A proximity-based indoor navigation system tackling the COVID-19 social distancing measures

Maria Fazio*†, Alina Buzachis*, *Student Member, IEEE*, Antonino Galletta*, *Student Member, IEEE*, Antonio Celesti*, *Member, IEEE*, and Massimo Villari*,*Member, IEEE*

* MIFT Department, University of Messina,
Viale F. Stagno D'Alcontres 31, 98166 Messina, Italy
{mfazio, abuzachis, angalletta, acelesti, mvillari}@unime.it

† IRCCS Centro Neurolesi "Bonino Pulejo", Messina, Italy
maria.fazio@irccsme.it

***Abstract*—The emergency we are experiencing due to the coronavirus infection is changing the role of technologies in our daily life. In particular, movements of persons need to be monitored or driven for avoiding gathering of people, especially in small environments. In this paper, we present an efficient and cost-effective indoor navigation system for driving people inside large smart buildings. Our solution takes advantage of an emerging short-range wireless communication technology - IoT-based Bluetooth Low Energy (BLE), and exploits BLE Beacons across the environment to provide mobile users equipped with a smartphone hints on how to arrive at the destination. The main scientific contribution of our work is a new proximity-based navigation system that identifies the user position according to information sent by Beacons, processes the best path for indoor navigation at the edge computing infrastructure, and provides it to the user through the smartphone. We provide some experimental results to test the communication system considering both the Received Signal Strength Indicator (RSSI) and the Mean Opinion Score (MOS).**

***Index Terms*—Indoor navigation, Smart cities, Smart buildings, Beacon, Proximity-based positioning, Bluetooth Low Energy, COVID-19.**

I. INTRODUCTION

The emergency we are experiencing due to the coronavirus infection is changing the role of technologies in our daily life. Governments around the world are funding initiatives to identify new digital solutions to tackle the coronavirus crisis. For example, the European Commission has called for a common EU approach for using mobile apps and mobile data to assess social distancing measures, support tracking efforts, and contribute to limiting the spread of the virus [1]. In this context, IoT (Internet of Things) technologies and Indoor Navigation Systems (INSs) can really help us to reduce contagious risks and support the provisioning of services in smart cities after the lockdown.

Following this vision, we identified as strategic the opportunity to support the movement of people in a smart city and, in particular, in smart buildings, giving access to public and private services and facilities, but avoiding gathering of people, especially in small environments. In this paper we present an efficient and cost-effective web-based indoor navigation system the provides hints on how to arrive at destination to mobile users equipped with a smartphone. For example, let consider a patient at the hospital that has to arrive at a specific ward. He/she can use a web-app through his/her smartphone to ask for indications towards the destination. In our vision, the web-app should have the following features: 1) it should be able to detect the position of the user inside the buildings and track it during the time, 2) it should have knowledge of the environment, 3) it should be able to calculate the best path between the user and destination optimizing the metric of interest (e.g., the shortest path, the largest way and/or passage, the lowest people density level, and so on) and 4) it should drive the user till the destination visualizing a map and providing vocal or iconographic instructions.

From a technical point of view, our solution implements a multi-layer communication infrastructure integrating IoT, Edge and Cloud solutions (see Figure 1). At different layers, specific data are collected and processed to match user requirements (e.g., the destination that he/she has to reach), environment requirements (people density, size of passages,...) and distancing measure regulations for COVID-19 [2]. In this paper, since we have to limit the treatment of the proposed solution, we present the reference architecture and provide design and development details on user tracking and the indoor navigation service; algorithms running at the cloud to optimize paths will be investigated in our future works.

We will discuss some experimental results on the communication system according to two types of criteria: objective criteria (i.e., Received Signal Strength Indicator (RSSI) values) to provide quantitative evaluations of the proposed solution, and subjective criteria (i.e., Mean Opinion Score (MOS)) to analyze the experience in the adoption of the application. All these criteria suitably combined validates and verify the applicability of the presented Indoor Navigation Application.

