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Improving Crowd-Sourced Wi-Fi Localization Systems using Bluetooth Beacons

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***Abstract*—Crowd-sourced Wi-Fi-based localization systems utilize user input for RF scene analysis and map construction. Such systems reduce the deployment cost and privacy concerns that expert-based site survey systems can create. However, the main bottleneck of such crowd-sourcing localization systems is a bootstrapping stage, where lack of contributions by users results in no accuracy guarantee and frequent unnecessary prompting for users' input, even for explored areas. In this paper, we propose a crowd-sourcing localization system that uses both Wi-Fi scene analysis and Bluetooth beacons to address the insufficient contribution challenge. After prompting for user input, the mobile device not only submits Wi-Fi fingerprint to a map server, but also enables Bluetooth beacons to disseminate/share its location and fingerprint information to quickly populate the signal map. Then, subsequent user devices entering the area can discover the Bluetooth beacons and are able to instantly obtain room-level location information without causing unnecessary prompting to users. We implement our proposed system in the Linux OS and evaluate the prototype extensively through both experiments and simulation. Our evaluation results show that using Bluetooth beacons help to improve signal map growth, while maintaining reasonable localization accuracy.**

I. Introduction

Recently, thanks to the increasing popularity of location-based service (LBS), a considerable amount of research effort has been made to develop indoor localization systems. Because of the rapid growth of smartphones, such localization systems often adopt various techniques that use sensory capabilities provided by commodity mobile phones and pervasive indoor Wi-Fi infrastructure. Among numerous existing solutions, scene analysis or fingerprinting approach [1], [2] is widely favoured because of its high accuracy and low complexity, compared to other schemes. However, the localization accuracy in this approach largely depends on a Wi-Fi signal map that is built through a dedicated scene survey. This survey normally conducted by expert is expensive, laborious and time-consuming. Furthermore, its results are often distorted by instability of the wireless signal and raise privacy or administrative concerns [3].

On the other hand, many LBSes today do not require more than room-level accuracy for location, which can be achieved using a signal map with mediocre quality fingerprints. Based on this observation, authors in [4]–[6] suggest crowd-sourcing the map-building task to users by accepting impromptu fingerprints and creating a map in an incremental way. Naturally, the bootstrapping stage of such a crowd-sourcing approach is crucial, since at which the lack of sufficient user input may adversely affect localization performance as well as user experience on the LBS.

To improve the bootstrapping performance of crowd-sourced Wi-Fi localization systems, two key questions emerge: 1) When does a user have to make a contribution and 2) How fast does the crowd-sourced localization system become operational, compared to an expert survey system. The former addresses the balance between faster data collection and less user prompting. The latter deals with how efficiently the system can handle user feedback with respect to localization accuracy. Most existing work (e.g., [5], [6]) dismisses these questions by assuming that there is a large group of users who are willing to actively contribute whenever they can. However, in practice, such assumption does not always hold, and thus users might receive localization service without any accuracy guarantee. Authors in [4] appreciate the importance of these two questions. They propose a spatial uncertainty metric that reflects coverage condition of the space around the estimated location. Nonetheless, spatial uncertainty could be too ambiguous to promptly and effectively represent the exploring and crowd-sourcing process in physical space, and the building of the association from physical space to signal map, due to low confidence of estimate.

If there is a guide stationed in these newly explored areas that can distinguish the explored areas from nearby unexplored areas with a high confidence, the spatial uncertainty suddenly becomes straightforward. The use of low-power short-range Bluetooth available in a mobile device can be a suitable candidate for the guide. In fact, Bluetooth-based applications have gained success in proximity marketing and medical scenarios [7], [8]. Bluetooth is practically ubiquitous in most mobile devices, and thus it is feasible to use the radio as localization beacons in a crowd-sourcing manner without requiring its careful deployment. Based on this intuition, we propose a new crowd-sourcing indoor localization scheme that allows users to set up Bluetooth beacon sites in local areas as a guide for other users. Once users are prompted for location, besides adding the record into signal map, they can also choose to encode this location information and the current Wi-Fi signal observation into a Bluetooth beacon. Then, subsequent user devices that enter the same location may scan for Bluetooth beacon. If beacon(s) is found, it can be localized instantly with significantly higher confidence. Otherwise, it can be prompted to improve coverage or resort to basic Wi-Fi localization using maps built by previous users.

In this paper, we design and evaluate an experimental system that augments Wi-Fi crowd-sourcing scene analysis localizer with Bluetooth beaconing capability. Similar to other crowd-sourcing schemes, our proposed system aims to provide room-level accuracy, yet avoiding expert-based site-survey cost. The use of Bluetooth beacons will provide several additional benefits: 1) It will facilitate the bootstrapping and decrease unnecessary user prompting, which can improve user experience. 2) It will provide room-level accuracy with high confidence even when only few fingerprints are available for the targeted area. This trait also ensures that the quality of such obtained fingerprints can be fair enough to be used for

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a signal map, which expedites the map construction process. 3) Leveraging beacons to locally share location information reduces the need of frequent communication with a remote map server for evolving updates, and thus potentially helps in power conservation. 4) Bluetooth protocol is designed to minimize interference, and beacons are set up in an ad-hoc and on-demand manner. These properties enable beacons to grow automatically to provide scalability.

Several technical challenges are encountered during the design of such a system. First, we observe that Wi-Fi signal characteristics such as temporal variations and available AP instability in our experimental environment are more complicated than we expect. Next, due to the wireless nature of Bluetooth beacons, detection delay, transmission range and reception rate of the beacons might cause adverse impact on localization accuracy. Further, it requires significant efforts to understand the effects of those factors and devise new mechanisms to alleviate them. Issues such as incentive for users to enable their Bluetooth interface working as beacon and the scanning delay are also discussed.

Our main contributions in this paper are summarized as follows:

- We study the feasibility of using the Class II Bluetooth component equipped in most of the mobile devices as a localization beacon site.
- We design a crowd-sourcing localization system that incorporates both Wi-Fi scene analysis and Bluetooth proximity approaches.
- We identify several major challenges in using Bluetooth beacons (e.g., penetrating beacons from adjacent space) via extensive experiments and propose novel approaches to mitigate the challenges.
- We implement the proposed localization system in the Linux OS and demonstrate its effectiveness via both experiments and simulations.

