# In-house Localization for Wi-Fi Coverage Diagnostics

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Abstract: Telecommunication operators and Internet Service Providers often face the problem of having residential customers complaining about deficient Wi-Fi coverage inside their houses and/or about the low quality of service while accessing the Internet. Addressing these complaints properly involves a comprehensive in-house diagnostic of the technical deployment, the use of specialized equipment and visits by qualified personnel. An alternative is to involve the users in a preliminary diagnostic, by leveraging the potential of current smartphones, aiming to identify possible causes for the complaints that can be solved remotely or through simple procedures to be executed by the customers. A key feature of such a diagnostic procedure is the ability to estimate the location of the smartphone indoors automatically. This paper proposes a simple indoor localization solution, based on Wi-Fi fingerprinting, that can be integrated into one such diagnostics procedure. The proposed solution was implemented and tested in real-world houses by emulating the behaviour of non-qualified users. The obtained results show that Wi-Fi fingerprinting, when used in such an uncontrolled environment, still poses some challenges as its precision is still significantly low.

## 1 INTRODUCTION

In most countries around the world, the typical configuration for residential Internet access is based on an all-in-one-box router and Wi-Fi Access Point (AP), connected to the Internet through a point-to-point link: ADSL, cable or optical fibre (FTTH). Inside the house, costumers use their own devices to connect to the local Wi-Fi network. Being based on a single Access Point, this solution often struggles to provide a convenient radio coverage of the entire house, namely for large houses or in dense residential areas where radio interference can significantly degrade the performance of Wi-Fi networks. These coverage problems can vary over time due to changes in the house layout (e.g. moving furniture from one place to another) or due to the deployment of other Wi-Fi networks in the neighbourhood, making them difficult to detect during the first installation of the service by the technicians of the Internet Service Provider (ISP). These problems are the cause of many complaints by the customers about the provided service, as their quality of experience is highly dependent on the quality of the in-house Wi-Fi network. Similar problems are also observed for cellular coverage indoors, but these are not usually understood by costumers as a break of the service contract rules.

In-house diagnostics of Wi-Fi coverage in residential environments, executed by the customers using their Wi-Fi enabled devices (e.g. smartphones, tablets, etc.), has the potential of identifying the causes for simple problems that can be solved remotely by ISP technicians. This diagnostic testing procedure benefits from automatic indoor localization capabilities as it enables the comparison of test results performed in different time epochs and the identification of locations with recurring issues. If properly crafted, a smartphone App can even help customers in self-diagnostic procedures and in tuning their setup (e.g. by moving the Wi-Fi Access Point slightly, changing its orientation or even changing some configuration parameters such as the radio

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channel number, or by changing the position of some furniture objects) to get a better service without any intervention from the ISP technicians. One key enabler of one such self-diagnostic tool is the ability to estimate the location of the smartphone/tablet inside the house.

Many indoor positioning and tracking technologies have been proposed in the last decade, targeting different scenarios and aiming to support different applications (a good overview of the many solutions can be found in (Mautz, 2012) or (Davidson, 2016). Among those technologies, Wi-Fi fingerprinting has become very popular, both within the research community and also as the base for many commercial products, mainly due to its simplicity and easy of deployment. Given the current ubiquity of Wi-Fi networks in indoor spaces and since the large majority of mobile devices are Wi-Fi enabled, an indoor positioning solution can be created based entirely on software components, without the need to deploy any infrastructure. Other similar solutions, based on Bluetooth Low Energy (BLE), are also becoming popular at airports, hospitals and shopping malls, despite demanding the installation of a dense network of BLE beacons (Faragher, 2014).

Sound and ultrasound propagation in indoor environments have also been investigated for supporting indoor positioning solutions (Harter, 2002; Priyantha, 2001), but they also require the installation of a dedicated infrastructure. The systems described in (Rishabh, 2012) and (Nakashima, 2011) are examples of solutions that use the loudspeakers available in offices or shopping malls to implement indoor positioning systems. They disseminate barely audible controlled sounds or watermarked signals, which are then captured by the mobile users' devices and used to estimate the receiver position. Other solutions, namely those based on infrared or UltraWideBand (UWB) have the potential of achieving high accuracy at the cost of requiring the use and deployment of specific, and often expensive, hardware (Alarifi, 2016).