The main scientific contributions of this paper can be summarized as follows:

- we identified innovative technologies, such as Bluetooth Low Energy (BLE) short-range wireless communication technology and proximity based positioning systems, that can be usefully adopted for indoor navigation;

- we designed a multi-layer indoor navigation solution that works over IoT, Edge and Cloud infrastructures;
- we implemented indoor navigation algorithms to efficiently process user movements in a smart building;
- we implemented a web-app to interact with users and drive him/her in the environment.

The remainder of this paper is organized as follows. We survey related works in Section II. An overview of the designed Indoor Navigation system is discussed in Section III, whereas its implementation is described in Section IV. Performances analysis are presented in Section V. Conclusions in Section VI summarize our work and highlight future developments.

II. Background and Related Work

A key issue for indoor navigation is the system at the basis of position identification. One of the most popular methods is trilateration. Here, the Received Signal Strength Indication (RSSI) is converted into a distance value to pinpoint an intersecting position from drawing two or more circles or other ellipsoids. Raghavan et al. [3] implemented trilateration coupled with a particle filter for robot navigation, replacing the more costly passive RFID approach. The system is not designed to be highly scalable, and accuracy is highly fluctuating (0.427% $\pm$ 0.229 m). Estel and Fischer [4] introduced a system composed of BLE beacons in which the location is estimated by trilateration, yielding an accuracy of about 5m, they argued that it is not enough for indoor localization. Another classical method for indoor localization is fingerprinting. Faragher and Harle [5] implemented this method with Bluetooth beacons. They used 19 beacons over 600 m^2 and were able to achieve localization accuracy of less than 2.6 m error in 95% of the case. Despite the interesting result, fingerprinting is based on empirical mapping of the radio signals and thus needs to be done for every floor plan configuration, making it unrealistic for any large-scale deployment. Kavitha. S et al. [6] also analyzed the characteristics of the BLE signals of two models (Estimote and pebBLE) by obtaining the path loss of both models and then using that information for conducting simulations on a random distribution of beacons using KNN fingerprinting. [7] discusses the research and production details of the developed hybrid indoor localization and navigation system (HILN). The proposed technical solutions are based on cheap Bluetooth beacons and mobile sensors. The mobile positioning system provides 1-2 m accuracy, and works on Android and iOS devices on a real-time basis.

While many improvements and original solutions attempted to improve indoor navigation by way of technology, there are still several challenges ahead for the deployment, such as those expressed in the introduction (cost, complexity of installation, scalability). Locations based on closeness (Proximity-based positioning) to known reference points, coupled with a widely deployed wireless technology, can reduce the cost and effort for localization in local and indoor areas [8]. In general, Proximity-based positioning is used to determine the closeness to a known location; it tells where the user is within its range. It is used for advertising in mobile applications. In addition to proximity-based positioning, there are also two different methods, such as symbolic and absolute positioning. Absolute positioning is a method that determines the exact location, such as GPS. It can be calculated with the triangulation method, and the results are coordinates. Accuracy depends on the technique; GPS can provide 1 m for civilians, and around 2 cm for military usage in open terrain. Symbolic positioning is between absolute and proximity-based ones in accuracy. In [9], a novel development of a Bluetooth Beacon-based Indoor Navigation System in Android is proposed. Based on the distance from the beacons, the users' location is estimated using symbolic positioning.

We have used proximity-based positioning in our system using BLE Beacons, given their simplicity and lowest cost. According to the current state-of-the-art, and to the best of our knowledge, or solution is the first indoor navigation system based on proximity-based positioning and BLE beacons.

III. Design

Our solution implements a multi-layer communication infrastructure integrating IoT, Edge and Cloud systems, as shown in Figure 1 where also the main architectural components of our solution are drawn. In particular, at the IoT layer,

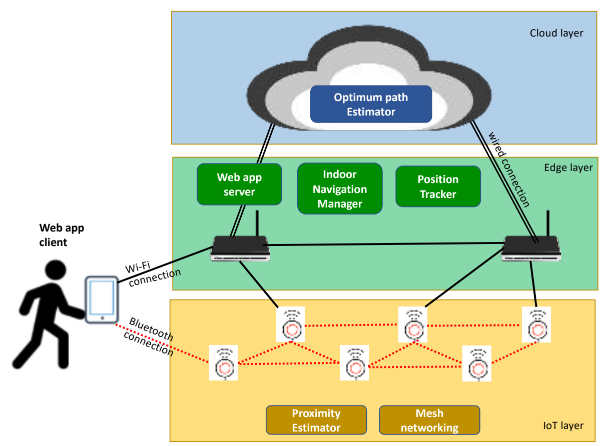


Fig. 1: Layers and reference architecture.

