Designing an Indoor Real-Time Location System for Healthcare Facilities

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Abstract. This paper performs a feasibility analysis to find the best-fitting solution in terms of quality/price ratio for designing and developing a Real-Time Location System for Indoor Positioning inside healthcare facilities. In particular, an overall comparison of all the available solutions is done, highlighting pros and cons of each technology (WiFi, RFID, WLAN, Ultra-Wide Band, Bluetooth Low Energy, ZigBee, magnetic fields, infrareds, ultrasounds, computer-vision and Pedestrian Data-Reckoning) for accuracy, price, coverage, infrastructure development and installation, and maintenance. A preliminary scope-review is also produced, which summarizes the obtained outcomes in similar studies. In the results section the proposed system is illustrated via flowcharts and block diagrams, both for off-site and on-site scenarios.

Keywords: RTLS · IPS · Healthcare · Hospitals

1 Introduction

Navigation portable applications have largely grown during the last years, especially because of the huge diffusion of smartphones with inner localization hardware, such as Global Navigation Satellite System (GNSS), wireless antennas (IEEE 802.11 WiFi and IEEE 802.15 Bluetooth) and inertial sensors. However, the majority of these applications works just for outdoor positioning and routing, due to their architecture based upon GPS (Global Positioning System) signals, which have extremely low power, therefore they cannot be received inside a building.

New technologies and algorithms have been developed and adopted during the recent years to face Indoor Positioning System (IPS), such as Radio-frequency Identification (RFID), Wireless Local Area Network (WLAN), Ultra-wide Band (UWB), Bluetooth Low Energy (BLE), ZigBee, magnetic fields, infrared (IR), ultrasounds (US) or computer-vision based systems [1–3].

J. Hasic Telalovic and M. Kantardzic (Eds.): MeFDATA 2020, CCIS 1343, pp. 110–125, 2021.
https://doi.org/10.1007/978-3-030-72805-2_8

Real-time Location Systems (RTLS) is a topic of research which is becoming wider and wider. No universal standard is currently available, due to the peculiarities of each building and to the positioning requirements each application has. In fact, mixed technologies are often implemented depending on the features of the spaces. The application architecture is also very heterogenous depending on the type of users it is developed for. A drive system for robots requires a millimetric precision while a public application for general users, needs less accuracy, but on the other hand, it must be compliant with multiple operative systems and hardware of different brands of smartphones. Moreover, some of these systems only works when additional infrastructures have been installed, which result in extra price and maintenance. Consequentially, the building and field of application affect the system and the algorithms to choose [4].

The scope of this paper is to find the best-fitting solution for developing a RTLS for the hospital of Le Scotte in Siena (Italy). The hospital is made out of 12 pavilions and covers an area of about 208,000 m^2 with 800 beds and 8,100 rooms. Each pavilion is located on a topography which is largely hilly, thus the inner paths and alleys which link together different buildings are not on the same constant level throughout the hospital area. In fact, it is very likely to have the first or second basement storey of a building at the same elevation of the ground floor of an adjoining pavilion. This implies a very complex spatial management of the whole premise [5–7]. This spatial unicity together with the heterogeneity of the users of a hospital (patients with limited mobility, visitors, suppliers, technicians) represents a valid opportunity for implementing a navigation system in order to improve the user's experience. The first obstacles which come to mind in applying such technology to a hospital is the limited availability of a consistent WiFi coverage throughout the whole premise together with the presence of a lot of metal devices, some of which may also be moved.

2 Methods

An Indoor Position System is a network of devices which allows accurate and real-time indoor people and items localization. Generally, an IPS can be divided in 3 main blocks:

- Inner positioning system module
- Navigation module
- Human-machine interaction (HMI) module.

The first one estimates the user's spatial position, the second one evaluates the available routes between the starting point and the final destination, while the latter improves the user's interaction with the system and gives him/her useful instructions and information [1].

Several technologies are available for implementing the inner positioning system module, which can be categorised in: radio frequencies (WLAN, WiFi, RFID, UWB, ZigBee and Bluetooth), magnetic fields, computer-vision based systems, IR systems, US systems, Pedestrian Dead-Reckoning (PDR). Each of the above listed wireless technology utilises a dedicated positioning model which may change in terms of coverage and precision according to the selected medium (electromagnetic waves, optical waves or mechanical waves). The main criteria to keep in consideration while choosing the appropriate technology are: accuracy (the average Euclidian distance between the actual ground position and the estimated position coordinates), precision, coverage, scalability, medium and infrastructure, robustness, power consumption, price, usability, safety and privacy [1].