In the next section, we describe the related works. Then, we explain the motivation of our approach in Section III. In Section IV and Section V, we provide background information about Wi-Fi scene analysis approach and characteristics of Bluetooth transmission, respectively. In Section VI, we detail the design of our proposed system. Performance evaluation of a prototype implementation is given in Section VII. Section VIII discusses remaining issues and future work, and Section IX concludes the paper.

II. Related Work

Authors in [1] introduce the RADAR system that relies on Wi-Fi scene analysis. This approach has attracted much research effort [9], thanks to its favorable properties such as utilizing existing infrastructure and resilience to multi-path effect, compared to traditional triangulation method or proximity-based approach. Most work from the effort focuses on improving accuracy with a given signal map, by adopting different classification techniques, such as k-NN in [1], its variant [10], and Bayesian or probabilistic method [2].

However, the quality of signal map is a key to localization accuracy. Building a high quality signal map requires a tremendous cost in both labour and time. In order to reduce such cost, approaches proposed in [11], [12] require a few fingerprints collection and then use propagation models to derive the signal map. In [3], authors propose an adaptive survey system that identifies and reduces survey spaces, instead of rebuilding a whole map. Solutions that eliminate a dedicated map construction task and crowdsource the task to users are proposed [4]–[6]. However, they assume enough number of crowd-sourcing users.

Use of Bluetooth for localization has been studied in the past. Some work requires the deliberate placement of Bluetooth devices to infer proximity [13]. While others perform scene analysis on metrics such as Bluetooth RSSI [14] or response rate [15]. By contrast, in this work, we use user-managed Bluetooth beacon as a mean to facilitate the crowd-sourcing map construction.

III. Motivation

As Bluetooth is widely adopted in most of mobile devices, we propose to use Bluetooth beacon to enhance the performance of crowd-sourced Wi-Fi localization systems. This approach not only keeps most of the salient properties provided by Wi-Fi crowd-sourcing localizer: room-level accuracy, symbolic location, adaptation to variation, and low deployment costs, but also helps solve key design challenges of indoor localization systems as follows:

- *Prompting Efficiency*: When a user is located at unknown locations, a localization system should promptly ask for user inputs in order to improve the map coverage. However, frequent prompting will disturb users, and this becomes even worse if the system cannot distinguish explored areas from unexplored areas with a high probability [4]. By introducing Bluetooth beacon, users in explored areas will not be falsely prompted, thus improving prompting efficiency and usability of the system.
- *Accuracy with High Confidence*: While existing Wi-Fi crowd-sourcing localizer produces meaningful estimate only after the certain amount of fingerprints have been accumulated over a large part of the areas, using Bluetooth beacons system can *immediately* provide accurate result with high confidence in areas where a user(s) has explored and beacon is set up.
- *Accelerating Map Growth*: Bluetooth beacons can work as a projection from signal map to physical space. Knowledge conveyed via beacons helps other devices generate reliable fingerprints, and thus quickly populate the signal map without frequent prompting, when the physical area is densely populated. When the signal maps need to be downloaded into local cache, beacons can be used as indices to minimize the size of map downloads.
- *Communication Overhead Reduction*: In practice, there should be a central map server for aggregating fingerprints measured by crowd-sourcing devices. During a bootstrapping period, a Wi-Fi crowd-sourcing localizer needs to frequently communicate with the server to obtain timely updates contributed by other contemporary users. Beacon in the physical space helps in reducing communication overheads, thus improving power efficiency.

Motivated by the above factors, we will first explain the limitations and potential enhancements of Wi-Fi scene analysis scheme (Section IV) and further describe challenges and approaches in using Bluetooth (Section V). Finally, we present a system design (Section VI).

IV. Wi-Fi Scene Analysis Localizer

Static Wi-Fi scene analysis is a statistical approach that exploits the temporal and spatial variation of received signal strength indicator (RSSI) from Wi-Fi infrastructure. Typical *Wi-Fi fingerprint* consists of a position descriptor, a list of visible access points and corresponding RSSI statistics, namely *observation*. For areas of interest, a map of fingerprints, the *signal map*, is compiled through site survey. When a mobile user is localizing, Wi-Fi observation at unknown location is collected and then is matched against reference fingerprints in the signal map. Here, localization accuracy depends on classification technique as well as distance metric that is used for the matching. The resolution of the signal map carries even more weight. In principle, map resolution is affected by temporal variation of fingerprints and site survey methods. To investigate such impacts, we have conducted experiments and established baseline observations for (room-level) localization accuracy. The experiment environment is a typical office floor that consists of offices, meeting room, and student laboratories, including rooms illustrated in Figure 4. The environment has moderate traffic and is stuffed with computers, mobile devices, and a number of APs, and the student labs are usually further partitioned by cubicle walls.

A. Temporal Variation in RSSI

Temporal variation in RSSI [2], [16] poses severe threat to localization accuracy because it decreases the correlation between map record and physical space over time, eventually invalidating the entire signal map. We measure RSSI in our experiment environment by using a laptop that continuously scans Wi-Fi signal at a fixed location (center of Room2106 in Figure 4) for 7 days. Figure 1(a) shows RSSI traces of 4 APs (out of 21 visible APs), which are picked to show different RSSI ranges, for the first day. As shown in the figure, severe turbulence and diversity among APs can be observed. Some of the turbulences can reach as large as 15dBm, which is enough to cause serious error in localization.

Overall, the above results reaffirm that signal maps should be updated frequently to maintain the desired level of localization accuracy. Compared to calibration and sensing monitors (e.g., [3]) in static scene analysis, a crowd-sourcing approach has intrinsic advantage of faster map updates with less cost.

B. Measurement and Distance Metric

As we mentioned, the accuracy of Wi-Fi localization systems heavily relies on a distance metric and a classifier (for fingerprint matching). Thanks to the simplicity and relatively stable performance [1], we begin with measurement study on Root-Mean-Square-Error (RMSE) as a distance metric (and 1-Nearest-Neighbor (1-NN) for a classifier in the next section). We then propose modification to RMSE to improve localization performance.

1) Measurement Methodology: The measurements are recorded using probabilistic method used in [17]. A mobile device issues ten consecutive Wi-Fi scans, and then the mean and standard deviation of the reported RSSI values are calculated for each visible AP. Finally, they are stored as fingerprint along with a valid record count, which keeps the number of observations for each AP in the 10-round-scan.

