New trends in machine learning techniques for human activity recognition using multimodal sensors

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Abstract. The ageing of today's society, according to demographic and epidemiological data, presents a significant increase in the elderly population. Following the experienced pandemic, research in telemedicine to improve the lives of elderly people through a comprehensive program developed by multidisciplinary teams has become a top priority. This enables the provision of remote healthcare services, facilitating access to specialists, disease monitoring, medication management, and health indicator tracking to address the medical, social, and emotional needs of elderly individuals. This study proposes a sensor-based approach to identify activity patterns without prior labels. The system architecture responsible for collecting data from the monitored user in the assisted living facility consists of a beacon, multiple anchors, and various sensors for motion, opening and closing, temperature, and humidity. The experimentation was carried out with distinct activities such as sleeping, eating, taking medication, walking, showering, and brushing teeth, inferred from the identified patterns. This approach offers an automatic and objective way to understand the routines and behaviours of older individuals, thereby improving their care and attention through personalized interventions tailored to their individual needs. Furthermore, it lays the groundwork for future research on the detection and monitoring of changes in activities over time, identifying possible signs of impairment or changes in the health of elderly people.

Keywords: Machine Learning · HAR · multimodal sensors · smart environment.

1 Introduction

In recent decades, technological advances have played a fundamental role in improving people's quality of life. These advances have enabled experiments and the development of new methods that aim to improve different aspects of our daily lives. One of these advances is human activity recognition (HAR), which in short is a technique that uses sensors to identify and classify the actions that a person performs on a daily basis.

HAR is based on the use of sensors that can distinguish between different everyday activities, such as walking, running, showering, cooking, lying down, etc. These sensors can be found in mobile devices such as smartphones and smartwatches. These sensors can be found in mobile devices such as smartphones and smartwatches. These devices are equipped with a variety of sensors, such as accelerometers, gyroscopes, GPS, microphones, Bluetooth, Wi-Fi, and heart rate meters, which allow a large amount of data and information to be collected about a person's activities and behaviour.

In addition to mobile sensors, there are also fixed sensors that are placed in specific locations to constantly collect information. Examples of these sensors are video cameras, acoustic sensors, proximity sensors, opening and closing sensors, temperature sensors, light sensors and others. However, fixed sensors pose additional challenges, such as the privacy of individuals, as they may collect information without their authorisation, and they may also have difficulties in collecting reliable data in changing environments or environments with more than one inhabitant. For this reason, fixed sensors are often installed in supervised locations or in assisted living facilities[1, 2].

Our focus of work is in the field of healthcare, specifically in the monitoring and care of elderly people with diabetes living in sheltered housing. These supervised flats offer significant advantages for elderly people, as they provide them with a homely, familiar and welcoming environment. Furthermore, they allow them to maintain their independence and autonomy, making decisions according to their individual preferences. The presence of specialised staff available 24 hours a day provides security and reassurance in case of need, and social interaction and the enrichment of relationships between residents is promoted.

In this context, it is essential that elderly people follow specific routines for the management of their disease, and this is where sensors play a crucial role. Using sensors, we can monitor and verify whether the established daily routines and activities are being accomplished. This allows us to keep an accurate track of their state of health and well-being. In addition, doctors make regular visits to the residents to assess and make any necessary adjustments to their care planning. In each supervised flat, where two people live, one of them is monitored by a smart wristband. This smart wristband allows the person being monitored to be identified and distinguished, providing specific data on their activity.

A study is currently being conducted in ten supervised flats to assess the effectiveness of monitoring and its impact on the quality of life of elderly people with diabetes. The primary goal is to develop a comprehensive system of care and support that will improve the health and wellbeing of these people, giving them greater independence, confidence and security in their daily lives.

The remainder of this paper is structured as follows: in Section 2, the related work is reviewed. Thereafter, in Section 3, we propose an architecture for HAR using multimodal sensors. Section 4 summarizes the experimentation carried out. The paper finalizes with the conclusions (Section 5).

2 Background

The selection and placement of sensors play a crucial role in human activity recognition. In the early studies conducted in the 1990s, the accelerometer was the most commonly used sensor [3]. Subsequently, it was concluded that the most effective placement for differentiating human activities was on the thigh [4] [5].