A list of all the available technologies follows, highlighting the pros and cons for each one (which are also summarised in Table 1).

1. **WiFi** is a RF technology used in WLAN based upon the standard IEEE 802.11. IPS which uses WiFi infrastructure is often implemented in internal environments with an already existing access point (AP) architecture for data transferring. In order to adopt this technology for a full RTLS, multiple wireless access points (WAP) need to be installed so that the actual coverage can be increased, improving the accuracy of localizing items and people, with smartphones acting as wireless clients. In WiFi RTLS, the accuracy is about 3–5 m, which is a non-acceptable value for the scope of this study, even though new approaches are being developed to improve the precision of the measurement [8–10]. Another disadvantage is the lack of API for indoor localization via WiFi for iOS devices. Apple Inc. Stopped designing and deploying API for signal strength detection via WAP. This results in a practical difficulty in designing a universal system, requiring the installation of iBeacon as a support for Received Signal Strength Indication (RSSI) [11].
2. **RFID** systems are made of tags which contain data that can be recovered with a radiofrequency reader by employing the Received Signal Strength (RSS), the Angle of Arrival (AOA), the Time of Arrival (TOA) or the Time Difference of Arrival (TDOA) for estimating their position. RFID tags can be active, passive or semi-active. Current RTLS based on RFID use passive tags because they do not need any internal power supply: the radio waves emitted by the reader provide sufficient energy to transmit the whole data. This results in a limited reading area of a few meters: the price of the system is kept low, but the number of needed antennas increase. Another problem which need to be faced when adopting passive tagging is whenever the reader is not able to evaluate multiple responses from different tags at the same time (collision), affecting the scalability. Moreover, metals may cause electromagnetic interferences and distortions. Finally, all the above-cited approaches, except RSS, may not be able to accurately estimate the tag position in an indoor environment.
3. **UWB** is a radio technology that can use a very low energy level for short-range, high-bandwidth communications over a large portion of the radio spectrum. They ensure very precise spatial position estimation with deviation of about 0.01 m and a wide signal coverage of about 30 m. The high-bandwidth ensures a high data-transfer speed together with a high robustness, also in a multipath environment. The system uses TOA, AOA, TDOA and RSS for position estimation just like RFID. UWB is the most accurate system but it is very expensive due to its type of tag and infrastructure. Besides, the installation may also be very complex [12].
4. **ZigBee** is an IEEE 802.15.4-based specification for a suite of high-level communication protocols used to create personal area networks with small, low-power digital radios, designed for small scale projects which need wireless connection. Hence, Zigbee is a low-power and close proximity (i.e., personal area) wireless

ad hoc network. The high coverage (between 10 and 100 m) and the low-power working rate is however at the expense of the data rate and precision (about 5 m).

