

The Tale of Two Localization Technologies: Enabling Accurate Low-Overhead WiFi-based Localization for Low-end Phones

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ABSTRACT

WiFi fingerprinting is one of the mainstream technologies for indoor localization. However, it requires an initial calibration phase during which the fingerprint database is built manually by site surveyors. This process is labour intensive, tedious, and needs to be repeated with any change in the environment. While a number of recent systems have been introduced to reduce the calibration effort through RF propagation models and/or crowdsourcing, these still

have some limitations. Other approaches use the recently developed iBeacon technology as an alternative to WiFi for indoor localization. However, these beacon-based solutions are limited to a small subset of high-end phones.

In this paper, we present *HybridLoc*: an accurate low-overhead indoor localization system. The basic idea *HybridLoc* builds on is to leverage the sensors of high-end phones to enable localization of lower-end phones. Specifically, the WiFi fingerprint is crowdsourced by opportunistically collecting WiFi-scans labeled with location data obtained from BLE-enabled high-end smart phones. These scans are used to automatically construct the WiFi-fingerprint, that is used later to localize any lower-end cell phone with the ubiquitous WiFi technology. *HybridLoc* also has provisions for handling the inherent error in the estimated BLE locations used in constructing the fingerprint as well as to handle practical deployment issues including the noisy wireless environment, heterogeneous devices, among others.

Evaluation of *HybridLoc* using Android phones shows that it can provide accurate localization in the same range as manual fingerprinting techniques under the same deployment conditions. Moreover, the localization accuracy on low-end phones supporting only WiFi is comparable to that achieved with high-end phones supporting BLE. This accuracy is achieved with no training overhead, is robust to the different user devices, and is consistent under environment changes.

CCS CONCEPTS

• **Human-centered computing** → *Ubiquitous and mobile computing*;

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KEYWORDS

Indoor Localization; WiFi Fingerprinting; BLE-based Localization

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1 INTRODUCTION

Recent years have witnessed the advent of indoor localization systems harnessing the many untapped capabilities of the smartphones [1, 2]. The development of wireless technology in smartphones and the widespread availability of IEEE 802.11 have enabled the introduction of many indoor localization solutions that can provide meter-level accuracy. WiFi-based indoor localization techniques leverage the Received Signal Strength (RSS) overheard from WiFi access points as the metric for the location determinations, building a WiFi fingerprint to combat the noisy wireless channel. Typical fingerprint-based WiFi localization techniques work in two phases: The first phase is initial training (i.e., calibration) during which RSS measurements (i.e., fingerprints) received from the multiple access points (APs) installed in the area of interest are recorded at known locations. Then, in the tracking phase, RSS measurements from the overheard APs at an unknown location are matched against the fingerprint database to determine the best location match either deterministically or probabilistically. Nonetheless, the deployment cost is prohibitive as the WiFi calibration process is time consuming, labour intensive and vulnerable to environmental dynamics. To tackle this problem, a number of approaches for automating the fingerprinting process have been proposed including using RF propagation models [3, 4], combining RF localization with other sensors [5], or crowdsourcing the fingerprint; where users perform the required survey process in realtime either implicitly [5, 6] or explicitly [7]. These techniques, however, suffer from lower accuracy; require explicit user intervention; or work only on high-end phones.

To further address the issues of WiFi-based localization, the iBeacon technology has been introduced. Beacons are cheap, portable, and energy-efficient devices based on the Bluetooth Low Energy (BLE) standard that can be installed at known locations in the area of interest. iBeacons periodically broadcast their identifier along with other location information which can be overheard by nearby compatible smartphones. A number of commercial solutions leverage iBeacons to provide proximity-based localization [8, 9] and, more recently, researchers have started to use them to provide more accurate continuous user tracking [10, 11]. Nonetheless, the BLE

technology is currently limited to high-end smart phones, limiting their ubiquitous deployment on typical commodity devices with the majority of the users. In addition, the opportunity of using the existing WiFi-infrastructure for localization is missed in this case.

In this paper, we combine the best of both localization technologies. Specifically, we present *HybridLoc*: an accurate, robust, low-overhead, and ubiquitous **WiFi-based** indoor localization system. *HybridLoc* targets enabling WiFi-based localization for low-end phones in buildings with the iBeacon infrastructure while **removing the traditional WiFi calibration overhead**. The basic idea is to automatically crowdsource the construction of the WiFi fingerprint leveraging the high-end phones supporting the iBeacon technology. In particular, building users with *high-end smart phones* will scan for **both** BLE and WiFi APs concurrently in the area of interest while using the system. BLE scans are used to get an estimate of the user location. The user location is used with the scanned WiFi signals to construct the WiFi fingerprint in an automatic manner. This WiFi fingerprint database grows incrementally by users with high-end phones visiting the area of interest. Later, users with low-end phones, i.e. those that support only WiFi but not BLE, can provide *HybridLoc* with the WiFi scans to get an estimate of their location. Therefore, by leveraging the ground-truth location information “donated” by users with high-end phones, *HybridLoc* can provide ubiquitous localization to any WiFi-enabled phones in areas with iBeacons deployment.

To achieve *HybridLoc*'s goals, a new set of challenges still need to be addressed: First, the ground-truth location obtained from the BLE localization has an inherent error in the order of few meters. This error leads to a mis-assignment of WiFi scans to the wrong fingerprint point. Second, to construct a probabilistic fingerprint for localization; which is proven to provide better accuracy than deterministic techniques [12–14]; traditionally a user has to stay at each fingerprint point for a certain amount of time to construct the signal strength histogram. This adds significantly to the overhead of the fingerprint construction process, and cannot be performed while the users are moving naturally in the building. Third, different phones will measure the RSS differently at the same location due to different WiFi chips, form factors, or chip placement inside the phone. This device heterogeneity needs to be addressed to avoid excessive localization error or per device-calibration. Finally, due to the noisy wireless channel, there may be some missing APs in successive scans that lead to a mismatch between the set of heard APs at the same location. *HybridLoc* presents a number of modules to address these challenges.

