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Challenges of Fingerprinting in Indoor Positioning and Navigation

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1 Motivation

Since the beginning of humanity, localization and positioning have been a worry of human beings. This has driven to the creation and search of many different mechanisms to localize: the Sun, the Moon, the Stars, the magnetic field, radio beacons, etc. And this information has been represented in several kind of maps.

Everything changed with the apparition of Global Navigation Satellite Systems (GNSS) in the 1960s that drove to the apparition of the American Global Positioning System (GPS) in 1995, and later to the Russian GLONASS, in 1996 or, more recently, to the European Galileo and the Chinese Beidou. GNSS systems have two important roles: (1) allow to get position with centimeter precision and, in some cases, even milliliter precision[1]; and (2)

[1] See https://www.gps.gov/systems/gps/performance/accuracy/ (Accessed July 2018).

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allow to get that precision to anyone who owns the appropriate device, whatever his or her knowledge in positioning would be.

Although GNSS were born with military objectives, by the end of the 1990s receivers of GNSS became commercially available and very popular. By then, military restrictions did not allow high accuracy (more than 10 m), but this restriction disappeared in the 2000s and thus, people became used to have high accuracy localization and navigation.

The next step came with the inclusion of GNSS receivers in smartphones and its popularization which has driven most of people (78% in Europe) to wear a GNSS receiver. This situation has driven to an explosion of location-based systems (LBS). According to a Mobile Life study[2] 19% users use LBSs and 62% think of use LBSs. Navigation is the most popular.

One special kind of applications, Context Aware Recommender Systems have become many popular in marketing and, for example, *FourSquare* allows users to obtain different offers and discounts. In the social area, applications such as *Google Now* send users recommendations of events. There are also projects of tracking of patients such as *Ekahau*[3]; projects to include systems that automatically call emergencies in case of an accident (*eCall*[4]); projects that provide virtual information over reality (*Ingress*[5]); or the project *Fieldtripglass* to add augmented reality to what the user is seeing.[6]

All these LBS need for a reliable and real-time localization, which in most of these systems is obtained via GNSS, although a first localization is performed by using other signals such as Wi-Fi, Bluetooth, or GSM and, once GNSS is available, the high precision position is obtained (Laitinen, 2017).

Despite the successes achieved, the problem of GNSS is that they are affected by Non-Line-Of-Sight problem, multipath propagation issues, signal blockage, intentional and unintentional interferences, etc. (Bhuiyan, 2011). This drives to a signal attenuation that fails to get position in urban canons or indoor environments. Thus, all those LBS fail when going indoors.

Then, the question that arises is: Is indoor positioning and navigation important? This is important, since people spend 80% of their time indoors (Wadden and Scheff, 1983), and, according to Gartner, in 2020 indoor revenues will be as high as 10 billion dollars. Thus, it can be seen that indoor environment has an important social and economic relevance.

The chapter is structured as follows: first, a brief review of indoor positioning systems is performed; then we focus on fingerprinting techniques and show some examples; in the following sections, the problems of indoor maps and privacy and security are presented; and finally, the chapter ends with the conclusions and future challenges.

[2]See http://www.tnsglobal.com/press-release/two-thirds-world%E2%80%99s-mobile-users-signal-they-want-be-found.

[3]See https://www.airistaflow.com/wp-content/uploads/2016/07/AiRISTAFlow_-Ekahau_RTLS_BR.pdf.

[4]See http://europa.eu/rapid/press-release_IP-13-534_en.htm.

[5]See https://www.ingress.com/.

[6]See http://www.fieldtripper.com/glass/.

2 Indoor Positioning Systems

Nowadays, there are still no universal standards for indoor positioning, similarly with what we can find outdoors with GNSS (Lymberopoulos et al., 2015). However, there are several techniques and methodologies that can solve the problem in some specific situations. In this section we will show some generic aspects of indoor positioning systems and which systems exist in the literature or on the market. However, first of all, some important concepts are defined in order to make the chapter (and the book) more understandable.

2.1 Position, Location, and Navigation

The first point to take into account is the difference between three key concepts: position, location, and navigation.

The *position* corresponds to the coordinates of a specific point in a coordinate system, such as the GPS latitude-longitude-altitude coordinates.

The *location* gives the position, but in the context of the specific point, for example: "you are situated in front of H&M shop at third floor of the Mega mall." Location is what gives position its meaning to the user. Location can be given for static elements or for dynamic elements. Although location of dynamic elements might appear like locate the same element several times, the reality is that techniques applied for both types of location (static and dynamic) can be very different.