5. **Bluetooth Low Energy** (Bluetooth LE or BLE) is a wireless personal area network technology designed and marketed by the Bluetooth Special Interest Group (Bluetooth SIG). Compared to Classic Bluetooth, BLE is intended to provide considerably reduced power consumption and price while maintaining a similar communication range. Mobile operating systems including iOS, Android, Windows Phone and BlackBerry, as well as macOS, Linux, Windows 8 and Windows 10, natively support Bluetooth Low Energy. Bluetooth beacons are usually used as RF sources to trace the devices' position by implementing proximity detection, RSS fingerprinting or trilateration. Accuracy is of 2–3 m, with a coverage of 10–20 m (which can be widen at the expense of the battery duration).
6. **Magnetic fields** localization systems rely on the interferences caused by structural steel elements of the building to the earth magnetic field, which produce unique magnetic prints. This technique finds numerous advantages, such as no pre-implemented infrastructure, low price and no influences by human bodies or any other kind of barriers. Geomagnetic field ensures high precision despite a low-energy consumption with a subsequent mobile battery saving [13]. However, it may not perform well in a large area [4, 14] and it takes long time to build the initial magnetic map, which also needs updates every time a metal asset or furniture is added or removed to the scene [15].
7. **Vision-based** approach utilises computer-vision algorithm to place an image framed by a smartphone inside a 3D scene, by recognizing key items, shapes or texts. This technology offers scalable systems at a low price, but it affects the accuracy because the device needs to remain in a stable vertical position while targeting key pictures [16].
8. **Infrared positioning systems** are based upon IR receivers which can establish the location of IR transmitters spread throughout the building. IR have a very restricted coverage and require a Line of Sight (LoS) between transmitters and receivers. Furthermore, they are very sensitive to interferences of other IR sources (such as the sun itself) and they also need expensive hardware and maintenance.
9. **Ultrasounds** can also be used to define the position of ultrasonic tags, in addition to radio waves and IR. Unfortunately, US are more sensitive to obstacles then radio waves, and they are obviously also sensitive to sound interferences and to the heat [17].
10. **Pedestrian Dead-Reckoning** (PDR) technique estimates the position of a device by knowing its starting point, direction and travelled distance. Smartphones have one or more built-in inertial sensors (accelerometer, gyroscope) to perform the desired evaluation. Usually, these systems obtain the starting position by using other methodologies and then use the smartphone's accelerometer to get to know when and where the user steps over. Position is evaluated at every step by using the previous known position: in the long run, this brings to an additive error reliant to the sensor's precision (drift-error). On the other hand, these systems do not need any external infrastructure and they are not subject to external interferences.

Table 1. Highlighting pros and cons of different RTLS technologies.

	Accuracy [m]	Range [m]	Price	Pros	Cons
Wi-Fi	1 ÷ 5	20 ÷ 30	Medium	Existing infrastructure in modern buildings	iOS devices need iBeacons; high energy consumption
Passive RFID	2 ÷ 3	2 ÷ 3	Low	Passive tagging	Small coverage; tag collision; electromagnetic interferences
UWB	Less than 1	20 ÷ 30	High	High accuracy	Expensive tags and infrastructure; complex installation
ZigBee	3 ÷ 5	10 ÷ 100	High	Mesh topology; wide range	Low precision; long implementation times to reduce price
BLE	2 ÷ 3	10 ÷ 20	Low	Low energy consumption; scalability	Expensive infrastructure and maintenance
Magnetic Field	Less than 1	1 ÷ 10	Null	High accuracy; no infrastructure needed; low price	Not suitable for wide area; complex mapping
Computer Vision	1 ÷ 3	N/A	Null	Low price; no infrastructure needed; scalable	Stability of devices during image acquisition
IR	Less than 1	1 ÷ 5	Medium/High	Good precision at room level	LoS; interferences; short range
US	Less than 1	2 ÷ 10	Medium/High	Accuracy	LoS; interferences
PDR	1 ÷ 6	Null	Null	No infrastructure needed; low price; simplicity	Drift-error; recalibration needed

Some of the described technologies can be already excluded from this study because they do not have properties which well suit the features of a healthcare facility: US and IR systems are too sensitive to interference with very common signal sources for hospitals, and ZigBee is specifically designed for low-scale projects. Moreover, UWB is excluded due to its high price. RFID is often used in hospitals for medical device [18] and patient tracking [19] or sampling recording, but it is not a successful solution for RTLS purposes [2, 20].

The remaining technologies (WiFi, BLE, magnetic field, computer vision and PDR) are analysed in detail by comparing the dedicated literature in Tables 2, 3, 4 and 5.

Table 2. RF systems applications for indoor navigation.

