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Radio Maps for Fingerprinting in Indoor Positioning

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1 Introduction

Knowledge of own absolute position, or relative position regarding other known humans, objects, or places, has always been necessary for human activities ever since. With today's technology, that can be achieved continuously, almost in real time, with the help of positioning devices increasingly accurate and increasingly cheaper. Positioning systems are available on vehicles, mobile phones, personal computers, and many other smart devices that can be carried around, giving support for new applications or new features in existing ones. Localization requires the existence of a map and a coordinate system. Navigation requires the knowledges of possible traveling paths between two or more points in the map (Zhang et al., 2017). But *mapping* and *navigation* are just two examples of a new set of a variety of location-based applications (LBA) for humans nowadays. Other important examples include emergency assistance, first responders aid, social interactions, event dissemination, localized marketing, nearby places, and augmented reality.

In 3GPP (2008), the 3GPP forum presents a clear definition of LBA and also a taxonomy for them. According to 3GPP (2008) an LBA is an application software processing location information or utilizing it in some way. The location information can be provided by a user, detected by the user equipment (UE) or by the network. Mapping and navigation are location application examples. 3GPP also identifies and standardizes the type of services that the user, or in more clear terms the Location Client, may need, in the perspective of a global network operator. They can be categorized in four distinct categories. First one is called *Commercial Services* or *added value services*. With the provided terminal location, many useful information can be provided or acquired by the user for that location. This includes nearby places and events, marketing of products and services, etc. The second category is *Internal Services*, which are important to the network operation, like assisted handovers. The third category is *Emergency Services*, which can help emergency providers locate the terminal on an emergency call. This type of service is vital and may be

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mandatory. Finally, *the lawful intercept* for legally required services. The last two categories are considered mandatory in many countries.

Outdoors, location information can be obtained by Global Navigation Satellite System (GNSS) available worldwide (Kahvecı, 2017). GNSSs are based on two components: the satellites on space and the terminal receivers on earth. The user terminal computes its own location based on received time differences between signals from different visible satellites. This type of outdoor localization system became popular in the 1970s, with the advent of the US Global Positioning System (GPS). GPS was first developed to support military operations, but soon it was clear its enormous potential for civil usage. Besides the US GPS system, GNSS includes the Russian GLONASS and the European Union GALILEO systems.

Satellite-based positioning systems are, however, usually not available for indoor positioning systems, and also in some dense urban scenarios (Locubiche-Serra et al., 2016), due to high attenuation of signals and nonline-of-sight (NLOS) propagation. In those scenarios, carrier-to-noise ratio (C/N0) is typically below 20 dB Hz (Locubiche-Serra et al., 2016). GNSS position systems need therefore to be complemented, even outdoors, and various approaches have been proposed to solve those problems. One possible way is to use global wireless networks, available in those scenarios as a network supported positioning system. Cellular networks like 4G and 5G/LTE can provide simple cell coverage positioning methods. But also more complex methods based on radio signal measurements that can be processed to estimate the location. According to Peral-Rosado et al. (2012), new long-term evolution (LTE) specification (3GPP, 2008) provides network-based mechanisms to compute terminal location. The method can only be used by the network, and not by user terminals, because it uses the difference in the arrival times of downlink radio signals from multiple base stations to compute the user position, and so it may be provided as service by network providers.

Similar methodologies can also be explored in more universal WLAN networks like IEE802.11x Wi-Fi, due to their popularity, low cost, and global availability in mobile phones and smart devices. Radio signal methodologies for localization are surveyed in Liu et al. (2007) and Yassin et al. (2017). Not all of them can be applied with good accuracy to Wi-Fi signals, but some of them provide very good results, specially the ones based on the *scene analysis* methodology. In Yassin et al. (2017) the authors identify measuring principles and positioning algorithms, organizing them by techniques into three major categories: *proximity*, *triangulation*, and *scene analysis*. Proximity uses relative position to a nearby reference point (RP) like an Access Point to provide a less accurate and descriptive position information. Triangulation uses geometric properties of triangles to compute location. It has two derivations: *lateration* and *angulation*. Lateration-based techniques include (i) Time of Arrival (TOA) where distance is assumed to be proportional to the measured time; (ii) Time Difference of Arrival (TDOA) where a relative measure of time between multiple signal arrivals is used instead of the absolute time of arrival; (iii) Receiver Signal Strength (RSS) attenuation, which assumes a theoretical model for signal strength attenuation with distance, that can be used to compute distance from signal sources; (iv) Round-trip time of flight (RTOF), that uses time measured from the transmitter to the receiver and back again; and (v) Phase of Arrival (POA), that uses received signal phase or carrier phase to estimate the range. Regarding *angulation* techniques, receiver use at least two RPs and two measured angles of arrival to compute position.

A complete different type of techniques is based on scene analysis (Liu et al., 2007). This type of algorithms first collects features (called fingerprints) of signals on a scenario at a set of RPs, and then later uses online measurements to find the *closest* offline collected fingerprints. This technique is called Location Fingerprint and is based on the assumption that the features observed and measured are location dependent. Localization is done in two phases. In the first phase, called the offline phase, a *FingerPrint Map* or radio map has to be constructed for the scenario. On the second phase, called online phase, the user device uses the same features (measured signal properties) as an input to a localization algorithm that estimates the location. RADAR (Bahl and Padmanabhan, 2000) is considered as the pioneer work on this type of location systems using Wi-Fi networks. Since then, extensive research has been done on Wi-Fi Fingerprinting-based systems, published in specific publications and special conferences like (IPIN, 2018).[1]

Fingerprint Maps, or radio maps, are a crucial component of those systems and the main focus of this chapter. They can be constructed for Wi-Fi networks, but also for many other radio frequency (RF) alternative technologies, as described in next sections.

2 Radio Maps for Different Radio Technologies

A *radio map* is defined by Kjaergaard (2007) as a model of network characteristics in a deployment area. It is used to estimate a position, using a *localization algorithm*. The localization algorithm, sometimes also called *estimation method*, uses the information collected and stored in the *radio map* in a deterministic or probabilistic way to predict positions. Fig. 1 (from He and Chan, 2016) shows the relation between those components. In order to construct the radio map, a selected number of points, designated as *reference points*, must be identified in the scenario. Each RP must be sampled to construct the

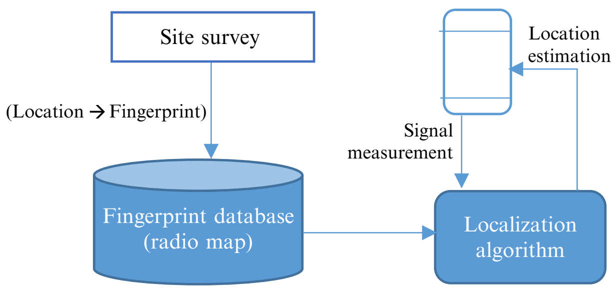


FIG. 1 Radio map and Localization Algorithm relationship. *(From He, S., Chan, S.H.G., 2016. Wi-Fi fingerprint-based indoor positioning: recent advances and comparisons. IEEE Commun. Surv. Tutorials 18 (1), 466–490.)*

[1] See http://ipin2018.ifsttar.fr/

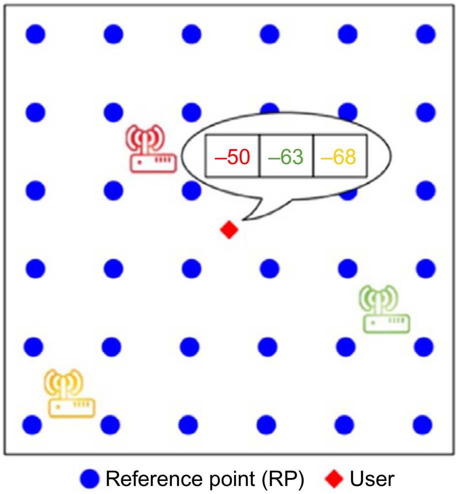


FIG. 2 Scenario area with sampled referenced points (He and Chan, 2016).

location fingerprint, as shown in Fig. 2. The *radio map* can now be defined as a *(Key, Value)* relationship between each *reference point* and its *location fingerprint*.

