A Smart Remote Elderly Monitoring System based on IoT Technologies

V. Mighali, L. Patrono, and M. L. Stefanizzi
Department of Innovation Engineering, University of Salento, Lecce, Italy
vincenzo.mighali@unisalento.it, luigi.patrono@unisalento.it, laura.stefanizzi@unisalento.it

Joel J. P. C. Rodrigues
National Institute of Telecommunications (Inatel), Brazil;
Instituto de Telecomunicações, Portugal;
University of Fortaleza (Unifor), Brazil
joeljr@ieee.org

Petar Solić
University of Split, Faculty of Electrical Engineering, Mechanical Engineering and Naval Architecture, Split, Croatia
psolic@fesb.hr

Abstract— The aging population phenomenon is more and more increasing. In this context, the elderly’s behavioral analysis through the Internet of Things technologies can help to prevent Mild Cognitive Impairment and frailty problems. In particular, since movements and body motility are good indicators of behavioral changes, this work aims to define a reliable system for controlling the position and the body motility of the elderly in unobtrusive, low-cost and low-power way. The system represents the basis of a complete architecture for behavioral analysis and risk detection developed within the City4Age project, funded by the Horizon 2020 Programme of the European Commission.

Keywords— Behavior Analysis; Bluetooth Low Energy; Smart Environments; Internet of Things; Wearable

I. INTRODUCTION

In recent years, due a rapid increase in the number of elderly people, many efforts have been made to develop systems for monitoring the elderly’s behavior and for supporting them in daily life activities. It is estimated that 50% of the population in Europe will be over 60 years old in 2040, while in the USA it is estimated that one in every six citizens will be over 65 years old in 2020 [1]. In 75-year-old people, the risk of Mild Cognitive Impairment (MCI) and frailty increases. While some physical and mental decline is part of the healthy aging process, premature decline may be an early indicator of more severe conditions, such as Alzheimer’s disease (AD). The early detection of risks related to a specific health condition can help clinicians to enact appropriate interventions that can slow down the progression of the condition itself, with beneficial effects on both patients’ quality of life and treatment’s costs.

The Internet of Things (IoT) [2], [3], [4] with its advanced technologies could be the way to guarantee better life conditions for the elderly as well as to monitor their health through the development of innovative smart environments [5], the so-called Ambient Assisted Living (AAL) systems. AAL technologies can also provide more safety for the elderly, offering emergency response mechanisms [6], fall detection solutions [7], and video surveillance systems [8]. Moreover, they provide support in the daily life, by monitoring the activities of daily living (ADL) [9], by generating reminders [10], as well as by allowing older adults to connect with their family and the medical staff.

One of the key elements of a successful monitoring system for elderly people is its unobtrusiveness, meaning that it should be able to detect the desired parameters without interfering with user’s activities. To this purpose, the parameters more suitable for monitoring user’s behavior are positioning and body motility. In this direction, a significant help is given by the recent advancements in mobile and wearable devices. Indeed, latest devices are equipped with different sensors such as accelerometer, gyroscope, Global Positioning System (GPS) and so on, which can be used for detecting user position and motility.

Focusing on positioning, specifically in indoor environment, several works have been already proposed in the literature basing on different technologies [11]. Among these technologies, vision techniques guarantee high accuracy level [12], but suffer of very high cost. The infrared (IR) technology is also widely used for indoor localization, as shown in [13] and [14], though multipath effect drastically reduces the accuracy. Another widespread technology for positioning system is Radio Frequency Identification (RFID), whose main advantage is the capability to work in absence of Line of Sight (LoS). Finally, Bluetooth (BT) technology represents a valid alternative for indoor localization [15], [16], since it is able to guarantee low cost and poor invasiveness. Moreover, the spread of the emerging Bluetooth Low Energy (BLE) technology makes the BT also energy-efficient, which is a key requirement in many indoor applications. The recent rise of iBeacons by Apple has contributed to the rapid spread of this technology, used to provide information and location services [17] in a completely innovative way.

Regarding body motility, the classification of daily living human activities using wearable inertial sensors has been extensively investigated in the literature. Among all the sensors embedded into modern wearable device, triaxial accelerometers are the most broadly used sensors to recognize ambulation activities (e.g., walking, running, lying, etc.) [18], [19]. The majority of these studies, however, are based on the use of multiple accelerometers attached at different locations on the user’s body [20], [21]. Whilst a similar approach
provides sufficient contextual information, placing accelerometers in multiple locations can become cumbersome for the wearer. Furthermore, increasing the number of sensors also increases the complexity of the classification problem. On the contrary, the adoption of a single wearable device allows to satisfy the usability requirements for a long-term monitoring environment [22].