Thanks to technological advancements, various sensors have been developed to collect data on human activity. Depending on the sensors used, solutions can be classified into three groups:

- Video-based HAR, which employs fixed cameras to capture images and videos.
- Wearable sensor-based HAR, which utilizes devices such as smartphones and smartwatches equipped with integrated sensors.
- Non-wearable sensor-based HAR, which relies on sensors placed in the environment (thermal, acoustic, etc.)

The processing and analysis of collected data are fundamental stages in human activity recognition. Techniques such as preprocessing, data segmentation, feature extraction, and activity classification are applied [6]. However, there are significant challenges in this field, such as attribute selection, realistic data collection, system adaptability to new users without retraining, and the development of portable and cost-effective data collection systems [7].

Accurate identification of the person performing an action is crucial to avoid errors. Indoor location tracking, also known as indoor localization, plays an essential role in this aspect. However, current devices often exhibit false or incorrect activations, leading to misleading results [8]. To address this challenge, the Received Signal Strength Indicator (RSSI) value is utilized, which measures the power of a radio signal. Although RSSI offers advantages such as low cost and good performance, signal variability among devices can affect localization accuracy [9] [10].

The most commonly used method worldwide for indoor localization is the utilization of Bluetooth Low Energy (BLE) in conjunction with smartphones or wearable devices that implement this technology. This approach employs beacons that collect RSSI data. Although it has limitations such as signal variability and the need to install multiple beacons in large indoor spaces, it remains popular due to its ease of implementation and low cost [11].

In addition to using RSSI, this work employs the Message Queing Telemetry Transport (MQTT) protocol for sensor communication. MQTT is a lightweight and energy-efficient messaging protocol designed for efficient communication between Internet-connected devices [12] [13]. The ZigBee protocol is also utilized, which is a low-power wireless communication standard suitable for applications requiring extended battery life, such as home automation systems, health monitoring, sensor networks, and device control [14].

3 Architecture

This section will provide a description of the architecture used and a detailed explanation of the devices employed.

Firstly, multiple Raspberry Pi are used as anchors in the architecture. These Raspberry Pi are responsible for scanning BLE beacons, i.e., searching for and detecting nearby BLE beacons. They then collect the RSSI of each detected beacon and send it to the fog node. The fog node is a component of the fog computing architecture located at the network edge. The collected RSSI signal is sent to the fog node every second using the MQTT protocol.

Additionally, an activity wristband is utilized. This wristband has BLE connectivity and is used to locate the inhabitant using the RSSI signal.

The anchors are deployed evenly in relevant monitoring locations. In this case, the required locations are the bedroom, bathroom, kitchen, and dining room.

To detect the performance of activities, different types of sensors have been installed throughout the rooms. These sensors include motion sensors, interruption sensors to detect the opening and closing of drawers and doors, and temperature and humidity sensors. The sensors utilize the ZigBee protocol to facilitate communication between them, enabling the detection of patient activity and monitoring of relevant environmental conditions.

Figure 1 presents four rooms plans, one of which is the living room of the house. In the living room, there is a node and an anchor located on either side of the television. There is also a P1 motion sensor attached to the wall and focused towards the right-side couch. This sensor is associated with the monitored patient and is used to detect if the user is sitting at the table and eating.

In the bedroom plan, only two devices are placed. These include an anchor and a classic motion sensor located on the wall, pointing towards the right side of the bed. This sensor corresponds to the monitored patient and its function is to detect if the user is in bed and sleeping.

Furthermore, the kitchen plan is displayed, featuring an anchor and an open/close sensor housed in a plastic box on the table where the patient stores their diabetes medication. The purpose of this sensor is to detect whether the user has taken their medication.

Finally, the plan of the bathroom, similar to that of the other rooms, is shown with an anchor. In this case, there are two P1 motion sensors attached to the wall. One is oriented towards the shower area to detect if the user is taking a shower, while the other is focused on the area where the toothbrush is located to check if the user is brushing their teeth. Additionally, near the shower area, there is a sensor for temperature, pressure, and humidity, which also serves the purpose of detecting if the user is taking a shower.

Although not shown in the presented room plans, an open/close sensor has also been placed on the main door of the house. By combining this sensor with the other devices, it is possible to determine if the user leaves the house, allowing for the calculation of the duration of the walk along with the number of steps detected by the wristband.