In RADAR (Bahl and Padmanabhan, 2000), several important conclusions regarding Wi-Fi radio maps were presented. Authors used WaveLAN NIC interfaces to collect both *signal strength* (SS) and *signal-to-noise ratio* (SNR), both they soon concluded that SS feature was a stronger location function than SNR. SS is measured in units of dBm while SNR is expressed in dB. A signal strength of s watts is equivalent to $10 * \log_{10}(s/0.001)$ dBm. A signal strength of s watts and a noise power on n watts give an SNR of $10 * \log_{10}(s/n)$ dB. They also concluded that collected values varied in at least 5 dBm according to the user orientation so, at each (x, y) position in the map they also collected samples in four distinct directions d (*north*, *south*, *east*, and *west*). The authors collected multiple samples at each *reference point* and each direction, and then they merged them into a single record for each location, computing statistics like mean and standard deviation. The first Wi-Fi fingerprint map (Bahl and Padmanabhan, 2000) was therefore a set of (x, y, d, ss_i) records, where (x, y, d) is the key and (ss_i) the value associated, for each Access Point i found in the scenario. Besides user orientation, RADAR also studied other important factors in radio map construction, like (i) the number of RPs in the scenario; (ii) the number of collected samples per RP3; and (iii) different localization algorithms. They concluded that only a small amount of samples are needed per RP and few points are needed if physical locations are uniformly distributed by the floor (the results were not much different with 40 or 70 points in a 22.5×43.5 m area).

In Kjaergaard (2007) an important taxonomy for radio location fingerprinting is proposed, based on a survey of 51 published papers and 30 different Wi-Fi fingerprinting systems. This taxonomy is focused mainly on fingerprinting and not on general systems.

The paper starts by identifying the taxonomic units that are relevant to the problem of localization, pointing out that only four of them really distinguish RF fingerprint systems: (i) the *scale*, regarding the size of the deployment area for the system (a city, a campus, a building, a floor); (ii) the *output*, or the type of information that the system returns back to the user (description of the place in words or coordinates in a map); (iii) the *roles* in the system, if it is infrastructure based or not, based on the user terminal equipment with or without network support; and (iv) the *measurements*, referring to the types of measured network characteristics.

Regarding measurements, for all surveyed works, only a few signal properties were identified, besides the mandatory *Base Station Identifier*. The first two are the same already used by RADAR (Bahl and Padmanabhan, 2000), currently used by other systems: the *Receiver Signal Strength* (measured in dBm) and the *Signal-to-Noise Ratio* (measured in dB). Some works used combinations with other metrics like *Link Quality Indicator* (collected by radios to measure link quality), *Power Level* (of sender), and *Response Rate* (the frequency of received measurements).

But perhaps the best contribution of Kjaergaard (2007) regarding radio maps is the classification system used. Authors first distinguish between *empirical* and *model-based* maps. Empirical maps are obtained from measurements only, while model-based use signal propagation models (direct path or ray tracing) to help in radio map construction. Regarding representation, radio maps can be represented *empirically* or *probabilistically*, aligned with the estimation method (localization algorithm) to use with the map. An empirical representation keeps a single value for each RP, like RADAR, while a probabilistic representation uses probabilistic distributions for each point. In both cases, *outliers* can be previously removed, and values *aggregated* or *interpolated*. Interpolation is used to augment the map with extra RPs using some interpolation function. Aggregation can be done either by using a simple *mean* function or by using a Gaussian distribution fit function.

2.1 Deterministic Radio Maps

In Kaemarungsi and Krishnamurthy (2012), authors analyze in detail the receiver signal strength indication (RSSI) that is used to build the great majority of deterministic indoor location radio maps. The goal is to do extensive data analysis around the presumably unique relationship between an RSSI value of a WLAN and an indoor location. Since RSSI values can be viewed as sensor data that refer to indoor positions, the characteristics of RSSI should be carefully studied. There is extensive knowledge of signals but in a communication's perspective, not specifically for fingerprinting. Authors enumerate a set of factors that can influence the statistics of an RSSI fingerprint and focus on five of them: (i) make of the hardware card (different well-known card makers were considered); (ii) time of measure (time of day and day of week); (iii) period of measurement (second minute and hour); (iv) interference (cochannel and adjacent radio channel); and (v) building environment (corridor, small office, large hall). These are basically two types of factors: hardware and environment.

Regarding different cards, there is a clear conclusion that the differences in hardware cannot be ignored. The mapping between the actual RF energy value and the RSSI value varies from vendor to vendor. Although, while IEEE recommends a range of 0–255 for RSSI, many vendors assume a range between 0 and a Max_RSSI. Each vendor has its own range and accuracy. Regarding environmental factors, the authors show that a mean value stays stationary for long periods of time and usually only changes when there are changes in furniture or in human presence and movement. But the standard deviation changes with long periods of time, like different hours of the day. Due to this time dependency, the fingerprint collection should be done at different periods of a day. Other conclusion is that the interference by cochannel signals does not have any strong correlation. Signals from different APs may be considered independent. The most influential effect on the performance of location fingerprinting is the standard deviation of RSSI. The second most influential effect is time dependency, and the third is the quality of WLAN card used. The least influential effect is the cochannel interference or the correlation among signals from multiple Access Points (AP) using the same frequency. The study reported in Kaemarungsi and Krishnamurthy (2012) also confirms that the mean value used by RADAR (Bahl and Padmanabhan, 2000) can represent a fingerprint; however, the distance between two locations does not translate well to distance between two fingerprints. Therefore, simple Euclidean distance will perform worse than probabilistic methods or Mahalanobis distance. These conclusions are useful to determine the procedure for map construction. And according to the taxonomy presented in Kjaergaard (2007), radio map construction should address *spatial variations*, *time variations*, *equipment*, and *collecting agent*.

2.2 Bluetooth Low Energy Radio Maps

In Rahman (2017), a system for locating shoppers in a large wholesale shopping store indoor environment, using Bluetooth Low Energy (BLE) beacons, is presented. The system uses RSSI readings from multiple beacons, measured asynchronously using commercial devices. There are not much studies addressing BLE fingerprinting, compared with Wi-Fi fingerprinting, partially because it is a recent technology not yet widely available, that requires extra cost and complexity in deployment. Authors in Rahman (2017) used 136 beacons on a 6000 m^2 area. The Android devices used, record Beacon Identifier, RSSI, and timing data. Data were collected by walking continuously at a steady pace along pathways. Authors presented a mapping scheme that represents the environment as a graph traversed by the user. This is used to constrain the search space of the localization algorithm. Three localization methods were used: nearest beacon, averaged beacon-pair range, and particle filter-based tracking. Particle filter methods outperformed the others significantly.

