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A multimodal Fingerprint-based Indoor Positioning System for airports

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ABSTRACT Indoor Localization techniques are becoming popular in order to provide a seamless indoor positioning system enhancing the traditional GPS service that is only suitable for outdoor environments. Though there are proprietary and costly approaches targeting high accuracy positioning, Wi-Fi and BLE networks are widely deployed in many public and private buildings (e.g. shopping malls, airports, universities, etc.). These networks are accessible through mobile phones resulting in an effective commercial off-the-self basic infrastructure for an indoor service. The obtained positioning accuracy is still being improved and there is on-going research on algorithms adapted for Wi-Fi and BLE and also for the particularities of indoor environments. This paper focuses not only on indoor positioning techniques, but also on a multimodal approach. Traditional proposals employ only one network technology whereas this paper integrates two different technologies in order to provide improved accuracy. It also sets the basis for combining (merging) additional technologies, if available. The initial results show that the positioning service performs better with a multimodal approach compared to individual (monomodal) approaches and even compared with Google's geolocation service in public spaces such as airports.

INDEX TERMS BLE beacons, indoor location, indoor positioning, Internet of Things, Wi-Fi fingerprinting

I. INTRODUCTION

Indoor positioning and navigation services are more and more demanding nowadays and increasing research is being performed from both academia and industry, as there are a large variety of context-aware and location-based applications interested covering different fields such as security, healthcare and tracking. Outdoor location is widely performed via the Global Position System (GPS), but it is not suitable for indoor environments for several reasons, such as no line-of-sight, interference and noise, etc. [1][2]. Some theoretical alternatives for indoor GPS have been proposed in the literature [3][4][5][6], but they provide either no real tests or impractical scenarios for standard users as they require additional equipment.

Though multiple technologies have emerged specifically in the indoor localization arena, many of them, such as Radio Frequency Identification (RFID) or Ultra-Wide Band (UWD), are not commonly used: special infrastructure setup is typically required with the deployment of location sensing devices which incurs in additional costs. Complex calibration process, moderate robustness or high installation costs are additional general drawbacks. Unless a high level of accuracy is mandatory, there is a common trend in providing a flexible and low-cost positioning technology using existing indoor infrastructure and exploiting communication and processing capabilities of users' mobile devices. Wi-Fi is already deployed in many private and public buildings (airports, shopping malls, universities, etc.) and can provide an acceptable positioning technique in terms of accuracy and cost compared to similar systems.

Bluetooth Low Energy (BLE) sponsored by Apple is also being deployed in many sites in form of iBeacons (small, cheap and autonomous devices easy to install) and can also be used as proximity and even positioning technology [7] [8]. From user's and device's perspective both network technologies are suitable as they are present in current user mobile phones. In fact, people are getting used to Google maps to self-locate not only outdoors, but also in indoor environments; Google geolocation plugin available in smartphones is able to scan for available Wi-Fi networks to determine indoor location and is expected to start using BLE information in the positioning algorithm. This is clear evidence that multimodality is gaining acceptance and is probably the best approach to increase the accuracy and reliability for the location estimation by exploiting all current available off-the-self deployed networks. We have followed a similar approach in this paper focussing on merging the information from scanned BLE and Wi-Fi networks but we differ in the way the process is built: our approach is based on fingerprinting whereas Google is based on a crowdsourcing operation.

The process of fingerprinting uses empirical data to estimate location and is composed of two phases. First, a radio map of the whole location is built by collecting the measured RSSI of known locations known as calibration grid. Second, the location of a user is estimated by comparing the real time measured RSSI values with the radio map. From a basic approach there is no need to model the complex signal propagation in the area and also no need to know the locations of the Access Points (APs). However, the first offline phase (calibration) can be tedious depending on the grid granularity and the area to be covered. Besides, some adjustments are typically required in the location algorithm in order to provide a moderate accuracy in real time environments. Although a pretty good indoor accuracy can be obtained in controlled environments with reduced space and low experimental timeframes [9] [10], real living buildings (e.g. universities, airports, etc.) require robust location algorithms to provide acceptable estimations throughout time. This paper will investigate and provide results in such open living spaces.

There are typically two different methods for implementing a positioning system: self and remote positioning. In self-positioning, the physical location is self-determined by the user's device using transmitted signals from terrestrial or satellite beacons (e.g. GPS for outdoor scenarios). The location is known by the user and can be used by applications and services operating on the user's mobile device. In remote positioning, the location is determined at the server side using signals emitted or captured from the user device. The location is then either used by the server in a tracking software system, or transmitted back to the device through a data transfer method. This second approach is typically used in commercial indoor solutions as it provides a centralized management platform to better exploit business cases. Besides, enhanced features can be provided at server side. It is also important to highlight that the indoor estimation is typically offered as an indoor service to users where additional features are relevant and help self-determining the location. For example, whenever a user requests an indoor location estimation it typically expects a visual result in form of a (georeferenced) indoor map, and not just a point composed of latitude, longitude and altitude, which might not be helpful at all. Here a good indoor map implicitly provides additional information (e.g. stairs, elevator, toilets) allowing the user to automatically correct any potential deviation in the location algorithm's accuracy.

The paper is structured as follows: section 2 presents related work considering different technologies and techniques for indoor positioning specially focussing in fingerprinting mechanisms. Section 3 presents the architecture of the system composed of three modules: map service, POI location and the indoor module with additional sub-modules. After that, the performance evaluation is presented providing real results obtained from a mobile app. Finally the paper ends with the conclusions and further work.

II. RELATED WORK

Although there are various taxonomies for indoor localization in the literature, there is a general classification in two separate groups: those based on RF approaches and those using other kind of technology. Among RF-based techniques one may cite GPS, wireless local area network (including Wi-Fi and BLE), and RFID localization. Non-RF-based techniques may include different and alternative technologies based, among others, on audio, visual, ultrasonic, infrared and laser sensors. In this paper, we will primarily focus on RF-based techniques. Table 1 summarizes main RF technologies.

TABLE I
OVERVIEW FOR POTENTIAL INDOOR TECHNOLOGIES

Technology	Pros	Cons
GPS	Moderate to high outdoor accuracy High availability	Low to minimal indoor accuracy
A-GPS	Moderate outdoor accuracy	Minimal indoor accuracy
Pseudolite GPS	High indoor and outdoor accuracy	Very expensive equipment
Cell tower	Long range	Highly inaccurate for both indoors and outdoors
Wi-Fi	Readily available throughout most buildings Minimal costs for implementation Medium range	Network strength can vary due to multipath propagation
Bluetooth	Low power Low financial cost	Moderate to low range High cost of implementation
Infrarred	Moderate to high accuracy	High costs for implementation Sunlight can affect outcome Low range
UWB	High accuracy Low power density Wide bandwidth	High cost for implementation Not commonly used

Nowadays developing indoor navigation systems for the common user is a hot topic. Researchers have explored several alternatives of Indoor Positioning Systems (IPSs) that use Wi-Fi signal intensity to estimate position [11] [12] [13]. Other wireless technologies, such as Bluetooth [14] [15] [16], Ultra-Wide Band [17] [18] and RFID [19] [20] have also been proposed. Another innovative approach uses geo-magnetism to create magnetic fingerprints to track position from disturbances of the Earth's magnetic field caused by structural steel elements in the building [21] [22]. Other alternatives for dealing with the problem of indoor location are the (combined) use of inertial sensors [23] [24], exploiting the smartphone accelerometer and gyroscope to build a reliable indoor positioning system without any infrastructure assistance. This paper will focus on the use of Wi-Fi and BLE technologies for the implementation of the indoor service.