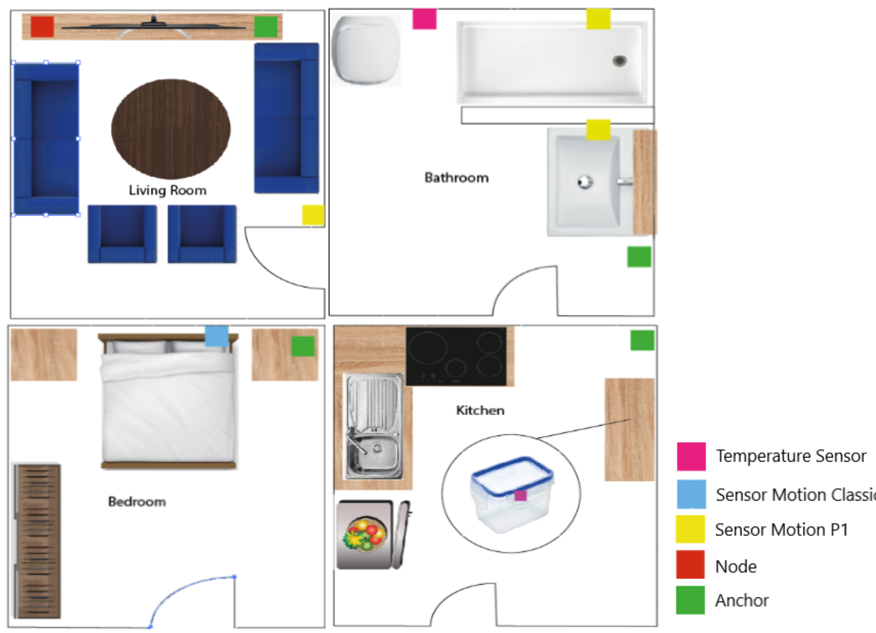

Fig. 1. House Plans.

4 Case study

The focus of this work is to examine the effectiveness of various sensors, anchors, and beacons installed in a floor to monitor the routines of users suffering from a disease, specifically diabetes.

The main idea is to track the daily routines and activities of users by installing sensors. These activities are prescribed by a family physician and encompass actions such as brushing teeth three times a day, going for a walk, showering, sleeping, eating, and taking medication.

The physician conducts regular visits to assess the patients' health status. In order to enhance monitoring and facilitate the physician's work, the collected data is utilized to generate graphs that provide the physician with a quick overview of the patients' routines over the past days, weeks, or months. This will enable the physician to promptly identify any potential anomalies, non-compliance, discrepancies, or deception by the users, which would not be beneficial for their health condition.

We are working with various datasets formed by the collected data, and one of them contains information about the RSSI that allows us to determine the user's location within the house at any given moment. To ensure data accuracy, we apply a filter to work only with RSSI values above -55, which provides confidence that the user is in the same room where the sensor capturing that signal is located.

In Figure 2, the analysis for a selected day is displayed, which facilitates the identification of patterns in the patient's routine. The obtained RSSI value is highly useful when combined with other sensors as it allows us to ensure that the intended activities are being performed and helps to eliminate potential detection failures from a single sensor.

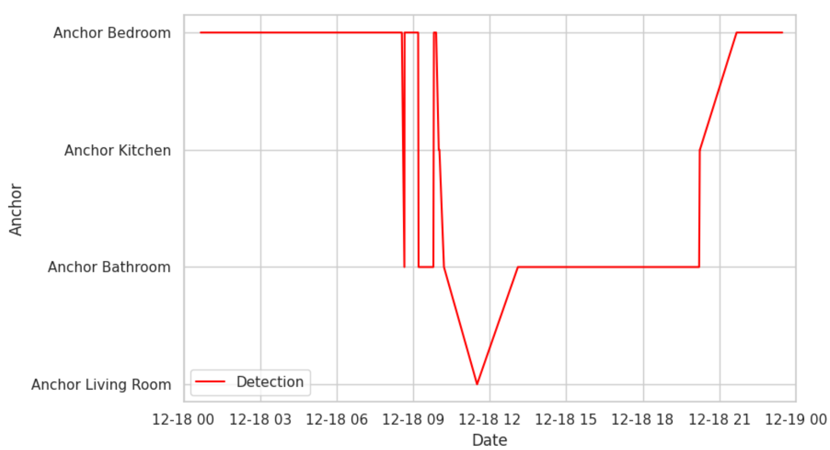

Fig. 2. RSSI Analysis.

The dataset containing information about the sensor states proves useful for verifying their update rate and ensuring they are functioning correctly. Additionally, it provides benefits when studying the moments when a sensor's state changes to 'on', particularly in the case of open/close sensors.