We have implemented *HybridLoc* on different Android phones and evaluated it in a university building instrumented with the iBeacon BLE technology and the already installed WiFi infrastructure. Our results show that *HybridLoc* can achieve a consistent median accuracy of 4.1m under different scenarios, which is comparable to the accuracy of manual fingerprinting techniques under the same conditions. In addition, the system accuracy on low-end phones supporting only WiFi is comparable to that achieved with high-end phones supporting BLE. This accuracy is achieved with no training overhead and is robust to the different user devices, and wireless channel noise.

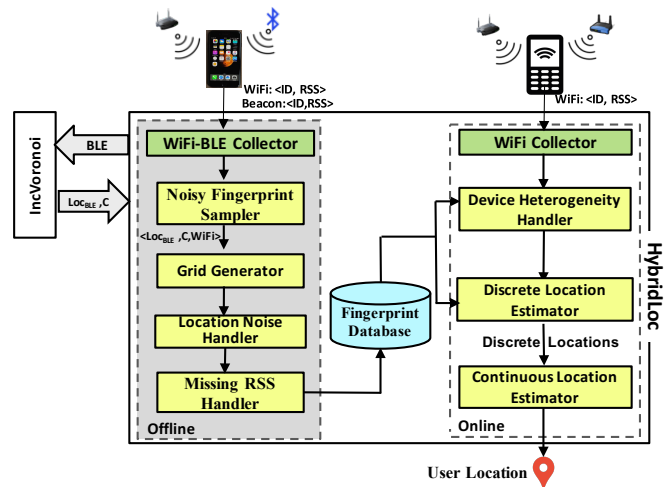


Fig. 1. *HybridLoc* system architecture.

The rest of the paper is organized as follows: Section 2 presents an overview on how *HybridLoc* works and introduces the mathematical model. Section 3 gives the details of *HybridLoc* and how it handles different practical considerations. We evaluate the system performance in Section 4 and compare it to the state-of-the-art. Section 5 discusses related work. Finally, Section 6 concludes the paper.

2 OVERVIEW AND MATHEMATICAL MODEL

In this section, we start by an overview of how *HybridLoc* works to illustrate the high-level flow of information through the system architecture. Then, we discuss the mathematical model of our approach.

2.1 System Overview

Figure 1 shows *HybridLoc* architecture. *HybridLoc* is designed to be deployed in areas where the iBeacon technology is already installed for localization and WiFi is deployed for coverage. Therefore, by default, it can provide BLE-based localization to users with high-end phones that support the iBeacon technology. *HybridLoc* works in two phases: an offline fingerprint construction phase and an online tracking phase. During the offline phase, *HybridLoc* aims to **automatically** build a probabilistic WiFi fingerprint, where the RSS histogram for each AP at given locations in the area of interest is estimated.

As users with high-end phones move naturally inside the building, the *HybridLoc* software installed on their phone continuously scans the environment for **both** BLE and WiFi signals transmitted from the installed beacons and WiFi APs respectively. These WiFi and BLE scans are submitted to the **Noisy Fingerprint Sampler** module. This module forwards the collected vector of BLE RSSs to a BLE-based indoor localization technology to get an estimate of the user with high-end phones location¹. **Without loss of generality**, we use IncrVoronoi [10] as an example of a calibration-free

¹Note that these users are incentivized to install *HybridLoc* software on their devices to navigate using the BLE technology.

BLE-based indoor localization system due to its high accuracy, robustness to heterogeneity in user devices, and adaption to dynamic changes in the environment and APs transmit power. In addition, IncVoronoi also provides a confidence measure of the estimated location [11]. This location label is annotated with the collected WiFi scan at that point and the pair is recorded a candidate WiFi fingerprint in the database.

To build the WiFi histogram at the every location, traditionally the user has to stay for a certain period of time in the same location, which may be inconvenient for users. To reduce this overhead of the histogram construction (i.e. allow building the histogram while the user is continuously moving), *HybridLoc* uses a gridding approach, where the area of interest is divided into square cells of arbitrary size using the **Grid Generator** module. The RSS histograms are then built using the collected fingerprint points inside each grid. This not only removes the extra overhead of fingerprint construction but also increases the scalability of system as the fingerprint size can be arbitrarily reduced by increasing the cell size. However, as the cell size increases, the accuracy and computational-efficiency decrease. Thus, the cell size (density of the grid) should be configured by the system designer to trade-off accuracy and computational overhead.

Given that the BLE-based estimated locations have inherent noise, which may results into many mis-assignment of WiFi scans to fingerprint points; to mitigate this effect; the **Location Noise Handler** module incorporates different approaches to handle these noisy location labels building on the estimated location confidence provided by the IncVoronoi system.

The **Missing RSS Handler** module further handles the cases where some RSSs are not heard in different scans from some APs during the training and/or tracking phases, due to the wireless channel noise, possibly limiting the localization accuracy.

The **Device Heterogeneity Handler** module provides a mathematical approach to make the system independent from the used device, hence increasing the system robustness to different heterogeneous phones.

Finally, during the online phase, end users; even those with phones that support WiFi only but not BLE; are tracked in realtime by forwarding the scanned WiFi APs that can be heard at the current unknown user location to the *HybridLoc* WiFi tracking service. Specifically, the **Discrete Location Estimator** module consults the constructed WiFi probabilistic fingerprint and the center of the discrete grid that has the maximum probability is returned as the estimated user location. To enable user tracking in the continuous space, the **Continuous Location Estimator** module further processes the estimated discrete grid locations to return a more accurate estimate of the user location.

Note that since the system is crowdsensing-based, the fingerprint is continuously being updated in the background with the data collected from system users with high-end phones, allowing *HybridLoc* to counter environment changes.