Depending on how the RF signal is treated one may classify the positioning process. Table 2 summarizes a list of available (indoor and outdoor) positioning techniques based on external beacons.

TABLE II
POSITIONING TECHNIQUES

Technology	Pros	Cons
Cell of Origin	Base stations exist (cell towers) Base stations never move	Highly inaccurate
Angle of Arrival	Moderate accuracy with appropriate hardware	Requires directional antenna(s) Requires knowledge of orientation
Angle Difference of Arrival	Doesn't require knowledge of orientation	Requires and additional base station
Time of Arrival	Moderate indoor performance	Base stations must be synchronized Low overall accuracy
Time Difference of Arrival	Moderate indoor performance	Low overall accuracy
Triangulation	Very simple	Requires determination of angles
Location Fingerprinting	High accuracy	High calibration time requirement

- *Cell of Origin (CoO):* this mode returns the closest base station to the user. It has normally been employed in cellular networks with an inaccuracy of at least the size of the cell. For better precision other technologies and techniques are combined, such as GPS, Time of Arrival and even some improvement algorithm [25].
- *Angle of Arrival (AoA):* this technique is mostly suitable for areas with direct Line of Sight (LoS) between mobile users and reference points. The estimation is determined by measuring the angle between a line that runs from the reference point to the user and vice versa with a predefined direction [26] [27]. Though good accuracy, the biggest drawback lies in the need of special reference points to sense the exact direction of the received signal.
- Time of Arrival (ToA): it is based on the measurement of the propagation delay from a user to one or more reference points [28] [29]. This technique is considerably difficult to perform accurately and requires synchronicity at clock level between user and reference points.
- *Angle Difference of Arrival (ADoA)* and *Time Difference of Arrival (TDoA)* are similar to AoA and ToA, respectively, by just changing measured values with measured difference values. The obtained accuracy is somehow also similar.
- *Triangulation*: it is a trigonometric method where the angles of a triangle formed by three reference points are measured. Some extensions have been proposed for the triangulation algorithm to improve the robustness [30] [31]. If distance instead of angle is measured, the technique is called trilateration.
- *Location Fingerprinting*: It is a mechanism which compares the Received Signal Strength (RSS) from each wireless access point (other devices might also be possible) in the area with a set of pre-recorded values taken from several locations. This technique is usually broken down into two phases: offline sampling (training phase) and online location (positioning phase). With a great deal of calibration, this solution can yield very accurate results. However, this process is time consuming and has to be repeated at every new site.

In order to reduce the scope of the research we will focus only in location fingerprinting, as it provides relatively good results. Regarding this approach, the K-Nearest Neighbours (KNN), decision tree, Bayesian classification and neural network methods are the most common techniques [32]. As they are quite different methodologies, this paper will concentrate in KNN algorithms as they will be used in the proposed system. The usage and comparison of other techniques is considered further work.

KNN constructs distance vectors from RSSI data and calculates the position of the mobile user by comparing its fingerprint vector to the training vectors. After that, the signal space distances are sorted. The K samples with the smallest distances are chosen. Distance can be measured in various ways (e.g. Euclidean, Manhattan), with slightly different accuracies in most cases [33]. KNN is probably the most widely used method due to its simple approach, but current implementations often include weights in the selected K samples (WKNN) to better estimate the location by just considering that smaller error introduces larger weight. Additional improvements on top of the WKNN algorithm have been proposed in the literature. Authors in [34] propose a Differential Coordinate method (DC-WKNN) to reduce potential errors caused when calculating weights. Wang et al [35] investigate the impact of signal fluctuations in the positioning accuracy and suggest the use of a Gaussian filtering pre-process as well as a signal strength AP selection policy for the region decision policy. Gholoobi and Stavrou [36] advocate for the construction of the radio map of the localization environment based on the signal fading statistics of multiple short paths, instead of a homogenous grid.

Besides location fingerprinting mobile users can also take advantage of present inertial sensors in their phones (accelerometer, gyroscope, and magnetometer) [37] [38]. However, Inertial Navigation Systems (INSs) are usually subjected to “integration drift,” which is the error in measurement of acceleration and angular velocity. Since these errors are integrated each iteration, they will be compounded into greater inaccuracy over time. Therefore, INSs are often used to supplement another navigation system to provide a higher degree of accuracy. Authors in [39] present a fusion algorithm that integrates a typical Wi-Fi indoor positioning system with a Pedestrian Dead Reckoning (PDR) system resulting in an increased accuracy.

RFID is also a technology that can be considered to some extent as COTS. Many of the RFID papers found in the literature compare results with the traditional LANDMARC algorithm [40], such as [41] and [42]. Though internally the localization mechanisms in such papers are using some kind of WKNN approach, the obtained results are commonly based on reduced layouts (e.g. 3.6m x 4.8 m) to provide high accuracy, but no result is provided for big open spaces such as airports, which differ in form and shape significantly. From another perspective, in contrast to Wi-Fi and BLE, RFID is not deployed on the pilot sites used in this paper and therefore cannot be easily considered a COTS approach as it would require deploying an important number of RFID readers to cover the whole airport area; furthermore, there are some privacy issues challenging the approach as travellers typically are reluctant to carry RFID tags and be tracked. Such issues are investigated in the PASSME European research project [43].

In summary, indoor positioning is a hot research topic with plenty of technologies and algorithms being used and under experimentation. Improved accuracy is typically obtained when a hybrid approach is chosen combining different techniques. However, to the best of authors’ knowledge this combination is mainly produced between radio and inertial systems, but not between two or more radio technologies. This paper focuses on the combined use of Wi-Fi and BLE and an enhanced WKNN algorithm to estimate indoor locations in public living spaces such as universities and airports.

III. SYSTEM ARCHITECTURE

In order to correctly manage indoor location there are two additional modules to be considered if there is an aim for providing a standalone positioning service. The first module refers to the map service: if a user is to be graphically located on a place, it makes sense to do it on a map. Though strictly the feature of indoor location might involve only a name (e.g. room A), it turns out that for every day (mobile) applications users want their location to be displayed on a map, so that they get an overall picture of the scenario. Sometimes it is better the name of positioning, as this feature provides a more detailed level of accuracy. The other component to be included as part of the overall architecture is the POI (Points of Interest) module, as they are also a relevant piece of information for the user at presentation level.

A. MAPS SERVICE

Valid indoor maps are typically not provided and the very first task should start on this topic. In general terms, in public spaces such as universities and airports, the process starts from an architectural (CAD) map and should end into a georeferenced map. The georeferenced map can be of type either rasterized or vectorial. The latter is obviously the preferred format in order to preserve quality as the user performs zoom in/out. The typical vectorial format for georeferenced images are Shapefiles (SHP) which has been chosen in this paper.

The conversion from proprietary CAD formats (e.g. DWG or DGN) to shapefile is not a one click process and should be typically left to an expert for a professional outcome. There are tools (e.g. ESRI’s ArcCatalog) able to make an initial conversion, but one has to select the different types of entities to be considered (e.g. Annotation, MultiPatch, Point, Polygon, Polyline) and it is not possible to anticipate the best option for each map. Thus, a trial-and-error approach needs to be performed in order to obtain the best output. In any case, the resulting output is often not clean and some additional (manual) adjustment is necessary. Additionally, when exporting the map to shapefile format, spatial reference information is typically lost, and spatial adjustment is required using some background cartography: OpenStreetMaps (OSM), Google Maps or national reference cartography via Web Map Service (WMS). A result example can be seen in Fig.1 for the Palma de Mallorca (PMI) airport. All the resulting shapefiles are imported into a GIS Server (the open source GeoServer) in order to provide all maps through a standard WMS (Web Map Service) service.