In Figure 3, we can observe the moments when both the main door sensor and the medication box sensor were activated. This information assists us in determining, along with the data captured by the rest of the system, when the monitored user takes their medication and when they leave the house for exercise.

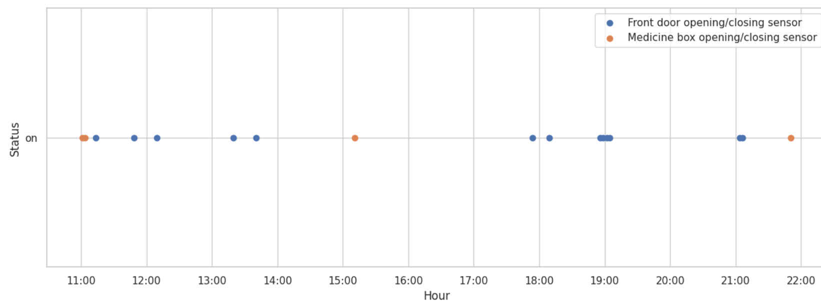

Fig. 3. Sensor Status.

The dataset recording information from the temperature, humidity, and pressure sensor placed on the bathroom wall has also been analyzed to evaluate its usefulness in detecting whether the user is taking a shower. It has been observed, as shown in Figure 4, that representing the humidity variable reveals clear peaks indicating the presence of a person showering.

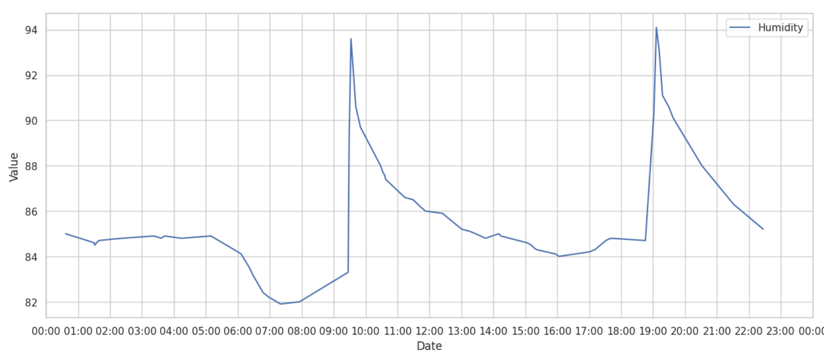

Fig. 4. Humidity Analysis.

However, to confirm that the activity corresponds to taking a shower and not to another person in the bathroom (remember that there are two people living in the apartment and only one of them is monitored using the smart wristband), it is necessary to use the RSSI value to corroborate that the monitored patient is in the bathroom at that time.

After studying the different data captured by the components that form the system and combining them, we can create a dataset in which we label the activities performed by the monitored user by day and hour. The purpose is to create highly visual and easy-to-understand graphs and statistics to facilitate the physician's task when it comes to monitoring and ensuring compliance with the proposed routines.

In this case, graphs created with the labeled activity data for a user in December 2022 will be presented. Figure 5 displays a bar chart showing the frequency of the six activities to be performed. It can be observed that brushing, eating, and medication activities are the most frequent, as they should be done three times a day, while the rest of the activities are carried out once a day.

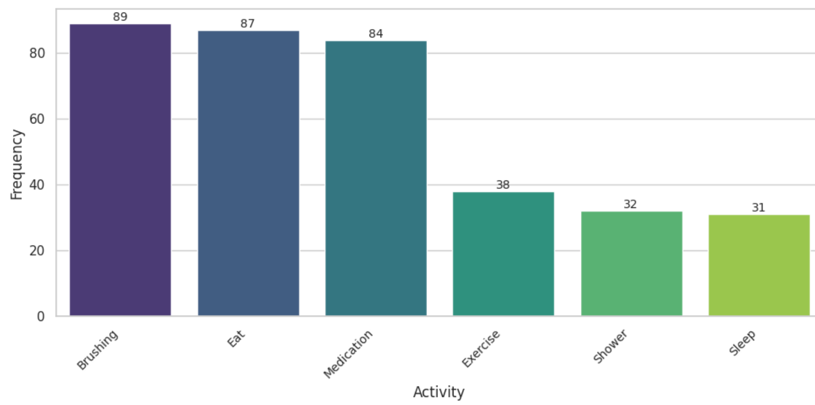

Fig. 5. Frequency of Activities in a Month.