a proximity-oriented beacon technology based on low cost devices and the Bluetooth Low Energy (BLE) short-range wireless communication technology are used to transparently interact with users and to identify their position in the building; at the Edge layer, solutions for tracking user movements and supporting his/her indoor navigation are implemented; at the Cloud layer, cloud based processing capabilities are exploited to compute the best path, also cross-relating all the information gathered from different users and the monitored environment [10]. Details on architectural components are provided below and their mutual interactions are shown in the flow diagram in Figure 2.

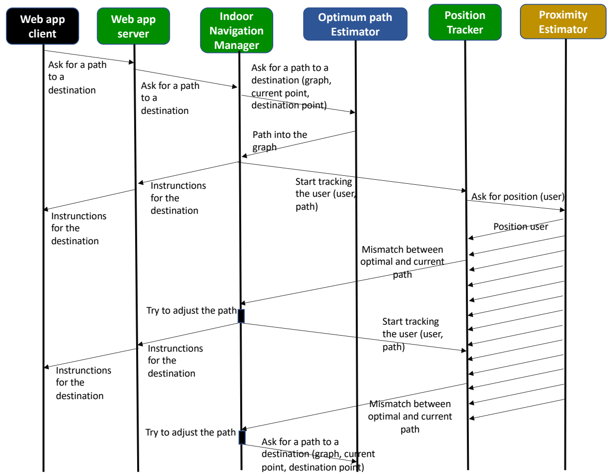


Fig. 2: Flow diagram.

IoT layer: At the IoT layer, Beacons based on low cost devices and the BLE short-range wireless communication technology are deployed in the environment. They interact in a transparent way with the smartphone of the user through the Bluetooth communication interface to perform proximity analysis. The proximity based algorithm running in the beacons locates the user's device depending on its distance from the beacon itself. The Proximity Estimator component indicates if a searched device is in range of another device even if cannot give an accurate position of it.

There is no unanimously accepted method for placing Beacons inside a building for indoor navigation. Using more Beacons is not always financially viable and does not necessarily lead to increased positioning accuracy. In our approach, during the setup step, Beacons are identified by their position with respect to a map of the place (i.e, coordinates x_i,y_i) and a unique identifier (i.e., UUID). Then, as second step, configuration and calibration processes are executed to tune the transmitting power P_{TX}. in order to minimize interference, improve communication quality and save battery energy.

Edge layer: The edge layer is responsible for supporting users during their indoor navigation. It uses wi-fi links to interact with users and Beacons on one side, and uses wired connections to interact with Cloud services on the other side. An user asks the path for a destination to the closest Edge node through the web app and receive from it the map of the building and indications on how to move around. The Indoor Navigation Manager component at the Edge layer (that is running in the Edge node closest to the user or in the less overloaded) asks the Optimum path Estimator for calculating the best path, whereas the Position tracker component tracks the user during his/her navigation. To this aims, the Position tracker gathers proximity information form the Beacons and maps the current position on the best path planned at the Cloud layer. If the user does not proceed following the navigation instructions, the Indoor Navigation Manager component try to adjust the path and provides the users new instructions; otherwise it can contact the Optimum path Estimator again to ask for a new path calculation.

Cloud layer: The Optimum path Estimator identifies the best path for each user, also cross-relating information from different users and the monitored environment. Beacons interact each others forming a distributed communication infrastructure as a mesh network. The mesh network is abstracted as a 2D graph at the Edge layer and the graph is sent to the Optimum path Estimator together with the current position of the user and the destination point in the graph. Metrics that can be evaluated and optimization algorithms can be different according to the distribution and geometry of the buildings and the distancing policies. Due to the limited treatment of this paper, this aspects will be detailed in our future works.