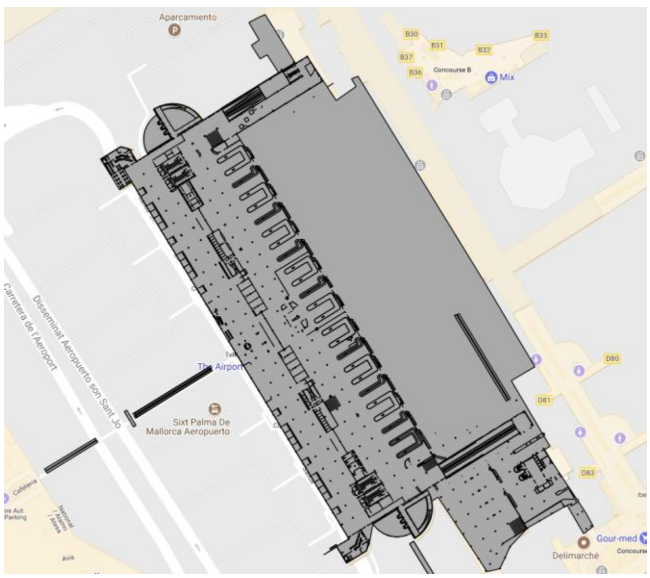

FIGURE 1. **Final shapefile example (PMI airport, Main Terminal, Floor 0).**

B. POINTS OF INTEREST

It is important to include POIs as an independent module as they provide added value when deploying a location service: a user may not only want to know its current location, but also the location of nearby entities (POIs) without explicit need for navigation. Regarding indoor location, and focusing on airports, POIs are:

- Interesting places for users (e.g. restaurants, information points)
- Special zones to be used or avoided (e.g. queues in security checks, stairs, lifts)
- Special points to monitor for status, availability and changing conditions (e.g. boarding gates, lifts)

Even if there are a large variety of POIs, 14 categories have been basically identified and selected, mainly focusing on mobility relevance, as the location service is expected to be later integrated with an indoor navigation service. The categories are: toilets, elevators, escalators, travelators, boarding gates, entrances, security checkpoints, check-in points, stairs, catering, shops, information points, luggage belts, meeting points, shuttle bus stations, car rental places, taxis, public buses, car sharing stations and bike sharing stations.

POIs are described in a generic and extensible format that includes, besides position and category, additional information as Key-Value-Pairs (KVPs).

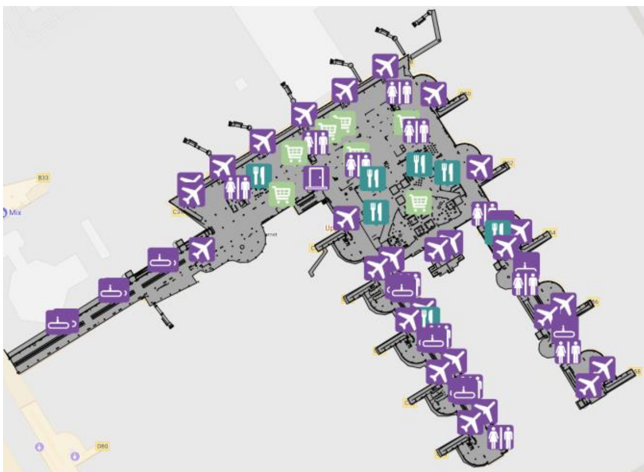

FIGURE 2. Georeferenced POIs (PMI airport, Terminal C).

C. INDOOR LOCATION

The indoor positioning process involves three main actors:

- The environment itself as a series of deployed devices able to provide or broadcast information that help estimating user's location. For indoor environments, it is typically referred to as Wi-Fi APs or iBeacons.
- The user's device, typically a mobile phone able to sense the environment and collect measurements that serve as basic input for the estimation algorithm. Once the algorithm has been executed, the client's device presents the result to the user, typically on a georeferenced map.
- The server side, which performs the necessary process (location estimation). It may also provide related and/or additional features such as maps and POIs. In a general sense, the server also encapsulates the business logic defined by a company exploiting the service.

The process sequence is very simple: (1) the mobile user senses the environments and collects Wi-Fi/BLE measurements, (2) sends them to a remote server for location estimation and (3) finally presents the result to the user.

Location FingerPrinting (FP) has been selected in this paper as positioning technique. Thus, there is a need for a FP database based on RSSI measurements for each floor from each building/terminal. Each measurement can potentially include any radio source that the mobile user is able to sense, which normally maps to the use of Wi-Fi and BLE. The mobile network radio signal (3G/4G) was also considered initially, but provided poor results compared to Wi-Fi and BLE in indoor environments.

Even if the main sources of information are radio signals, it is possible to include additional information of the environment. Here we refer to the possibility of including inertial sensors (mobile accelerometer and gyroscope) that might help in the location estimation. Note that typically the obtained location result is much more accurate when the user is still (motionless) than when the user is moving (e.g. across the terminal). This makes sense because there is a time needed for collecting the measurements; if the user moves during this interval, the 'quality' of the measurements are compromised and thus the algorithm will provide a location result with less accuracy.

The general process that involves the different tasks performed to provide an indoor location service is depicted in Fig.3. It consists of six building blocks: data model, maps, Fingerprinting Grid, Algorithm implementation, Mobile tests (probes) and analysis of the obtained results, which has an impact on some of the previous processes in case an error is detected or some enhancement is suggested. Each process will be described in the following subsections.

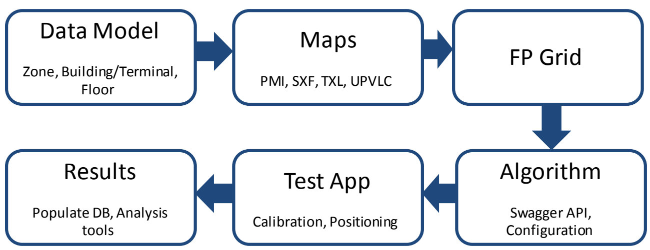

FIGURE 3. General overview of the indoor service process.

1) DATA MODEL OVERVIEW

The indoor service is considered a standalone service and therefore requires a data model to represent the different entities involved according to its own architecture. Without going in deep detail into the data model, some general aspects might be highlighted in order to better understand data representation and the relevant entities to be considered in the architecture:

- Basic entities are floors, which is the normal scenario where a user is located indoors. A collection of floors represents a building (a Terminal according to airport terminology) whereas a collection of buildings represents a zone (an airport according to airport terminology). For each entity a management console has been developed to add, edit or delete items.

- Measurement data is treated in two steps: raw data and average measurements. Raw data can store as many data (RSSI values per each detected radio signal on a specific location) as needed and allows performing an independent (signal) analysis without linking to other information available in other tables. Processed data (measurements) represent average values that are assigned to a specific FingerPrinting node and is therefore linked to other tables, and used by the positioning algorithm.
- The FingerPrinting database is mainly composed of the fingerprinting nodes that make the link between specific locations on a floor with the associated RSSI average values provided by the measurement data.
- POIs should also be represented on this model, but are not linked to measurement data. They contain geolocation and additional information, similar to overlay georeferenced maps that are linked to floors.

2) MAPS OVERVIEW

This process has already been described in a previous section (maps service)

3) FINGERPRINTING GRID OVERVIEW

The insertion of FingerPrinting nodes on each floor is typically a manual process. Once the maps are available, some specific points (nodes) have to be defined where measurements will be collected during the calibration phase. It is difficult to generate the radio map automatically for several reasons (building orientation, wall order, specific places to omit, etc.). Besides, one has to consider that node separation cannot be very small (neighbor nodes will get practically the same measurements, the process may become really though) or very high (accuracy will diminish), and the best separation value is not always possible to anticipate.