Finally, *navigation* refers to how one goes from point A to point B. There are two main constraints: (1) there are some rules for going to one point to the other (such as speed limit, or staying in a track); and (2) navigation deals with localized elements (position is not enough). It is important to note that navigation is always associated with elements that are moving (dynamic location).

This chapter is mainly focused on position and location (static and dynamic).

2.2 Classification

All positioning systems can have two parts:

- *Interaction device*: is the device where the user can receive position, localization, navigation instructions, etc., and interact with the information. It can be a specific dedicated device, a computer, a tablet, or, more commonly, a smartphone. It is something that the user takes with himself or herself.
- *Infrastructure*: corresponds to all the devices to be located in the environment in order to get position together with the devices or access nodes used to help the position estimate. Usually, indoor positioning systems can be divided in two main categories, regarding the infrastructure they need:
    - *Infrastructure-based systems*: require equipment (e.g., proprietary transmitters, beacons, antennas, cabling) to provide location signals. They can also be divided in two categories:

  - *Systems with dedicated infrastructure*: use devices added specifically to provide location, such as Bluetooth, Ultra Wide Band (UWB), or RFID. Some examples of systems are:
    - Bluetooth Low Energy (BLE) beacons: iBeacons (Apple) (Newman, 2014)
    - Ultrasound: ALPS (CMU) (Koehler et al., 2014)
    - Visible light: EPSILON (Microsoft Research) (Li et al., 2014)
    - UWB: Decawave (Ye et al., 2012)
  - *Systems that use another infrastructure*: use devices of the environment that have another purpose, like using Wi-Fi (Laitinen and Lohan, 2016) or GSM.
- *Infrastructure-less systems*: do not require dedicated equipment for the provisioning of location signals. These systems are free of any infrastructure in the environment, such as using magnetic field, or inertial navigation systems (INS). In this last case as inertial device can be used the smartphone or an Inertial Measurement Unit (IMU). In the latter case, a smartphone or an IMU can be used as an inertial device.

2.3 Localization Mechanisms

The kind of system determines the methodology to get location. The more common position techniques are (Zekavat and Buehrer, 2011; Liu et al., 2007; Hakan Koyuncu, 2010):

- *Proximity*: This method can be used with GSM, and assigns the smartphone to the cell to which is connected. Accuracy will depend on the distance between cells.
- *Distance based*: This method uses the path loss model of the received signal strength (RSS) to get position. It needs to know the position of the emitters and the mean accuracy got is about 4 m (Bose and Foh, 2007).
- *Time of arrival (ToA)*: This method obtains the position from the time of arrival from the emitters. Its main drawback is that receivers need resolutions lower than $\simeq 1\ \mu s$ (Bocquet et al., 2005).
- *Angle of arrival (AoA)*: Position is obtained by triangulation. The position of the emitters has to be known. It can get accuracies of about 4 m. For GSM, accuracy can be of 150 m, in case of 4 km spacing of BTSs (Wong et al., 2008).
- *Inertial*: This method applies kinematics to obtain position from the sensors carried by the user, which can give information about orientation or speed. This method has the problem that error grows with time and it is important to recalibrate the system from time to time (Jimenez et al., 2010).
- *Fingerprinting*: This method is based on comparing RSS values with a reference map of RSS (radiomap) that associates values with positions (Honkavirta et al., 2009; Kaemarungsi and Krishnamurthy, 2004).

It is important to note that when talking about users, we refer not only to persons, but also to robots or any other element that we are interested in localizing indoors.

These techniques can be applied with different technologies that can be dedicated to indoor positioning, such as UWB (Gigl et al., 2007), RFID (Li and Becerik-Gerber, 2011), Bluetooth (Faragher and Harle, 2014); or not dedicated, such as Wi-Fi, as will be shown in Section 3.1. As it can be seen, there are many different technologies to solve the indoor positioning problem. It is important to note that many times several technologies are fusioned in a system and they can use information from several sensors (what is known as sensor fusion). There are systems that use GNSS outdoors, only if they have good signals. But when this is not the case, one can use GSM or Wi-Fi as backup, since Wi-Fi is generally present in most of urban environments. When indoors, Wi-Fi signals and GSM can be used as backup solution, both combined with inertial information.

Fig. 1 shows several technologies and the range of precision of everyone of them.

Despite their possibilities, using so many different technologies affect interoperability between systems and standardization. On the other hand, which method or methods to choose? To answer this question there are several items to take into account:

- *Application*: Guiding a robot within a building is a different application than guiding a person indoors, since a robot requires much more precision (a robot can crash a wall because a lack of precision, but a person will see the wall). Knowing the application to build will give also information about the accuracy needed.