IV. Implementation

The prototype of our system has been developed using ESP32 microcontrollers acting as IoT Beacons and a Raspberry Pi 3 Model B+ as Edge nodes. We chose these devices for their low costs and good technical specifications; in fact, *ESP*32 costs about 3.53$ and Raspberry Pi Model 3 about 35$. The device is illustrated and fully described in our previous work [11]. Each Beacon works in dual-mode BLE-Wi-Fi. The script allowing the dual-mode is implemented in C programming language using the Arduino IDE. The proximity estimation indicates if a device (e.g., the mobile phone of the user) is in range of another device (e.g., the Beacon). The solution we implemented is based on the signal strength of the BLE Beacons, where to transmition power is tuned with different values (see Section V).

In order to implement the infrastructureless Wireless Mesh Network (WMN) among beacons (see Figure 4), we adopted the painlessMesh protocol. PainlessMesh allows creating a self-organizing and repairing network where all the nodes are connected. painlessMesh is designed to be used with Arduino, but it does not use the Arduino Wi-Fi libraries. We got networking functionalities using the native ESP32 and ESP8266 SDK libraries, which are available through the Arduino IDE. We used Mosquitto as Message Queue Telemetry Transport (MQTT) broker on Raspberry Pi. The broker is responsible for receiving and filtering messages, deciding who is interested in them, and publishing the messages to all subscriber clients. The infrastructureless WMN is fully described in our previous work [11].

We have developed the Indoor navigation application to work on both Android and iOS smartphones and tablets. It is composed by two main components: the *Web app server*, which manages all the necessary information within the navigation system, and the *Web app client*, which allows the user to select the desired destination and get the shortest available path. The Web app client is a user-friendly application so that anyone can use it easily. After managing Beacons and location data, information are exported from the Web app server to the Web app client. Hence, the Web app client helps in navigation the user towards the desired destination. The Web app was developed using PhoneGap, an open-source framework released by Adobe Systems, used to develop native cross-platform mobile applications through the use of web technologies such as HTML, CSS, and JavaScript and tested on Samsung Galaxy A5 and iPhone 7 Plus. In Figure 3, some screenshots of the Web app client are shown.

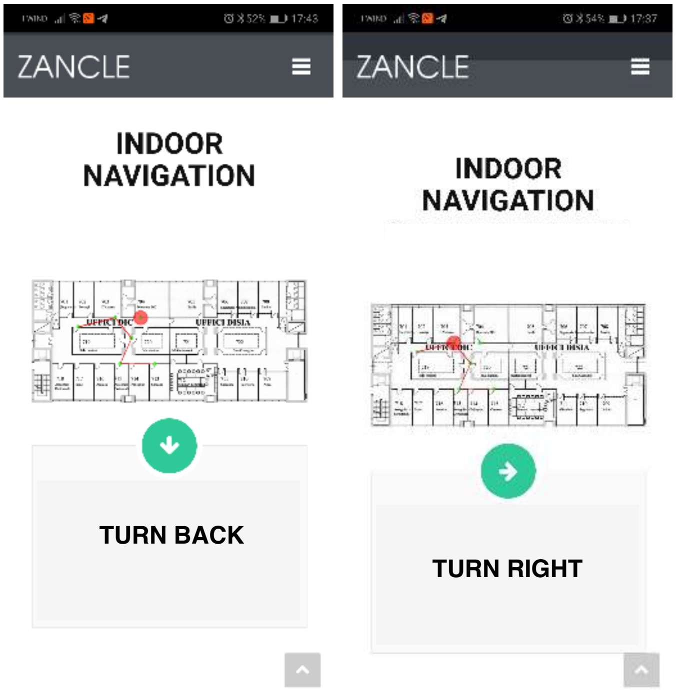


Fig. 3: Android Application: Indoor Navigation Service.

With reference to the architecture in Figure 1, we implemented and validated four key components, that are the web app, the proximity Estimator and the mesh networking components, Position tracker and Indoor Navigation Manager.