Authors	Method	System	Performance	Test size
Sadowski S. e Spachos P. [21]	ZigBee, BLE and WiFi	Trilateration	Average error: ZigBee: 5.1317 m BLE: 1.1143 m WiFi: 0.5183 m	5.6 m × 5.9 m
Wang X. et al. [22]	WiFi	BiLoc, bi-modal deep learning and fingerprinting	Errore medio TEST 1: 1.5743 m Errore medio TEST 2: 2.5101 m	Test 1: 6 × 9 m^2 Test 2: 2.4 × 24 m^2
Ibrahim M. et al. [8]	WiFi	WiFi fingerprinting and Fuzzy logic	Average error: 1–2 m Max error: 3–4 m Accuracy: <2 m al 95%	10 m^2
Joseph R. e Sasi S. [23]	WiFi	Fingerprinting	Accuracy: 93% above 20 interactions	–
Yu J. et al. [24]	WiFi, PDR	Fingerprinting, KDE and PDR, UKF	Average error: 0.76 m	43.5 × 11.2 m^2
Abdulkarim H.D. et al. [25]	WiFi, PDR	RSS normalization proximity values, EKF integrated PDR (self-calibration extended Kalman filter)	Average error: Non-normalized: 2.05 m Normalized RSS: 1.96 m	179 m^2
Tian Z. et al. [26]	WiFi, Micro Electro-Mechanical Systems (MEMS)	Fingerprinting WiFi, EKF integrated PDR	RMSE: 0.8 m Accuracy: 90% < 1.7 m	TEST 1: 64.6 × 18.5 m^2 TEST 2: 81.2x18.5 m^2
Cui Y. et al. [10]	WiFi, MEMS	Fingerprinting WiFi and SKF integrated PDR (self-calibration Kalman filter)	Average error: 0.6086 m	110 × 30 m^2

Table 3. Geomagnetic field systems applications for indoor navigation.

Authors	Method	System	Performance	Test size
Selamat M.H. e Narzullaev A. [27]	WiFi and Magnetic field comparison	Fingerprinting WiFi, fingerprinting for magnetic field	Average error: Magnetic field: cm WiFi: 1–3 m	–
Ashraf I. et al. [28]	Magnetic field integrated with smartphones' sensors	Fingerprinting, PDR	Accuracy: Galaxy S8: 50% 0.88 m 75% 1.68 m LG G6: 50% 1.21 m 75% 2.20 m	$85 \times 40\ m^2$ $50 \times 35\ m^2$ $30 \times 30\ m^2$ $50 \times 35\ m^2$ $90 \times 32\ m^2$
Chen Y. et al. [29]	Magnetic field	Fingerprinting, Magnetic Field Sorting (MFS)	Average error: [2.13–3.27]m	–
Shu Y. et al. [30]	Magnetic field	Magicol	Accuracy: 80%: Office: 4 m Market: 3.5 m Underground parking: 1 m	Office:4000 m^2 Market:1900 m^2 Underground parking: 3800 m^2
Chen L. et al. [13]	Magnetic field	MeshMap	Accuracy: 70% $<$ 2 m 95% $<$ 4 m	–
Li P. et al. [31]	Magnetic field	Converging Stepped Magnetofluid Seal (CSMS) by integrating Chemical Shift-resolved Spectroscopic Imaging (CSI) and MFS fingerprinting	Average error: 0.5 m	Laboratorio: 8 m $\times$ 20 m Corridoio: 2.4 m 30 m
Lee N. et al. [32]	Magnetic field	Accurate Magnetic Indoor Localization (AMID), deep learning	Hallway [1]/Lobby [2] Average error: [1]: 0.76 m /[2]: 2.30 m Accuracy 90%: [1]:1.50 m/[2]: 8.14 m Accuracy 50%: [1]:0.60 m/[2]:0.90 m	Hallway: 15 m 65 m Lobby: 15 m 22 m
Bhattarai B. et al. [14]	Magnetic field	Fingerprinting, Deep Recurrent Neural Network (DRNN) based on Long Short-term Memory (LSTM)	Accuracy: 97.2%	Hallway: 100 m $\times$ 2.5 m Lab: 7 m $\times$ 7 m
Ning F.S. et al. [33]	Magnetic field integrated with smartphones' inertial sensors	PDR, magnetic field mapping	Average error: Male: 1 m/Female: 0.6 m Accuracy: 80% $<$ 1 m 50% $<$ 0.64 m	33 m $\times$ 85 m

Table 4. Hybrid systems applications for indoor navigation.