This paper reports on the development of a technical solution to assist residential customers of Internet access services in performing self-diagnostic tests in their houses. The developed solution includes a software library with several methods to run performance tests, including upload and download rates, latency statistics, link speed, RSSI - Received Signal Strength Indicator, and Wi-Fi radio interference level (based on the number of access points using the current and adjacent Wi-Fi channels). The library also includes methods to estimate the location (at room level) where each test has been performed, thus enabling the geo-referencing of each set of test results.

This paper is focused on the development and testing of an indoor localization solution based on Wi-Fi fingerprinting. Section II provides an overview of the fundamental principles of Wi-Fi fingerprinting, with its advantages and limitations. The proposed solution for the in-house localization component is introduced in section III. Its evaluation in real-world settings is described in section IV, along with a discussion of the obtained results. The paper ends with conclusions and some ideas for future developments, in section V.

## 2 WI-FI FINGERPRINTING

Wi-Fi fingerprinting is a scene analysis method of positioning (Bahl, 2000). It is based on the fundamental principle that the characteristics of the radio environment are unique at each location, and involves two main stages. In its first stage, samples of the radio environment (strength of the received signal from each observable AP, frequency channel, or other characteristics of the radio signals) are collected at known locations and subsequently stored in a database to form what is known as a Radio Map. Collecting samples can be achieved by querying the network interface of Wi-Fi enabled devices through the devices' Application Programming Interface (API), thus using simple software components. In most of the reported solutions, multiple samples are collected at each location, with one or more distinct orientations of the collecting device (e.g. with the device heading North, South, etc.). Collecting multiple samples aims at capturing the variability of the radio signals at each location. In some systems, the set of collected fingerprints is pre-processed, namely by averaging the measured signal level from each AP or by filtering data from specific APs, to produce the final radio map. This is considered, by some authors, one additional stage added to the two conventional ones.

In the operational stage, also known as the on-line stage, a device at an unknown location collects one sample of the radio environment (operational fingerprint) and an estimation method is used, together with the radio map, to estimate the position of the device. Two main approaches are used to estimate the position - deterministic and probabilistic, with none of them being clearly superior to the other. The probabilistic approach is based on a probabilistic model that describes the probability of observing a given signal level from a particular AP at a given position, and is usually built by approximating the distribution of the measured signal level to a Gaussian distribution. The unknown position of the device is then estimated through a Bayesian method (see, e.g. (Youssef, 2005) and (Ledlie, 2012)). With the deterministic approach, a distance function is used to compute the similarity between the operational fingerprint and all the fingerprints in the radio map. The most similar fingerprint or the k most similar fingerprints in the radio map are then selected and their corresponding positions are used to estimate the position of the target device (usually the centroid or weighted centroid). This is known as the k-Nearest Neighbour (kNN) method. Many alternative distance functions have been proposed to compute the similarity between fingerprints, with the Euclidean and Manhattan distances being the most popular (Torres-Sospedra, 2015). When estimating the location at room level, majority rules can be used to pinpoint the most probable compartment indoors (Marques, 2012). Other classification methods have also been proposed, including decision trees, random forest, Support Vector Machine and Neural Networks.

Due to the variability of the radio environment, the typical performance of Wi-Fi fingerprinting-based indoor positioning solutions is characterized by an accuracy (mean error) around 5 meters, with the frequent observation of very large errors (larger than 15 meters). One good reference regarding the performance of these positioning methods is the set of results obtained in indoor positioning competitions, such as the IPIN (Torres-Sospedra, 2016) and Microsoft competitions (Lymberopoulos, 2017), although paying attention to the fact that most of the competing systems are not pure Wi-Fi fingerprinting-based but, instead, hybrid system fusing data from multiple sensors.

Indoor positioning based on Wi-Fi fingerprinting is, however, very challenging. Firstly, creating radio maps for large buildings is a very tedious and time-consuming task, even when resorting to advanced localization and mapping (SLAM) approaches (Ferris, 2007; Wu, 2012; Jiang, 2012). Moreover, radio maps degrade with time due to changes in the radio environment, requiring frequent recalibrations. Some of the causes of these changes in the radio environment are modifications in the layout of the space (e.g. furniture moving, doors opening/closing), alterations in the layout of the Wi-Fi network (APs being relocated, added or removed, nearby networks being deployed/modified) and the presence of mobile hotspots (temporary APs created by mobile devices). Wi-Fi-fingerprinting also suffers from the use, in the operational phase, of devices different than those used for creating the radio map, including different versions of the Android OS API version, from the orientation of the devices that affect the measured received radio signals due to body shadowing, and also from how the devices are handled (carried in the pocket, in the hand, etc.) while collecting a fingerprint.