2.2 Mathematical Model

Without loss of generality, we assume a 2D area where n WiFi APs and m BLE beacons have been installed. A user carrying a device at an unknown location l scans for the nearby APs and beacons. The scanned WiFi APs can be represented as a vector $s =$

Symbol	Description
n	Total number of installed WiFi APs.
m	Total number of installed BLE beacons.
s	Vector of RSS from the heard APs in a scan.
q	Number of WiFi APs in a given scan ($q = s $).
b	Vector of RSS from the heard beacons in a scan.
p	Number of BLE beacons in a given scan ($p = b $).
l_b	Estimated ground-truth location by IncVoronoi (BLE-based).
c	Degree of confidence in IncVoronoi estimated location.
\mathbb{G}	Universe of grid cells in the area of interest.
g	A specific grid cell, $g \in \mathbb{G}$.
g_l	Representative location of a grid cell.
μ_i	Average RSS from AP_i .
σ_i	Standard deviation of RSS from AP_i .
k	History window size used to estimate the continuous user location.
N_s	Number of scans used in the training .
G_S	The cell grid length (i.e., grid spacing).
λ	The common offset between RSSs collected by different phones.

Table 1: Notation table

(s_1, \dots, s_q) , where $q \leq n$ is the number of heard APs and each s_i is the signal strength of the i^{th} heard AP. The scanned beacons can be represented as a vector $b = (b_1, \dots, b_p)$, where $p \leq m$ is the number of heard beacons and each p_i is the signal strength of the i^{th} heard beacon.

During the offline phase, where the fingerprint is constructed using high-end phones, the BLE scan (b) is forwarded to the IncVoronoi system to estimate the user location l_b and its confidence c (represented as a circle with radius c around the estimated location l_b). A location-tagged WiFi scan (l_b, c, s) is assigned to a specific grid cell g out of the possible \mathbb{G} grids in the area of interest. Each grid cell g is represented by a single location g_l .

During the online tracking phase, our problem is that, given some WiFi RSS vector s , we want to find the grid cell $g \in \mathbb{G}$ that maximizes the probability $P(g|s)$. The estimated user location is g_l , the representative location of the cell with the highest probability.

Table 1 summarizes the notations used in the paper.

3 THE HYBRIDLOC SYSTEM

In this section, we present the details of the *HybridLoc* system architecture for indoor localization. We elaborate the following main functionalities: WiFi Fingerprint construction (offline) phase and tracking (online) phase. In addition, we discuss the different practical challenges that need to be addressed by *HybridLoc* to enable its realtime deployment.

3.1 Construction of the WiFi Fingerprint-Offline Phase

This module aims to automatically construct the WiFi fingerprint. It addresses a number of challenges including handling the error in the ground-truth BLE locations, missing APs, and heterogeneous devices.

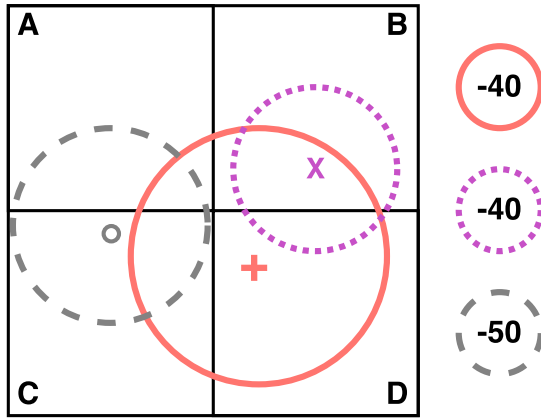


Fig. 2. Example showing the different techniques for assigning a WiFi scan to a grid cell based on the estimated BLE ground-truth location (center) and its estimated confidence (circle). The numbers represent the heard RSS in each scan.

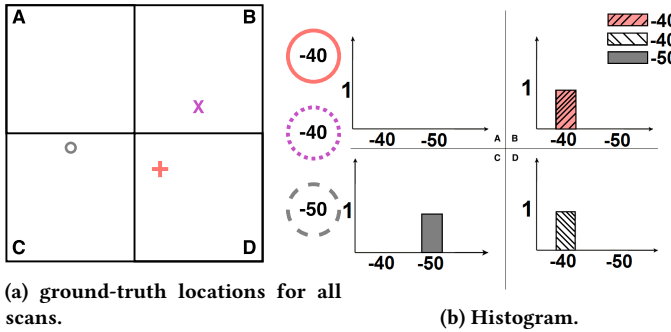


Fig. 3. WiFi samples assignment to cells generated by the location only approach. Subfigure a shows that the confidence circles are ignored and the estimated location is deemed as the ground-truth location. In this case, each WiFi sample is assigned to the cell where the estimated location lies in as shown in subfigure b.

The input to this module is the WiFi and BLE scans collected by high-end smart phones. The module first queries the employed zero-calibration BLE-based localization (i.e., *IncVoronoi* [10]) to retrieve and estimate of the user location given the BLE beacon RSS vector. *IncVoronoi* is based on the idea that the relative relation between the received signal strength from two APs at a certain location reflects the relative distance from this location to the respective APs. Building on this, it incrementally reduces the user ambiguity region based on refining the Voronoi tessellation of the area of interest. It also provides a confidence measure for the estimated location, represented by the radius of the ambiguity circle [10, 11]. The retrieved location label, its confidence, along with collected WiFi scan are stored at a temporary fingerprint database for later processing. This process is continuously performed in the background of the system operation through a crowdsensing manner, increasing the system coverage and keeping the fingerprint up-to-date.