To provide a clearer visualization, Figure 6 presents a horizontal bar chart showing the percentage of each activity completed throughout the month. The bars are depicted in red if they do not reach 100% and in blue if they do.

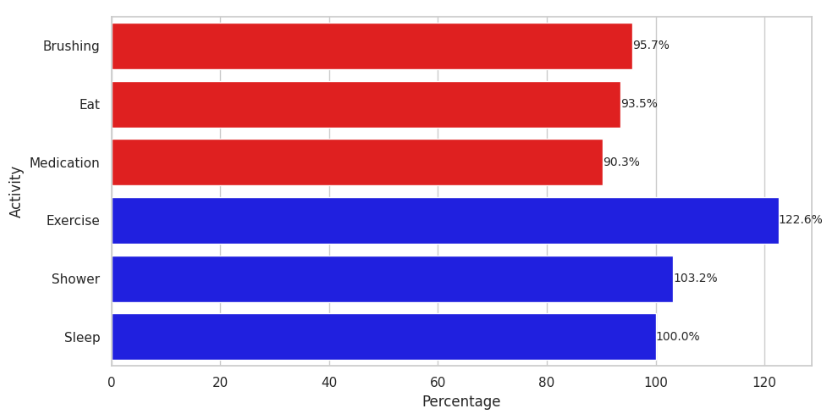

Fig. 6. Percentage of Each Activity Completed Throughout the Month.

It is important to highlight that medication has the lowest percentage of compliance, which is relevant information to communicate to the family physician and review, as it is likely the most crucial activity for the patient's health care.

However, it is important to note that even if a bar is blue, it does not guarantee that the activity was performed the correct number of times every day, as there may be days with fewer or more activities performed. To identify this, time series can be created, as shown in Figure 7, to observe at what time of the day each activity is carried out and verify if a routine is being followed.

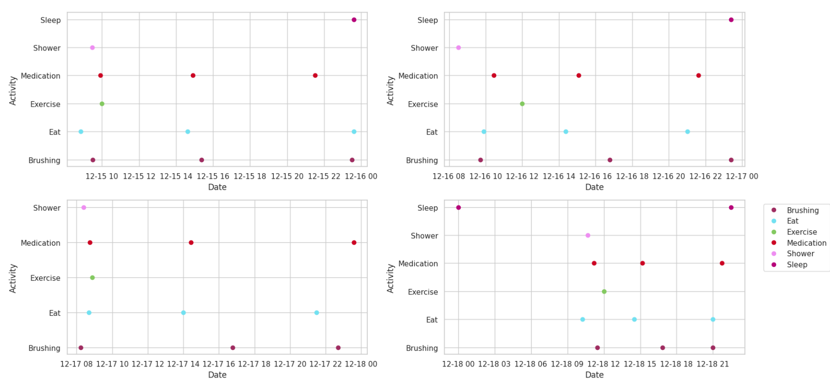

Fig. 7. Analysis of the Routine of Activities.

From the Figure 7, we can observe how, during the 4 days analyzed, the user has performed all the activities required by the physician. When examining the graph, we can identify patterns in the user's daily routine. Generally, the user starts the day between 8:00 and 10:00 and goes to sleep around 23:00, indicating compliance with the recommended minimum of 8 hours of sleep. It is also observed that most of the time the user brushes their teeth after meals, which usually occur shortly after waking up, at 14:00, and at 21:00. Additionally, the user typically showers in the morning before going for a walk to exercise.

By analyzing this graph, we obtain valuable information about the established routine of the monitored user. This is useful for assessing if the routine is maintained over time, and in the case of treating another user with a less established routine, it could be helpful in providing advice on how to correct certain habits and determining if they are being improved.

Additionally, it is also possible to study the duration of activities, but this information is only recorded for exercise and sleep. For this purpose, a time series spanning the entire month has been created, as shown in Figure 8.