## 3 ROOM-LEVEL LOCALIZATION

The aim of the positioning system described in this paper is to detect when network performance tests have been run in the same room inside the house where similar tests were run earlier. Therefore, it is a problem of recognizing (recalling) a previously visited room. In its simplest form, the user of a smartphone App visits each and every room inside his/her house and collects enough fingerprints to properly characterize them, also labelling these fingerprints with the room name. This approach for building the radio map can be easily and rapidly performed in a regular house with the help of a smartphone App based on a wizard. In a more automated form, the fingerprints are collected automatically, in the background, by the smartphone App while also running the other performance tests. In any case, the collected fingerprints are then used to characterize and later recognize each room.

The proposed approach for this system is based on pure Wi-Fi fingerprinting, running completely in the smartphone, without depending on any network service. The reason for this design choice is to ensure total privacy of the users. On the other hand, this choice imposes some limitations on the choice of the estimation method (e.g. deep learning might not be practical to implement).

Following a tradition approach, based on a deterministic estimation method, let *R* be the set of all labelled fingerprints (*fp*), collected at each room, during an initial calibration, that form the radio map. Each fingerprint is described as:

$$fp_i = (l, \{(M_1, RSSI_1), \dots, (M_N, RSSI_N)\}) \quad (1)$$

where *l* is a unique label identifying each room inside the house, *M* is the MAC address of an observed AP, *RSSI* is the Received Signal Strength Indicator representing the measured signal level (represented in dBm), and *N* is the number of APs observed at a particular location in a particular time instant.

In the operational stage, a deterministic method is used to estimate the room associated with a given fingerprint ($fp_0$) collected at an unknown location. First, the similarity $S$ between $fp_0$ and all the fingerprints $fp_i$ in $R$ is computed using a modified version of the Manhattan distance, defined as:

$$S(fp_0, fp_i) = \sum_{j=1}^{N} \left| RSSI_j^0 - RSSI_j^i \right| - \alpha \times nCM \quad (2)$$

where $RSSI^0_j$ is the measured RSSI of $AP_j$ in the operation fingerprint ($fp_0$), $RSSI^i_j$ is the measured RSSI of $AP_j$ in the radio map fingerprint ($fp_i$), $N$ is the total number of APs observed in the $fp_0$ and $fp_i$, $nCM$ is the number of APs than are observed in both $fp_0$ and $fp_i$, and $\alpha$ is a parameter that gives more or less weight to the number of common APs ($nCM$). Since not all APs are observed in all fingerprints, whenever an AP is missing (not observed), the corresponding RSSI value is replaced by a constant representing a weak signal (we found -90 dBm to provide good results).

Let $B$ be the set of radio map fingerprints ordered by decreasing similarity (meaning increasing value of $S$) with $fp_0$. The location (room) associated to $fp_0$ is estimated by applying a majority rule to the top $k$ fingerprints taken from $B$: the most frequent room is the most probable location for $fp_0$ (k-Nearest Neighbours – k-NN). This method assumes that $R$ includes more than one labelled fingerprint per room. Otherwise, $k$ must take the value 1, and the estimated location is that of the most similar fingerprint (1-NN), i.e. that of the top fingerprint in $B$.

The location estimation method described above was implemented as a Java library including classes and methods to collect fingerprints, manually label fingerprints (to get ground truth), to build the radio map, and to estimate the location associated to a given fingerprint. Other methods, used to assess the performance of Wi-Fi networks have also been implemented, including a feature to upload the results to a server.

# 4 EVALUATION IN THE REAL WORLD

The developed system was evaluated in three different houses, of varying configuration, in order to assess the performance in recognizing a previously mapped room. Three distinct persons performed the evaluation using three different smartphones. As much as possible, the evaluation was performed trying to mimic the behaviour of non-technical users. This process was performed without altering the normal behaviour of the space inhabitants or changing the physical layouts, such as the position of furniture and other large objects. These experiments were conducted in the first days of February 2019.

## 4.1 Experimental Setup

The infrastructure created to evaluate the developed solution (the Java library, with emphasis on the localization solution) includes an Android App and a data server, and three houses where the system has been tested.