This paper aims to present a sensing architecture that exploits IoT technologies to capture positioning and motility data for automatically detecting behavioral changes in elderly people in an unobtrusive, low-cost and low-power way. The system architecture is defined according to the City4Age [23] project. This project aims to create an innovative framework on ICT tools and services that can be deployed by European cities, in order to: enhance early detection of risk related to frailty and MCI, and provide personalized intervention that can help the elderly population to improve their daily life and also promote positive behavior changes [24].

The proposed system consists of two sub-systems: a positioning sub-system that is in charge of detecting indoor user position, and a motility sub-system that constantly detects the body activity. The positioning sub-system leverages (i) a set of BLE beacons deployed in the house, (ii) the user’s smartphone, and (iii) a BLE-equipped wearable device to detect the current position of the user. On the other hand, the motility sub-system exploits the inertial sensors embedded into the wearable device to identify, in an unobtrusive way, the activities performed by the user.

The rest of the paper is structured as follows. In Section II, a description of the overall system architecture is provided. Section III and Section IV give a description of the positioning and motility sub-systems respectively. Section V describes the system validation, whereas conclusions are drawn in Section VI.

II. SYSTEM ARCHITECTURE

Fig. 1 shows the overall structure of the proposed system architecture. Macroscopically, two main building blocks can be identified: Local Building Block (LBB) and Cloud Building Block (CBB). It is worth to notice that in this paper only the LBB is described and evaluated, while a complete description of CBB is remanded to future works.

The LBB is responsible of gathering raw data from physical sensors independently of their specific technologies and communication protocols, and eventually processing them to calculate aggregated information for the upper layers. More in detail, the LBB is in charge of abstracting the heterogeneity of the physical technologies and providing a common vision of data to the core logic. To make possible this kind of approach, LBB is equipped with appropriate software modules, which are able to communicate with the sensing technologies according to the respective standards and protocols. This feature allows to easily extend its functionality to new technologies by developing the corresponding modules. The data collected by each module are then sent to the CBB through REST API. From an implementation point of view, the LBB can be indifferently represented by the user’s smartphone or a more powerful device, such as a single-board computer, installed into the patient’s home to collect raw/elaborated data provided by simple physical sensors or a wearable device.

The CBB represents the functional core of the proposed monitoring system, since it is responsible for analyzing the received data and alerting registered users in case of possible critical situations. The elaborated information is also stored into a custom database and makes easily accessible to doctor’s and authorized user’s family members through REST API.

More in detail, the designed architecture aims to provide support to the following services.

- Indoor Positioning Service: the positioning service runs on the wearable device (or directly on the user’s smartphone) and relies on an infrastructure of BLE devices, i.e. beacons. It detects the current user’s position and communicates it to the Cloud platform. Here, the localization information is stored and made available to other services.

- Motility Service: It is able to detect, in real time, the user’s body state. Specifically, by exploiting the inertial sensors embedded into the wearable device, it can identify the activity performed by the user with high accuracy and reliability. The result of the processing activity is then sent to the CBB for further analysis.

Data provided by these services help to identify elderly people behaviors and, above all, their variations, which may represent an early indicator of more severe conditions.

III. INDOOR POSITIONING SUB-SYSTEM

As said in the Introduction, one of the most suitable technologies for indoor positioning systems is BLE. Indeed, it represents a low-power and less-invasive way to detect the user’s position with enough precision (at least, the granularity is represented by the room in which the user is located). In more detail, the system consists of two main components: an infrastructure of BLE emitting landmarks that periodically send localization information and a software service installed on the user’s smartphone (or wearable device) that collects the
information from the landmarks to determine its position. In other words, the receiving device detects all the beacons in its reading range and identifies which is the nearest one. In this way, assuming that only one beacon is installed in each room (so that it is possible to consider a one-to-one mapping between beacons and rooms), the device can detect the user’s position inside home.