2.3 Other Technologies: FM and AM Radio Maps

In Chen et al. (2013), authors propose a robust indoor fingerprinting system using frequency modulation (FM) broadcast radio signals. With an experimental setup implemented in different buildings in United States, they demonstrate that FM broadcast signal strength (RSS) can be used to achieve room-level indoor localization with similar or better accuracy than Wi-Fi fingerprinting. FM broadcast radio signals have lower frequency and are less susceptible to multipath, fading, and human presence. They also penetrate very well in buildings. Authors show that accuracy can be further improved with more than five signals available. And since errors are not correlated with Wi-Fi obtained errors, both techniques can be combined to improve results. FM signals range from 88 to 108 MHz and are stronger than Wi-Fi. They cover areas of hundreds of kilometers and FM towers are also separated by hundreds of kilometers. This means that the variation of RSS experienced in the received signals is not significant in nearby locations. To overcome this difficulty, the RSS values are augmented with extra information collected from physical layer, like multipath indications. The extra values allow to distinguish between similar values of RSS. As in other fingerprinting systems, the system uses an offline and an online phases. In the offline phase, the system recorded FM signal strengths from 32 distinct radio stations, in parallel with normal Wi-Fi fingerprints. The radio map is composed of records with the following structure (r_i, s_i, m_i, f_i) for each RP and radio station i, where r_i is the RSS measured value, s_i is the SNR value, m_i is the multipath physical indication, and f_i is the frequency. As the authors point out in the paper, the most challenging aspect in this approach is how to engineer the setup, due to the required extra hardware.

In Rahman (2017), authors designed a system to use Amplitude Modulation (AM) radio broadcast signals. They argue that AM signals provide extensive coverage in urban environments and that receivers consume minimum power. A radio map was constructed using only RSSI values captured using a real-time spectrum analyzer for a total of eight AM broadcasting channels. Authors conclude, based on results obtained in one experimental setup, that accuracy results are very similar to the ones obtained using FM fingerprinting.

3 Building and Updating Radio Maps

Generically, two wireless devices can communicate if they are within the coverage area. That is, the devices can communicate if the radio signal propagates and the receiver is within the propagation area. A coverage map indicates the service area of a certain emitter. The coverage area depends on a number of factors including the transmission power, RF, orography, buildings, and other constructions and the sensitivity of the receiver. For long-range systems, the coverage area is frequently defined based on computerized models that estimate the signal propagation.

Many indoor positioning systems are built based on the principle that each location has a different radio signature, that is, the radio waves/signals that can be detected in a location are different from another location and the difference is enough to differentiate locations that are nearby. Radio waves propagate from one point to another being affected by several phenomena, including attenuation, reflection, absorption, etc.

A Wi-Fi radio map includes, for each location, the MAC address of the observed AP and the corresponding signal level. Optionally it may include information like the Service Set IDentifier (SSID) and the frequency channel.

3.1 Build a Radio Map

Building a radio map, a task often referred to as calibration or survey, is a time-consuming and labor intensive task. Several dimensions influence the time necessary to build a radio map, including the overall size of the building, the building structure (number and size of the interior divisions, like rooms, corridors, etc., and kind of materials used in the construction), the density of the RPs, and the number of samples collected in each RP.

To build a radio map means to use a specific application or tool and move along the building to collect radio data in different places. In a building with large rooms, the locations for the radio survey are often defined based mostly on the area, having the number of scanning locations defined by the density of the map to be built. Often the scanning locations are defined over a grid, collecting data in equidistant locations. In buildings with small rooms, the locations can be also defined considering a grid of points but adjusting it in a way that ensures that at least one RP is surveyed.

The propagation of a wireless signal is influenced by several factors including the building wall materials. A wall made of glass has low influence on a wireless signal while one built with large stones may completely block a signal. Furniture and other appliances installed nearby or between the sender and the receiver may also influence the signal level. Such scenarios may lead to the need for a more dense radio map, collecting data in more locations.

To build a radio map for very large building such as hospitals, universities, shopping centers, airports can be a challenging task since the number of scanning locations for an average dense radio map can easily grow to hundreds of locations. An additional challenge is to link the radio data to a place inside a building since there is no standard to represent the space or to represent the indoor maps.

3.2 Crowdsourcing

Crowdsourcing is an interesting solution to build Wi-Fi radio maps for large buildings. Instead of having a person or team collecting data all around the building, the idea is enroll the final users in this process and have them collaboratively contributing to the creation of a radio map. This way, big building and facilities can be surveyed more quickly, since the end users would help in the process of creating a radio map, avoiding the time-consuming task of doing it room by room (often several times in the same room if it is a larger one). Another advantage is that rooms with more people will get more scanning and thus the radio map coverage will increase faster in the more crowded areas, bootstrapping the quality of the maps for largely crowded areas.

To build a radio map it is necessary to link the collected radio data to a specific location inside a building. Unfortunately, there is no universal standard for interior maps.

CIMLoc (Zhang et al., 2014) and GraphSLAM (Zhang et al., 2016) are two crowdsourced solutions: CIMLoc is an example of a crowdsource solution to build indoor maps and GraphSLAM combine inertial sensor-based user motion measurement and sensed Wi-Fi signals to build a crowdsourced Wi-Fi fingerprint radio map.

Some authors propose to use techniques based on Simultaneous Location and Mapping (SLAM) and based on Pedestrian Dead Reckoning (PDR) to continuously update the radio maps. Lim et al. (2013) proposes a solution where the APs with weak signal strengths should have more chances to be updated into the radio map using scoring function. Ma et al. (2017) proposes to combine PDR trajectory matching with floor maps to crowdsource Wi-Fi radio maps.

Many other systems try to combine data from several sensors and from multiple users to improve the accuracy of indoor positioning systems. The AcMU system introduced in Wu et al. (2018) exploits the static behavior of mobile devices, using it to collect new fingerprints when the device is static at specific location. Liu et al. (2015) describes a system that uses the motion sensor of a smartphone to build a radio fingerprint map in a short time while Zhao et al. (2018) proposes a crowdsourcing and multisource fusion-based fingerprint sensing to replace the traditional site survey approach.

3.3 A Crowdsourcing Solution to Build a Radio Map

This section describes a crowdsourcing solution to build Wi-Fi radio maps in large buildings. The Where@UM app (Where@UM, 2018)[2] is an Android application based on a social network concept that uses an indoor positioning system based on Wi-Fi fingerprinting. In particular, the aim was to try to create a complete Wi-Fi radio map for all the buildings of university campi and simultaneously deploy a large-scale indoor positioning.

The University of Minho has two large campi and a set of other buildings spread around two towns, including students' dorms, old historical building, and offices. This is an example of a very large institution where creating and maintaining a complete Wi-Fi radio map updated is a very demanding task. Since a big number of persons, including students, faculty staff, and employees, use the buildings everyday, it was decided to try to engage those persons to crowdsource the Wi-Fi radio map.