During the 10-round-scan, we notice that a few RSSI values drastically deviate from others, which could swing the mean. Based on closer analysis on scanning results, we found that the deviation is caused mainly by *overheard signal* from adjacent channels. The 802.11 scanning mechanism scans one channel at a time looking for available APs on current channel, and repeat this until it goes through all 11 channels. When performing scan on a current channel, wireless interface may accidentally capture and report beacons from channel(s) that the interface is not currently listening on, with a significantly lower RSSI. We consider such RSSIs not the representative ones and perform a clustering on the 10-round-scan before the averaging. The clustering excludes any RSSI value that differs more than 30 dBm from half of the rest values.

2) Fingerprint Normalization: Each fingerprint collected from different time and locations may include the list of different observed APs. Before applying the distance metric (i.e., RMSE) to the fingerprint for calculating the distance between observation and record, different fingerprints have to be formatted into such lists that consist of the same set of APs. For such normalization, a fusion step is necessary to examine all fingerprints and generate an aggregated AP list. For APs that are not observed in certain fingerprints, their RSSI values are replaced with an 'invalid' one (i.e., -100dBm).

Throughout our experiment, some APs temporarily appear on site-survey phase and then disappear on localization phase or vice versa, we call them *transient APs*. They are most likely the result of misconfiguration or malfunction rather than physical distance and transmission range. Such inconsistency becomes a source of error when calculating the distance metric, especially as the fusion process assigns the penalty of -100dBm value to RSSI of transient APs. To avoid such errors, we define and use the valid record count (w), which is defined as the ratio of record count over total scans (10 in our case), as a weight factor to such APs. Here, transient APs typically have very low valid record count.

3) Modified RMSE Metric: Bearing the aforementioned issues in mind, we define a modified RMSE metric as our distance metric for Wi-Fi localizer, in Equation (1).

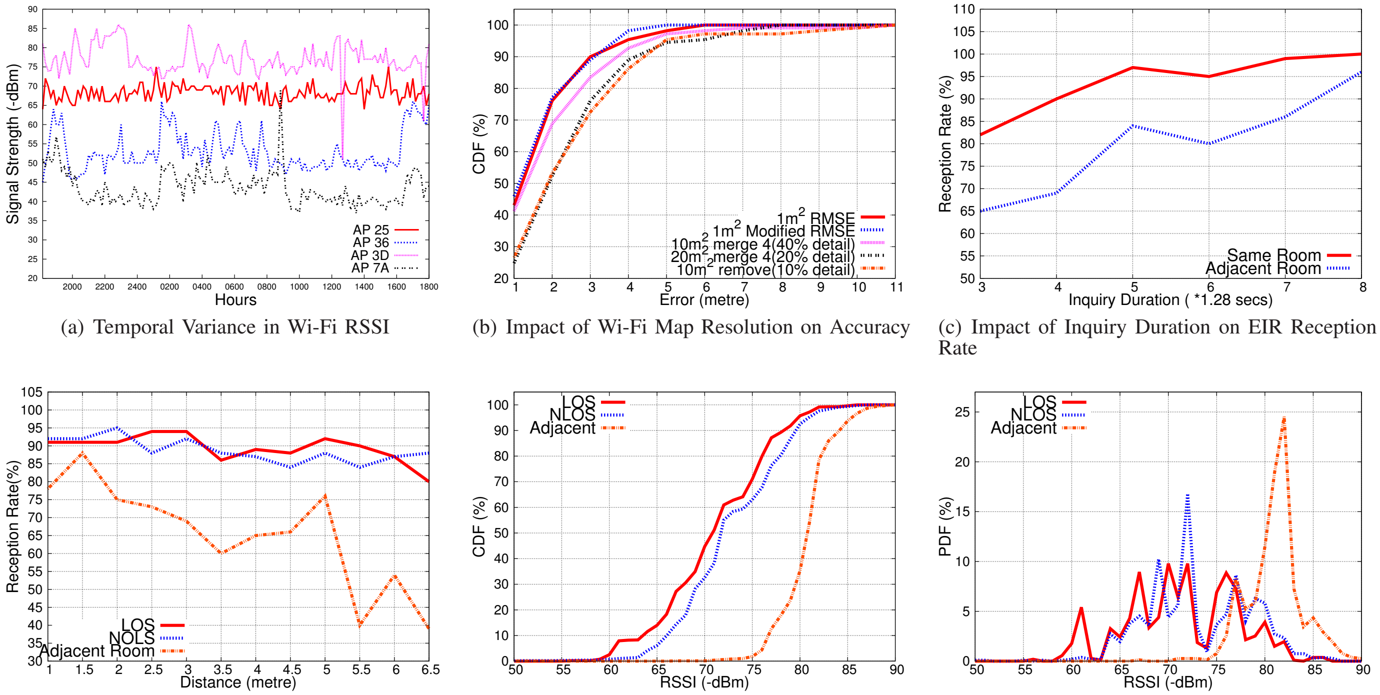
$$D_{om} = \sqrt{\frac{1}{c}\sum_{i=1}^{n} w_i (r_i^o - r_i^m)^2}, \qquad (1)$$

where D_{om} is a distance from observation o to fingerprint m, c is the number of APs observed by both observation o and fingerprint m, n is the total number of APs after fusion, r_i^o represents RSSI value of ith AP in observation o, r_i^m represents RSSI value of ith AP in fingerprint m, and w_i is the valid record count of ith AP. D_{om} as a distance metric for Wi-Fi localizer is used in all subsequent experiments. Note that the summation of n determines AP observed by only one party will introduce a penalty to distance. Normalized by c indicates that more common APs observed suggests closer distance.

C. Map Resolution and Localizer

Resolution of a signal map determines how many fingerprint samples should be collected for a given area and has significant effect on accuracy. The larger the unit sampling grid is, the more is the signal diversity exhibited within a grid [3], and the coarser is the location descriptor per observation. We performed site survey in accessible areas of our office floor for localization. The experiment space is gridded into $1m^2$ tiles. One fingerprint is collected within each unit grid—109 fingerprints in total. The map with the highest resolution is denoted as $1m^2$-map. Several lower-resolution maps are built backwards to simulate the crowd-sourcing map construction phases, using the following two methods:

- Remove: A granularity region with varying sizes is a combination of unit grids that are defined to represent the accuracy we expect to achieve. Within each granularity region, we randomly remove samples from $1m^2$-map and leave one sample only. This mimics the evolution of a crowd-sourcing system, where few fingerprints available to represent a large area. Using these approaches, we create $4m^2$ $remove$-map and $10m^2$ $remove$-map, whose granularity region sizes are $4m^2$ and $10m^2$, respectively.
- Merge: As suggested in [2], one can merge samples in the granularity region by fitting them into a Gaussian distribution and use the resulting distribution parameters to



(a) Temporal Variance in Wi-Fi RSSI

(b) Impact of Wi-Fi Map Resolution on Accuracy

(c) Impact of Inquiry Duration on EIR Reception Rate

(d) Impact of Distance on EIR Reception Rate

(e) Bluetooth Beacon RSSI Distribution

(f) Bluetooth Beacon RSSI Histogram

Fig. 1. Measurement results for Wi-Fi Localizer (a)-(b) and Bluetooth EIR Beacon (c)-(f).

represent each region. In addition to different granularity region size, we also study the impact of different numbers of samples used in merge by randomly removing samples before merging. For this approach, we use $4m^2$, $10m^2$, and $20m^2$ as granularity size and vary sample number parameter according to multiple of 2.