The App implements a simple graphical user interface that facilitates the access to the main library functions (see Figure 1): *Add Place* – to collect a set of fingerprints, label the corresponding location and add them to the radio map; *Get Location* – to collect one single fingerprint, estimate the corresponding location, collect ground truth (Figure 1.b), and send the result to a server. All the other functions are used to manage the radio map: reset it (*Delete Places*), rename a place, delete a place, and list all places.


(a) (b)

Figure 1: Android App used for the validation of the localization system: (a) main menu; (b) validating a recognized place.

The server is used only to collect the experimental results: every time a localization estimation is performed, the corresponding operational fingerprint, the used radio map and the ground truth are sent to the server, where these data is stored in a database for further processing. This allows the same data to be processed offline using variants of the estimation algorithm.

The system has been tested in three different houses:

- House A (hA) – a three-floor house with 12 compartments, 1 in the basement, 5 “spaces” in the ground floor and 6 compartments in the upper floor; all spaces in the ground floor are in an open space without any walls or doors separating them, except for the toilet and laundry; most interior walls are made of brick; the neighbourhood includes several similar houses around, with small gardens in between; no testing has been performed in the basement;
- House B (hB) – a 120 square meters single-floor house with 8 compartments; there is only one neighbour house that share a wall from kitchen and a room; all spaces are separated by walls made of brick and accessible by the hall;
- House C (hC) – a flat, with almost 130 square meters, on the 3rd floor of a multi-floor building, with 9 compartments; all spaces are separated by walls made of brick, except the laundry room which is separated from the kitchen by a glass; the neighbourhood includes three other flats on the same floor (with a double wall made of brick in between) and several other flats on the same floor but without direct contact; the same layout exists on the remaining four floors of the building.

Four different smartphones were used to collect the data: Nexus 5, Oneplus 5T, Xiaomi Mi8 Pro, and Lenovo Pb2. In all tests, the same device was used to build the radio map and to perform the localization tests. Experiments using one smartphone for building the radio map and a different one to perform the localization tests were not considered since those scenarios are not expected to happen in the real use of this system.

## 4.2 Evaluation Metrics

The main metric for evaluating the performance of symbolic location systems is *Accuracy* – it measures the percentage of times the system correctly recognizes the visited place. Since the performance of the location recognition is dependent on the total number of distinct places to recognize (the smaller the number of distinct places, the easier is to recognize the correct place), a secondary metric is defined as the gain over a random guessing. This metric, named *Relative Accuracy*, is defined as $Ar = Np \times Accuracy$, where $Np$ is the total number of rooms inside the house (number of classes in the classifier). $Ar$ is simply the gain over a random classifier, which accuracy is $1/Np$. In our evaluation, the number of samples (fingerprints) collected in each room to build the radio map is the same, so that there is no initial unbalance (bias) and the prior probabilities of each class are all equal.

## 4.3 Evaluation Procedure

An evaluation procedure was defined prior to any data collection at the houses referred above.

It is also well known that the movement of devices affects the propagation of radio signals significantly. However, despite the large number of location/positioning systems based on radio signals that have been proposed, their evaluation is usually performed with stationary devices. The exception is the class of positioning tracking systems based on pedestrian dead reckoning since the movement of the human body is fundamental to estimate displacement (e.g. through step counting and stride length estimation). Therefore, this work also aims at investigating the impact of movement in the performance of Wi-Fi based fingerprinting location systems.

Three different modes were tested:

- still-table: stationary smartphone over a table or similar object;
- still-hand: stationary smartphone being hold in the hand of the user;
- moving-hand: smartphone handled by the user while walking inside the house at normal speed (less than 1m/s).

Two sets of experiments were conducted: one with the radio map built with the smartphone placed on top of a table (still-table), and another with the smartphone in the hand (still-hand). This is intended to evaluate the impact of having the smartphone in the hand while collecting the fingerprints. For the first radio map (still-table), two localization tests were performed: still-table and moving-hand. For the second radio map (still-hand), the localization tests were performed for the modes still-hand and moving-hand.

Data collection involved two stages. First, a user registered all the places inside the house to create the radio map. In the second stage, the user visited all the spaces/rooms, many times, and asked the system to recognize his location while being stationary (still-table), while holding the smartphone in the hand (still-hand), and while walking without stopping (moving-hand).