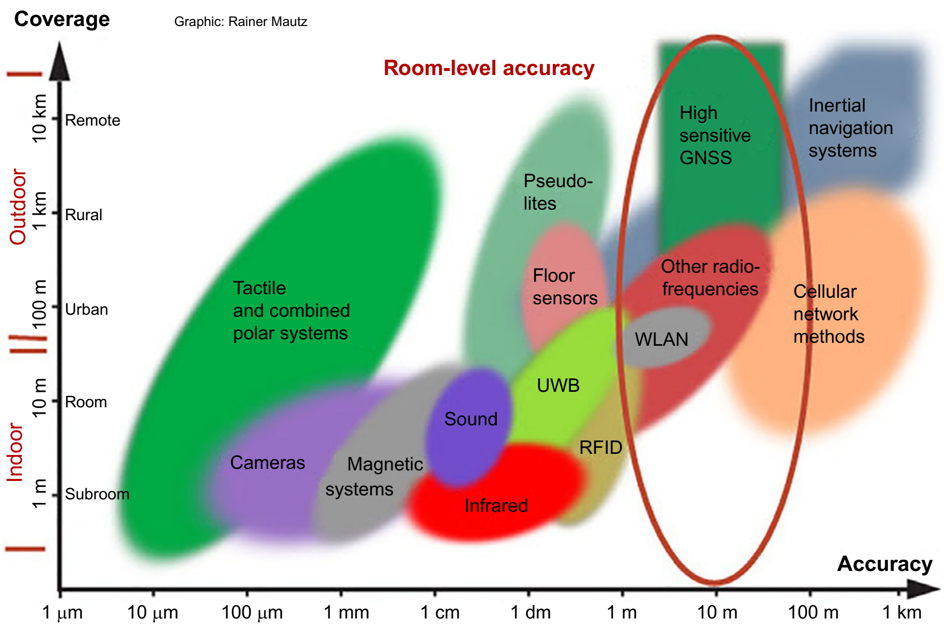

FIG. 1 Methods of positioning regarding their applicability (indoor-outdoor) and their accuracy. *(Adapted from Mautz, R., 2012.Indoor Positioning Technologies (PhD thesis). ETH Zurich, Department of Civil, Environmental and Geomatic Engineering, Institute of Geodesy and Photogrammetry Subject. https://doi.org/10.3929/ethz-a-007313554. Available from: https://www.research-collection.ethz.ch/handle/20.500.11850/54888.)*

- *Cost*: An application that needs to deploy beacons can increase the cost. It is important to take also into account the maintenance cost regarding hardware as well as data.
- *Scalability*: If the application has possibilities to grow to larger scales, it is important to take into account if the system chosen is easily scalable.
- *Environment*: A mall is different than a research facility. Therefore, it is important to observe the place where the system will be deployed in order to detect the drawbacks regarding every technology.

Among all these systems, the symposium “Challenges of Fingerprinting in Indoor Positioning and Navigation” was focused on fingerprinting, that will be presented more deeply in the next section.

3 Fingerprinting Indoor Positioning Techniques

Fingerprinting is becoming one of the most popular indoor positioning systems available. It has the advantage that needs no special infrastructure to be deployed, since uses a signal already present in the environment, such as Wi-Fi or magnetic field. Although Wi-Fi is the most popular nowadays, some solutions deploy their own beacons to make fingerprinting with their own signal.

The technique is based in two steps:

- In a first step, measures of RSS are taken with a device with specialized software. Every measure is associated with a position or zone and the signal to measure can be any signal available (Wi-Fi, magnetic field, etc.), that will be the signal to get position. The set of RSS values and its positions is known as *radiomap*;
- The second step refers to positioning itself and this position is obtained by comparing the value measured by the device to position with the reference radiomap.

To get position from the comparison, a positioning algorithm is needed. There are many different algorithms and, although many of them can be applied to different signals, some of them depend on the kind of signal (Wi-Fi, GSM, magnetic field, and even GPS, that can have enough intensity to make fingerprinting, although not enough to give a GPS position). Here we will focus mainly on Wi-Fi fingerprinting and give some notes about magnetic field fingerprinting.

3.1 Wi-Fi Fingerprinting

Wi-Fi fingerprinting is an indoor positioning system that is able to offer 2–3 m of accuracy in stand-alone mode, although the most common is about 6–7 m. There is a relation between transmitter and receiver, but in indoor propagation we cannot count on this, because Wi-Fi radiation is reflected by many different materials and is absorbed by life bodies, like human beings. The position of access points (AP) is usually not known (although it would be possible to find them by a signal study (Mendoza-Silva et al., 2016)).

Thus, multilateration is not a good option for indoor positioning via Wi-Fi, and using RSS and fingerprinting become the most common alternatives.