The Where@UM user can become a friend of other users, being able to see his/her friends' location and share with them its own location, facilitating real-life encounters. Users are motivated to use this app since it was specifically tailored to the university. The primary target is the students, creating a way to easily find their friends inside the campi. Additionally, the app also allows sending text messages to the friends. The messages are forward through a server that delivers the messages as soon as the friends are online. By integrating a social network concept, the Where@UM tries to make the user experience better and more attractive, increasing the number of users and thus widening the mapped area.

[2] See http://where.dsi.uminho.pt/. Accessed on July 2018.

The app uses a network base positioning engine that receives Wi-Fi fingerprints and provides the location estimation based on an existing Wi-Fi radio map. The update frequency of the user' location is configurable. Default value is 5 min, which does not compromise the mobile device battery. The application retrieves the Wi-Fi fingerprint from the mobile device wireless interface and submits it to a server that processes and provides the corresponding estimated location.

The server uses a preexisting Wi-Fi fingerprint database to compute the device location. If the fingerprint is not similar enough to any of the fingerprints that exist in the database then the user location is reported to be unknown. On these cases, the user is prompt to manually provide his own location using the application interface. The same interface may be used to correct the location if it has been poorly estimated. On both cases, the user' new defined location is linked to the collected Wi-Fi fingerprint enriching the Wi-Fi radio map.

The lack of a universal space model for indoor positioning continues to be a problem. The Where@UM app was tailored to the university campi and thus the authors created a fixed hierarchical symbolic space model that includes four levels: area, building, floor, and room/space. For the first three levels, the user can select only between a predefined set of values. The University has eight locations in two different towns that constitute the top-level "area." In each of these locations, it is possible to find one or more buildings (layer two of the symbolic space model) and each building has a predefined number of floors. The last level is open, allowing the user to define the name or ID of the rooms that exist on each floor. To minimize the chances of creating more than one name for the same room the app shows all the existing rooms' names before allowing adding a new one.

Outside the University premises, each place is defined by the fields' country, city, address, and place. The app uses the Foursquare API to get a list of nearby places that suggests to the user. This prefiled information helps some of the users that for chance are in fact in one of the nearby places identified by Foursquare and it helps others because it makes easy to clearly identify a part of the address (e.g., the street name).

Wi-Fi fingerprints are stored linked to positions. When a user claims to be in a specific place (because the server was not able to estimate the position or because it was poorly estimated), the new data are stored into a secondary database and it is not assumed immediately as being trustable. When creating a radio map from a crowdsource application, it is necessary to consider that not all data are correct. Some users are honest and provide data that is correct but accidentally they can also contribute with wrong information. Some other users may be malicious and provide, intentionally, wrong information aiming to hinder the system. The wrong information will contribute to a low-quality radio map that will influence the quality of the indoor positioning system. Several problems were identified: wrong annotation of a fingerprint (eventually later providing the correct information); different users giving different names to the same place; a user providing wrong information to try to fake his current location or to try to attack the system.

To solve the quality problem it is important to assess the quality of the contribution. Fingerprints collected for the same place should be similar, that is, they should have a similar set of AP. Similarity allows defining a Place Discrimination metric that measures the similarity between all fingerprints associated with a place. Based on the Place Discrimination metric, it is possible to calculate a Contribution Credibility (for each new fingerprint): new contributions that are not similar to previous ones should not be considered. The Contribution Credibility of the most recent fingerprints allows creating a user' reputation metric. If a user has continuously low reputation then its data should not be considered at all, since he is probably just trying to hinder the system.

Radio map degrades over the time. As time goes by new APs are installed everywhere while existing ones can be moved or turned off. Additionally, changes in the environment (e.g., repositioning or adding or removing furniture) also influences the radio environment. Aging the radio maps, by removing the older records while new ones are added, leads to a more updated solution that will improve the indoor positioning systems.

4 Wi-Fi Radio Map Density

The first step toward indoor positioning using Wi-Fi fingerprinting is to build a radio map for the intended positioning area, which contains a number of samples corresponding to the various places where the location service is to be arranged. Collecting these samples usually represents a difficult and time-consuming task. A relevant aspect, which must be taken into account, is the location and determination of the number of RPs, that is, the locations where the samples for the Wi-Fi radio map will be collected. The RPs should be arranged throughout the environment and depend on the size and characteristics of the physical space itself. At each of RP, several measurements of RSS values are taken, processed and stored on the radio map. This is the most time-consuming and expensive process in the development of Wi-Fi fingerprinting localization systems.

In addition, the maintenance of the Wi-Fi radio map is also a difficult task. Any changes in the layout of the furniture, for example, can affect the validity of information stored on the radio map and consequently the accuracy of the estimates that are given by the location system, that is the localization environment is dynamic and it may be necessary to rebuild the Wi-Fi radio map very often or at least when some significant environmental changes are made.

To mitigate the large amount of time needed to build the Wi-Fi radio map, the main goals are to reduce the time spent at each sampling point and the number of points needed to obtain the Wi-Fi radio map. This includes not only the initial construction of the initial radio map, but also its updating over time. Several studies suggest that adding more references points with the interpolation method to the radio map can save time and improve localization accuracy. According to this strategy, Received Signal Strength values are measured in some positions and the rest of fingerprints are calculated using the values measured and different interpolation methods. In this way, since it is only necessary to take samples at some of the positions, the time needed for radio map creation is reduced. Other studies suggest the use of propagation models to predict signal strengths or even hybrid models that require only a few RSS samples being the rest of the radio map estimated using an RSS prediction algorithm based on propagation models.

4.1 Radio Map Construction Using Interpolation

Interpolation is a mathematical method to estimate the value of a function at a certain point using other available values of this function at different points. Spatial interpolation is a particular case of interpolation, which assumes that the available values of the function are continuous over space. This allows the estimation of unknown function values, at any location within the available values boundary. Another assumption is that the data are spatially dependent, in other words the values closer together are more likely to be similar than the values farther apart.

As a first approach, the interpolation can be performed combining in some manner the known function values. Since the known points closer to the new estimated function value should have a greater influence in the interpolation, the known values have to be combined by using a weight function where weights are chosen to be larger for nearby values than for more distant ones. For example, weighting could be chosen as a simple inverse function of the distance.