In order to facilitate edit and management functions, a web user interface tool was developed to place georeferenced nodes on any available floor (containing maps). Besides, for each node the administrator can set a radius to look for adjacent nodes which is independently of node density. This might be useful for the positioning algorithm in order to reduce the target FingerPrinting space or even predict trajectories. In general terms, a distance of around 5m between nodes has been (empirically) considered as an appropriate default value for large spaces (halls, corridors, etc.).

FIGURE 4. **Fingerprinting Grid (PMI airport, Floor 4).**

Each FingerPrinting node collects not only Wi-Fi but also BLE measurements. In fact, iBeacons is the approach proposed by Apple, which drove the market to the release of an 'Android' branch called Eddystone. It is not exactly the same, but the data model has been adapted to store the three types of measurements (Wi-Fi, iBeacons and Eddystone). In all cases an RSSI value is obtained from each technology. Last, the data model can be extended to incorporate additional radio signals.

4) ALGORITHM OVERVIEW

The algorithm is called DORA and is responsible for estimating the user location depending on the collected real time measurements, by comparing this collection with the ones available in the Fingerprinting database (radio map). Basically, the value to be taken as comparison is the RSSI, and the node providing the least distance value in signal space is the one selected as the candidate value (NN approach), but it is also possible to take the K nearest nodes and interpolate (KNN approach). The various configuration parameters are:

- *Positioning algorithm*: currently weighted NNSS (Nearest Neighbor in Signal Space) is used. Other algorithms, such as HLF (Hyperbolic Location FingerPrinting), are expected to be introduced and analyzed in the future but are beyond the scope of this paper and considered further work. Also statistical processing to better characterize the signal behavior such as the Spearman correlation factor [44] is considered further work.
- *Maximum sample size*: this represents the maximum number of measurements considered within a sample. In practical terms, if a value of 50 is set, this means that the mobile device is able to provide one RSSI value for up to 50 different SSIDs. This value is configured for each technology. Wi-Fi works with SSIDs whereas iBeacon and Eddystone work with UUID.
- *Missing MAC penalty*: In order that the comparison between collected measurements and FP database can be performed, it is necessary to 'homogenize' the field. A missing MAC (related to an SSID) in the user's request

will be interpreted by the algorithm as a ‘virtual’ measurement with a configurable value (e.g. -200dB). This parameter is necessary but can be sometimes tricky as it can have an impact on the final distance value and therefore on the estimation.

- *Candidate set size*: this parameter allows diminishing the FP space to the top T nearest FP nodes of the previous calculated node. In practical terms, if the user is not moving quite fast, and was at node N at time interval t, it makes sense to try to position him/her on the neighbor nodes at interval t+1. Even if the FP space is not reduced, it seems more sensible to locate the user near the previous estimated node if the algorithm gets two candidate similar values, one far away and the other close to the previous node.
- *Checks before hop*: the previous assumption might not be always appropriate and may guide the algorithm to fail. If a distant node from a previous estimation gets a ‘better’ distance than another one close to the previous estimation for various consecutive time intervals, then the distant node is selected.
- *Distance algorithm*: this parameter refers to the way the distance in signal space is calculated. Typically, the Euclidean distance is used (norm 2), but other alternatives are possible: Manhattan, Chebyshev, and Minkowski.
- *Distance algorithm arguments*: additional arguments (if any) required by the previous chosen selected distance algorithm. For example, the Euclidean distance algorithm does not require additional parameters, whereas the Minkowski approach does.
- *Filter sequence*: The algorithm allows the inclusion of several filtering expressions with the obtained result. Note that the result at an intermediate level of the algorithm is not just a candidate node, but the whole set that can be ordered. For example, one can be able to obtain the best N candidate nodes (NHIGHEST filter), or skip a certain SSID during the evaluation (REGEX filter).

The core algorithm process is initially decomposed into three parallel threads treating the different technologies (Wi-Fi and BLE). For each technology, a best estimation (or a list of best candidates) is given. Afterwards, both technologies are merged in order to provide a better and more stable result. Note that it is impossible to compare directly Wi-Fi and BLE values because the sensitivity and the signal space size are quite different. Therefore, the raw values of distance for both technologies differ and have to be somehow normalized. For our algorithm, we have established a basic approach similar to WKNN for establishing the weights to the best candidates for both technologies. There are also some special cases or exceptions to consider in the process: for small distances BLE is typically more accurate than Wi-Fi and it is recommended to omit Wi-Fi estimations which would increase the confidence radius. In the next section estimation results will be presented for both Wi-Fi and BLE technologies.

In order to promote interoperability with other internal or external services (e.g. indoor navigation) a swagger REST API has been developed. Basically, the algorithm only needs to know a space (floor, building or zone) and a collection of taken measurements (provided in the HTTP body). Optionally, the user may also provide a previous node, in order to facilitate (speed up) the search. The response provides the best candidate node and a position that results from interpolation of the three best candidates nodes, among other parameters (floor identifier, level, etc.).

IV. PERFORMANCE EVALUATION

Initial tests have been performed at the Universitat Politecnica de Valencia (UPVLC) premises for practical reasons. Afterwards, the tests have also been performed in two airports: Palma de Mallorca (PMI) and Berlin-Tegel (TXL).

A. APP OVERVIEW

In order to test the service, a mobile app has been developed that allows not only getting the measurements (training phase), but also displaying the results on a map (positioning phase). The app has been developed in the cross-platform environment Ionic and thus allows to be compiled for both Android and iOS devices. Development for Android resulted with no problem; however, there is a serious drawback in the current iOS SDK: it does not allow scanning for Wi-Fi signals. There might be non-standard (non-official) SDKs that allow this functionality, but it will be detected by Apple if the final app is to be placed in the Apple marketplace and will be withdrawn. The reason for that is unclear but it seems that Apple prefers for its devices to use iBeacon technology, offering an SDK for this. This issue motivated the support for iBeacons (and Eddystone) in the positioning service in order to reach both Android and Apple users. In the remaining paper results will be presented from those obtained from Android devices. From an algorithmic point of view, Wi-Fi localization is more challenging than BLE localization, so a special analysis and considerations will apply for Wi-Fi measurements.

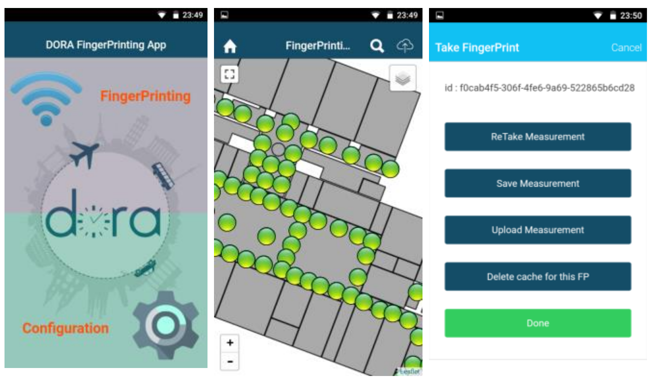

FIGURE 5. App for taking measurements

B. WI-FI CONSIDERATIONS

The success (accuracy) of a FingerPrinting approach depends on a relatively stable radio signal strength along time as the algorithm has to compare an average measurement taken at time T with another measurement taken in the future at time T+t. If the signal fluctuations are significant, this may have an impact on the calculated estimation. For this reason, we made an initial radio analysis and scanned continuously for a whole day the signal fluctuation of one of the APs available at UPVLC premises (see Fig.6) in the 2.4 GHz frequency band. It turned out that during nights there is some internal recalibration mechanism where the signal strength diminishes by more than 10 dB. This fluctuation led to the additional use of special Wi-Fi beacons manufactured by the company Creative Systems Engineering (CSE) with a more stable beacon signal.