Authors	Method	System	Performance	Test size
Li Y. et al. [34]	WiFi, Magnetic field and inertial sensors	WiFi fingerprinting, magnetic matching (MM), PDR	RMS: - Area E: 3.2 m - Area B: 3.8 m	Area E: 120×40 m^2 Area B: 140×60 m^2
Bellutagi G.S. et al. [35]	BLE, QR code and inertial sensors	QR code, iBeacon	High accuracy Low maintenance price Medium infrastructure price	–
Chirakkal V. V. et al. [36]	QR code and inertial sensors	PDR	Average error: 0.64 m	–
Real Ehrlich C. e Blankenbach J. [37]	Inertial sensors and Building Information Modeling (BIM)	Sequential Monte Carlo (SMC), WLAN fingerprinting, RSS BLE, Magnetic Anomaly (MA)	Average error: (Sony Z5/Google Pixel 2 XL) 11.19 m/11.78 m + WLAN fingerprint: 7.22 m/7.03 m + BLE beacon: 1.98 m/3.27 m + MA:18.2 m/10.45 m + WLAN FP + BLE: 2.95 m/3.25 m + MA + BLE: 2.24 m/2.06 m Together: 2.54 m/3.28 m	83.325×50.50 m^2
Park J.W. et al. [38]	BLE, BIM and inertial sensors	RSSI BLE, PDR, BIM	Average error/(Standard deviation) 1st SCENARIO: 1.15 m/(0.72 m) 2nd SCENARIO: 2.03 m/(1.22 m)	27.4×39 m^2

Table 5. Computer-vision systems applications for indoor navigation.

Authors	Method	System	Performance	Test size
Elloumi W. et al. [39]	Computer-vision, inertial sensors	Harris-Based Matching, ZUPT (Zero Velocity Update)	Average error: Computer-vision: from 0.519 m to 1.503 m Sensors: from 1.276 m to 4.146 m	Different route lengths
Zhou Y. et al. [40]	Computer-vision, BIM	Visual matching between artificial target (BIM) and smartphones' cameras	0.01 m	Few meters
Huang G. et al. [41]	WiFi, visual sensors	Wi-Fi fingerprint	Average error: <0.5 m	Area 12 000 m^2
Kunhoth J. et al. [42]	Computer-vision with BLE, trained deep learning computer-vision (CamNav) and QR code computer-vision (QRNav) comparison	Scene analysis with smartphones' camera; BLE fingerprinting and multilateration; deep learning with Tensorflow; QR code	Standard deviation: Route 1/Route 2 CamNav 3.1 m(0.56 m)/6.1 m(1.10 m) QRNav 3.3 m (0.48 m)/5.5m(0.84 m) BLE APP 4.3 m(0.94 m)/8.7 m(1.33 m)	–
Neges M. et al. [43]	Augmented Reality (AR) and inertial sensors integration	Recalibration occurs every time a natural marker is identified	Good accuracy	–

3 Results

The ideal solution for the main scope of this project, a RTLS for indoor navigation of patients and general users throughout Le Scotte Hospital of Siena, would be the adoption of a hybrid system with Augmented Reality (AR) techniques with QR-code identification

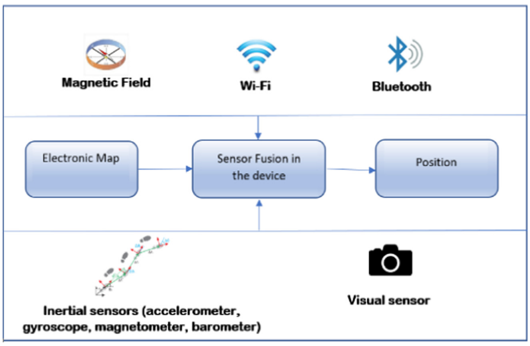

Fig. 1. Ideal RTLS model.

wherever a junction is, in order to re-calibrate the position, magnetic field systems along the hallways, WiFi and BLE to better perform in terms of accuracy, and PDR algorithms (Fig. 1).

Unfortunately, this solution results in a very expensive system, because it would require a massive WiFi coverage and iBeacons for iOS compatibility. Furthermore, the system itself would also need frequent re-calibration due to the normal moving of metal medical devices through the facility [44]. A better solution, in terms of price/quality ratio is the adoption of an AR system wherever the environment is wider