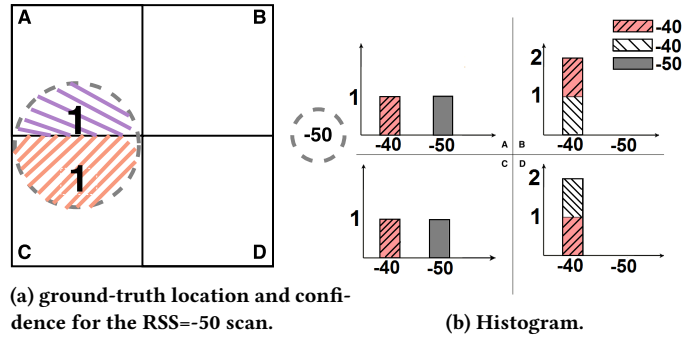


Fig. 4. WiFi samples assignment to cells generated by the unweighted confidence approach. Subfigure a shows that the ground-truth location for RSS= -50 will be assumed to be in the two cells intersecting with the confidence circle. In this case, the WiFi sample is assigned with an equal weight to all cells where the estimated location lies in as shown in subfigure b.

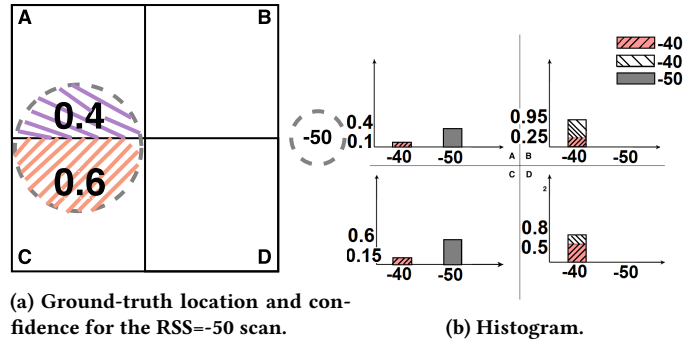


Fig. 5. WiFi samples assignment to cells generated by the weighted confidence approach. Subfigure a shows that the probability that a ground-truth location lies in a given cell depends on the intersection area of this cell and the confidence circle of that location. In this case, the WiFi sample is assigned to all cells where the estimated location lies in with different probability based on intersection area as shown in subfigure b.

3.1.1 Handling ground-truth location noise. This module is responsible for handling the inherent noise in the ground-truth BLE location. The input of this module is location-tagged WiFi scans and the estimated confidence of the BLE location. The goal is to determine the grid cell(s) to assign these scans to. We experimented with three different techniques that either leverage the estimated location only, fuse the location and the unweighted confidence, or fuse the location and the weighted confidence.

Without loss of generality, and for ease of explanation of these techniques and their differences, we present a simple deployment scenario where only one AP is installed in the area of interest. Figure 2 depicts a part of the area of interest divided into four grid cells A,B,C and D. Assume that the phone hears three successive WiFi scans with RSS -40, -40 and -50 from the installed single AP

with the estimated location labels and their confidence (the center of each circle is the estimated location and the circle represents the confidence in this location label). Now, we illustrate the difference among the three techniques by highlighting how they assign those three WiFi scans to the different grid cells:

(1) **Using the estimated location only**

This technique assumes that the estimated BLE location is the true location. Therefore, it ignores the confidence estimate and assigns the WiFi scan to the grid cell enclosing the estimated BLE location. This is illustrated in Figure 3a, where the centroids of the circles (estimated locations) are deemed as the absolute locations of the collected samples. The outcome of the assignment using this technique on the example in Figure 2 is shown in the histogram in Figure 3b.

(2) **Using the unweighted confidence**

This technique assumes that the user should be located anywhere inside the confidence circle. Therefore, it assigns the WiFi scan to *all* grid cells that intersect with the confidence circle. Figure 4 shows the assignment results for the RSS=-50 scan, where the scan is assigned to cells A and C.

(3) **Using weighted confidence**

This technique extends the previous one by taking the intersection area between the confidence circle and grid cell into account. The larger this intersection area is, the higher probability that the true location lies inside the cell. The assumption here is that the user can be located equally probable anyway inside the confidence circle.

More formally, assuming that the user true location label is uniformly distributed inside the confidence circle, the grid cell weights can be calculated as:

$$w_i = \frac{1}{\pi c^2} \oint dA_i = \frac{A_i}{\pi c^2} \tag{1}$$

Where c is the radius of the confidence circle and A_i is the intersection area between cell i and the confidence circle. Note that Monto Carlo Simulation can be used for more efficient estimate of the intersection area if needed.

Figure 5 shows the assignment result of the collected WiFi scans using this technique for the RSS=-50 sample. Note that the histogram is built using all the samples within each grid cell. Therefore, it will be normalized to a proper density function.

3.1.2 Handling missing RSS. After handling the noisy ground-truth location label problem, *HybridLoc* should construct a probabilistic WiFi fingerprint for each grid cell. However, due to the noisy wireless channel, the number of APs in different scans may be different, especially for APs with a low RSS (Figure 6). In addition, some RSS values may not be heard. To address these issues, we choose to use a parametric distribution to estimate the signal-strength distribution. This leads to smoothing the distribution shape and avoids obtaining a zero probability for any signal strength value due to noise (Figure 7). In addition, using a parametric distribution (i.e., Gaussian) is more memory-efficient than using a non-parametric distribution.

More formally, *HybridLoc* approximates the AP RSS histograms as a Gaussian distribution. Therefore, the probability density of

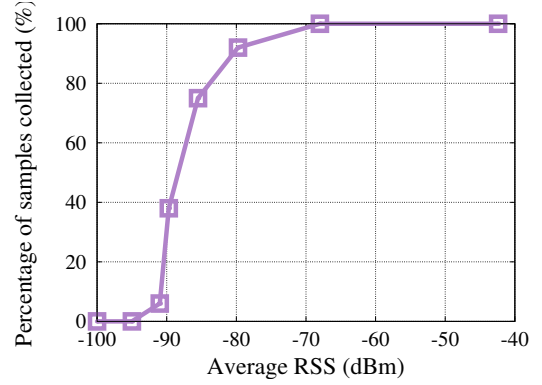


Fig. 6. Percentage of samples where the AP appeared versus its average RSS. The higher the RSS, the more samples expected from the AP. The sharp drop around RSS=-88 dBm is due to the receiver’s sensitivity.