4.1.1 Inverse Distance Weighting Interpolation

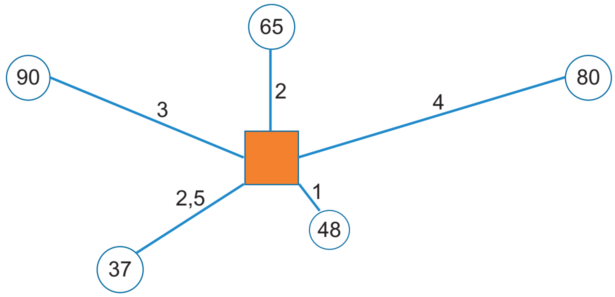
The inverse distance weighting (IDW) interpolation (Kuo and Tseng, 2011) is a deterministic, nonlinear interpolation technique where the weight function is a simple inverse power function in $\Re$ expressed as: $w(x) = x^{-a}$, where the constant a is a positive value. The final expression of the interpolation function using these weights is:

$$y\left(x_0\right) = \frac{\sum_j w(d_j) \cdot y(x_j)}{\sum_j w(d_j)} \tag{1}$$

being $y\left(x_j\right)$ the set of known values of the function, and d_j the distance between these points $\left(x_j\right)$ and the new estimated point $\left(x_0\right)$

In the example presented in Fig. 3, the circles represent known sample points and the square is an unknown point for which we would like to estimate a value $(y\left(x_0\right))$. The distances between the sample points and the unknown point are shown in black text, while the attribute values of the sample points are shown inside the circles. Using Eq. (1) and the inverse distance-squared relationship to establish the weights, we obtain 52, 19 for the unknown point. As already mentioned, the distance affects the influence of a point on the estimated value in the equation, nearer points have a significantly greater effect on the estimated value than more distant points.

This type of interpolation method may be used to estimate an unknown RSS value in a predefined location using effective measured values of RSS values in other known locations. In order to get a good estimate, the algorithm can be enhanced. For example, when distance is larger than a specific value, the measurement on that reference location can be ignored.



$$w(x) = x^{-2} = \frac{1}{x^2}$$

$$y(x_0) = \frac{\frac{1}{1^2}.48+\frac{1}{2^2}.65+\frac{1}{2{,}5^2}.37+\frac{1}{3^2}.90+\frac{1}{4^2}.80}{\frac{1}{1^2}+\frac{1}{2^2}+\frac{1}{2{,}5^2}+\frac{1}{3^2}+\frac{1}{4^2}} = 52.19$$

FIG. 3 Example of using the IDW interpolation method.

4.1.2 Radial Basis Function Interpolation

A radial basis function (RBF) is a real function whose value depends only on a distance from some point called origin (Krumm and Platt, 2003). These basis functions are radially symmetric around the origin and decline toward zero as we move away. Some examples of RBFs calculated at a point s in $\Re^2$ are:

- The Euclidean distance linear basis function: $f(s) = \| s \|$
- The multiquadratic function: $f(s) = \sqrt{1+ \| s \|^2}$
- The inverse multiquadratic function: $f(s) = 1/\sqrt{1+ \| s \|^2}$
- The thin plate spline function: $f(s) = \| s \|^2 \log(\| s \|)$

Using this interpolation method, the origin of each of the basis functions is placed at every position where a known function value is available and then the unknown values are estimated using a weighted combination of all the RBFs used. For example, suppose that you are using three RBFs, the value of each RBF at the prediction location can be taken from $f1(si)$, $f2(si)$, and $f3(si)$, which simply depend on the distance from each data location si. The predictor is formed by taking the weighted average $w1 \cdot f1(si) + w2 \cdot f2(si) + w3 \cdot f3(si)$.

The calculation of the weights w_j is made in such a way that ensures the equality between the interpolation results and the initial known values at the origins of the RBFs. The calculation of the weights can be carried out solving the following system of linear equations:

$$yi(si) = \sum_{j=1}^{m} wjf \cdot j(si), \quad i = 1, \ldots, n \tag{2}$$

where $yi(si)$ is the set of known values used in the interpolation, si are the points where the known values were taken, wj are the weights, and $fj(si)$ are the RBFs, each one centered at a different si point.

When comparing RBF to IDW, IDW cannot estimate above maximum or below minimum measured values, which is not the case when using RBF.

In Krumm and Platt (2003) a new location algorithm is presented to work in spite of missing calibration data based on RBFs. It takes a set of signal strengths from known locations in a building and builds an interpolation function giving (x, y) as a function of signal strength. The authors evaluated this new algorithm on one floor of a building with 118 rooms. The location error was 3.75 m using, on average, one RP every 19.5 m^2 of floor area.

4.1.3 Kriging Interpolation

Like IWD and RBF interpolation methods, the basic idea of kriging interpolation (Binghao et al., 2005; Zhao et al., 2016) is to estimate the value of a function at a given point using the weighted average of the known values of the function in the neighborhood of the point. However, kriging interpolation considers both the distance and the degree of variation between known data points when estimating values. It is based on statistical models that include the statistical relationships among the known points, also called auto-correlation.

Kriging uses a formula similar to the one used by IDW to derive a prediction at an unmeasured location.

$$\hat{Z}(x_0) = \sum_{i=1}^{N} \lambda_i Z(x_i) \tag{3}$$

where $Z(x_i)$ is the measured value at the ith location, λ_i is an unknown weight for the measured value at the ith location, x_0 is the prediction location, and N is the number of measured values.

In IDW, the weight, λ_i, depends only on the distance to the prediction location, the measured values closest to the unmeasured locations have the highest weights. However, with the kriging method, the weights are based not only on the distance between the measured points and the prediction location but also on the overall spatial arrangement of the measured points. Kriging weights come from a semivariogram that should be developed by looking at the spatial nature of the data.

In Binghao et al. (2005) a method based on kriging for obtaining the Wi-Fi fingerprint radio map has been presented. It utilizes the spatial correlation of measurements to generate the database during the offline phase. An experiment was carried out and the results indicate that the proposed method does work efficiently. On the basis of results obtained, only 1/4 or 1/8 of the number of RPs are needed using the proposed method compared with other methods that do not take into account spatial correlation. Another method based on universal kriging interpolation is presented in Zhang et al. (2016). With just 28 observation points the authors claim that it was possible to achieve an average error of 1265 m and the proposed system can be compared with other indoor positioning methods with 112 observation points.

4.1.4 Other Interpolation Methods

Besides IWD, RBF and kriging other methods have been proposed to build Wi-Fi fingerprinting radio maps. In Lee and Han (2012) a new interpolation method based on higher-order Voronoi tessellation is presented. Unlike other interpolation methods, the proposed method adopts the log-distance path-loss model and takes into account the signal fading caused by walls and obstacles. The authors claim that this method achieves better accuracy than other conventional methods such as RBF and IDW through experiments with two infrastructures.

4.2 Radio Map Construction Using Propagation Models

An alternative to radio maps made of a set of collected samples, or a filtered subset of those samples, is to build a model representing the expected signal strength of the radio signals transmitted by each AP across the operational area. These models are particularly useful when probabilistic methods are used to estimate the position as both the mean and standard deviation of the signal strength can be represented in the radio map. One advantage of model-based radio maps is that a much sparser set of RPs can be used, therefore reducing the time and effort associated with the site survey. Liu et al. (2014) proposed a method to determine the optimum cell size that balances the effort in collecting data in the offline phase with the positioning accuracy in the online phase.

The most common propagation model used to build a radio map is the log-distance path-loss (LDPL) model, which is expressed as follows:

$$PL = PL_0 + \gamma * \log_{10} \frac{d}{d_0} \tag{4}$$

where PL represents the total path loss, PL_0 the path loss at reference distance d_0, γ the (environment-specific) path-loss exponent, and d the distance from the transmitter. According to this model path loss varies exponentially with distance. The advantage of using this model is that it eliminates the need of taking RSS measurements at the cost of decreased localization accuracy. In Lim et al. (2006) a localization algorithm for building a zero-configuration indoor localization system is presented. To allow unmodified, off-the-shelf APs to be used the authors propose the use of Wi-Fi sniffers at known locations. These sniffers measure the RSS from the various APs and use the LDPL model to construct the Radio Map.