V. Performance Assessment

The goal of our validation tests was to verify the effective functioning of the provided services. To this aim, we carried out the analysis on the Received Signal Strength Indicator (RSSI) values gathered during the indoor navigation by user mobile devices. This allows understanding how the quality of service (QoS) for the indoor navigation is influenced of the BLE beacons positioning and configuration. Together with RSSI, we also evaluated Mean Opinion Score (MOS) that is the score assigned by users to evaluate the indoor navigation service. MOS ranges between 1 and 5, where 1 is the lowest score, while 5 is the highest one.

In the experiments, P_{TX} of BLE Beacons is set to different levels to understand which is the best configuration allowing the best coverage also saving battery life. We also considered different distances among Beacons in order to understand the impact of this parameter in the experimentation. The ESP32 BLE Beacon covers 100 m in the Line-Of-Sight (LOS) with a P_{TX} of 20 db. Based on this specification and considering that the longest walking distance in the indoor navigation in almost 50 meters (6 beacons in the Far configuration) overall, we decided to consider three adequately P_{TX} levels of 10 db (high), 5 db (medium), and 2 db (low).

TABLE I: Without RSSI Limitation: Average MOS Values

Power (db) / **Distance (m)**	2 db	5 db	10 db
3 m	1.60	2.00	1.00
7 m	2.00	1.84	1.80
10 m	3.43	2.20	1.40

TABLE II: With RSSI Limitation: Average MOS Values

Power (db) / **Distance (m)**	2 db	5 db	10 db
3 m	3.00	4.00	2.67
7 m	5.00	4.33	4.00
10 m	5.00	4.00	4.33

The test environment was the Department of Engineering at the University of Messina. It is a 9 floors building. For simplicity, we only covered the 5_th floor of block A on the simple case shown in Fig. 4. Each user asks to be directed to the Elevator in the room Q and starts navigating inside the building for this purpose (dotted lines represents wrong paths).

To have accurate validation results, we repeated the experiments several times for each configuration. During the indoor navigation, users moved at a constant walking velocity of 1.3 m/s.

In the evaluation of RSSI, we adopted two approaches in the evaluation of incoming signal: without and with a threshold to filter the RSSI signals scanned by the mobile phone. The threshold value was chosen based on a series of trials around $-70dBm$. In particular, this threshold value allowed to consider only the RSSI values of those BLE Beacons close to the user. Conversely, when the RSSI detected value is less than the chosen threshold value, the BLE Beacon is considered far from the user. Therefore its under-threshold values do not interfere with the values closest one.

A. *On-Field Experimental Results*

Starting from the average MOS evaluations collected during the indoor navigation in each configuration and focusing in particular on two configurations with and without limitation on the receiver RSSI values, illustrated in Table I and II, for each configuration, we selected the case with the best evaluation and worst one as well. Hence, we show in the following the comparison of the validation results obtained in these cases.

a) Without RSSI Limitation: Here, as Table I shows, it is possible to notice that the best evaluation is obtained with the configuration where each BLE Beacons is positioned at 3 m away from the previous one and the P_{TX} is 10 dB. In contrast, the worst one is obtained when Beacons are positioned at 10 m away from the previous one, and the P_{TX} is 2 dB. In both Figs. 5a and 5b we can see that the measured RSSI values of each BLE Beacon follow a Gaussian-shaped trend, whereas we approach the BLE Beacon, we have a growing trend, and as we move away from the BLE Beacon we have a decreasing trend; RSSI degrades with distance. Analyzing the average RSSI values over distance, illustrated in Fig. 5a,