To create the radio map, the user visited each place/room, selected a location near the centre of the room, placed the smartphone on top of a table or other surface at similar height (still-table), with the screen pointing to the ceiling, pushed the ADD PLACE button (see Figure 1), and typed in the room name. Ten fingerprints were collected per room. No specific order was defined to visit the several rooms. Each room was visited only once. In the second set of experiments, this procedure was repeated while holding the smartphone (still-hand). Table 1 shows a summary of the collected data, including the number of fingerprints collected in each house for each testing mode (#fps) and the total number of observed Access Points (#APs).

Table 1: Summary of the collected data (radio maps).

| House | Mode | #rooms | #fps | #APs |
|---|---|---|---|---|
| hA | still-hand | 11 | 110 | 7 |
| hA | still-table | 11 | 110 | 8 |
| hB | still-hand | 8 | 80 | 11 |
| hB | still-table | 8 | 80 | 7 |
| hC | still-hand | 9 | 90 | 23 |
| hC | still-table | 9 | 90 | 22 |
| hC | still-hand | 9 | 90 | 29 |
| hC | still-table | 9 | 90 | 21 |
| Total: | | | **740** | |

The second stage was devoted to evaluate the performance of the system in recognizing previously mapped rooms. To collect the corresponding data, the user repeated the same procedure as for creating the radio map but, instead of pushing the ADD PLACE button, the user used the GET LOCATION function of the App. After receiving a reply from the App, the user confirmed the estimated location, if correct, or selected the correct place from the list of registered places, otherwise. An "unknown" location could also be selected in case the user was at a place not previously registered into the system. In this stage, each room was visited three times. This procedure was repeated for the modes still-table, still-hand and moving hand.

Since all these data was sent to a server during the evaluation, the performance of the system was computed offline.

# 5 EVALUATION RESULTS AND DISCUSSION

The results presented in this section were obtained by using the following values for the system parameters:

- default RSSI value for missing APs: -90 dBm
- $\alpha$ (see equation (2)): 4
- $k$ (number of top fingerprints to use when applying the majority rule): 5

A summary of the evaluation results is shown in Table 2. These results are, apparently, disappointing, since the accuracy is quite low. It means that, in too many cases, the localization system is not able to estimate the correct room, even though the performance of the system is way better than a random classifier.

Table 2: Overall Accuracy (A) and Relative Accuracy (Ar).

| | **Radio map (still-table)** | | **Radio map (still-hand)** | |
|---|---|---|---|---|
| | ***A*** | ***Ar*** | ***A*** | ***Ar*** |
| **hA** | 0.563 | 6.19 | 0.508 | 5.59 |
| **hB** | 0.612 | 4.89 | 0.430 | 3.44 |
| **hC** | 0.598 | 5.38 | 0.719 | 6.47 |
| **Average** | 0.591 | 5,49 | 0.552 | 5.17 |

These results also show that the difference in performance across the three houses is not very large when the radio map is built with the smartphone standing on top of a table (still-table), but larger variations are observed when the smartphone is in the hand while building the radio map (still-hand). This was an expected result, as it is known that the human body attenuates the radio (Wi-Fi) signals significantly. On the other hand, the average results, considering the three houses, are similar for both radio maps.

A deeper analysis of the results revealed that, many times, the incorrect location estimates are on rooms adjacent to the correct one, or that the second or third guesses include the correct room. This is illustrated in Table 3, where it is shown that in around 80% of the estimates, the correct room is within the three best guesses. One possible explanation for these results is that, in the houses used for testing, some rooms are not clearly separated by walls and/or doors – they are just different areas in a large open space. Therefore, it is not easy to distinguish the different areas since there are no obstacles to differentiate the propagation of the radio signals clearly. The results in Table 3 also show that, when considering the aggregated data, there is no significant difference between the two radio maps.

Table 3: First, second, and third best guesses.

| Guess | Radio map (still-table) | | Radio map (still-hand) | |
|---|---|---|---|---|
| | *A* | *Ar* | *A* | *Ar* |
| **1** | 0.592 | 5.46 | 0.594 | 5.49 |
| **1+2** | 0.697 | 6.42 | 0.700 | 6.46 |
| **1+2+3** | 0.802 | 7.38 | 0.797 | 7.35 |

Table 4 shows results about the impact of movement, aggregated for the three houses. It compares the results (first guess only) for the two radio maps and the performed testing modes.