Yiu et al. (2017) recently reported on the comparison of traditional radio maps with parametric and nonparametric regression models. In their work, they concluded that non-parametric regression models based on Gaussian process perform better that traditional parametric models by providing smaller mean errors. These authors also concluded that their proposed GP model-based radio map is not significantly affected by a large reduction on the number of visible APs, and that it can be created from a small fraction of the entire set of RAW samples without a significant degradation, one feature that contributes to reduce the time needed to collect the samples across the operational area.

5 Radio Maps Filtering

Estimating the position of a device based on fingerprinting, whether using a probabilistic or deterministic method, benefits from the availability of a dense radio map. This trend results from the nature of the fingerprinting method: the more samples the radio map includes, collected at each RP, the better that location is characterized and the easiest is to distinguish it from other locations. A denser grid of RPs is also assumed to contribute to a better accuracy. Moreover, the higher the number of AP covering the space, the better each location can be characterized. However, very dense radio maps are associated with some known problems. In the first place, building very dense radio maps by collecting samples over a dense grid of RPs is a tedious and time-consuming task. Second, if the number of AP is large, the grid of RPs is very dense, and a large number of samples is collected at each RP, the time taken to estimate the position of a device might turn too large since the operational fingerprint (the fingerprint collected during the online phase) needs to be compared against a too large number of samples represented by a large number of radio strength readings. Third, and not less important, some previous works demonstrated that a smaller and higher quality radio map leads to more accurate position estimates than a larger radio map that includes all the collected samples.

5.1 Radio Map Density and Positioning Performance

It is widely accepted that large radio maps contribute to improve the positioning accuracy and/or precision in estimating the user's location (Kim et al., 2013). Fig. 4 illustrates this trend, obtained from a simulated system using synthetic radio samples.

One interesting conclusion obtained from this simple simulation is that increasing the density of the radio map (distance between adjacent RPs) provides performance improvements in terms of mean positioning error, but only to some extent. Above a certain

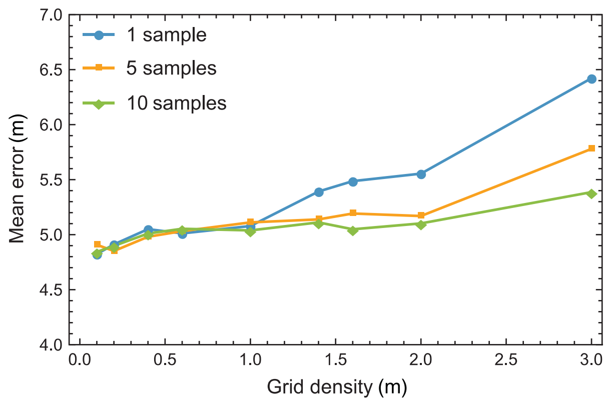


FIG. 4 Mean positioning error as a function of the grid density and number of samples per reference point (noise standard deviation = 4 dBm).

point, no significant improvements are obtained by using a denser radio map. Given that the time required to estimate the position increases linearly with the number of RPs in the radio map (and with the number of samples per RP in some cases), above a certain point the error improvements do not compensate the time penalty. Therefore, even if a large number of samples is collected to create a dense radio map, some potential computational time improvements are expected if the RAW radio map is preprocessed before being used during the online phase.

5.2 AP Selection

One approach to optimize the radio map is based on selecting only a subset of all the APs that are observed across the operating area. AP selection can be performed offline or during the online positioning phase. When performed offline, the RAW radio map, made of all the samples collected at all RPs and including signal strength measurements from all visible APs, is filtered to result into an optimized radio map that include only the APs that best discriminate among different locations. On the other hand, online AP selection is performed at the positioning phase based on each newly measured sample.

5.2.1 Offline AP Selection

Several research teams addressed the problem of AP selection aiming at reducing the computation effort and/or the energy required to obtain a position estimate. The work described in Chen et al. (2006) is focused on reducing the energy consumption on battery-powered devices by optimizing the computational cost associated to estimate their position. The proposed solution is based on an offline AP selection method, where the discriminative ability of each AP is assessed using information theory. The authors propose a *InfoGain* metric to rank the APs that best contribute to distinguish between different locations. Then, only the top k APs are retained in the radio map. The authors also propose to divide the operational area into clusters of RPs, and to further reduce the number of APs describing each cluster in the radio map by using again the *InfoGain* metric to select the best APs. The samples in each cluster are then used to create a model to be used by a decision tree algorithm in the online phase. The final result is a radio map made of a set of models, one model per cluster. With this solution, the authors claim to obtain better positioning accuracy when compared with other methods (e.g., the *MaxMean* method reported in Youssef et al., 2003) while also reducing the computational cost and energy consumption of the client device. However, the computational cost gains achieved by reducing the number of APs in the radio map are obtained at the cost of a slight degradation on the positioning accuracy.

A similar solution, also based on the information gain of each AP, is described in Deng et al. (2011). The authors propose a method where the discriminant ability of each AP is measured considering all the APs, and not individually, named Joint Location Information Gain. The provided experimental results show that this solution outperforms previous approaches reported by other teams, and also that a slightly better accuracy is achievable by using only a subset of all the APs.

The work from Lin et al. (2014) includes a Group Discriminant AP selection method where the importance of a subset of all the APs is determined based on the risk function from support vector machines. The results reported in Lin et al. (2014) demonstrate the benefits of this criteria when compared to AP selection methods where the relevance of each AP is assessed independently from the contributions of the other APs to the positioning accuracy.

A later, more comprehensive, study reported in Laitinen and Lohan (2016) compares several offline AP selection approaches combined with three positioning methods. Experimental results, obtained from data collected in three multistorey buildings, show that the *maxRSS* AP selection method (a method similar to *MaxMean*) performs better with the three positioning methods, and is more consistent across the three buildings. These results suggest that benchmarking AP selection methods should not be based on data from a single building floor, as is the case with the works described earlier (Chen et al., 2006; Deng et al., 2011). This study also evaluates the impact of the grid size in the positioning error, showing that both the fingerprinting and path-loss-based methods perform considerably well even for large grid sizes, such as 10 m. This is consistent with the result shown in Fig. 4, especially if multiple samples are collected at each RP.

5.2.2 Online AP Selection

In Feng et al. (2012), three online AP selection schemes are evaluated as part of a positioning system based on Compressive Sensing theory. The three schemes, namely strongest APs, Fisher criterion, and random combination, are used to select a subset of all the observed APs for each new position estimate. An experiment, conducted on a single floor of a building at the University of Toronto, reveals the superiority of the Fisher criterion. However, all the three schemes show to provide better results with a subset of all the APs than when all the APs are used, meaning that some APs can actually degrade the positioning performance. This is in contrast with most of the other AP selection solutions, where reducing the number of APs often results into a degradation in the position accuracy, even if slight.