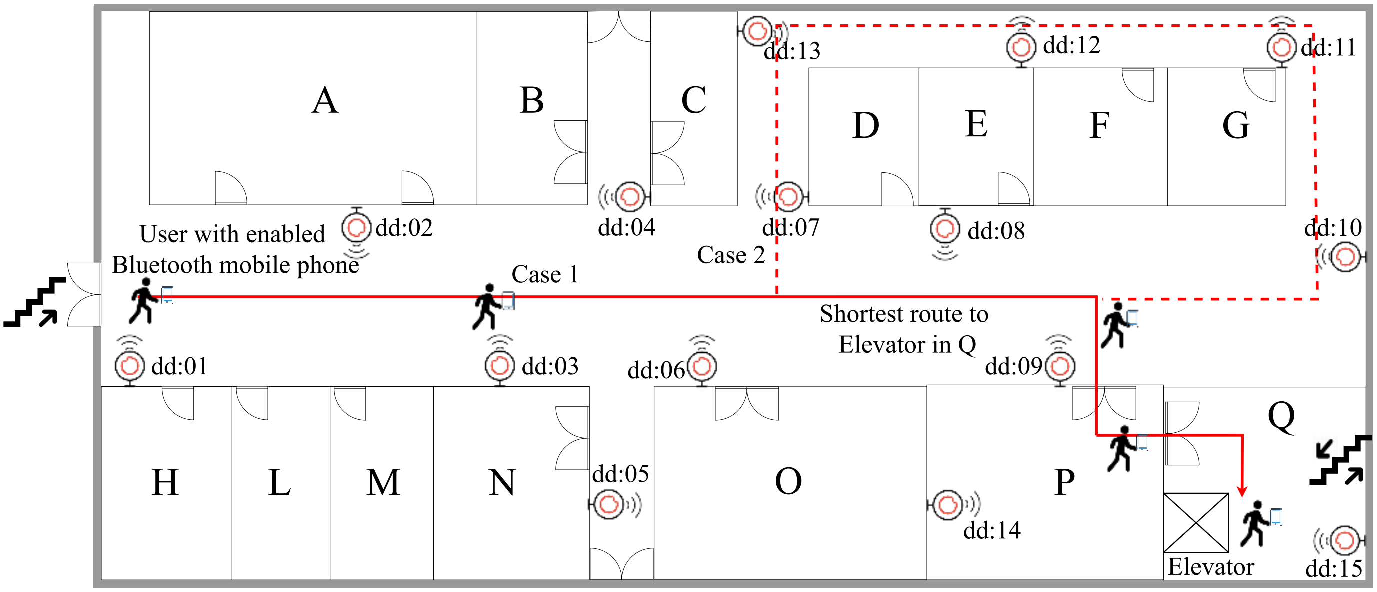
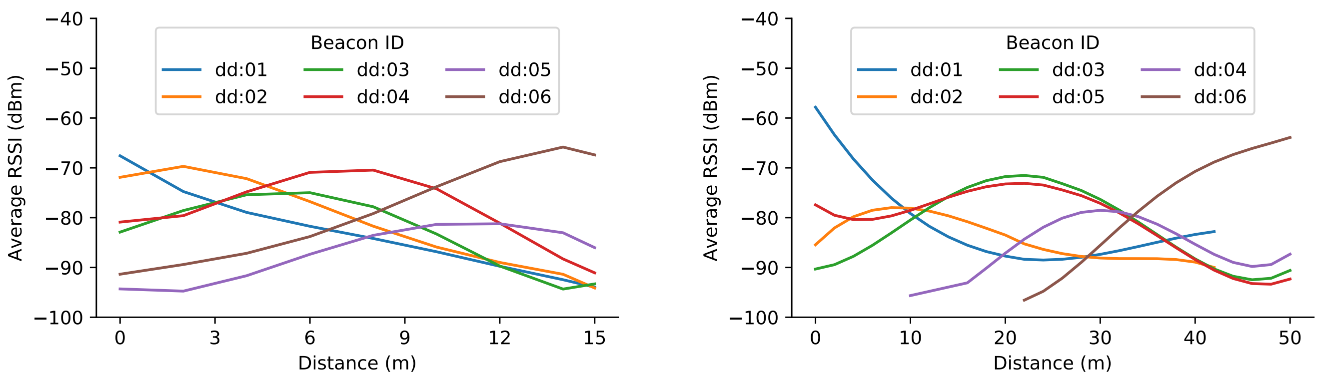