We feed all collected samples as input into the 1-NN-based localizer with the modified RMSE metric, using different maps we generated. We only show the case that is most relevant to our room-level accuracy setting. The result in Figure 1(b) indicates that with a detail map of $1m^2$ resolution, even a simple 1-NN-based localizer can achieve an approximate accuracy of 3.2 metres for 90%. It is comparable to existing work using similar techniques [1]. When reducing the resolution of the map to 2 samples per $20m^2$ as in $10m^2$ $remove$ case, the accuracy dropped to 4.8 metres for 90%. It also verifies that collecting more fingerprints to increase map detail has positive impact on accuracy.

V. Bluetooth EIR as Localization Beacon

Once one mobile device acquires its location information through either Wi-Fi localizer or user input, it can share this information with new users coming into its area. Bluetooth beacons can be used for such sharing, thanks to its wide adoption in mobile devices, and energy-efficient design. In addition, Bluetooth specification [18] defines a frequency hopping inquiry process for neighbor discovery and an Extended Inquiry Response (EIR) procedure that allows a message of 240 bytes to be sent immediately after inquiry response without the need of establishing connection. *We propose to use this inquiry process for localization beacon discovery, and use EIR to carry fingerprint information from the beaconing node.*

Even though the idea of using EIR as beacon carrier is straightforward, we encounter several challenges to take advantage of it. In a lossy and indoor environment, EIR data might be lost or corrupted due to frequency hopping, collision, and obstacles. Such loss might lead to false negative on the beacons, triggering unnecessary user prompting. Furthermore, the EIR data that traverses through wall into adjacent room may lead to false positive and suppress necessary prompting. Therefore, the reception rate of EIR data, defined as the ratio of successfully received EIR count over total inquiry count, determines the feasibility of using Bluetooth for localization beacon in practical terms.

In the remaining part of this section, we will discuss the effects of key parameters, including inquiry duration, physical distance, and neighboring beacons with measurement results. Note that other parameters, such as data length, packet type, and inquiry type do not show significant impact on EIR reception and thus we omit their results due to page limit. In subsequent experiments Bluetooth ACL packet types are automatically chosen and inquiry type is set to Standard Inquiry Scan.

A. Inquiry Duration

We first study the impact of inquiry duration on EIR reception. The Bluetooth specification specifies that an inquiry should last for 10.24 secs to maximize the discovery probability. Analysis in [19] concludes that the inquiry duration can be reduced to 5.12 secs without endangering the effectiveness of discovery. To validate this analysis indoor, we place one beacon in the same room as a mobile device is in, and another beacon node is placed in the adjacent room where both are 2 metres apart from the mobile device. The device performs 100 inquiries with inquiry duration ranging from 3.84 secs to 10.24 secs, and we measure the reception rates. The results shown in Figure 1(c) suggest a weak trend under the decrease of reception rate for the above two cases (same and adjacent rooms), although it has more negative influence on adjacent rooms case. It also confirms that a 5.12-second-inquiry (i.e., inquiry duration slot 4 in the Figure 1(c)) would be sufficient for the discovery of beacons in the same room, achieving the balance between delay and desirable reception rate ($> 90\%$).

B. Environmental Factors

Because Bluetooth is a short-range radio, the reception rate of Bluetooth transceivers may be relevant to their surrounding environment as well. We perform a set of experiments to investigate the impact of the physical distance, obstacles on the propagation path, and interference from other Bluetooth devices.

- *Line-of-Sight (LOS) Scenario*: A beacon node and a mobile device are placed in the same office room with no obstacle in between. The distance between the nodes is increased from 1 metre to 6.5 metres, and a 5.12-sec inquiry is repeated 100 times for every 0.5 metre.
- *Non-LOS (NLOS) Scenario*: Same settings as in LOS scenario are used in this experiment, except that both nodes are moved to the other part of the room where obstacles such as plastic cubicle partitions, metal frames, and electronic devices are present.
- *Adjacent Room Scenario*: Bluetooth beacon is moved to adjacent room and the transceivers are separated by an approximately $5cm$ thick, wooden wall.
- *Interference Free (IF) Scenario*: Scenarios aforementioned are exposed to interference from multiple background Bluetooth devices, five of which are computers and two mobile devices. To study the impact of interference, immediately after each test in LOS and NLOS scenarios, we redo the same test with all interference sources eliminated.

Figure 1(d) shows the results of the first three scenarios and the interference free counterparts for LOS/NLOS scenarios. Overall, at least in our settings, distance does not show significant influence on the reception rate. In both LOS and NLOS scenarios, the reception rate stays above 85%, when transceivers are located within less than 6 metres. In the adjacent room scenario, the wooden wall does not act as a strong isolator to Bluetooth signal. The signal has transmission power enough to penetrate the wall and reach a neighboring room, and the reception rate varies between 60% and 75%. Nevertheless the decreasing trend and large variance compared to the relatively stable one in NLOS case still suggests large obstacles such as walls will have greater impact than smaller obstacles, which is in fact a desirable feature for our case. Therefore, in terms of reception rate, given distance within transmission range different kinds of obstacles will show more diverse influence than physical distance does, while both are not significant enough for isolating beacons from adjacent rooms. We can also note that the impact of interference from other Bluetooth devices is negligible, most likely due to the frequency hopping nature of Bluetooth discovery process.