Another AP selection method that determines the best APs in the online phase has been proposed by Zou et al. (2015) . Their approach is to select the best APs by measuring the discriminative ability of each AP taking into consideration all the APs using a mutual information metric. In their paper, the authors claim that this approach is capable of better adapting to changes in the environment after the calibration (offline) phase, and also that it outperforms other AP selection methods, namely the offline *MaxMean* and *InfoGain* methods. However, this method requires that many samples be collected at the same location during the online phase (the authors used 100 samples in their experiments), which limits the approach to stationary devices. Moreover, the mean error (positions were estimated using the weighted k-nearest neighbor method) increases if too many APs are removed. In their experiments, the authors were able to reduce the number of APs from 16 to 8 with no degradation on the mean error. The gains in the computational load obtained from the reduction on the number of APs were not discussed or measured.

5.3 Samples Filtering

All samples in a radio map are affected by noise, interference, multipath fading, and shadowing that occurs while the RSSI values are being measured at each RP. It happens that some samples are more affected than others, meaning that some samples collected at a given RP represent that location better than other samples collected at the same location. Therefore, some potential gain can be obtained by filtering out samples that degrade the positioning performance. Quite often, a simple method to minimize the impact of low-quality samples is used where all the samples collected at the same RP are averaged to create a single aggregated sample. An alternative is to create a single sample from the maximum signal strength value observed from each AP.

A solution, where the RAW radio map is filtered to preserve only a subset of the collected samples, has been proposed by Kim et al. (2013). In their work, clustering is used to segment the samples collected at each RP into a set of clusters. Then, a representative sample is selected from each one of the clusters as the one more similar to all the other samples in the cluster. The result is a much smaller radio map (5.4 samples, on average, per RP against 130 samples originally collected), obtained at the cost of just a small degradation of the positioning precision (from 0.88 to 0.76). This method contributes mainly to the scalability of the radio map.

A similar approach has been proposed in Eisa et al. (2013). In this work, simplification of radio maps aims mainly at reducing the time needed to compute each position estimate. The proposed approach includes a reduction on the total number of samples and a reduction on the number of APs. Filtering of samples is achieved by computing the estimated position for each sample in the radio map using all the other samples. Position estimation is done by using the J48 classification algorithm. All samples that are not classified into the correct room are discarded from the radio map. Filtering of APs is performed by computing a set of statistical features for each AP, such as the number of distinct RSSI values, percentage of missing RSSI values, and overall standard deviation of the RSSI values across all samples. Then, by applying a set of rules with proper threshold values, some APs are retained while others are removed from the radio map. Experimental results obtained by applying these methods to real-world data showed to reduce the processing time by more than 50% while improving the precision in detecting the correct room by more than 3%.

6 Standards

In recent years, the expectations about the penetration of location-based services (LBS) and Real-Time Location Systems (RTLS) have grown considerably, and indoor positioning and tracking technologies are a fundamental building block of such systems. However, a limited number of indoor positioning systems are actually being used around the world and use of LBS indoors is far from being ubiquitous as is the use of cellular and wireless local area networks. Within the wide range of positioning technologies, systems based on Wi-Fi fingerprinting have been extensively studied due to its potential to exploit already deployed radio-based communication infrastructures, and also due to the ubiquity of powerful mobile devices that can be used to run software modules capable of estimating their position/location without any additional hardware. However, even solutions based on Wi-Fi fingerprinting are just now starting to be used in real-world contexts. In the following we discuss some of the causes for such a slow deployment rate by arguing that standards, or the lack of them, might have a significant role in this process.

6.1 Fundamental Building Blocks of an Indoor Positioning and Tracking System

As discussed earlier, we focus this analysis on indoor positioning systems based on Wi-Fi fingerprinting. However, similar considerations also apply to many other techniques, such as those based on cellular and FM radio fingerprinting, BLE proximity, magnetic field fingerprinting, and, to some extent, to inertial navigation systems.

The fundamental building blocks of an indoor positioning system based on fingerprinting are depicted in Fig. 5. On this system, we assume that a person carrying a mobile device is using an LBS that needs to know its position within the operating area, including the 2D position, floor and building.

Depending of the specific solution, the position of the mobile device can be estimated at the mobile device or at a network component, or even by a combination of local and remote computations. In any case, a radio map, previously created for the operational area,

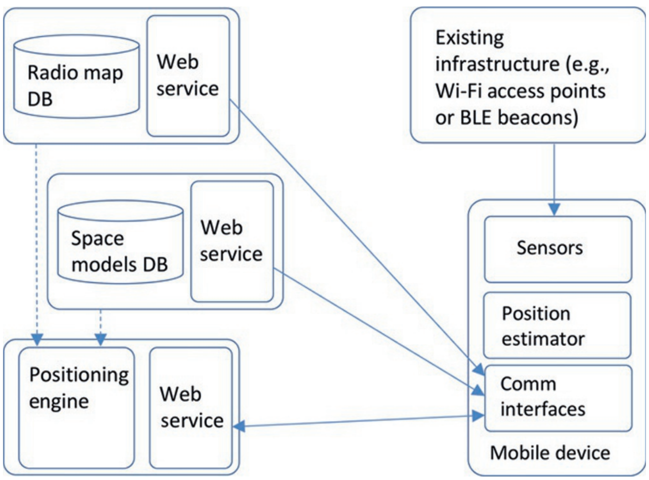


FIG. 5 Anatomy of an indoor positioning system.

must be made available to the components performing the position estimations. These estimations rely on the comparison of the data collected locally at the mobile device[3] through the existing sensors with data stored in the radio map.

The estimation process might also rely on the geometry of the space, for example, when particle filters are used or when fingerprinting is combined with inertial navigation. Information about the geometry of the operational area is also required for the users' interface, such as to support indoor navigation. Additionally, the topology of buildings might also be required to compute shortest paths in indoor navigation or safety applications. All that data might be stored on a remote Space Models component.

6.2 The Need for Standards

Currently, each particular indoor positioning solution uses its own proprietary architecture, data formats, access protocols, and estimation methods. We envision a future where standards play a significant role in promoting interoperability among different systems, in contributing to the wide adoption of indoor positioning systems and LBS, and in creating a larger market that can benefit from large economies of scale. Such a vision is illustrated through the following scenario.

> *After landing at a foreign airport, Claire opens the MyIPS app in her smartphone to find the best route to the baggage claim area. After leaving the security area, Claire uses the same app to find the car rental desk of the company where she previously booked a car. In her way to the hotel, Claire stops at a shopping mall to look for some flowers to offer to her friend on this evening diner. Upon entering the mall's underground car park, MyIPS helps her in spotting an empty place to park the car. As Claire is using MyIPS for a long time, she quickly finds two flower shops in the mall. MyIPS also helps her in easily finding her way back to the car.*

This scenario looks like the script of any advertising promoting an indoor positioning system. However, it is far from what can be achieved today as it encompasses many practical challenges, as described in the following sections.