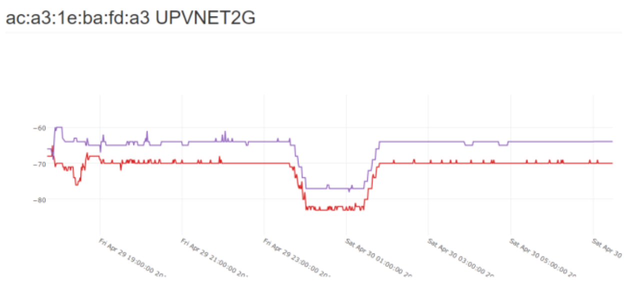

FIGURE 6. **RSSI fluctuation for an Access Point at UPVLC.**

C. INITIAL POSITIONING RESULTS

In order to pre-test the algorithm and anticipate up to some extent the possible result, we integrated a basic Wi-Fi heat map tool into the service management console in order to calculate the 'signal distance' from one FP node to the other nodes in the same floor. This must be performed for each of the nodes, detecting up to 3 different situations (see Fig. 7):

- *Desired situation*: the signal at one FP node is quite different to the others. For the algorithm, it will be easy to decide if the user is at this location.
- *Acceptable situation*: the signal at one FP node has similarities with adjacent nodes. The algorithm will have some difficulties to estimate the best location, but as long as the nodes are close to one another, the deviation might be acceptable.
- *Undesired situation*: the signal at one FP node is similar to many nodes, not only adjacent ones. The algorithm will probably perform poorly here, as there might be no means to associate a best candidate accurately. This situation may happen for various reasons: the adjacent radius between nodes is very low; nodes are in open space quite distant from APs (thus the received signal is similar), etc. One possibility to alleviate this situation consists in introducing another technology (e.g. iBeacons) and giving priority to special signals. Another possibility is to consider previous location estimations (if provided), infer trajectories and setting a small potential candidate size.

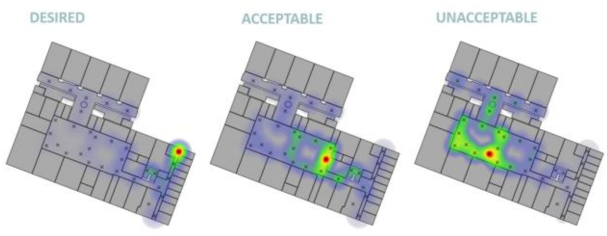

FIGURE 7. **Heat map analysis at UPVLC (ETSIT, Floor 2).**

Another series of results is depicted in Fig. 8. We took various measurements at each of the 32 FP nodes building the radio map throughout a short period of time (5 minutes for each FP node). We identified how many of these (in %) provided an accurate result (i.e. the algorithm provided the same FP node were the measurements were taken). The first (top) bar chart depicts a relatively poor performance for basic configuration parameters of the algorithm; in average, in only 50% of the cases the algorithm provided the right node. This is not necessarily a bad performance as in most of the cases (78%) an adjacent node was estimated and the perception by the user might be acceptable.

In a second iteration, we introduced three filter sequences in order to increase the accuracy level (see Fig. 8). The correspondent (low) bar chart demonstrated that the algorithm performed better providing in average a right result in 80% of the cases and an adjacent node in 94% of the cases).

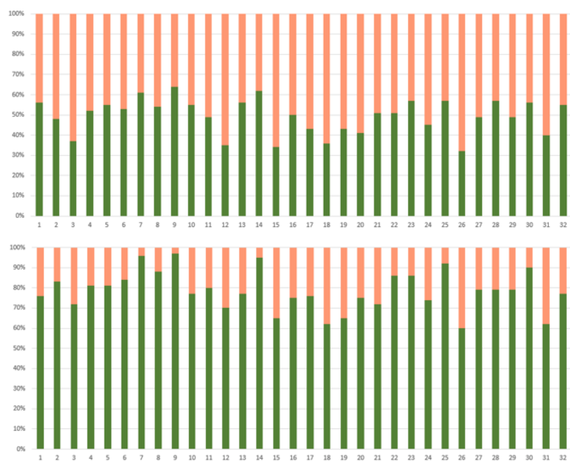

FIGURE 8. **Location results.**

Regarding results at mobile phones, the developed app was tested on an Android device and the results were compared with the built-in geolocation plugin (available also through Ionic), which is used e.g. in Google Maps. Our indoor service outperformed the internal geolocation plugin: Google's plugin places sometimes the user directly on the street even if it is in an indoor environment, and sometimes it converges to a more accurate location, but sometimes not. This situation is depicted in in Fig.9, where the real place is depicted in red, Google's internal geolocation plugin estimation is represented in blue and the DORA algorithm estimation is depicted in green. This Figure shows the best and worst case scenario for both estimation (DORA algorithm and Google's estimation) in two different screenshots. In our experiments at UPVLC premises the results were always better (more accurate) with our approach than using Google's plugin. Our indoor service provides an accuracy of less than 5 meters in 80% of the cases, and less than 15 meters in 99% of the cases. On the other side, Google internal geolocation plugin is providing errors of up to 30 meters in 50% of the cases, which in some cases corresponds with outdoor locations even if the user is located indoors. However it is important to highlight that Google's algorithm is dynamic and converges after a couple of minutes in 70% of the cases, providing acceptable values. From another perspective, our algorithm is able to provide z-coordinate (level) whereas Google's plugin is not (yet) providing this information.

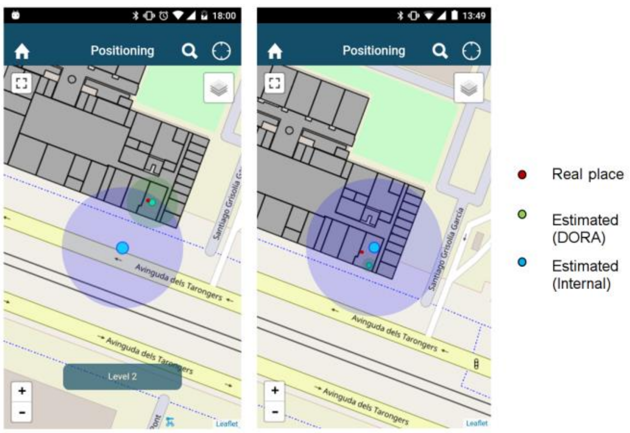

FIGURE 9. Location estimation (indoor algorithm vs Google built-in geolocation plugin).

D. POSITIONING RESULTS IN AIRPORTS

The positioning service has been tested in the airports of Palma de Mallorca (PMI) and Berlin (TXL). For Tegel airport (TXL), 461 FP nodes were defined to cover Terminal C, Terminal B, part of Terminal A and an external car rental station (see Fig. 10). Note that some nodes (yellow nodes) did not get any associated signal scan during the calibration phase. This is the case of some nodes on an outdoor path where GPS should provide positioning information. The offline phase detected up to 220 different SSIDs across the whole scanned area; most of these SSIDs had to be filtered as they related to temporal or untrusted Wi-Fi networks resulting in a final list of 15 relevant SSIDs to be considered.

Some results are depicted for Terminal C at TXL (see Fig. 11) in form of screenshots extracted from the mobile app. The screenshots have been taken in different time intervals (but from the same location) in order to check the variability for the estimation and trying to show best and worst case scenarios. As can be observed, the indoor service average accuracy (around 5 meters) outperforms the internal geolocation plugin (around 10 meters). In this case, the reason mainly lies in the usage of BLE technology (besides Wi-Fi) as Terminal C is fully covered with iBeacons. Though in most cases the indoor service provided a reduced confidence radius, in 10% of the cases it could increase up to 19 meters (worst case).