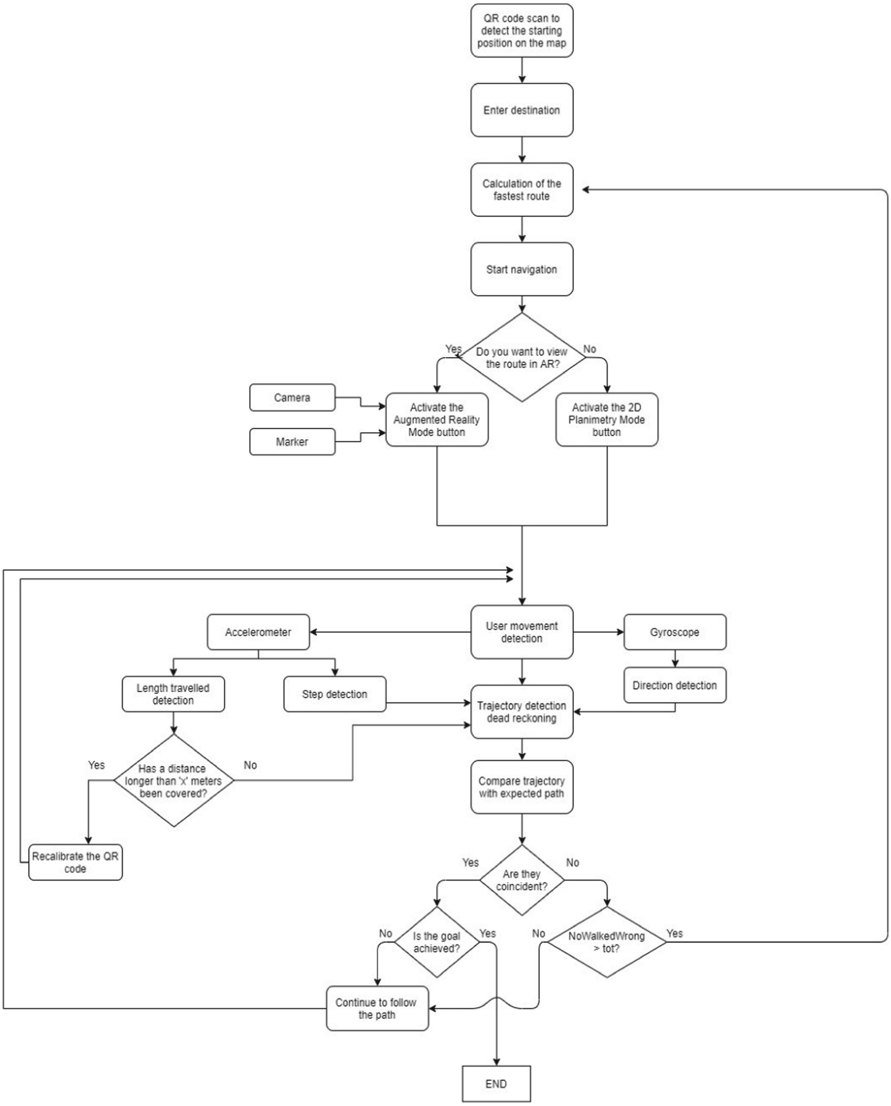

Fig. 2. Flowchart of a hybrid solution with AR, PDR and QR-code.

and more complex. PDR can be used along the hallways, by implementing equally spaced QR-code to perform re-calibration of devices to avoid drift-error divergency (Figs. 2 and 3).

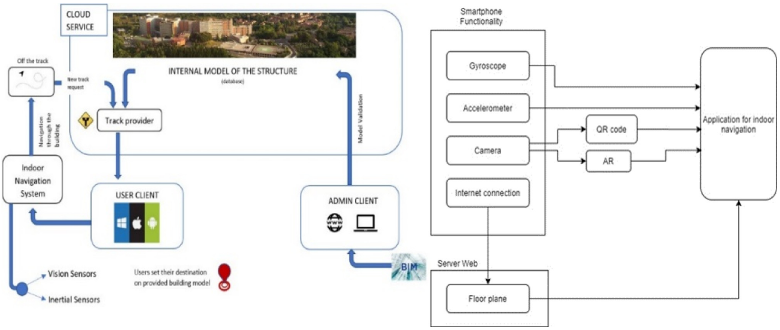

Fig. 3. Map-loading diagram (left) and functional diagram (right).

Two different scenarios must be taken into consideration: off-site and on-site navigation. The former helps the users to prior analyse the route of interest before reaching the hospital, while the latter guides the users to the desired destination step by step, directly in place.