From an implementation point of view, each beacon sends a unique identification code (e.g., its MAC address), which is received by the receiving device with a specific Received Signal Strength Indication (RSSI) value. By exploiting this information, the smartphone (or wearable device) computes a proximity index $d$, using the following equation (1):

$$RSSI = -10\log_{10}(d + A)$$

where $A$ is the received signal strength at 1 m, $n$ is a signal propagation constant depending mainly on the environment, and $d$ is the distance from the sender. The beacon with the lowest value of $d$ represents the user’s current position. Due to the fluctuating nature of RSSI value, the position detection could sometimes suffer of unreliable results especially at the edge of each room, i.e. near the door between two rooms. To avoid this undesired result a further mechanism, called stability period, has been integrated in the position detection algorithm. The stability period is a time period ensuring that the user is durably in the new location. For example, the new position could be considered valid if the user is there for a predefined time period. The use of the stability period allows the so-called soft handover (i.e., transition) between two rooms and it is also useful to give a statistical validity to the position value. Fig. 2 shows a flowchart related to the indoor positioning algorithm. To summarize, if the nearest beacon is found, the algorithm checks if this beacon correspond to the previous position. If so, no room change is detected, otherwise the stability period is used. When this period expires, if the user is still in the new position, the current position is updated.

As said, the device that executes the positioning algorithm could be the user’s smartphone or a wearable device. In the most part of real scenarios, the wearable device should be preferred because there is a good chance the user does not keep the smartphone with him. Anyway, if the smartphone is used, the execution of the algorithm is straightforward since the smartphone is in charge only of position detection. On the other hand, if the wearable device is used, a proper switching mechanism has to be carried out because the wearable device is also responsible of detecting the user’s motility, as describe in the next Section. More specifically, the wearable device should constantly monitor user’s motility and periodically scan the environment looking for the nearest beacon. Then, it should send the position information to the smartphone as soon as it is in its reading range. Irrespective of whether the smartphone executes the positioning algorithm or not, it is in charge of sending the position information to the CBB for further processing.

IV. MOTILITY SUB-SYSTEM

A. Preliminary Considerations

The complex nature of human body movements makes the automatic recognition of daily activities a challenging goal. Furthermore, sensors’ properties, and their placement on the human body, have a direct impact on the recognition process, especially in terms of the variety of activities and the precision of their classification. This makes the definition of an activities recognition algorithm a complex task. In this perspective, commercial solutions, such as wristbands or smart watches, could represent a good starting point, providing an easy way to collect motility data. However, these devices are generally quite expensive and they usually not provide flexible APIs to interact with them.

To overcome these limits, the proposed motility sub-system has been developed by considering only low-cost and open devices. Specifically, our choice fell on the new multi-standard SensorTag. It is equipped with the MPU-9250 9-axis MotionTracking device, which combines a 3-axis gyroscope, 3-axis accelerometer, 3-axis magnetometer and a Digital Motion Processor (DMP). Its reduced size makes the SensorTag particularly suitable to be used as bracelet so as not to hinder the user's movements. Moreover, the embedded Bluetooth Low Energy (BLE) transceiver simplifies the communication with personal mobile devices, such as smartphones and tablets. Finally, the new SensorTag is equipped with an ARM Cortex M3 Microcontroller, whose ultralow power consumption allows the SensorTag to be battery powered, and offer long lifetime from a single coin cell battery.

However, the constrained nature of this device introduces several constraints and requirements that must be taken into account. First of all, the limited memory and processing capabilities of the SensorTag reduces the range of movements that may be classified. Any classification involving computationally intensive tasks should be avoided or appropriately simplified. Furthermore, the power consumption should be minimized to ensure the longevity of battery life in the SensorTag and relieve the user from the task of regularly recharging or replacing the battery.

Starting from these considerations, a motility sub-system able to detects still/moving periods by exploiting the sensors
embedded into the SensorTag has been designed. The ability to distinguish between periods of activity and rest provides, in fact, valuable insight about the user’s level of physical activity and general health status. Furthermore, performing the movement classification on-board means that only the classification information must be transferred, thus significantly reducing the duration of data transmission, and hence the power consumed by the transmitter module.

**B. Classification Algorithm**

Fig. 3 shows the flowchart of the developed classification algorithm. As introduced in the previous section, it exploits the tri-axial accelerometer embedded into the SensorTag to distinguish between “still” and “moving” periods. Only the acceleration data has been considered for the study, since this represents the most prevalent sensor modality in previous activity recognition contributions [19].

Because essentially all measured body movements are contained within frequency components below 20 Hz [25], each axis of the on-board accelerometers is sampled at 25 Hz. After each sample is acquired, a median filter with \( n = 3 \) is applied to the raw signal to remove any abnormal noise spikes produced by the accelerometers. Then, the three-axis raw accelerometer data are pre-processed to extract the Signal Magnitude Vector (SMV):

\[
SMV = \sqrt{acc_x^2 + acc_y^2 + acc_z^2} \quad (2)
\]

In this way, the resulting signal is independent of the orientation of the SensorTag. No further pre-processing of the data is applied to avoid the removal of relevant information.