FIGURE 10. FP grid for TXL airport.

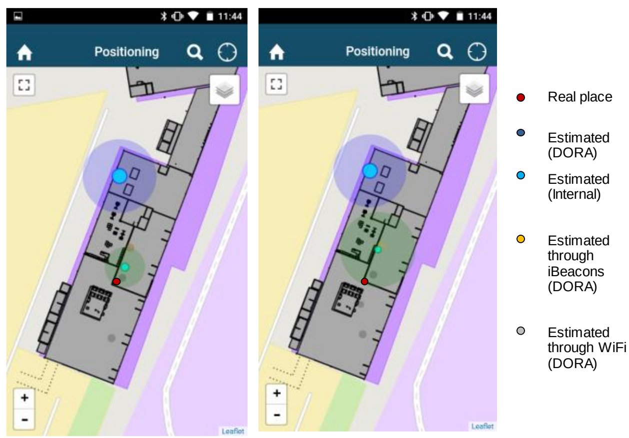

FIGURE 11. Positioning results (Terminal C, TXL).

The airport in Palma (PMI) is much bigger than TXL airport and therefore the FingerPrinting process took longer and was performed Terminal by Terminal. 720 FP nodes where defined for Terminal C where 40 different SSIDs were scanned. For the main Terminal there were 287 FP nodes and 62 different SSIDs for floor 0, 297 FP nodes and 42 different SSIDs for floor 2, and 205 FP nodes and 35 SSIDs for floor 4. After a proper filtering a set of 5-11 relevant SSIDs were selected for each floor. Some results are depicted in Fig. 12, Fig. 13 and Fig. 14. In general terms, the results were not that successful compared to TXL airport, because there was no BLE technology deployed and also because of a larger amount of metallic objects deployed (e.g. travelators). The latter reason has probably caused more signal fluctuations with a real impact on the estimated position and accuracy. In fact, the DORA WKNN algorithm did not provide the real nearest FP nodes in most cases (see Fig. 12). However, compared to Google's internal geolocation plugin, our indoor service still provides a clear better estimation in 70% of the cases, with average accuracy of 5 meters in 60% of the cases, though the confidence radius varies from 5-15 meters. However, in some cases (see Fig. 12), the provided result including the confidence radius does not cover the real location and thus resulting in a bad estimation. Here Google's internal plugin does not 'converge' and provides the same estimation continuously (except for Fig. 14).

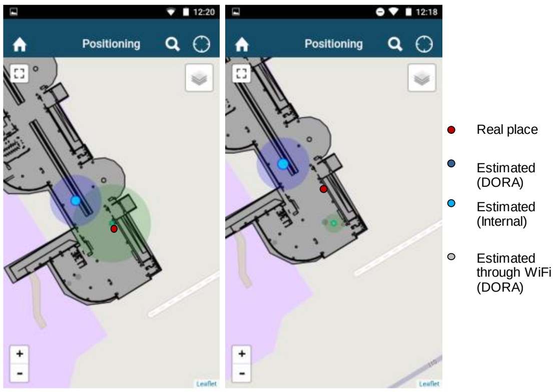

FIGURE 12. **Positioning results (Terminal C, PMI). DORA variability.**

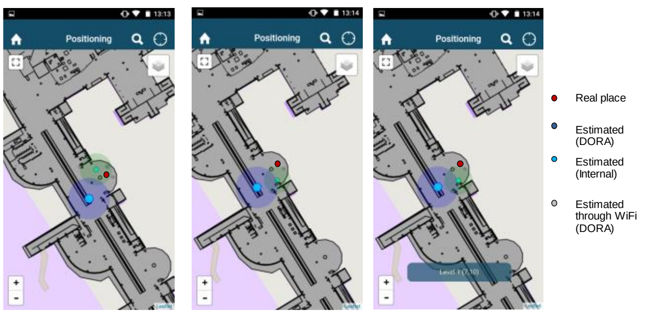

FIGURE 13. **Positioning results (Terminal C, PMI). No Google's plugin convergence.**

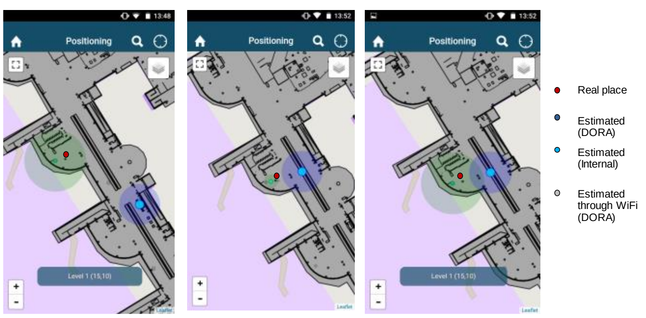

FIGURE 14. **Positioning results (Terminal C, PMI). Google's plugin convergence.**

We firmly think that this is caused because of the strong signal variability (see Fig. 15) that has been detected on several areas of the airport. We could not change it because access to infrastructure in airports is very limited and takes too much time. The situation in our preliminary results was not that bad but variability was also detected due to overlap in the Wi-Fi channels at 2.4 GHz band. However we expect to repeat the experiment in the near future, as the PMI airport operator plans to deploy iBeacons in several months; thus the comparison improvement is considered as further work.

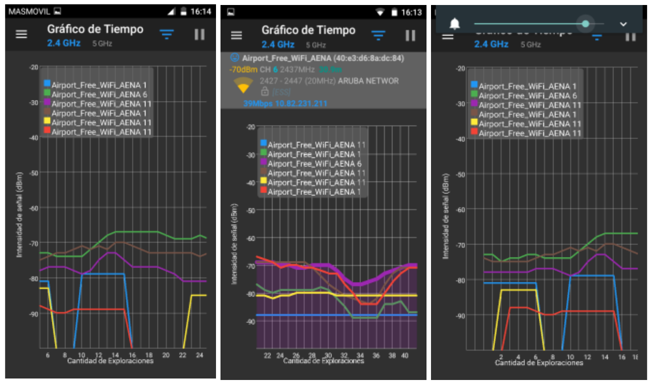

FIGURE 15. **Wi-Fi signal variability at PMI airport.**

E. FURTHER IMPROVEMENTS AND RESULTS

In order to minimize or mitigate the potential errors that could appear at Wi-Fi level in real scenarios the algorithm has been improved in several aspects:

- *Support for 5 GHz band*: current deployed access points are supporting both 2.4 and 5 GHz bands, therefore the attenuation impact is mitigated. Furthermore, there is no overlap in 5 GHz channels and so the signal strength is more stable (some access points reconfigure TX power at 2.4 GHz when strong interference is detected).
- *Infrastructure deployment awareness*: now the algorithm considers the location of access points, the relevant SSIDs involved, the involved MACs as well as the TX power at each band. As will be shown later, such awareness reduces the target node set, the average accuracy and the average response time.
- *Internal geolocation plugin support*: the algorithm supports also as optional input parameter the estimation provided by a third party, in this case the internal geolocation plugin of the smartphone. This has several advantages. First, it is an independent estimation that can be also used either as input for a data fusion technique or as a comparator with the internal result of the algorithm in order to check which one is providing the best accuracy. Second, it can be used as default value if the algorithm has no way to provide an estimation; this could be the case when the traveler is wandering across the terminals through an outdoor path without Wi-Fi coverage but GPS support.