C. Penetrating Beacon Discrimination

As shown in the previous experiment (i.e., the adjacent room scenario), the beacons can travel across rooms, and such penetrating beacons can cause significant impact on localization accuracy. Ideally, if Bluetooth beacon can be very well confined within a room, a prompting policy can only depend on whether a beacon is successfully received or not. However, in practice we found that Bluetooth signal from Class II adapter that is widely used in mobile devices has certain probability to penetrate walls into adjacent rooms, despite the use of low transmission power. If one device is located in a room without beacon nodes but accidentally receives penetrating beacons from an adjacent room, it will cause false positive—incorrect 'association' with the adjacent room. Therefore, the system has to be able to identify/exclude those penetrating beacons.

	$-RSSI_b \leq 79$	$79 < -RSSI_b \leq 83$	$83 < -RSSI_b$
p_b	0	0.5	1
	$D_{ob} \leq 7$	$7 < D_{ob} \leq 9$	$9 < D_{ob}$
p_w	0	0.5	1

TABLE I
EMPIRICAL PENALTY VALUES OF BLUETOOTH BEACON (p_b) & WI-FI (p_w)

To discriminate such penetrating beacons, lowering the transmission power of Bluetooth device is a straighforward approach. However not all off-the-shelf devices support power adjustment feature at the moment. Instead, we propose a threshold-based approach that uses both RSSI of Bluetooth beacon packet and the Wi-Fi fingerprints the beacon carries. We first show the benefit of using the beacon RSSI and then present a unified metric to integrate the both.

1) Using RSSI of Bluetooth Beacon: While RSSI of Bluetooth beacon is a weak indicator for inferring distance between adjacent nodes [14], [15], the RSSI does exhibit characteristics to distinguish beacon between rooms and wall-types obstacle. Figure 1(e) shows the CDF of RSSI for scenarios used in our previous experiments. As shown in the figure, in the adjacent room scenario, RSSI shows clear difference from ones in the same room scenarios. Thus, we use this value as another dimension to better discriminate penetrating beacons. Note that the impact of interference from background Bluetooth devices on RSSI distribution is again insignificant.

However, there are two major questions to answer before we use RSSI. First, because the frequency band of Bluetooth is divided into 79 slots, during an inquiry process, a device may receive multiple responses from the same beacon node in more than one frequency slot and their RSSI values might be different. We calculate the mean of all received RSSI values and use the mean as the received power of the beacon.

Next, we have to define a threshold to identify between the same room and the adjacent room. Figure 1(f) shows empirical statistics of RSSI values. We use the intersection of Adjacent Room Scenario and NLOS Scenario to derive a threshold for identifying neighboring spaces. However, considering the instability of wireless signal, as opposed to using an absolute threshold, we divide the RSSI range into three categories and assign penalty values to them for the space discrimination. The penalty values (p_b) are abstracted from empirical measurements (90th percentile in Figure 1(e)) and shown in Table I. We apply the same classification to Wi-Fi RMSE distance using empirical data from experiments in the previous section and derive penalty values for Wi-Fi (p_w).

2) Unified Metric: We now define a unified metric that jointly uses the RSSI of Bluetooth beacons and the Wi-Fi fingerprint carried by the beacons, as follows:

$$U_{ob} = (1 + p_b) \cdot (\frac{-RSSI_b - 50}{N}) + (1 + p_w) \cdot (D_{ob}), \quad (2)$$

where U_{ob} is the unified distance from observation o to beacon fingerprint b, $RSSI_b$ is the RSSI value extracted from beacon b, D_{ob} means the RMSE distance from observation o to beacon fingerprint b, calculated using Equation (1), p_b is penalty value given to beacon RSSI component, p_w is penalty value given to Wi-Fi RMSE component D_{ob}, and N is a constant for normalizing $RSSI_b$ to the same numerical scale as D_{ob}, so that the metric will not bias towards either Bluetooth or Wi-Fi. We choose $N = 4$. Once a Bluetooth beacon is received, RSSI of the beacon will be extracted, and so is the Wi-Fi

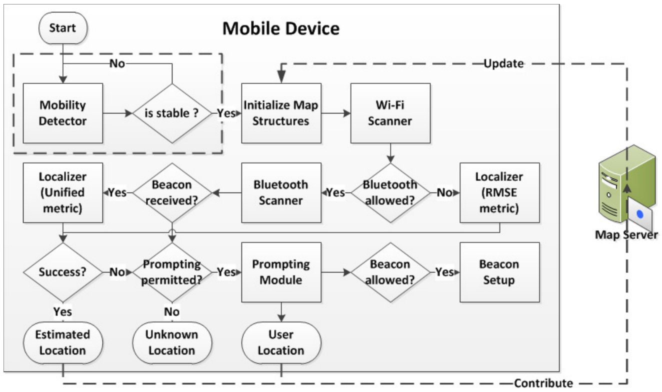


Fig. 2. System architecture

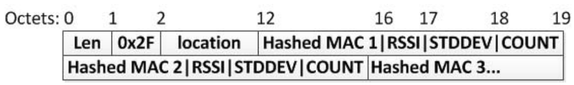


Fig. 3. EIR Payload Format - Fingerprint Consists of Location Information and Wi-Fi Observation List

fingerprint it carries. With fingerprint from beacon and local Wi-Fi observation, RMSE distance from local device to the beacon node is calculated, according to Equation (1). Based on their values and empirical thresholds shown in Table I, penalty values are assigned to the beacon RSSI and Wi-Fi RMSE distance, respectively as in Equation (2).

We will explain how U_{ob} is used to discriminate penetrating beacons, especially for prompting policy in the next section.

VI. System Design

This section describes our proposed system design to improve the performance of crowd-sourced Wi-Fi localization systems, based on the aforementioned observations and metrics defined. Note that we assume that a user device is equipped with both Wi-Fi and Bluetooth radios and that a user should be relatively stationary during localization.

Figure 2 illustrates the architecture and operation of our proposed design, which can be explained in the following steps. First, a Wi-Fi scan is performed to collect local Wi-Fi signal observation. If Bluetooth capability is disabled, the device should try to localize with standalone Wi-Fi localizer (i.e., modified RMSE). If Bluetooth is enabled, then it should start Bluetooth inquiry searching for nearby beacons. Here, the beacon search result determines the user prompting whose policy is described in Algorithm 1. If beacons are received, the device first identify whether the beacon(s) is transmitted from neighboring rooms by using the unified metric in Equation (2) (line $4-14$). If not (i.e., beacon from the same room), the device uses the location information from the received beacon (Figure 3 shows the message format of the beacon) with minimal unified metric value to localize. If no beacon is in the range or if the value derived from the unified metric is greater than a predefined threshold, the localizer considers current location as unexplored areas and prompts user for location input (line $15-25$). Once the system receives user input, the user can opt in enabling Bluetooth beacons for subsequent users entering the same space. Then, a beacon device should periodically perform Wi-Fi scan and compare the recent Wi-Fi observation to historical record in terms of RMSE distance. If drastic change that may imply re-location or movement is observed, then the beacon device should relinquish itself from beaconing and start re-localizing.