6.3 Automatic Discovery Protocols

The implementation of the scenario described earlier calls for the capability of the MyIPs app to discover local services, at each one of the visited premises, from where to retrieve local radio maps, local floor maps, and other data such as the location of AP or BLE beacons, and/or local positioning engines able to estimate the position of Claire's smartphone. No such discovery protocols exist today, and very few steps have been given toward that direction. Among them is the work described in Sousa et al. (2014)

[3] In some solutions, the sensors are part of the infrastructure. These cases are not considered here as they require the deployment of specific hardware.

that proposes the use of the Domain Name System (DNS) to enable a mobile device to retrieve its location from a DNS server. Other related contributions are described in Tschofenig et al. (2006) and Maass (1998). In Tschofenig et al. (2006), the Geopriv protocol is proposed, enabling the exchange of location information over the Internet by exploiting some capabilities of the Dynamic Host Configuration Protocol. Maass (1998) proposes a solution to facilitate the development of LBS and applications based on the use of a directory service (X.500). While these efforts contribute to a solution for automatically discovering of local localization/positioning services, no complete solution exist, not to mention its wide acceptance.

6.4 Radio Maps: Formats and Protocols

Fingerprinting-based positioning systems rely on the availability of radio maps for each area visited by Claire, in the scenario described earlier. A global and distributed positioning system would benefit from the possibility of accessing, or downloading, local radio maps upon entering a certain operational area. In addition to the need to discover a local server from where to retrieve the radio map, an access protocol and a normalized format for representing the radio map are required. Accessing local radio maps could be easily solved through a predefined protocol implemented over REST to communicate to a local web service. On the other hand, security (e.g., access control) issues should also be addressed in order to control when and who have access to local radio maps.

With more or less variations, radio maps are widely accepted as being represented by a set of vectors, each one of them made of a collection of radio Received Signal Strength (RSS) measurements from each one of the visible AP and of the geometric representation of the Reference Point where it was obtained (e.g., a pair of coordinates, floor and building identifiers). Therefore, it would not be difficult to define a standard for the representation of radio maps. On the other hand, representing maps about magnetic field signatures, images, of BLE beacons requires a more comprehensive solution. Unfortunately, no such universal solution exists.

6.5 Floor Maps and Other Space Models

Floor maps are an essential part in many LBS (e.g., a map showing the location of the flower shops in the scenario described earlier). In addition, a description of the geometry and topology of the space is also fundamental for some indoor positioning and tracking techniques and a key requirement for indoor navigation. In a universal indoor positioning solution, mobile devices should be able to access local servers providing this kind of space models. Similarly to radio maps, as described in the previous section, a global solution depends on the wide acceptance of access protocols and data formats.

Some companies and research groups have been addressing the problem of creating floor maps for use in indoor positioning and LBS. Among them are the efforts of companies such as Google,[4] Microsoft,[5] Apple,[6] MapsPeople,[7] IndoorAtlas,[8] Cartogram,[9] MazeMap,[10] and the OpenStreetMaps (OSM) indoorOSM project.[11] This current situation illustrates how the indoor positioning market is being take seriously due to its potential for big business, with major players trying to find their market share, while also highlighting how difficult will be to develop a standard for indoor space models.

Moreover, creating space models for indoor spaces is difficult and costly. For large buildings, and in particular for old buildings, creating floor maps requires a considerable manual effort. In order to automate this task, or at least minimize the amount of human labor required, many research teams have been proposing methods and software tools to create space models. The reader is referred to the works reported in Stahl and Haupert (2006), Schäfer et al. (2011), Xuan et al. (2010), Zhang et al. (2014), Philipp et al. (2014), and Pintore et al. (2016) for set of proposals related to the task of building floor maps.

One of the major steps toward the creation of a standard for indoor maps has been given with the indoorGML[12] proposal from OGC (Open Geospatial Consortium) (Kim et al., 2014). However, this standard has been criticized for being too complicated and very difficult to implement, not being widely used yet. Other related standards are CityGML and IFC, whose characteristics are discussed by Chen and Clarke (2017).

6.6 Remote Positioning Engines

As shown in Fig. 5, the position/location of a mobile device can be estimated at the mobile device, with advantages in terms of privacy, at a remote positioning engine, with advantages in terms of energy consumption of the mobile device, or through a hybrid solution involving both local and remote computations. Using remote positioning engines specially deployed to serve a specific area (e.g., a positioning engine for a shopping mall), and accessible over a local area network contribute to shorter delays and can benefit from the specific configuration of the deployed infrastructure. As an example, consider a positioning solution where the coarse position of the mobile device is estimated from the Wi-Fi network side, while the more accurate position is estimated at the mobile device. This functionality requires the definition of a protocol to enable the communication between mobile devices and remote positioning engines, as well as standard formats for the representation of data such as fingerprints, magnetic signatures, and position/location representations. Such a specification might even extend to the standard representation of the data collected from the sensors embedded in smartphones and other mobile devices.

[4] See https://www.google.com/maps/about/partners/indoormaps/.
[5] See http://www.bing.com/maps/.
[6] See http://www.theverge.com/2015/11/2/9657304/apple-indoor-mapping-survey-app.
[7] See http://mapspeople.com.
[8] See https://www.indooratlas.com.
[9] See http://www.indoormaps.com.
[10] See http://www.mazemap.com.
[11] See https://wiki.openstreetmap.org/wiki/Indoor_Mapping.
[12] See http://www.indoorgml.net.

This level of detail would, eventually, enable the negotiation between the mobile device and the remote positioning engine about the available sensors on the client side and the available features at the server side.

6.7 Standardization Initiatives

Besides the standardization projects referred previously, very few initiatives are currently working on standards for indoor positioning, tracking, and navigation. Among them is an ad hoc group recently created within the context of the IPIN conference[13] that is addressing some of the issues and challenges associated with standards for IPIN (indoor position and indoor navigation).

Another initiative has been coordinated by the National Institute of Standards and Technology of the US Department of Commerce, especially in what concerns testing and evaluation of localization and tracking systems.[14] One of the outcomes of this initiative is the ISO/IEC 18305 Standard published in 2016.[15]

None of the above referenced standards or standardization projects addresses the representation of radio maps, which is not that strange given that the market for IPIN is still dominated by proprietary solutions.

7 Conclusion

An indoor positioning system based on fingerprinting is made of several elements. Building and updating a radio map is a challenging task but a fundamental one for many indoor positioning systems. The quality of a radio map may influence largely the accuracy of the position estimates, leading to the need of having dense and up to date maps to achieve the best results.

Crowdsourcing, by enrolling the final users, has been proposed a solution for large buildings where the number of scanning locations for an average dense map can grow to hundreds of locations. Crowdsourcing is a solution not just to build radio maps in large buildings but also to update them. As expected, the quality of the contributions must be accessed to avoid degrading the maps quality by accepting data from malicious users.

Different interpolation methods and propagation models can be applied to increase the density of radio maps. Denser maps are expected to lead to solutions that are more accurate but it can increase the computational power necessary to estimate the position. On the other hand, filtering the radio map, by selecting the appropriate APs and/or selecting the best samples, may lead also to a better map (improved accuracy and/or faster processing time). The wide number of constraints that may influence the interpolation methods, propagation models, and filtering techniques shows that this should continue to be a research area for some years to come.

[13] See http://ipin-conference.org.

[14] See https://perfloc.nist.gov.

[15] See https://www.iso.org/standard/62090.html.

The creation of standards, promoted by some international organizations, is fundamental to boot the deployment of large-scale ubiquitous indoor positioning solutions. Universal radio map formats and protocols for indoor positioning service discovery, along with indoor floor maps and space models, are currently still missing.

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