In Wi-Fi fingerprinting, in the offline phase, Wi-Fi RSS in specific reference points is collected. Usually more than one measurement at every point is taken, in order to minimize problems of signal propagation in indoor environments, and optionally take the average of all measurements. Since values fluctuate, usually several values during some time are taken and the mean is taken as a representative. Then a vector is built with the strength and the name of the AP. However, since the absolute value of RRS has a strong dependence on the receiver, some times relative values between APs are taken for the vector. The set of all these vectors associated with every position is known as the *radiomap*.

In the online phase, measures are taken by the device to position. Then, these measures are compared with the radiomap and position is obtained with an algorithm. It is important to keep the algorithm as simple as possible and, at the same time, able to give enough accuracy.

There are several algorithms to get positioning but, besides the algorithm, a distance or similarity metric has to be decided. Usually matching algorithms, such as *k*-nearest neighbors (*k*NN), have to be applied in the online phase, which require the aforementioned distance or similarity metric. Several metrics can be used: Euclidean, Minkowsky, Sorensen, Manhattan, inner product between vectors, etc.

Usually, the space where vectors of fingerprints *live* is known as *fingerprints space, RSSI space, features space*, or *phases space* and the distance between two points in this space is defined by the similarity metrics decided. It is important to note that this is not the geometrical indoor space where users and objects live, but Wi-Fi fingerprinting assumes that two vectors near in the fingerprints space, will be near in the geometrical space.

The algorithms that calculate position, work in the fingerprints space, and obtain a *location* in that space, that then is transformed to the geometrical space. There are two main kind of algorithms:

- Probabilistic, such as Bayesian algorithms (Madigan et al., 2005).
- Deterministic, such as the Nearest Neighbor (NN) algorithms, which is the most common (Ma et al., 2008). It has three variants:
  - *NN algorithm:* It takes as position the position of the vector in the radiomap closer to the online vector.
  - k*NN algorithm:* It takes as position the mean of the positions of the *k* vectors closer to the online vector. *k* can be obtained by test-error, or calculated from a formula; and can be the same for all the position calculations, or a dynamic number can be used. Usually it takes a value between 1 and 10.
  - *W*k*WNN algorithm:* It is like the *k*NN, but it gives different weights (W) to vectors. Usually closer vectors have higher W.

Besides all these metrics and algorithms, which can be considered as the base line, many scientists developed their own solutions, such as the *P*-value matrix (Caso and De Nardis, 2015, 2017; Caso et al., 2015a,b; Lemic et al., 2016), or applied some refinements, such as saying that strong values are closer to the vector in the features space to position than weak values (Torres-Sospedra et al., 2017a,b).

In case the position of APs is known, the centroid method can also be used. Then we can have a fingerprint calibrated centroid radiomap and calculate the positions of the access points from this radiomap with a weighted centroid, which will have fewer points (Knauth et al., 2015). Accuracy will not be as good as a detailed radiomap, but this method allows to create a simpler radiomap in situations when high accuracy is not so important.

3.2 Problems of Wi-Fi Fingerprinting

Although Wi-Fi fingerprinting has become very popular and many applications use this method for indoor positioning, these types of systems have several drawbacks that is important to take into account (Torres-Sospedra et al., 2014):

- *Creation and maintenance of the radiomap:* Creating the radiomap is a very laborious, heavy, and time-consuming task. In large buildings, many fingerprints need to be taken and at every point several measures have to be taken. On the other hand, once the radiomap has been build, any change in the Wi-Fi infrastructure (movements or changes of APs), can make the map useless and has to be created again.
  This is the main drawback that Wi-Fi fingerprint systems face and in the next section we will show several approximations that try to minimize it.
- *Lack of uniformity of the signal:* Wi-Fi signal might be irregularly available inside buildings due to poor WLAN planning or due to budget constraints.
- *Energy consumption:* Power efficiency is a crucial element when dealing with smartphone applications. Two tricks that use nowadays algorithms are: reducing scanning intervals and not scanning all the channels. If possible, the positioning algorithm can be moved to the server, although this has the drawback that connectivity is mandatory for getting location. Many algorithms also use mechanisms to reduce complexity, like clustering (Feng et al., 2012).
- *Initial heading:* For magnetic field or INS-based positioning, since the compass does not work as expected in the building and RSS measures depend on the orientation of the smartphone, initial heading affects accuracy and reliability of the system.
- *Outband area:* It is not only the problem of signal strength propagation and triangulation, but also the *k*NN algorithms and similar. We want to detect that we are out of the band and have specific algorithms to detect it.
- *Absorption by living tissues:* Since Wi-Fi is absorbed by water and people are mainly water, fluctuations in the number of people affect the RSS and can affect accuracy (Garcia-Villalonga and Perez-Navarro, 2015).
- *Device dependence:* Differences in sensors of different devices make that measured values are different.