Algorithm 1 Prompting Policy

1: INPUT: Local observation $fgpt_o$; Received beacon count $bconcnt$; Received beacon list $bcon[bconcnt]$; Minimal distance $mindist$; Maximum distance MAX_DIST; Distance Threshold $THRESHOLD$;
2: OUTPUT: $prompt = \{TRUE, FALSE\}$
3: INIT: $mindist = MAX\_DIST$
4: **if** $bconcnt > 0$ **then**
5:   **for** $i = 1$ to $bconcnt$ **do**
6:     Extract $fgpt_b^i$, $RSSI_b^i$ from $bcon[i]$
7:     $D_{ob}^i = RMSE(fgpt_o, fgpt_b^i)$
8:     Decide penalty values p_w^i, p_b^i
9:     $U_{ob}^i = UM(RSSI_b^i, D_{ob}^i, p_w^i, p_b^i)$
10:     **if** $mindist > U_{ob}^i$ **then**
11:       $mindist = U_{ob}^i$
12:     **end if**
13:   **end for**
14: **end if**
15: **if** $bconcnt == 0$ **then**
16:   $prompt = TRUE$
17:   $setbeacon(fgpt_o)$
18: **else if** $bconcnt >= 1$ **then**
19:   **if** $mindist > THRESHOLD$ **then**
20:     $prompt = TRUE$
21:     $setbeacon(fgpt_o)$
22:   **else**
23:     $prompt = FALSE$
24:   **end if**
25: **end if**

VII. Performance Evaluation

To evaluate our proposed system, we first describe our Linux-based implementation and then show our evaluation results via both experiments and simulations.

A. Implementation Overview

We have implemented the proposed system as illustrated in Figure 2. For simplicity of implementation, we use Dell 5400 laptops equipped with Cirago (CSR chipset) BTA-3210 Class II Bluetooth USB dongle and Intel Wireless 5300AGN adapter, as our mobile device. We prototype the proposed components on Linux 2.6.41 kernel. Briefly, the Wi-Fi scanner (in Figure 2) calls *iw_scan* routine in Wireless Extension [20] and collects RSSI reported by the driver. To start inquiry and set up Bluetooth beacon, the Bluetooth scanner makes a system call provided by the HCI utility of Bluez [21] stack, and then extracts RSSI and EIR data using event filter. The fingerprints are stored based on their source: signal map, local cache, or Bluetooth beacon. Fingerprints in local cache can be appended to the signal map file for sharing purpose when needed. We expect all functionalities can be port to smartphones embedded with similar off-the-shelf chipsets.

B. Experimental Results

Using the implementation, we have performed experiments to evaluate the technical foundation of the proposed design, with respect to the probability of unnecessary prompting and accuracy. We examine two variables concerning the trigger of user prompting:

- Receive Failure: The probability that a device fails to discover an established beacon due to loss or corruption of Bluetooth beacon.
- Over-threshold Failure: The probability that a received Bluetooth beacon is discarded by the discriminator due to its U_{ob} distance being larger than the preset threshold.

Experiments are set up in our laboratory office with the size of approximately $5m \times 8m$ (see Figure 4). The office is

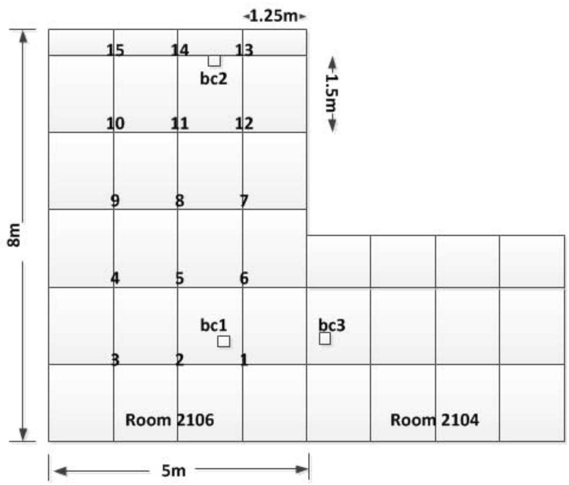


Fig. 4. Experiment Layout

gridded into 20 unit grids of a $1.25m \times 1.5m$ space, and a total of 15 sampling positions are drawn from the junction of unit grids.

1) Unnecessary Prompting Probability: In the above setting, we first study the probability of unnecessary prompting that is induced by the use of Bluetooth beacon. Users to be prompted are assumed to agree to set up Bluetooth beacons. Once the beacons are set up, unnecessary prompting probability is due to the aggregation of receive failure and over-threshold failure. At each sampling position, we let the system perform the localization 20 times and count the number of prompting out of 20, in the following two scenarios.

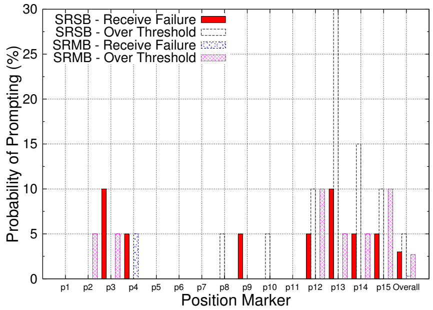
- *Same Room and Single Beacon (Scenario-1.1)*: One beacon, 2106_bc1, is set up to cover a entire room. A distance threshold value is set to 19 (moderate). The result for 15 sampling positions is illustrated in Figure 5(a) (SRSB cases). As shown in the figure, different positions possess varying characteristics in prompting probability. However, unnecessary prompting due to receive failure occurs with the probability of lower than 10%. Note that over-threshold failure accounts for a large portion of promptings at some positions. Nonetheless, if we assume the probability of a user appearing at each sampling position follows uniform distribution, the unnecessary prompting imposed by introducing Bluetooth beacon is 3% due to receive failure, and 5% due to over-threshold failure – only 8% in total.
- *Same Room and Multiple Beacons (Scenario-1.2)*: Result from scenario 1.1 suggests a single beacon may not be enough to cover the entire $40m^2$ room. In this experiment, one additional beacon, 2106_bc2, is set up near position $p13$ where the largest over-threshold failure has been observed, as indicated in scenario 1.1. Then, we performed the same experiment as in the scenario 1.1, and Figure 5(a) (SRMB cases) shows its result. As shown in the figure, the overall prompting probability from either beacon decreases significantly, and only one receive failure is recorded at position $p4$. The over-threshold failure is reduced as well owing to the additional beacon that covers its area.
  One interesting finding is that since the inquiry duration is fixed, areas that are crowded with beacons may experience increase in receive failure of individual beacon, despite the decrease in overall prompting. Since the rendezvous chance of Bluetooth frequency hopping is not necessarily related to distance between a mobile device and a beacon node, there is a possibility that such reduction happens to the beacon node that is actually closer to the mobile device. This contributes in part to the over-threshold failures as the mobile device only receives the signal from the distant beacon node rather than the nearby one. Even so, setting up multiple beacons reduces the unnecessary prompting in large space. It is possible to adopt an adaptive inquiry-duration that dynamically increases inquiry time in subsequent scans, if the mobile device stays in a crowded-beacon environment.