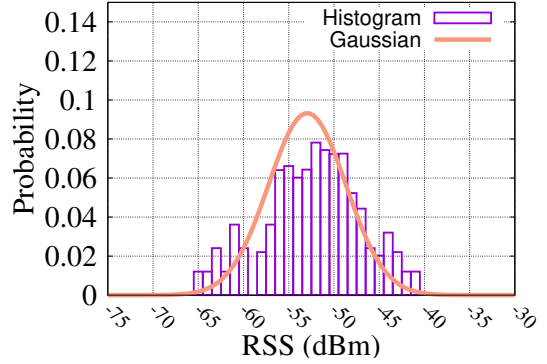


Fig. 7. Parametric and non-parametric representation of the RSS probability density function. The parametric distribution smooths the missing values, e.g. at RSS=-60 and is more space-efficient.

obtaining RSS s_i from AP_i at a specific grid cell (g) is given by:

$$P(s_i|g) = \frac{1}{\sigma_i \sqrt{2\pi}} e^{-\frac{(s_i - \mu_i)^2}{2\sigma_i^2}} \tag{2}$$

where μ_i is mean of all RSS values inside the grid cell g and σ_i is its standard deviation.

3.1.3 Handling devices heterogeneity. To handle the devices heterogeneity, one can build a fingerprint for each type of phones or a mapping function can be used to map the RSS values between the different types of cell phones [15, 16]. Nevertheless, the range of available user devices in the market, which keeps growing each day, makes this process not scalable and have a high overhead. Vaupel et al. [17] proposed a pre-calibration process for different devices to increase the performance of their localization system. However, pre-calibration incurs an extra overhead.

To tackle the device heterogeneity problem in an *automatic manner without calibration*, we observe that there is an offset in signal strength collected by different phone models at the same location

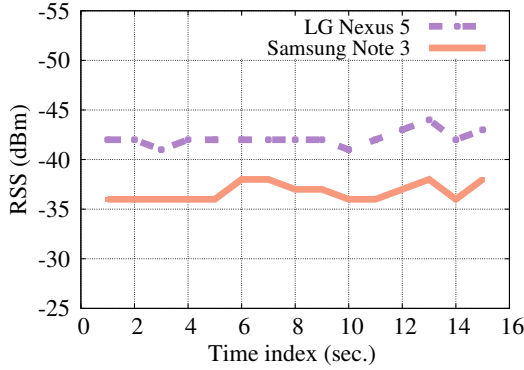


Fig. 8. An example of WiFi RSS's collected by two different phone models at the same location from one AP.

(Figure 8). This offset is almost constant across different APs and can be attributed to the difference in chip type, phone form factor, and/or antenna location and gain. Therefore, we estimate this offset as the average difference between the heard RSS and those stored in the fingerprint over all APs. More formally, the *common offset* λ is estimated as:

$$\lambda = \frac{\sum_{i=1}^q (s_i - \mu_i)}{q} \quad (3)$$

where s_i is the RSS heard from access point AP_i by the device during the online tracking phase, μ_i is the mean RSS of the AP_i as recorded in the fingerprint database during the offline phase, and q is number of heard APs in this scan.

Therefore, we replace the random variable s_i by the random variable $s_i - \lambda$. This new variable still follow a Gaussian distribution with mean $\mu_i - \lambda$ and variance $\sigma_i^2 + \frac{\sum_{i=1}^q \sigma_i^2}{q^2}$.

Note that the same approach can be used to construct the signal strength distribution using heterogeneous phones during the offline phase.

3.2 Tracking Users- Online Phase

In this phase, *HybridLoc* works in two subsequent modules to enable continuous tracking of the user location as they move freely in the area of interest. The first module, the **Discrete Location Estimator** module, determines the fingerprint cell that has the maximum probability given the received signal strength vector from the different access points. The second module, is the **Continuous Location Estimator** module, processes the discrete estimated user location returned by the previous module and returns a more accurate estimate of the user location in the continuous space. The rest of this section discusses the details of each module.

3.2.1 Discrete-Space Estimator Module. During the online phase, a user is stationed at an unknown grid cell $g \in \mathbb{G}$ hearing a WiFi scan with signal strength vector $s = (s_1, \dots, s_q)$ from the nearby q APs, where s_i is the RSS measurement from AP_i . We want to find the grid cell g^* that has the maximum probability given the received signal strength vector s . That is, we want to find:

$$g^* = \arg \max_g [P(g|s)] \quad (4)$$

Using Bayes' theorem this can be rewritten as:

$$g^* = \arg \max_g [P(g|s)] = \arg \max_g \left[\frac{P(s|g)P(g)}{P(s)} \right] \quad (5)$$

Assuming all grid cells are equally probable², this can be simplified as:

$$g^* = \arg \max_g [P(g|s)] = \arg \max_g [P(s|g)] \quad (6)$$

The $P(s|g)$ term can be calculated using the Gaussian densities that have been constructed during the offline phase as:

$$P(s|g) = \prod_{i=1}^q P(s_i|g) \quad (7)$$

A representative location (g_l) for the most probable grid cell (g^*) is returned as the estimated location. This location can be simply the grid geometric center. However, we found that representing the cell by the center of mass of the points inside it gives a better estimate as quantified in Section 4.