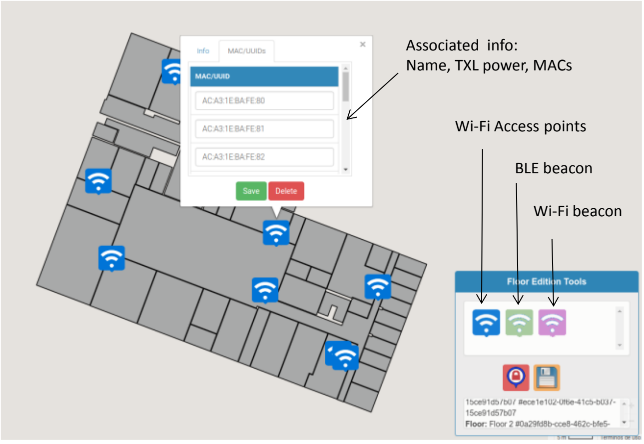

FIGURE 15. **Awareness of infrastructure deployment information (UPVLC).**

FIGURE 16. **Node set associated to access point ar1-tel4d2sc at 2.4 GHz band (UPVLC).**

FIGURE 17. **Node set associated to access point ar1-tel4d2sc at 5 GHz band (UPVLC).**

The node set for each access point deployed is built after the FingerPrinting process. For each fingerprint of the floor/building, the strongest signal measured is associated to an access point according to the MAC. The result is that every access point has an assigned node set which corresponds to its strongest area of influence, and is different depending on the frequency band (see Fig. 16 and Fig. 17). Several partial conclusions can be extracted. First, the assigned node set is not only dependent on frequency but also on TX power from nearby access points; some fingerprints on one floor may be even assigned to access points located in a different floor. Second, the aggrupation of fingerprints in node sets can be exploited to reduce the target node set in the online phase:

- In the first version of the algorithm, whenever a measurement is taken at a given location, the target node set may be the whole floor, building or the entire airport. Obviously the required time for calculating distances increases as well as the potential accuracy error.
- In the new version, the measurement is processed in order to extract the closest (strongest) access points, and the target node set is built as the union of such access points (APs) node sets. It is clear that such target node set is significantly reduced, among all compared with the whole airport and the potential accuracy error also diminishes. The usage of more than one AP node set (if detected) makes the algorithm more reliable, because due to signal fluctuations one may think that some fingerprints may have been assigned to one or another access points depending on the moment the measurement is taken. Considering up to 3 APs node sets for building the target node set (if detected) provides enough confidence and guarantee that the target node set is correct and the remaining nodes can be filtered out.

Some results are presented in the following Figures for the 5 GHz Wi-Fi band. In order to better describe the location process some extra nodes have been depicted as described in Fig. 18. At a given real place (red node) measurements are taken from the smartphone and sent to the indoor positioning service. First, measurements are filtered to consider only relevant SSIDs. Second, RSSI values are ordered in order to get those with strongest signal, and the corresponding access points are detected. As can be observed in Fig. 17 two nearby access points have been detected, and the target node set is built from the union of both AP node sets (yellow nodes). Therefore there is no need to get the node set of the whole floor, reducing the processing time. Finally, the target node set is compared with the taken measurement and the three nearest ones (in signal space) are selected (grey nodes around yellow ones). A weighted approach (WKNN) is applied resulting in a final estimation (green node) including level/floor detection as well as an accuracy radius. The accuracy radius depends on the target node set and the distance between nearest access points.

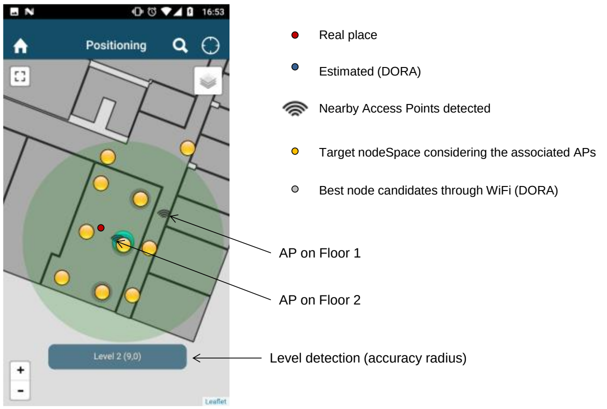

FIGURE 18. Positioning results at 5 GHz band (UPVLC, SATRD lab).

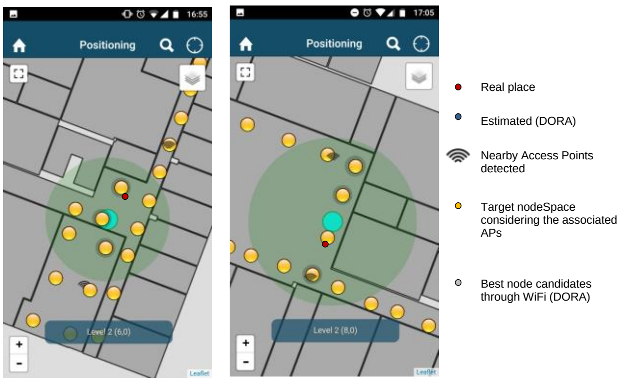

FIGURE 19. Positioning results at 5 GHz band (UPVLC, corridors 1).

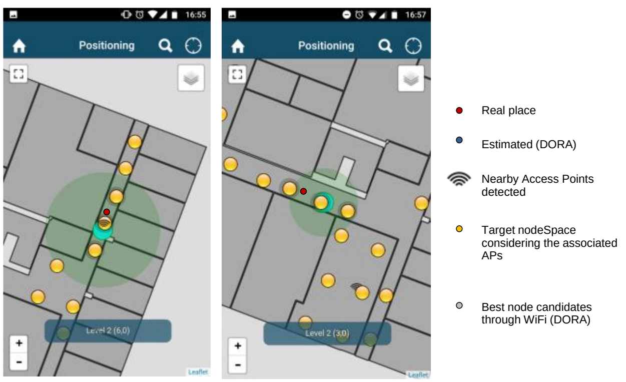

FIGURE 20. Positioning results at 5 GHz band (UPVLC, corridors 2).

The response time of the indoor positioning service has also been evaluated. Whereas the first version of the algorithm provided responses within 1-2 seconds, depending on the target node set (floor, building, airport), the second version is providing values below 0.5 seconds. Even for 20 simultaneous requests values below 0.7 seconds are obtained. This is in fact not relevant for the user because the smartphone is not continuously scanning for Wi-Fi, but periodically after 6-8 seconds for battery savings reasons. Besides, reliable BLE scanning may take around 5 seconds in smartphones, and the service response time is considerably below such value.

F. INTEGRATION IN IOT ENVIRONMENTS

It is common to find in IoT context models the location of the objects (entities) as an attribute; it can be either fixed for static entities or dynamic for entities with mobility capabilities. Usually, mobile entities are equipped with GPS enabled support providing location data that is acceptable for outdoor environments; however, they struggle to provide an accurate position when the entities enter indoor facilities.

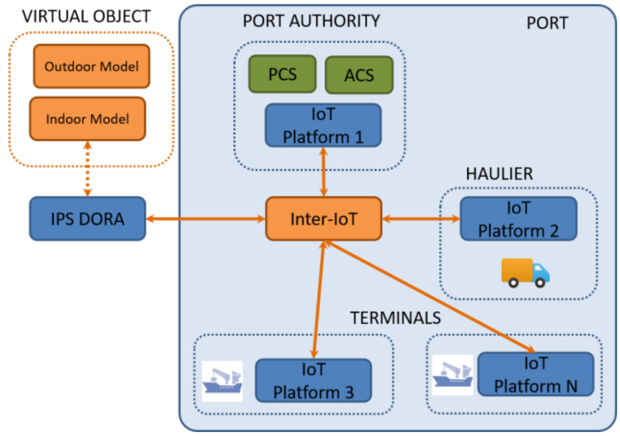

FIGURE 21. DORA IPS integration with the Port IoT environment.