2) Accuracy: Next, we measure the location accuracy of our proposed system. When using Bluetooth as localization beacon, the localization accuracy might suffer due to false positive—mobile device hears the beacons from other rooms and incorrectly associates with the rooms. Therefore, we define accuracy as the complement of the sum of receive failure and over-threshold failure from beacon in the next room. Experiment settings are similar to Scenario 1.1 except that we place another beacon, 2104_bc3, at the adjacent room 2104 to investigate how much penetrating beacons affect different positions and the room as a whole. We also observe how the penetrating discriminator performs in these scenarios.

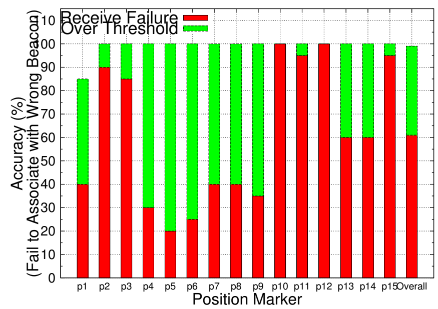
- *Adjacent Rooms and One Beacon (Scenario-2.1)*: This scenario simulates the early stage of crowd-sourcing when users walk into an unexplored area that is next to a populated region with beacon set up.
  Only 2104_bc3 is active. As shown in Figure 5(b), impacts of penetrating beacons are diverse, depending on their positions. The central area (p4 - p9), where only one wall stands between the beacon and mobile device, suffers from severe penetrating beacons. The rest of the room that is separated by office cubical partition shows a relatively mild effect. However, we can also observe that the penetrating beacon discriminator successfully excludes most of such beacons, even with a moderate threshold. *More than 95% of the penetrating beacons are filtered out.*
- *Adjacent Rooms and Two Beacons (Scenario-2.2)*: This scenario resembles the case where both rooms are explored and have beacon set up in each one. Both 2106_bc1 and 2104_bc3 are used, and Figure 5(c) shows a result. Similar to the previous scenarios, a total of 2% of packets from 2106_bc1 are lost, while for 2104_bc3 the probability is 54%. There are $18\,(6\%)$ unnecessary promptings being triggered, 3 of them are caused by receive failure from both beacons. However, the device is never incorrectly associated to 2104_bc3, the beacon from the other room. Penetrating beacons are either dismissed by localizer in favor of local beacon which is in shorter distance, or excluded by our beacon discriminator.

C. Simulation Study

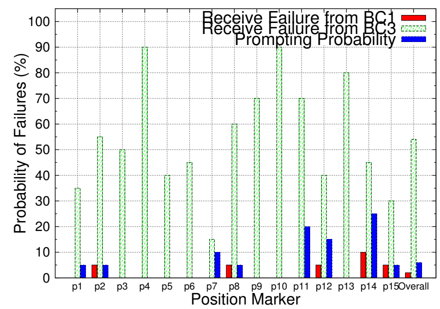
We also perform simulation study to evaluate the performance of the proposed design and compare it with existing crowd-sourcing scheme, under different user mobility patterns. For consistency, we use system parameters and threshold values obtained from our experiments. A 10×10 grid is used as a simulation layout to best resemble a large floor with a few dozen rooms. We generate random moving trace for users, but limit that a user can only stay or move to rooms that are immediately next to his current location in any single time slot. For simplicity, we consider a single beacon scenario and use a beacon reception rate of 92% as indicated in previous experiments. We also assume all penetrating beacons are filtered out by the beacon discriminator, resulting in a



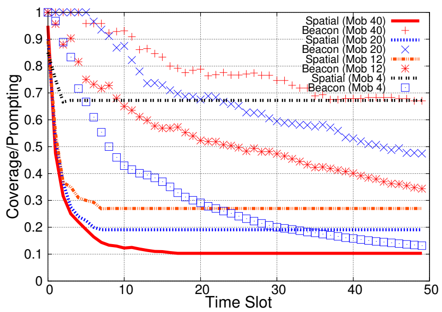
(a) Prompting Probability



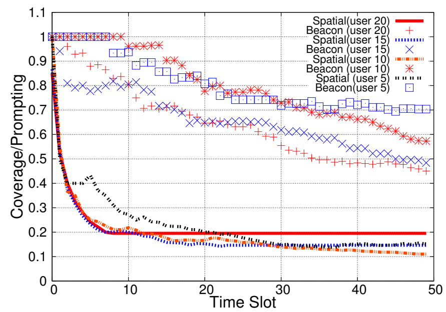
(b) Accuracy - Adjacent Room & Single Beacon



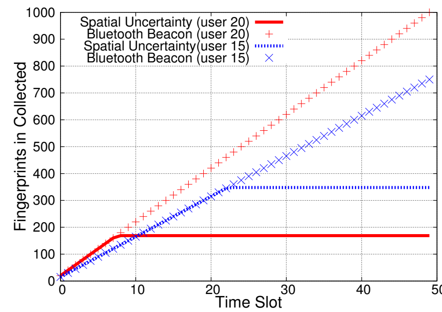
(c) Accuracy - Adjacent Room & Both Beacons



(d) Impact of Mobility Pattern on Prompting Efficiency



(e) Impact of User Number on Prompting Efficiency



(f) Comparison of Fingerprint Number

Fig. 5. Performance Evaluation: Figures (a)-(c) show experimental results and Figures (d)-(f) show simulation results

100% accuracy. For comparison, we also implement a spatial uncertainty approach [4]. All simulations are executed 50 times.