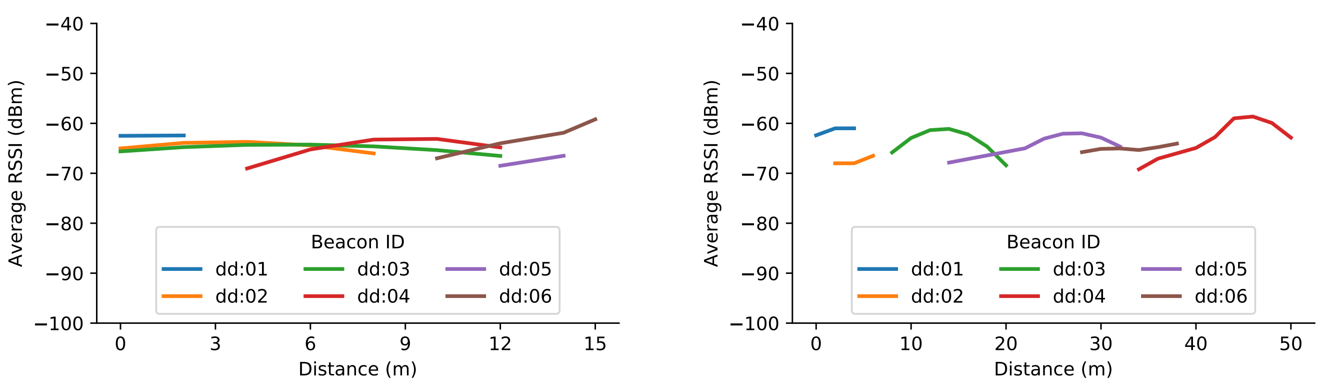
Fig. 4: High-level overview of the designed system.



(a) The Worst MOS value: BLE Beacons are positioned at 3 m and the P_{TX} is 10 dB

(b) The Best MOS value: BLE Beacons are positioned at 10 m and the P_{TX} is 2 dB

Fig. 5: Without RSSI Limitation: RSSI Distribution (dBm) over Distance (m)



(a) The Worst MOS value - BLE Beacons are positioned at 3 m and the P_{TX} is 10 dB

(b) The Best MOS value: BLE Beacons are positioned at 10 m and the P_{TX} is 2 dB

Fig. 6: With RSSI Limitation: RSSI Distribution (dBm) over Distance (m)

which corresponds to the worst MOS value, we note that all BLE Beacons interfere with each other for the entire period of navigation. As for the results obtained with the best MOS value, we can see how the coverage has slightly improved as there are regions in which not all BLE Beacons interfere with each other. In particular, it is possible to note the BLE Beacon "dd:04" is detected for the first time when the distance is equal to 10 m, and the BLE Beacon "dd:06" that is detected instead around 20 m. It is possible to note, as we expected, that due to the arrangement, the BLE Beacons "dd:03" and "dd:04" are detected almost simultaneously as they are very close to each other both have almost similar behavior. We can also note that in this case, it is possible to better distinguish the Gaussian-shaped trend of each BLE Beacon from the previous case; this is because the interference between devices is slightly reduced compared to the previous case.

b) With RSSI Limitation: As for the results obtained with the limitation on the value of the RSSI received, it can be pointed out that the best evaluation is obtained with the configuration where each BLE Beacon is positioned at 10 m away from the previous one and the P_{TX} is 2 dB. In contrast, the worst one is obtained when each BLE Beacons is positioned at 3 m away from the previous one, and the P_{TX} is 10 dB (see Table II). Comparing the results obtained in this case (see Figs.6a and 6b) with the correspondents obtained without limitation on the RSSI received, we can see a significant improvement in terms of coverage and interference between the various BLE Beacons. In particular, it is possible to notice how the interference between the various BLE Beacons is limited since the coverage range of each BLE Beacon is minimized. At the same time, it is possible to notice how the range of variation of the detected RSSI is significantly reduced from -25 dBm (Fig. 5a and 5b) to -10 dBm.

As for the results obtained with the highest MOS value (5), we can see a marked improvement compared to the results obtained with the worst MOS value. Also, in this case, as mentioned above, the interference between the BLE Beacons is minimized. We can see a more evident Gaussian-shaped trend of the RSSI detected (see Fig. 6b). The coverage of each BLE Beacon is reduced; in fact, with this configuration, it is possible to obtain an almost optimal overall coverage as the overlapping areas between the various BLE Beacons are minimized. In addition to obtaining an almost optimal coverage and minimum interference levels, this configuration allows to minimize costs as with a lower number of BLE Beacon, it is possible to cover a wider surface area but also to reduce the energy consumption of the BLE Beacon themselves as the power levels are low. From this validation results, we can state that the threshold value allows to obtain a better QoS and a coverage, maximizing the average MOS and minimizing the interference between BLE Beacon and energy consumption.