3.2.2 Continuous Location Estimator Module. The previous module returns the representative location of the most probable grid cell as the estimated user location. However, if the user is moving normally in space, using this module only will lead to having the estimated location jump from one cell location to the next. To reduce this effect and enable tracking the user in the continuous space, this module aims to smooth the estimated discrete user location. To achieve that, it uses two complementary approaches:

- (1) **Center of mass of the estimated discrete locations (Spatial average):** Since the "Discrete Space Estimator Module" calculates the probability of each grid cell $g \in \mathbb{G}$, the first approach is to estimate the user location as the center of mass of all grid locations, taking the probability of the cell as its weight. More formally, let $P(g_l)$ be the probability of the representative location of cell $g \in \mathbb{G}$, the center of mass technique estimates the current user location l as:

$$l = \frac{\sum_{g \in \mathbb{G}} p(g_l)g_l}{\sum_{g \in \mathbb{G}} p(g_l)} \quad (8)$$

- (2) **Time averaging of location estimates (Temporal Average):** This technique uses a time-average window to smooth the resulting location estimate. It calculates the average of the last k location estimates to obtain the final location estimate. More formally, given a stream of location estimates l_1, l_2, \dots, l_t , the technique estimates the current location \bar{l}_t at time t as:

$$\bar{l}_t = \frac{1}{\min(k, t)} \sum_{t-\min(k, t)}^t l_i \quad (9)$$

Note that both techniques are independent and can be applied together to further enhance accuracy.s

²If the user profile over the different cells ($P(g)$) is known, it can be used directly in Equation 5.

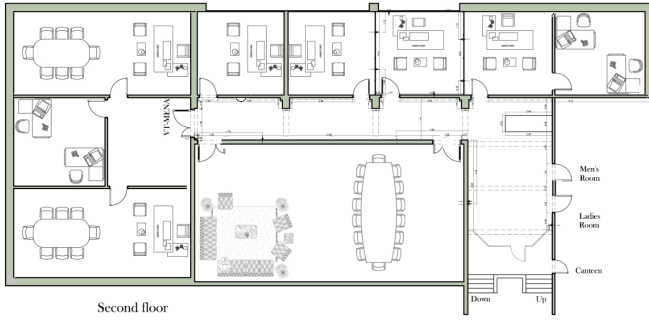


Fig. 9. Environment testbed

Parameter	Range	Default value
Cell size (G_S)	1 - 64 (m)	1
Number of averaged locations (k)	1 - 16	10
Number of training samples (N_s)	100-700	700
Cell assignment method	Location only, Unweighted confidence, Weighted confidence	Weighted confidence

Table 2: Default parameters values.

4 PERFORMANCE EVALUATION

In this section, we evaluate the performance of *HybridLoc* in a typical indoor environment. We also describe the effect of different parameters on *HybridLoc* performance. Finally, we compare our system with the traditional manual fingerprint techniques.

4.1 Data Collection

To collect the necessary data for evaluation, we deployed our system in a floor of our university campus building with a $37m \times 17m$ area containing offices, labs, meeting rooms as well as corridors (Figure 9). The ceiling height is 3m. We installed 20 iBeacons at the same height of 2.5m uniformly across the rooms with an average density of one beacon/ $33 m^2$. We use the already installed WiFi infrastructure in the building, mainly four APs in addition to 12 APs overheard from other floors/buildings. The data is collected by four participants using different Android phones (e.g., LG Nexus 5, Samsung Galaxy Note 3, Samsung Galaxy 4, Galaxy Tab, among other). Two independent data sets are collected for constructing the fingerprint and evaluating the system. This captures the time-variant nature of the WiFi fingerprint as well as the heterogeneity of users and devices

We implemented a scanning program using the Android SDK to simultaneously scan APs and beacons. The program records the (MAC address, RSS, timestamp) for each heard WiFi access point and the (UUID-major, minor, Tx power, Bluetooth address) for each BLE beacon. The scanning rate was set to one per second. Test points were collected on a uniform grid with a 1m spacing.

4.2 Effect of Changing *HybridLoc* Parameters

In this section, we study the effect of the different parameters on the system performance including cell assignment method, the grid cell spacing, number of location samples used in the training phase, ground-truth location accuracy, and the number of most probable

locations averaged to obtain the final location. Table 2 shows the default parameters values used throughout the evaluation section.

4.2.1 Effect of the cell assignment method. Figure 10 shows the box-plot for the localization accuracy when using the three employed cell assignment methods described in Section 3.1.1. The figure shows that the using the two confidence assignment methods lead to better accuracy as they handle the location noise better. In addition, the “unweighted confidence” and the “weighted confidence” methods have comparable localization accuracies with a slight advantage in favor of the weighted confidence approach. Therefore, the system designer can use the more computationally-efficient “unweighted confidence” technique.

4.2.2 Effect of grid spacing (G_S). Figure 11 shows the effect of the grid spacing on the median localization accuracy achieved by *HybridLoc*. The figure shows that, as expected, the localization accuracy increases with smaller cell lengths. This increase comes at the expense of a larger fingerprint and more time required to construct it due to the larger number of cells. However, this is performed only during the offline phase and; since *HybridLoc* is a crowdsensing-based system; is amortized over the number of system users.

4.2.3 Effect of the number of samples used for training (N_s). Figure 12 shows the effect of the number of collected BLE ground-truth training samples from high-end phones on the median WiFi localization accuracy achieved by *HybridLoc*. Evident from the figure, as the number of training samples increases, the localization accuracy increases; till it saturates when the number of samples reaches 600. This can be explained by noting that as the training samples density increases, the estimated histogram becomes more accurate and representative of the fingerprint at that cell, leading to better accuracy. Note again that this is amortized over all system users.

4.2.4 Effect of the number time-averaging window size(k). Figure 13 shows the effect of the number of averaged locations in the continuous location estimator module on the system median accuracy. The figure shows that as more location samples are aggregated to obtain the user location, the localization accuracy increases. However, using a large window size leads to an increased latency in response to user movement. Therefore, we have a trade-off between accuracy and latency of the location estimate that should be optimized based on the end user needs in a particular deployment.

4.2.5 Effect of the cell representative location method. As discussed in Section 3.1.2, the location that represents the grid cell may be the geometric center of the cell or the center of mass of all samples that are collected within that cell. Figure 14 shows the box-plot of localization error for the two techniques. The figure confirms that the center of mass representation of the cell location has a slight improvement over the geometric cell center. This is because the former implicitly better captures the building geometry and where people move.