Table 4: Impact of movement.

| Mode | Radio map (still-table) | | Radio map (still-hand) | |
|---|---|---|---|---|
| | *A* | *Ar* | *A* | *Ar* |
| **still-table** | 0.623 | 5.77 | - | - |
| **still-hand** | - | - | 0.650 | 6.00 |
| **moving-hand** | 0.562 | 5.15 | 0.538 | 4.98 |

Here it is more evident the impact of performing tests (localization) while moving: for both radio maps there is a clear degradation on the accuracy when the fingerprints are collected while the user was walking.

In one of the houses, the tests were performed using two different smartphones, aiming to evaluate if the use of different devices has a significative impact on the accuracy. For each test, both the radio map fingerprints and the online fingerprints were collected using the same device. The corresponding results are shown in Table 5, and are inconclusive. While for the first radio map there is a clear advantage on the performance of the Xiaomi smartphone, for the second radio map the results are, coincidentally, exactly equal.

For the house with multiple floors, the correct floor rate was calculated and found to be 93,1%.

Table 5: Impact of using different smartphones.

| Mode | Radio map (still-table) | | Radio map (still-hand) | |
|---|---|---|---|---|
| | *A* | *Ar* | *A* | *Ar* |
| **Xiaomi** | 0.718 | 6.46 | 0.719 | 6.47 |
| **Lenovo** | 0.478 | 4.30 | 0.719 | 6.47 |

Given the obtained results, which suggest that there is room for considerable improvements, other localization methods, were evaluated. Among them, well-known classifiers such as Naïve Bayes, Decision Trees, Random Forest (ensembles), Neural Networks and Support Vector Machine were evaluated using the radio maps for training and the testing fingerprints for testing, using the vector of all RSSI values observed from all APs as the single feature. The obtained results (accuracy) were consistently worse than those obtained with the method described in this paper.

## 6 CONCLUSIONS AND FUTURE WORK

In this paper we reported on the evaluation of an indoor localization system, at room level, based on Wi-Fi fingerprinting. The particular characteristic of the developed system is that it is to be used in residential houses by non-qualified people using a simple smartphone App. Therefore, no initial setup and/or calibration should be made by professionals. In order to preserve the privacy of the users, the system should also implement all the required functions in the smartphone App, and no external server should be used. This requirement prevents the use of advanced methods that imply a high computational burden, incompatible with the processing capabilities of average smartphones/tables or required high energy consumption.

The proposed system is based on Wi-Fi fingerprinting and a simple deterministic estimation method (similarity and majority rule). Its performance has been evaluated in three real houses.

The results reported in this paper show that recognizing previously mapped rooms inside the house is a difficult task, and the obtained accuracy was in the range of 55 to 80%. These results are worse than initially specified. One reason for this level of performance might be the small number of Access Points observed in a house, compared with what is now typical in more network-dense places such as universities, hospitals or airports. On the other hand, these results are in line with the typical positioning results reported in the literature for Wi-Fi fingerprinting, where the accuracy is around 5 meters. With this level of accuracy, it is quite easy to estimate the wrong room inside a house with typical room sizes (~10-15 $m^2$).

A direct comparison with the results of other authors is a difficult task, as reported in (Torres-

Sospedra, 2017), since the evaluation conditions are often very different and the reported methods are difficult, if not impossible, to replicate. Moreover, the room-level accuracy depends deeply on the layout of the space and materials used. Results reported in (Yasmine, 2016) show an accuracy of 0.88. However, these results were obtained in a test performed in a shopping mall, with shops spreading a much larger area than is typical in a house. This larger spread facilitates the distinction among rooms (shops in this case) that are far apart, which is not the case in a 100 $m^2$ house.

As future work, and in order to improve the accuracy, a few hybrid solutions will be evaluated, including the combination of Wi-Fi fingerprinting with fingerprinting based on cellular networks radio signals (Otsason, 2005) or with sound-based fingerprinting. In these hybrid methods, the use by non-professionals should be evaluated and its impact measured.

One other area deserving further investigation, for this particular application, is the use of multiple fingerprints collected at each room during the localization (online) phase. Multiple fingerprints can be combined to reduce the inherent variability of the RSSI values. This technique can be easily incorporated in the developed App at the expense of longer data collection periods at each location.

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