As it has been said, the main drawback among all of these is the radiomap creation. The next section expands on this problem and gives some clues on how to overcome it.

3.2.1 Solutions to Radiomap Creation

Wi-Fi fingerprinting has the advantage that no special infrastructure is needed nor any special device. As has been stated before, the creation and maintenance of the radiomap is the main drawback of Wi-Fi fingerprinting.

As an example, the first experience in the creation of the UJIIndoorLoc database (Torres-Sospedra et al., 2014, 2015), 20,000 fingerprints were collected by 20 people. Then 1000 measures were taken for validations and 5000 for test. The second experience was to collect 20,000 points for a conference. Two mappers mapped a building during 3 days, but 10 people performed route-based mapping.

To overcome the problem of database maintenance, the main solutions are:

- reducing the number of fingerprints to take;
- reducing the time needed to take a fingerprint; and
- simplifying the maintenance of the radiomap.

These solutions are not mutually exclusive, and can be implemented together.

Reduction of the Number of Fingerprints to Take

To decrease the number of measurements to take in the offline phase, the most common approximation is to take few measurements and then create virtual fingerprints. There are several methods to create virtual fingerprints:

- *To estimate the position of APs to apply a path loss model.* Thus, some measurements are needed at the beginning to estimate parameters. The important thing is that initial set of measurements will be uniformly distributed (Caso and De Nardis, 2015, 2017; Caso et al., 2015a,b; Lemic et al., 2016).
- *To increase resolution without increasing site-survey time, by using continuous space estimator (CSE) (Hernández et al., 2015, 2017).* This process is made in two stages:
  - *Training stage:* An RSS map is created using discrete information for each AP. From this information, continuous surfaces are estimated using the vector machine algorithm. Then we have the real information and the virtual information obtained with the vector machine algorithm.
  - *Localization stage:* When the RSS is measured at an unknown position, the algorithm searches those RSS values in the corresponding continuous surface. Thus, possible positions are obtained for the device in the surface corresponding to every AP. After that, all the surfaces are added together and that gives zones with more likely positions. Then, a smooth filter is applied and finally, an environment mask is applied to match the solution with the accessible zones.

Table 1 shows the accuracy obtained with different algorithms in static positioning, and in dynamic positioning in two different trajectories. As can be seen, CSE accuracy is maintained in discrete positions and is better than SVM and *k*NN when measuring trajectories.

Table 1 Accuracy Obtained With Several Algorithms

	CSE (m)	SVM (m)	*k*NN (m)
Discrete positions	1.56	1.53	1.56
Trajectory 1	2.72	4.07	4.13
Trajectory 2	3.60	5.34	5.56

CSE, continuous space estimator; *kNN*, *k* nearest neighbors; *SVM*, support vector machine.

Reduction of the Time Needed to Take a Fingerprint

As has been stated before, taking one fingerprint per point is very time consuming, since several measures have to be taken, and it is important to space them. Thus, every fingerprint takes between 30 s and 1 min, and user has to stand.

However, some applications allow to take fingerprints dynamically while the user is walking, is what is known as *route-based mapping*. This mechanism takes less measures at every single point, but it compensates with the great amount of measures taken. This kind of fingerprints is very useful for applications that try to match trajectories instead of points, that is, for dynamic positioning.

Simplification of the Maintenance of the Radiomap

To simplify the maintenance of the map, crowdsourcing seems the most accepted solution (Laoudias et al., 2013). In this solution, users not only get location from the applications, but also transmit information that helps to update information, as will be shown in the case of Samsung or Anyplace application in Section 3.4. Crowdsourcing collection of data can be passive, and then data are automatically collected by the system, transparent for users; or active, and then users involve themselves in data collection. In order to improve users' commitment, gamification techniques can be useful.

3.3 Magnetic Field Fingerprint

Previous sections have been devoted to Wi-Fi fingerprinting. However, as has been stated before, it is possible to apply fingerprinting techniques to any kind of signal. It has been seen in the last years, an increasing interest in the solutions based on magnetic field.

Magnetic field is generated by Earth and, therefore, it is present everywhere, and structures such as metal objects and columns disturb it locally; as well as magnetic fields created for elements in the environment. Therefore, these disturbances can be used to characterize points with magnetic field measures. On the other hand, many of actual smartphones are able to measure it; thus, the magnetic field is a signal with local features that can be measured with a smartphone.

The main advantages of using magnetic field for positioning are: (1) since the characterization comes from structural elements of the building, it is a system more robust than Wi-Fi, because it is difficult that these elements change with time; and (2) it is possible to capture magnetic field continuously (even more than 10 samples per second), instead of the time needed by Wi-Fi to take every single fingerprint, therefore, it is very suitable to make route-based methods.