4.2.6 Heterogeneity Effect. To demonstrate that *HybridLoc* is robust to different heterogeneous phones due to its “Devices Heterogeneity Handler” module, we perform an experiment where different phones are used for training and testing. Specifically, we carried

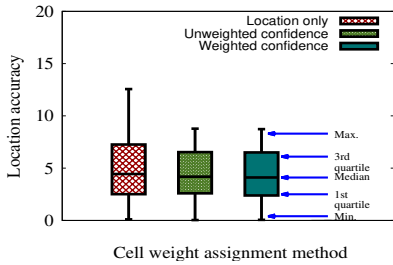


Fig. 10. Effect of the employed cell assignment method on the localization accuracy.

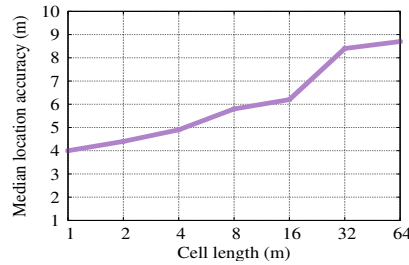


Fig. 11. Effect of the grid cell spacing on the median localization accuracy.

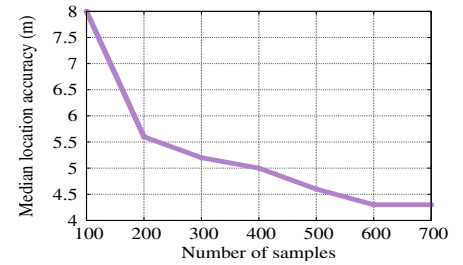


Fig. 12. Effect of number of training samples on the median localization accuracy.

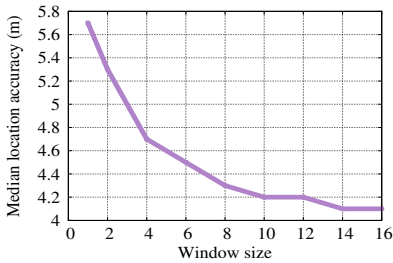


Fig. 13. Effect of the time-averaging window size on the median localization accuracy.

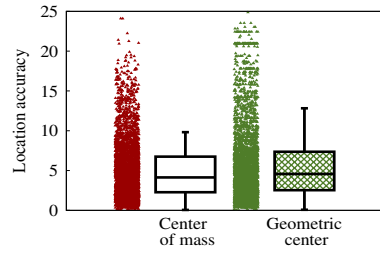


Fig. 14. Effect of the cell location representation method on the localization accuracy.

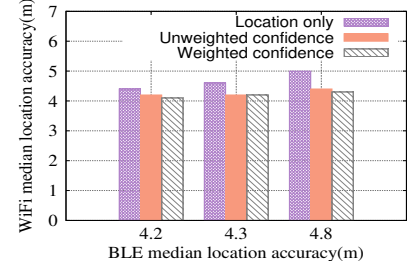


Fig. 15. Effect of the ground-truth accuracy on the WiFi localization accuracy.

out experiments on two different phone models: Samsung Galaxy Note 3 *tablet* and Samsung S4 *smartphone*. The two phones have a completely different form factor and WiFi chips.

Figure 16 shows the effect of employing the “Devices Heterogeneity Handler” module on the system accuracy when the Samsung Galaxy Note 3 tablet is used for training and the Samsung S4 smartphone is used for testing. The figure shows that the module does provide higher accuracy by 14%.

We also study the effect of the module when using the same device (Samsung Galaxy Note 3) for training and testing. Figure 16 shows even with the same model, the module leads to a better localization accuracy. This is due to reducing the effect of the noisy wireless channel.

4.2.7 *Effect of the employed BLE system accuracy.* To understand the effect of the ground-truth locations from the BLE indoor localization technology on *HybridLoc*, we plot the WiFi localization accuracy at different accuracies of the ground-truth locations provided by BLE-based technique (Figure 15). The figure shows that as BLE localization accuracy increases, the WiFi localization accuracy increases too. The techniques that use the confidence estimate are more robust and less-sensitive to the changes in the accuracy of the employed BLE localization system. Therefore, users with low-end phones with WiFi only can obtain comparable accuracy to those obtained using high-end phones with BLE.

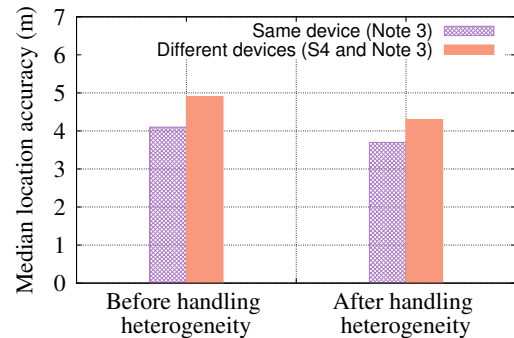


Fig. 16. Effect of removing the common offset using the same device (Note 3) and different devices (training: Note 3, test : S4).

4.3 Comparison with Other Systems

In this section, we compare the location accuracy generated automatically by the three different methods used in *HybridLoc* against a typical probabilistic *manual* fingerprinting technique (i.e., the Horus System [13]). Figure 17 shows the CDF of localization accuracy for these different algorithms. The figure illustrates that the confidence-based approach achieves approximately similar location accuracy as manual fingerprinting one as summarized in Table 3. This comes with no the costly or time-consuming calibration phase.

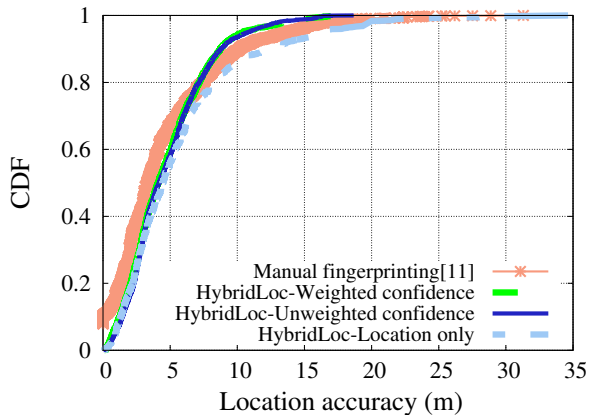


Fig. 17. CDF of localization error of different variants of HybridLoc against a manual fingerprinting technique [13].