Upon examining the graph, it is observed that there are three data points representing exercise durations exceeding 10 hours, which clearly must be attributed to measurement errors and do not reflect real values. To correct these

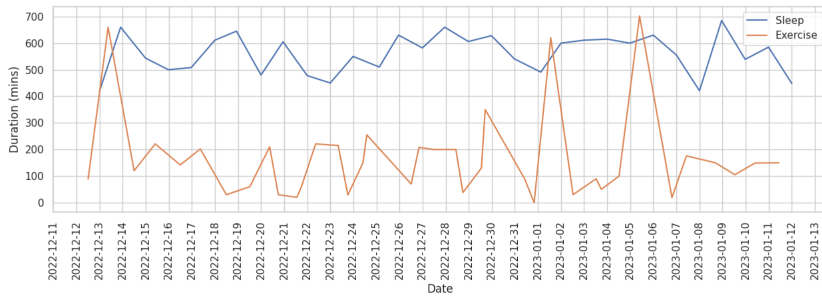

Fig. 8. Duration of Activities.

outliers caused by measurement errors, data points that exceed the upper limit of 2.5 times the standard deviation above the mean have been removed. By performing this procedure, the three identified outliers have been eliminated, as shown in Table 1, resulting in a significant change in the statistics.

Table 1. Comparison of Duration Statistics With and Without Outliers

Activity	count	mean	std	min	25%	50%	75%	max
Exercise	38.0	166.81	167.02	0.0	60.0	136.0	206.5	702.0
Exercise without outliers	35.0	124.48	83.04	0.0	55.0	120.0	200.0	350.0
Difference	3.0	42.33	83.98	0.0	5.0	16.0	6.5	352.0

Additionally, through the smart wristband worn by the monitored user, it is also possible to track the number of steps taken each day during exercise, and this data is represented in Figure 9 using a bar chart.

The presence of several days with 0 or very few recorded steps is noteworthy. These values are nonsensical since, as mentioned earlier, there was only one day without exercise. This error may be due to the smart wristband's battery being depleted or the user not wearing it due to charging or forgetting to put it on.

To correct this error, instances where the number of steps was below 500 have been removed. This is because, as previously determined, the average duration of the exercise activity is close to 2 hours, and therefore, fewer than 500 steps would indicate that the smart wristband ran out of battery or that the user did not wear it during the exercise session. Another possibility is that the user left the house without engaging in exercise in an attempt to deceive the physician. After correcting these data, the statistics are compared in Table 2.

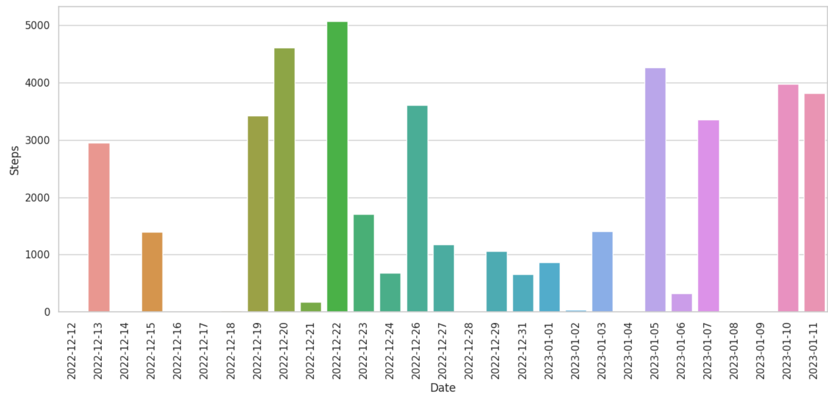

Fig. 9. Quantity of Steps.

Table 2. Comparison of Steps Statistics With and Without Outliers

Activity	count	mean	std	min	25%	50%	75%	max
Exercise	38.0	1173.05	1632.80	0.0	0.0	247.0	1626.75	5073.0
Exercise without outliers	17	2561.17	1562.72	597.0	1172.0	2952.0	3821.0	5073.0
Difference	21	-1388.12	70.08	-597	-1172	-2705	-2194.25	0.0

5 Conclusions

In this study, we propose a sensor-based approach to identify activity patterns. The architecture of the system in charge of collecting data from the monitored user in the assisted living facility consists of a beacon, multiple anchors, and several sensors for motion, opening and closing, temperature, and humidity. Experimentation was carried out with different activities such as sleeping, eating, taking medication, walking, showering and brushing teeth, inferred from the identified patterns. This approach offers an automatic and objective way of understanding elderly people's routines and behaviours, enhancing their care and attention through personalised interventions customised to their individual needs. Future lines are quite challenging although they are intended to be carried out in the long term. Clustering is intended to correlate the groups obtained with this unsupervised learning technique and the activities proposed by the doctors. Uncorrelated elements should be explored to try to deduce their meaning.

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