In order to facilitate third-party integration, the DORA IPS has been integrated and tested in a multi- IoT environment, considering as use case activity carried out at ports (see Fig. 21). Typically, the Port Authority is the entity in charge of providing security and managing the coordination of all involved parties in port transactions. Each party owns its own IoT platform to manage internal processes, and limited interoperability is exposed. In order to ease communication and optimize resources among all of them an interoperability platform, called Inter-IoT, has been proposed [40]. It encompasses a multi-level architecture so that interoperability between IoT platforms can be established at different layers (device, network, middleware, application, and semantics). The objective in our paper consisted in setting up the DORA IPS as an application service on top of Inter-IoT, so that different IoT platforms are able to use the service through an integrated interface (see Fig. 21).

Interoperability in Inter-IoT requires a meta-model for any entity subject to be interoperable between two or more IoT platforms. Thus there is a need to represent virtual objects covering multiple dimensions. The object representation must be extensible in order to fulfill present and future service requirements. In our use case, we have included an indoor model extension in order to cover those entities operating in indoor environments, conceptually similar as for a typical outdoor model. Basically, the indoor model relates the target radio map (fingerprinting grid), the scanned measurements and the positioning estimation. Note also that the radio map may be provided from each IoT platform operator, sharing just the access to the algorithm.

The use case tested in this paper relates to a third party transportation company entering the port of Valencia by truck. Here Access Control Systems (ACS) and Port Community System (PCS) verify the correct entrance of the truck and allow them to go to the destination terminal. In a typical scenario, the exchange of tracking information between systems mainly involves GPS coordinates, but there was no effort to include indoor positioning. In our system this is performed by incorporating the DORA IPS with support in some buildings at the port. Moreover, the positioning service can involve both the truck and the driver, which might not be on the same place necessarily in an indoor environment. Here indoor geo-Role Based Access Control (RBAC) policies can be established in order to assure that truck and driver only enter authorized zones.
Considering the generic approach of IoT platforms, entities may not only be trucks and drivers. Though this is not yet implemented and is considered as further work, the internal radio map (FingerPrinting Grid) typically provided by each building owner may be dynamically generated and updated by a special entity (mobile device) managed by an IoT platform (radio map provider).

Though it is difficult to evaluate the impact of integrating the positioning system in a multi IoT environment with numbers, some basic Key Performance Indicators have been established and listed in Table 3. The response time of the DORA IPS takes as average 6,3 seconds; this is caused if BLE is used as scanning technology because it takes a time for the ranging process; this is just a limitation of the internal plugin of the mobile device. If only Wi-Fi is used, the response time is reduces less than 1 second. Integrating the DORA IPS into the IoT environment does not have any practical impact as depicted in Table 3. Some additional milliseconds are needed in the IoT environment due to security checks for granting access. Regarding the management of radio maps, the DORA IPS was conceived as a central service and thus it has to manage all FingerPrinting grids (TXL airport, PMI airport). Integrated in a multi-IoT platform, the generation and updates of radio maps is delegated to each IoT platform, each one in charge of managing their own maps. In our use case, we were able to set up 2 FingerPrinting management entities, one radio map for the Port Authority IoT platform (1 building) and another one for one of the Terminals (1 building).

Considering the number of platforms integrated, we were able to test the interoperability with three different open platforms: FIWARE, Open-IoT and WSO2. In fact most of the work is done by the Inter-IoT platform and mainly the indoor model extension was necessary. Such integration allowed us to easily use the integrated DORA IPS from multiple services in the three platforms that can potentially make use of an indoor location for their internal processes. We successfully tested it with 9 services, three from each of the IoT platforms. Obviously this number may increase seamlessly; it just depends on the services requiring indoor positioning in each IoT platform. We tested it on 9 services in order to check and verify the integration process.

TABLE III
KPIS FOR THE DORA IPS INTEGRATION

KPI	DORA IPS	DORA IPS+IoT	Ratio
Response Time (ms)	6340	6597	1,04
FP Management entity	1	2	2
Platforms integrated	1	3	3
Services Integrated	1	9	9

As further work and considering potential business models, various IPS services may converge and register into the Inter-IoT platform, exposing different FingerPrinting technologies and accuracy. For example, DORA IPS is based on Wi-Fi and BLE but another IPS may support RFID and UWB. In this scenario, each IoT platform may request available capabilities and decide which one to use.

V. CONCLUSIONS

Indoor location is a trendy topic and is foreseen to grow in the upcoming years, once the outdoor scenario is already stabilized. Some of the first target indoor areas are airports and shopping malls, thus there is a recent approach to deploy indoor solutions.

A general indoor service has been developed based on Wi-Fi FingerPrinting and Wi-Fi beacons, with the possibility to include also iBeacons and Eddystone beacons. The indoor service is decomposed in various components and integrates smoothly with other related services (maps, POIs). Besides, there is a HTTP REST interface available with Swagger support that facilitates an easy integration with other software components (e.g. indoor navigation).

The developed service included not only a server side component but also a mobile app to target fingerprinting and location tests using Ionic, and the latter one can serve as initial basis for custom apps.

Indoor maps are really important not only for users but also for setting up the fingerprints. If the surface to cover is really huge, it is important to have important reference points (e.g. pillars) available in order to assure that the fingerprint is taken at the right place. From the end user perspective, some building details should be removed to provide a simple view. This is a work intended for a design professional worker from the airport.

In general terms, Wi-Fi does not seem to be well suited for accurate indoor location as single technology. It can provide good estimations at certain spots, but for big areas with changing conditions strange estimations might occur and on site adjustments are required. So it is important to combine different technologies (BLE and GPS if possible) in order to increase the accuracy and reduce the effect of signal strength variations. The usage of both bands (2.4 GHz and 5 GHz) for Wi-Fi helps also mitigating signal strength variability and thus reducing the average accuracy error.

The obtained accuracy in real live conditions can range from 2-15 meters; it depends on several factors, such as the fingerprinting grid and signal strength stability, among others. For very accurate estimation, additional investment is required, which will be no longer a COTS approach. The algorithm has been enhanced from an unaware infrastructure approach to an aware one, exploiting the knowledge of access point's locations, their MACs, TX power and relevant SSIDs. Under such circumstances, the target node set is reduced, as well as the response time and the accuracy error. This is also helpful in airports to mitigate the extreme population density in airports where signal strength severely reduces, as the algorithm infers the estimation based on the nearest (strongest) access points detected.

It is important to work with the airport staff in order to set the fingerprinting grid, deploy additional beacons and finally test the indoor location; a lot of different tests have to be performed across the target place (including restricted areas). Thus, some staff working daily at airports is required to make tests and help generating a model to overcome the details of an airport. Note that each airport is different and has different problems in terms of signal propagation that affects the quality of measurements taken, thus guiding to 'surprising' estimations unless the situation is detected and corrected or minimized.

Probably the most challenging aspect for indoor positioning relates to the location of users while they are moving, as the signal strength varies across the path. Here the DORA algorithm (and also Google's one) provides inaccurate results even if including inertial sensors and also time window filtering. Intensive work has to be performed in this direction to obtain good results without consuming too much battery (energy).

Long corridors with long metallic travellators seem to provide unexpected signal reflections and thus resulting in a poor estimation. Accuracy seems better at the waiting areas at both sides of the main corridors.

The positioning system has also been successfully integrated and evaluated in a multi IoT scenario where different services from different open IoT platforms were able to get an indoor positioning value enriching the capabilities of their services.

Further work can spread in different directions, but we are mainly focussed on improving the DORA algorithm for just Wi-Fi deployed areas as well as studying different positioning technologies (e.g. RFID) to better test and improve the merging process.

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