Thus, instead of obtaining a vector associated with a single point, such as in the case of Wi-Fi fingerprinting, we obtain a curve associated with a route. The fingerprinting process is performed, then, taking fragments of the curve and associating every fragment to a location. It is important to normalize data and to make the appropriate corrections in order to overcome differences between curves due to different speed.

The process of positioning using magnetic field as fingerprints is the same as that used for Wi-Fi fingerprinting (see Section 3.1). The metrics and algorithms used can be also the same, such as the NN algorithm and its derivatives (Torres-Sospedra et al., 2014, 2015).

However, using magnetic field has some drawbacks:

1. It is a vector and different orientations give different values, therefore, usually the module is used as measure.
2. Although magnetic field allows to capture continuously and using route-based mapping, user speed plays a key role since the same distance can be done in different times. Thus, curves corresponding to the same length are different. To deal with this problem, users try to maintain constant velocity and the device always in the same orientation when creating the radiomap.
3. It is possible that there is not enough local variability of the magnetic field to perform localization.
4. Mobile devices such as smartphones, tablets, or laptops emit magnetic fields that can affect stability and repeatability of the measured values.

To conclude, results of using the magnetic field as a signal for indoor positioning are promising, but this is still a very immature and challenging technology.

3.4 Examples of Solutions

In this section some examples of solutions are presented. These solutions were presented in the symposium “Challenges of Fingerprinting in Indoor Positioning and Navigation.”

Samsung Solution

Samsung presented in 2012 a solution based on fingerprinting, with few centimeter accuracy in testbed and the company got the second place in the EVAAL Indoor Competition held in Banff on IPIN 2015 Conference (Wilk et al., 2015).

The focus of Samsung is solutions for smartphones, with simple set-up and easy maintenance. Thus, they look for automatically update the databases to avoid remanufacturing it.

The application proposed has several parts:

- *Positioning engine,* which is within the smartphone. It uses a probabilistic approach with particle filter.

- *Datastore server,* which is responsible for the storage and maintenance of radiomaps. It works always and serves radiomaps to the clients.
- *Set-up tool,* which is an application on the smartphone that allows to walk in predefined paths where the application collects fingerprints and from time to time they collect real positions.
- *Venue creation wizard,* which is the web application, used to prepare venue-related information that will be later used by client applications. It includes few editors to edit the floor plan, which are used to map matching. Locations and access points can also be included.

To maintain radiomaps and avoid multiple surveys, a crowdsourcing application is used. Users do not need to report exact locations and the application, installed on the smartphone, collects: Wi-Fi fingerprints, pedestrians speed, and heading. Then the information is uploaded to the server and the algorithm decides if it wants to apply this maintenance to the map. If yes, it is merged with the radiomap. The process to make the merging is performed in two steps: the first step determines the walk of the pedestrian in the indoor environment and the trajectory goes to the server; in the second step crowdsourcing locations are assigned.

The position algorithm has four inputs: these crowdsourcing locations, fingerprints, the trajectories calculated, and fingerprints similarities. The system assumes that fingerprints near in the fingerprints space are closer in the geometrical space.

Anyplace

Anyplace (born as Airplace) is an indoor information service created by University of Cyprus. It is open source and work in Android, Windows, and iOS (Konstantinidis et al., 2012).[7] In 2012 it received the Best Demo Award at IEEE MDM'12 (Laoudias et al., 2012; Li et al., 2013). In 2014, it was awarded with the second place in the IPSN'14 Indoor Localization Competition (Microsoft Research) in Berlin, Germany, and the first position at EVARILOS Open Challenge, European Union, also in Berlin. Nowadays, it is a Outdoor-to-Indoor Navigation through URL, with 60 Buildings mapped and includes thousands of POIs (stairways, WC, elevators, equipment, etc.)

To easy the creation of the map, Anyplace uses a crowdsourcing mechanism to create and maintain the map (Laoudias et al., 2013). And to reduce computation load, the algorithm uses a clustering algorithm, Bradley-Fayyad-Reina (BFR), which is a variant of k-means designated for large datasets. It has room-level accuracy and is able to detect pretty well the change in floor. Anyplace allows to obtain position by using several algorithms: kNN, WkNN, and Bayesian.

The system has a connectivity threshold to RSS intensity of −30 to −90 dBm. Thus, if the user loses signal (can happen in a mall when a user gets into a shop), loses navigation. This situation is corrected by using historical data to get the trajectories.

[7] See http://anyplace.cs.ucy.ac.cy/.