VI. Conclusions and Future Work

This article provides a novel, cost-effective and scalable indoor navigation systems that implements indoor mapping, localization, and navigation. With our approach, we are able to orient users with a smartphone within smart buildings by gathering his/her position during the time and suggesting the best path towards the destination. Experimental results show how Beacons can be tuned considering their distance and/or transmission power according to the specific constrains of the environment where they are deployed.

In our future works, we will investigate in details algorithms for the estimation of the best path that will be executed in the cloud.

Acknowledgment

This work has been partially supported by the Italian PON project “Tecnologie di Assistenza personALizzata per il Miglioramento della quAlità della vitA (TALIsMAn)” Codice ARS01_01116 - CUP J66C18000360005, and by the Italian Healthcare Ministry founded project Young Researcher (under 40 years) entitled “Do Severe acquired brain injury patients benefit from Telerehabilitation? A Cost-effectiveness analysis study” - GR-2016-02361306.

We want to express our gratitude to Gianluca Catalfamo, student at the University of Messina, for his valuable support in implementation and field experiments.

References

[1] C. Dumbrava, “Tracking mobile devices to fight coronavirus.” https://www.europarl.europa.eu/RegData/etudes/BRIE/2020/649384/EPRS_BRI(2020)649384_EN.pdf. EPRS — European Parliamentary Research Service, April 2020.

[2] R. Ranjan, O. Rana, S. Nepal, M. Yousif, P. James, Z. Wen, S. Barr, P. Watson, P. Jayaraman, D. Georgakopoulos, M. Villari, M. Fazio, S. Garg, R. Buyya, L. Wang, A. Zomaya, and S. Dustdar, “The next grand challenges: Integrating the internet of things and data science,” *IEEE Cloud Computing*, vol. 5, no. 3, pp. 12–26, 2018.

[3] A. N. Raghavan, H. Ananthapadmanaban, M. S. Sivamurugan, and B. Ravindran, “Accurate mobile robot localization in indoor environments using bluetooth,” in *2010 IEEE International Conference on Robotics and Automation*, pp. 4391–4396, May 2010.

[4] M. Estel and L. Fischer, “Feasibility of bluetooth ibeacons for indoor localization,” in *DEC*, 2015.

[5] R. Faragher and R. Harle, “Location fingerprinting with bluetooth low energy beacons,” *IEEE Journal on Selected Areas in Communications*, vol. 33, pp. 2418–2428, Nov 2015.

[6] M. Ji, J. Kim, J. Jeon, and Y. Cho, “Analysis of positioning accuracy corresponding to the number of ble beacons in indoor positioning system,” in *2015 17th International Conference on Advanced Communication Technology (ICACT)*, pp. 92–95, July 2015.

[7] Y. Chervoniak and I. Gorovyi, “Mobile indoor navigation: From research to production,” in *2019 Signal Processing Symposium (SPSympo)*, pp. 96–99, Sep. 2019.

[8] Z. Turgut, G. Z. G. Aydin, and A. Sertbas, “Indoor localization techniques for smart building environment,” *Procedia Computer Science*, vol. 83, pp. 1176 – 1181, 2016. The 7th International Conference on Ambient Systems, Networks and Technologies (ANT 2016) / The 6th International Conference on Sustainable Energy Information Technology (SEIT-2016) / Affiliated Workshops.

[9] A. Satan, “Bluetooth-based indoor navigation mobile system,” *2018 19th International Carpathian Control Conference (ICCC)*, pp. 332–337, 2018.

[10] M. Fazio, M. Paone, A. Puliafito, and M. Villari, “Huge amount of heterogeneous sensed data needs the cloud,” in *International Multi-Conference on Systems, Signals Devices*, pp. 1–6, 2012.

[11] A. Buzachis, M. Fazio, A. Galletta, A. Celesti, and M. Villari, “Infrastructureless iot-as-a-service for public safety and disaster response,” pp. 133–140, 08 2019.