In addition, we study the prompting efficiency in terms of the ratio of explored grid numbers over total prompting counts, and the number of fingerprints collected by our Bluetooth approach and the uncertainty approach. Mobility pattern M is a parameter that determines user movement probability at each time slot. A user has a probability of $\frac{4}{M}$ to move and an equal chance in 4 directions. Number of user U specifies the number of contributors, who are the primary subjects we are interested in for crowd-sourcing systems.

1) Impact of Mobility Pattern on Prompting Efficiency: Figure 5(d) shows the impact of mobility pattern. We set u to 20 and measure the ratio of explored grid number over total prompting counts, as we increase M from 4 to 40. As shown in the figure, when $M = 4$ (i.e., users move every time slot), the Beacon approach has a low prompting efficiency since the beacon set up at previous time slot has to be relinquished as users move. However, as users become stationary, prompting efficiency of Beacon approach increases significantly and outperforms the spatial uncertainty approach.

In addition, we observe that at a certain point of the simulation, the spatial uncertainty approach simply stops prompting users even if only half of the area is covered. The reason for this behavior is that the uneven density of user movements eliminates spatial uncertainty around the explored areas too quickly, so that it confuses the localization system to believe there is no more unexplored area. On the other hand, in the Beacon approach, all areas can be explored eventually. As shown in Table II, at the end of simulation the coverage of Beacon approach is usually better than those in the spatial uncertainty approach.

2) Impact of Number of Users on Prompting Efficiency: Although more contributing users can improve coverage faster, it does not necessarily have a positive impact on the prompting efficiency. In this simulation, we fix $M = 20$ and increase U

	$M = 4$	$M = 12$	$M = 20$	$M = 40$
Coverage Count (Beacon)	100	89	83	57
Coverage Count (Spatial)	41	44	29	37
Prompting Count (Beacon)	760	259	175	85
Prompting Count (Spatial)	61	163	152	359

TABLE II
NUMBER OF COVERAGE AND PROMPTING AT THE END OF 50 ROUNDS

from 5 to 20. Results in Figure 5(e) indicate that the prompting efficiency of Beacon approach actually decreases as more users are added. This is due to the fact that more users may introduce more randomness in the mobility pattern, which creates an instability of beacon presence. In reality, mobility pattern is diverse. Some users are much stabler than others within certain particular space, who can work as anchor to minimize the effect of large group. In space where traffic is always dynamic, stationary anchor can be intentionally placed.

3) Comparison on Map Growth: We finally compare the effectiveness of the beacon approach in map growth with the uncertainty approach. In the Bluetooth beacon approach, because of its localization accuracy with high confidence, location estimates using Bluetooth beacon information can be considered as proper fingerprints and is used for signal map. On the other hand, for spatial uncertainty approach, when signal map is sparsely populated, the localization accuracy is low and thus only fingerprints provided by users can be treated as quality fingerprints. In Figure 5(f), we can see that fingerprints collected using the beacon approach have a linear relation with user number and time period, whereas the uncertainty approach becomes flat after certain time slots. The beacon approach collects more fingerprints, helping in populating signal map quickly.

VIII. Discussion

There are several remaining issues associated with the proposed localization system as follows:

User Incentive: The incentive issue is crucial for the success of any crowd-sourced system. Establishing Bluetooth beacon incurs two types of cost to beacon owner: power and privacy. However, as a beacon the Bluetooth device merely needs to be set in a discoverable mode and listen to the channel from time to time, which consumes only an additional power of 3mW [22], compared to its idle mode. Next, although Bluetooth MAC address revealed during inquiry might raise some privacy concerns, the effect is limited by the short transmission range of Bluetooth. Furthermore, we imagine most beacons would be set up by regular occupants of each space, who may willingly offer helps for guests and visitors. Nevertheless, since all beacon contributions can be recorded on the map, it is not difficult to provide contributors tangible incentive/reward.

Delay: When using non-modified wireless utility for Wi-Fi active scanning, the delay is approximately 1.2secs each round, and it becomes 12secs if we perform a full scan of 10 rounds. The total delay is around 18secs if one performs Bluetooth scans serially. This scanning period limits the viability of relying on the proposed system for real-time tracking or navigation. In the quest of trying to reduce this delay, we have found that it is undesirable to cut short the unit Wi-Fi scan duration, if accurate Wi-Fi observation is needed. As for the repetition times, [2] suggests a minimal 6-round scan is required to yield quality fingerprint. We will explore the possibility of performing Wi-Fi and Bluetooth scans in parallel as our future work, which can greatly alleviate the delay issue.

Erroneous Contribution: In current version of our prototype no error-detection mechanism is implemented yet. An outlier error-detection approach that clusters fingerprints in signal map described in [4] could work fine in our proposed system as well. The Bluetooth beacon scheme with the penetrating beacon discriminator can reduce the need for user input while improve fingerprint quality at bootstrapping stage, and thus reduce the probability of erroneous contributions to some extent. In the system, fingerprints collected through localizer are less trustworthy than those created by user, until the fingerprints pass error detection mechanism. Therefore, if a submitted fingerprint is associated with incorrect location, it will not affect the system immediately. However, there still remains the possibility of malicious users who set up misleading beacons. Because of the limited transmission range and penetrating beacon discriminator, the influence of malicious beacon will be limited to local areas.

IX. Conclusion

This paper has presented an indoor localization system that uses user-managed Bluetooth beacons to improve the crowd-sourcing performance of Wi-Fi localization systems. Use of Bluetooth beacons facilitates the construction of signal map, which is crucial for Wi-Fi localization, and can help reduce the prompting for new users. Further, we have identified several technical challenges in using the Bluetooth via experiments and propose new design and metrics, including the penetrating beacon discriminator. In addition, our prompt policy allows users to exploit existing Bluetooth beacons and/or help set up beacon nodes to improve signal map growth. A prototype has been implemented on Linux platform. Its evaluation results demonstrate the viability of the proposed system, and shows improvement over existing crowd-sourcing solutions in terms of prompting efficiency, accuracy, and map population.

As part of future work, we plan to carry out large-scale evaluations and user study with a large number of student volunteers. Furthermore, the feasibility of integrating non-RF elements such as ultrasound into the beacon discriminator to further improve its effectiveness will be investigated.

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