Technique	25 th percentile	50 th percentile	75 th percentile	90 th percentile
Manual Fingerprinting [13]	1.7	3.3	6.3	10.1
HybridLoc-Weighted confidence	2.4	4.1	6.4	8.7
HybridLoc-Unweighted confidence	2.5	4.1	6.5	8.8
HybridLoc-Location only	2.5	4.4	7.3	12.5

Table 3: summary of the location accuracy percentiles of different techniques

5 RELATED WORK

This section presents a brief background on the current techniques for WiFi-based indoor localization categorized into fingerprinting-based, propagation models-based, and crowdsourcing-based techniques.

5.1 Fingerprinting-based Techniques

In these techniques, the radio map is built by maintaining the RSS signature of heard APs at different locations in a database during the offline phase. During the tracking phase, the set of overheard APs is matched against fingerprints in the database for the closest location in the RSS space to the unknown location. This matching is done using either deterministic methods [18, 19] or probabilistic methods [13, 20]. In the deterministic case, the fingerprint is represented by a scalar quantity, e.g. the average RSS of the heard APs in a certain location. During the online phase, the RSS vector collected while scanning the unknown location is matched (based on some distance metric such as Euclidean, Manhattan, or Mahalanobis distance) against the fingerprints of all locations maintained in the radio map to find the nearest match [21]. On the other hand, probabilistic techniques construct signal strength histograms for the RSS received from each AP at each location in the area of interest. During tracking, the fingerprint is used to calculate the probability of the RSS vector at the unknown location at each location stored in the radio map. The most probable location is used as the estimated location. Many variants of probabilistic WiFi fingerprinting based indoor localization have been proposed to improve the performance. For instance, talking the high correlation between consecutive signal

strength samples from same APs into account can help to achieve better accuracy [22]. Another approach aims to detect small scale signal variations and perturbs the signal strength vector entries to overcome it, thus improving accuracy [23]. Clustering locations that share a common set of access points will significantly reduce the computational overhead [24]. Finally, probabilistic techniques have been proven to be superior to deterministic techniques [12].

Although fingerprinting-based methods are relatively accurate, their deployment is impeded by the high cost of calibration phase and the user inconvenience. In addition, they need to handle the fingerprint differences between heterogeneous devices.

HybridLoc, in contrast, automatically constructs the fingerprint without requiring direct user participation nor calibration measurements. In addition, it has modules to address the devices heterogeneity issue.

5.2 Propagation Models-based Techniques

Modeling-based techniques try to capture the relation between signal strength and distance using a propagation model. Therefore, they can automatically generate the fingerprint without expensive site surveying. For example, the Wall Attenuation Factor (WAF) model augments the free space path loss model with the attenuation caused by walls to handle the complex indoor propagation conditions [18]. Specifically, the direct path between the transmitter and receiver is used to calculate the number of walls between them, where passing through each wall leads to signal attenuation by a constant amount.

More sophisticated propagation models use the ray shooting technique to calculate the path of waves, augmenting reflections and absorption from walls and other objects into the model. ARIDANE [4] and Aroma [3] incorporate the 2D and 3D ray tracing techniques respectively to get better RSS estimation across the designated area. These models take as an input the 3D floor plan of the area of interest, obtained from CAD tools or generated automatically [25–29], and the location of APs. They then estimate the 2D or 3D paths between the transmitter and receiver along with their interactions with the materials in the environment[30] to compute the RSS values from all available APs at each reference point on a grid.

Propagation models-based techniques, however, has lower accuracy than fingerprinting-based techniques, still require samples from the environment to calibrate the model, require the locations of the access points in the building, require high computational requirements for ray tracing, and the model parameters still depend on the specific phone used for measurements.

5.3 Crowdsourcing-based Techniques

Another line of research on WiFi-based localization tries to reduce the calibration overhead by using crowdsourcing for the fingerprint construction through explicit [7] or implicit [5, 6, 31] user feedback. In [7], the user mobile periodically gathers a fingerprint of nearby APs and checks against the signal strength map to determine the user’s location. If it cannot do that with a certain accuracy, it prompts the user to indicate her current location on a displayed map. This on-the-fly surveying binds the fingerprint observed by the user to the relevant space.

Although this reduces the deployment burden of the system, prompting the user frequently to gain more coverage/accuracy is inconvenient.

To avoid prompting the user, Unloc [5, 31] and Zee [6] both leverage inertial sensors to get a rough estimate of the user location through dead-reckoning and associate a fingerprint with it. To reset the accumulated error, Zee performs map matching with the floor-plan while Unloc leverages unique anchors in the environment, detected based on the multi-modal sensors signature. However, inertial sensors in commodity cell phones are noisy, reducing localization accuracy. In addition, their accuracy depends on the phone holding position and orientation [32, 33], which is still an active area of research.

HybridLoc, on the other hand, does not depend on inertial sensors and provides accuracy comparable to manual fingerprinting techniques. In addition, it handles heterogeneous devices naturally.

6 CONCLUSION

We presented *HybridLoc*: a hybrid, accurate, and low-overhead indoor localization system that works with heterogeneous phones. *HybridLoc* leverages users with high-end phones in a crowdsourcing manner to automatically build the WiFi fingerprint. As part of *HybridLoc*, it handles different practical deployment issues such as handling the inherent error in the BLE-based ground-truth location, missing RSS samples, and devices heterogeneity.

Evaluation of *HybridLoc* in a typical building using different Android phones shows that it can achieve a median distance error of 4.1m using WiFi only, which is comparable to this obtained using manual fingerprinting as well as high-end phones with BLE chips. However, *HybridLoc* avoids the intensive, tedious and time-consuming calibration phase.

7 ACKNOWLEDGEMENT

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