To overcome device diversity and how it affects RSS values, there is a linear relation between RSS values of devices. The question is if it is possible to exploit this to align reported RSS values.

Modular Localization System

The modular localization system has been proposed by the University of Zilina, in Slovakia. It is based on using the appropriate localization module (Brida et al., 2014). The process followed by the system is:

- Make measurements and analyze the signals. If GPS is available with good quality, it is used.
- If GPS is not available, then Wi-Fi is used for positioning. Positioning with Wi-Fi outdoors is possible when there are signals available, but error is higher than 20 m.
- If GPS is not available, and there are not enough Wi-Fi access points available (three), GSM is used.

Wi-Fi positioning via fingerprinting offers 5 m on average accuracy. And 95% of positions gave less than 6 m accuracy. The best results were obtained with the *k*NN algorithm.

In order to reduce computational load, a two-phase map reduction algorithm is proposed. Thus, the algorithm distinguishes between areas with at least 1 transmitter and areas with highest similarity. However, time required for positioning by Wi-Fi is higher than time required for positioning with GSM.

iLocate

iLocate[8] is an indoor/outdoor location and asset management through open geodata funded by European Union.

The project faces with the lack of standards for localization-based services: there are many technologies for indoor localization, but they do not communicate between them. iLocate mix technologies and support standards. The project uses many different technologies: GPS, triangulation, UWB (that gives under 10 cm precision), etc. It gives real-time information with 100 measurements per seconds.

Since it promotes open technologies, the project has been the first implementation of indoorGML (see Section 4).

Nowadays, iLocate has 13 pilots working around Europe. The 13 pilots are running different localization systems. If a new technology comes into place and comes in iLocate, it is integrated to the system and the technology will function within it.

iLocate incorporates, also, an immersive 3D system that uses virtual reality (glasses) and augmented reality. The user can keep the device pointing to a place and receive indications.

3.4.1 How to Compare Solutions

We have seen in this section several solutions offering indoor positioning based on Wi-Fi fingerprinting. The question is: Which application is better?

[8]See http://www.i-locate.eu/.

The answer is not easy. As has been shown in Section 3.2, there are several drawbacks related with Wi-Fi fingerprinting that make these systems very environment dependent and affect its reproducibility. Thus, although every system gives an accuracy, it is not possible to know if in other environment the same system will have the same accuracy.

Then, how to compare different systems of indoor positioning?

A possible solution is having open public databases with fingerprint radiomaps and validation and test data. The first one of this kind of databases is the UJIIndoorLOC (Torres-Sospedra et al., 2014, 2015).

UJIIndoorLoc was created by University Jaume I and has thousands of fingerprints with their location, and thousands of test data obtained in the campus of the university. It also offers the maps of the zones. Lately, the platform has grown and allows users to register and upload their own databases and their own algorithms.

With this database, it will be possible to compare different systems with the same corpus of data and then knowing which algorithm is faster, which offers the best accuracy, which is more reliable in the application environment, etc.

Nevertheless, it is important to take into account that UJIIndoorLoc will allow to compare algorithms, but still, a deeper study has to be performed in order to know which is the more appropriate system for every situation.

Another comprehensive database containing also references to other open-source Wi-Fi databases and supporting Matlab and Python software has been published recently (Lohan et al., 2017).

4 Indoor Maps

To pass from position to location it is important to have the map of the zone. Therefore, indoor location systems need the map of the building. However, nowadays it is not possible to get maps for every single building, not even the public ones. In addition, many available indoor maps have errors. This is quite different from outdoor situations, where maps of around the world are digitally available since the mid-2000s and in general are very reliable.

On the other hand, maps can also be helpful to improve location by applying map matching techniques. These techniques allow to avoid impossible locations by taking into account the map. Thus, for example, if we are using an indoor system and obtain a position, obtaining the location with the map, we can know if it is out of the building and move it inside. As has been seen in the section with examples of solutions based on Wi-Fi fingerprinting (Section 3.4), many of the solutions make a comparison with the map in order to improve results.

But, which has to be the format of the map? Many solutions give the map only as an image under the position points, that helps user to locate them. However, in order to use the map to improve location, a richer map is needed. As has been shown in Section 3.4, the project iLocate uses indoorGML to create such rich maps.[9]

[9] See http://www.opengeospatial.org/standards/indoorgml.

indoorGML is an XML-based standard that is used to describe indoor spaces and indoor navigation paths. It is based on what is known as the Poincaré duality. Thus, it is possible to map everything to a node or an edge and can create a connectivity graph, much simpler to understand for a computer.

Nevertheless, although indoorGML is defined as an standard, it has not still been adopted by the community.

5 Privacy and Security Issues

Another aspect to take into account regarding indoor positioning is privacy and security issues (Konstantinidis et al., 2015; Lohan et al., 2017).