3.1 Off-Site Navigation

For off-site navigation the best designing option is a web-site with 2D digital plan navigation and virtual touring [45]. BIM data are used to obtain 3D images of the inner structure of the hospital, while panorama pictures, which are directly attached on the 3D model, are the main inputs for a virtual tour recreation: it offers navigation by images of the site with manual scrolling. The chosen software for this particular task is Unity 3D, because it is easily programmable via Javascript and C#, a lot of online helping material is available and freely accessible, and it also has cross-platform compatibility, avoiding dedicated Android and iOS programming. In particular, Navigation Mesh (NavMesh) functionality of Unity, may be helpful to find the shortest path between two given points once a 3D model is loaded into the software (Fig. 4). BIM data can also be used to extract 2D information for digital plan navigation [46–48].

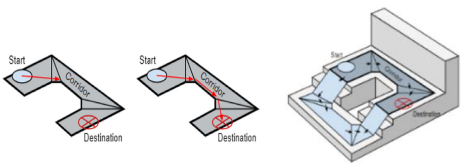

Fig. 4. NavMesh algorithm in Unity 3D

3.2 On-Site Navigation

When users are right on place, an easier way to guide them from their current position to the desired destination must be designed. During this preliminary designing phase, easy-access routing is not taken into consideration, because it requires different types of navigation according to the disabilities of the users, which is postponed to future development (Fig. 5).

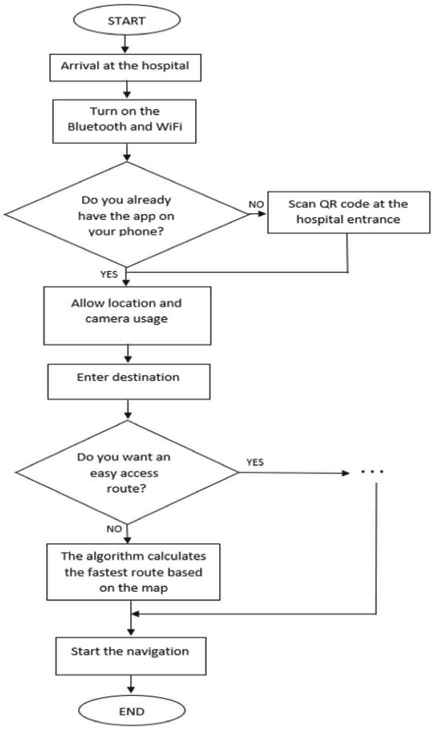

Fig. 5. User action flowchart.

In this scenario, a mobile-application is the best solution, because it can easily access the hardware of the device itself (accelerometer, gyroscope, camera), which is mandatory to perform the chosen hybrid RTLS (Chapter 2). The main problem when it comes to mobile application deploying, is the different framework each Operative System (iOS and Android) is compliant to. The adoption of cross-platform deploying framework, such as Apache Cordova or Xamarin, is the best option to avoid redundant programming and maintenance. These frameworks allow natively programming in Javascript, C#, HTML5, CSS, and then to compile the code for Android and iOS by using inner libraries. Apache Cordova has been chosen among the various possibilities because it can easily communicate with the needed hardware via API, in order to perform AR, QR-code identifying and PDR algorithms.

4 Conclusions

This work presented different solutions for indoor Real-Time Location System. WiFi, WLAN, UWB, BLE, magnetic fields, infrareds, ultrasounds, computer-vision and PDR have all been analysed and compared in terms of accuracy, coverage, price, installation complexity and maintenance. Actually, the main scope is to design a RTLS for both on-site and off-site navigation, for hospitals and healthcare facilities. The case study the project is focuses to is Le Scotte Hospital in Siena (Italy), so that the peculiarities of the premise have also been taken into consideration when it came to choose the best-fitting solution.

The result is a hybrid system, which combined computer-vision and PDR technologies, together with simple QR-coding. A web-site with virtual touring and plain map navigation developed with Unity 3D is the solution adopted for off-site navigation, while a mobile application with actual RTLS functionalities developed by using the cross-platform framework Apache Cordova, is the chosen solution for on-site IPS.

Future works will surely consist in developing and deploying the system, testing it on the case-study hospital, and they may also include easy-access routing for people with disabilities.

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