Movement is classified based on the data collected over a 3s interval. The acceleration data signals is segmented into windows of 3s each with a 30% overlap between two consecutive windows. The considered window represents an acceptable trade-off between accuracy level and memory occupancy on the embedded device.

During the training phase, to distinguish between periods of user activity and rest two different features have been considered: mean and standard deviation. These are some of the features most widely used in activity recognition [26], [27] for their discrimination potential and ease of interpretation in the acceleration domain. Furthermore, they can be easily implemented also on a computational constrained device, like the SensorTag. However, the performed analysis demonstrated that the standard deviation can be used as unique parameter for the classification algorithm. Values above the evaluated threshold identify a moving period, while values below the threshold mean the user is in a resting state. A suitable classification keyword is chosen to describe the type of movement associated with this time period. This information is transmitted, by exploiting the BLE communication, to the smartphone for further analysis. To reduce possible classification errors, the background service, installed on the user’s smartphone, forwards the new activity to the CBB only if the user performs it for a predefined time period. Similarly to the positioning algorithm, also in this case a proper stability period is evaluated before considering the new activity to be valid.

**V. System Validation**

Following the structure of the architecture, also the validation phase has been carried out in order to separately prove the effectiveness of both positioning and motility sub-systems.
TABLE I. SELECTED ACTIVITIES

<table>
<thead>
<tr>
<th>Main Activity</th>
<th>Task</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Still</td>
<td>Sitting</td>
<td>The subject sits on a chair.</td>
</tr>
<tr>
<td></td>
<td>Standing Still</td>
<td>The subject remains standing.</td>
</tr>
<tr>
<td></td>
<td>Lying</td>
<td>The subject lies down on a mattress.</td>
</tr>
<tr>
<td>Moving</td>
<td>Walking (normal)</td>
<td>The subject walks at their normal pace.</td>
</tr>
<tr>
<td></td>
<td>Walking (fast)</td>
<td>The subject walks at a pace reasonably faster than his/her normal.</td>
</tr>
</tbody>
</table>

Focusing on positioning sub-system, a one-to-one mapping between BLE beacons and rooms has been considered, so that the room represents the granularity of the positioning algorithm. That said, the correct user’s localization has been tested in two different cases (Fig. 4). In the first case, referred as best case, the BLE devices of two consecutive rooms have been placed on the partition wall and not in line of sight of each other. In the second case, referred as worst case, the devices have been placed in line of sight at 5 meters from the separating door. The results shown in the Fig. 5 were obtained by positioning the wearable device (or smartphone) at three different distances from the door. The measurements allowed us to identify the Successful Localization Probability, which is the probability of correct localization of the user inside the room. The Fig. 5 shows how the results obtained are optimal in the best case and next to the ideal ones in the worst case.

A set of experiments were also designed to derive the described classification algorithm and test its accuracy. The laboratory-based tests have been performed in an area that consisted of a room and a small corridor closely resembling an apartment/home or office setting. Ten healthy subjects (nine of ages 30 to 38 and one of age 60), with no walking impairment, participated in the experiments. Subjects were asked to wear the SensorTag at their left wrist and to perform the activities described in Table I without specific constraints. Each activity has been executed for a period of about 60 seconds. Specifically, in order to detect “still” periods the following tasks have been taken into account: sitting, standing still and lying. The “moving” periods, instead, have been evaluated by considering the following activities: walking, walking fast. They describe actions typically carried out by older people during day.

Let us observe that, during the training phase, only the 60% of the collected samples have been considered. The remaining samples have been used to test the classification algorithm. Table II shows the results of the activity classification algorithm in terms of confusion matrix, by considering the test datasets. The developed classifier, therefore, is able to correctly classify the user’s body state with an accuracy level equal to 97%.

VI. CONCLUSION

This paper presents a sensing architecture able to exploit IoT technologies to capture, in unobtrusive, low-cost and low-power way, important information for automatically detecting behavioral changes in elderly people. More in depth, the proposed system consists of two sub-systems: a positioning sub-system, in charge of detecting indoor user position, and a motility sub-system that constantly detects the body activity. The positioning sub-system leverages (i) a set of BLE beacons deployed in the house, (ii) the user’s smartphone, and (iii) a BLE-equipped wearable device to detect the current position of the user. On the other hand, the motility sub-system exploits the inertial sensors embedded into the wearable device to identify the activities performed by the user. The designed sensing architecture represents the basis of a complete system for behavioral analysis and risk detection developed within the City4Age project, funded by the Horizon 2020 Programme of the European Commission.

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