposed sleep parameters. The outputs are used by both our reasoning engine, and served in our platform's new responsive interface adapted for hand-held devices. The reasoning engine is operating on an ontology and provides context for each event that occurs.

We also described the most-recent post-processing, including other vital-signs monitored by the same optic fiber technology.

The overall results contribute to a quantification of the residents' behaviors and to a measurement of their quality of life.

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