An indoor service can continuously "know" (survey, track, or monitor) the location of a user while the system is connected. Location tracking can be considered, in some specific cases, unethical and can even be illegal if it is carried out without the explicit user consent.

This is an imminent privacy threat, with greater impact than other privacy concerns, as it can occur at a very fine granularity. It reveals the stores/products of interest in a mall, the book shelves of interest in a library, the artifacts observed in a museum, etc.

On the other hand, when publishing an indoor map, information about the building is being given. Therefore, if a company in one floor publishes the map of its offices, they are giving also some information about the other floors of the building (like the position of bathrooms).

6 Conclusions and Future Challenges of Indoor Positioning

How many people are using indoor positioning technology frequently? If we have Google Android or Apple iOS, maybe we are using it, even without knowing. Who is using indoor navigation? Just a small fraction of us. We have been working in indoor navigation for about 20 years. Maybe we are looking for technology of indoor navigation accuracy, but maybe we have enough accuracy for some applications.

There is a market for indoor positioning and indoor navigation. It is one of the top technologies from Gartner Group: 10 billions dollars for 2020. Google already provides indoor navigation. There is a huge market for factory plans, for locating people, but also for groups or robots.

However, as can be deduced from the chapter, there is still no a standard solution for indoor positioning, although there are many solutions that were shown to work with acceptable precision. Since there is no standard, it is difficult to arrive a massive number of users, since they should have to download a different application for every single environment.

Why is there no standard? In 1996 Wi-Fi standard was published and available technology satisfying that standard offered: 1 Mb/s and 2 Mb/s optional. IBM and other companies had better solutions, but they were proprietary solutions and were not interoperable. Thus, in 1996 it was given more importance to a standard than to the available technology.

Maybe it is time to look for a standard, sacrificing precision and accuracy, but giving more importance to accuracy.

On the other hand, to spread indoor applications we need not only a standard, but available indoor maps of the buildings. Nevertheless, it is not clear how to create an indoor map. Indoor spaces exhibit complex topologies. They are composed of entities that are unique to indoor settings, like rooms and hallways that are connected by doors. In addition, there is not even an standard to keep indoor maps useful for positioning and navigation, since indoorGML is not being used by the community.

Standardization of systems and maps, and spreading of maps are maybe the main challenges that indoor positioning is facing and they will condition the evolution of many other items and even the final standardized technologies.

Besides these two main goals, there are some other challenges to face:

- Seamless transfer between outdoor and indoor: The technology for outdoor is clear (GNSS), and several systems are being tested indoors, but how to make a fluid evolution from outdoors to indoors and the opposite?
- Quality: We find unreliable crowdsourcers, multidevice issues, hardware outliers, temporal decay, etc.
- Improve switching between modules and estimate reliability of positioning system.
- When to use hybrid positioning systems based on combination of heterogeneous networks.
- Regarding Wi-Fi fingerprinting, we need to build a quality radiomap, and we need to build the radiomap everyday. How many buildings, how many hours do we need to spend to collect all data? We have an scalability problem. Probably the solution to this problem is crowdsourcing. Wikipedia or OpenStreetMaps are good examples, even in navigation, such as Waze. It brings new challenges if we rely on crowdsourcing. But then we have to take care of privacy, take care of malicious users, or if the system goes down. How can we do it in large scales?
- The environment changes, even for a magnetic field. In some cases, such as in a factory, the plan can change. We need to take care of these changes and also, with repeated MAC addresses in different places. This can happen when several datasets are combined, which include thousands of APs created by thousands of users.
- Accuracy: It runs between millimeter with some technologies until room accuracy with some others. It is important to know what accuracy is needed for every specific application. We need more accuracy for some applications, like robot navigation; but maybe we already have enough accuracy for some other applications, like airport navigation.
- Standards for protocols to access the floor maps. Service discovery protocols: go inside a building and find the floor maps and indoor positioning engine available for that building.
- Exploitation of the capacities of chips: Wi-Fi chips support ToF measurements, and we should have to learn how to exploit it.

- High-dimensionality vectors. RSS vectors are not the only solution, we can look channel state information and combine it with magnetic field and atmospheric pressure.
- Normalization of quality measurements to do benchmarking.

As future work, maybe the next step in communication, 5G, will change the scenario of positioning and will facilitate time of arrival estimate. In the future we will have ultra-dense 5G networks with devices and can see/hear multiple access nodes. There will be multiple antenna arrays and high bandwidths with extremely high positioning accuracy that will be able to have, potentially, centimeter-scale.

Finally, it is important to take into account that solutions to indoor positioning can also help to solve the problem to outdoor (urban canyons).

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