INDOOR SMARTPHONE LOCALIZATION VIA FINGERPRINT CROWDSOURCING: CHALLENGES AND APPROACHES

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ABSTRACT

Nowadays, smartphones have become indispensable to everyone, with more and more built-in location-based applications to enrich our daily life. In the last decade, fingerprinting based on RSS has become a research focus in indoor localization, due to its minimum hardware requirement and satisfiable positioning accuracy. However, its time-consuming and labor-intensive site survey is a big hurdle for practical deployments. Fingerprint crowdsourcing has recently been promoted to relieve the burden of site survey by allowing common users to contribute to fingerprint collection in a participatory sensing manner. For its promising commitment, new challenges arise to practice fingerprint crowdsourcing. This article first identifies two main challenging issues, fingerprint annotation and device diversity, and then reviews the state of the art of fingerprint crowdsourcing-based indoor localization systems, comparing their approaches to cope with the two challenges. We then propose a new indoor subarea localization scheme via fingerprint crowdsourcing, clustering, and matching, which first constructs subarea fingerprints from crowdsourced RSS measurements and relates them to indoor layouts. We also propose a new online localization algorithm to deal with the device diversity issue. Our experiment results show that in a typical indoor scenario, the proposed scheme can achieve a 95 percent hit rate to correctly locate a smartphone in its subarea.

INTRODUCTION

Location-based services, such as targeted advertisement, image geotagging, and proximity social networking, have become more and more popular with the widespread use of smartphones. A smartphone can use its Global Positioning System (GPS) unit to obtain accurate location information in outdoor environments. However, a GPS unit often performs poorly in indoor environments due to its weak reception of satellites' signals. Many indoor localization techniques have been proposed, which have different hardware requirements and localization performances [1–3]. Among them, the fingerprinting technique has recently become a research focus.

The basic idea of fingerprinting is based on the assumption that each indoor spatial location can be identified by a unique measurable feature, just like a human fingerprint. Many ambient physical quantities can be used as a fingerprint, including radio signals, geomagnetism, light, sound, and so on. Since wireless local access networks (WLANs) are widely deployed as indoor access systems, the mostly used fingerprint is the received signal strength (RSS) from access points (APs) of WLANs. Fingerprinting localization generally consists of two phases: offline training and online positioning. In the offline training phase, site survey is conducted to obtain the fingerprints for some evenly distributed reference points (RPs). In the positioning phase, the observed fingerprint of a smartphone is compared to those pre-stored RPs' fingerprints, and its location can be estimated via deterministic or probabilistic positioning. For example, in deterministic nearest neighbor positioning, the RP with the least fingerprint difference is selected as the estimated location.

A key factor impacting the fingerprinting accuracy is the RP granularity (i.e., the number of RPs per unit area). In general, increasing the RP granularity may help to improve localization accuracy. However, conducting a site survey for a large environment with dense RPs is very time-consuming, labor-intensive, and cost-prohibitive. In a traditional site survey, a surveyor needs to collect and annotate measurements at one RP for some time to reduce variations. In our previous experiments, it took about 10 h for two graduate students to complete a site survey for 150 RPs in an office floor of 281 m^2. Furthermore, a site survey may become very expensive if it is contracted to professional surveyors. Even worse, once an indoor environment changes, such as by furniture relocation, or AP exclusion or inclusion, extra site surveying is needed to update the fingerprint database.

To relieve the burden of site survey, crowdsourcing has recently been promoted as an alternative for fingerprint collection. The essential concept is to allow common users to contribute

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their measurements in a participatory sensing way. The Indoor Maps project by Google[1] and OpenStreetMap project by Microsoft[2] are examples. As crowdsourcing shifts the tedious site survey to crowds, it can not only help save costs, but also enable adaptive database update according to environment changes. For its promising commitment, however, new challenges arise to successfully practice crowdsourcing for indoor localization.

In this article, we first survey the state of the art of fingerprint crowdsourcing, analyzing its challenges and comparing recent approaches. In [1], Gu *et al.* provide a comprehensive survey of various indoor localization systems, with the emphasis on comparing the use of different types of hardware. Harle [2] surveys pedestrian dead reckoning systems via wearable inertial sensors, such as accelerometer, gyroscope and magnetometer. In [3], Subbu *et al.* provide a brief review of indoor localization based on smartphone platforms, focusing on the comparison of energy consumption, sensor variation, and computational cost. Compared to these studies, our emphasis is on the taxonomy and comparison of different smartphone-based fingerprint crowdsourcing techniques. Furthermore, we propose a new indoor subarea localization scheme. Building on the crowdsourced and unlabeled fingerprints, it first constructs fingerprint clusters, and relates them to an indoor subarea layout via our cluster-subarea matching algorithm. We also propose a new online localization algorithm to deal with device diversity. Our preliminary experiments validate its effectiveness in terms of over 95 percent hitting rate as well as the improvement of dealing device diversity over the classic nearest neighbor (NN) localization algorithm.

Localization via Fingerprint Crowdsourcing: Challenges and Approaches

Challenges

The philosophy of the fingerprinting technique is to obtain the mapping from the physical space to the fingerprint space via training, and use the inverse mapping for localization. Although the idea of fingerprinting is simple, many challenging issues need to be addressed first for its successful application. Some common challenges include the fingerprint composition, data collection, mapping construction, online localization, energy consumption, computation complexity, and and so on.

Fingerprint crowdsourcing mainly changes the fingerprint collection paradigm by shifting the site survey from professional surveyors to common users. However, measurements by crowds are no longer guaranteed to be performed at the specified RPs, and they may be obtained from different devices, which causes new challenges pertaining to fingerprint crowdsourcing-based indoor localization. In this article, we identify two main challenging issues: *fingerprint annotation* and *device diversity*.

In order to link the fingerprint signal space to the physical Euclidean space, each training fingerprint needs to be annotated with the location information on where it is collected. Fingerprint annotation with location information can be performed explicitly with user intervention, and we call such approaches *active fingerprint crowdsourcing*. An alternative is to infer the fingerprint location without user intervention, which we call *passive fingerprint crowdsourcing*. Location inference can be achieved by exploiting the smartphone built-in sensor measurements that can be simultaneously obtained with fingerprints.

Device diversity is another challenging issue. As diverse smartphone brands and models are used by crowds, their different hardware specifications may cause inconsistencies of fingerprint measurements and AP detection, even at the same location and time. How to build on a cross-device fingerprint database and appropriately apply it in the online positioning phase are important to the success of crowdsourcing-based localization.

Active Fingerprint Crowdsourcing

In traditional fingerprinting localization, surveyors explicitly annotate fingerprints with the RP location information, normally the Cartesian coordinates. As active crowdsourcing, on the other hand, shifts the annotation work from professional surveyors to common users, it is not practical to request them to do sampling at specified RPs. To facilitate user annotation, several systems have been designed with the aid of a floor plan [4–6] or without [7–10].

Redpin [4], OIL [5], and OIL extension [6] prompt a user to bind her/his measurements with her/his recognized location on the floor plan, just like putting a pin on the displayed map. Instead of using exact floor maps, Molé [7], Elekspot [8], and FreeLoc [9] propose to use semantic labels to bind measurements with locations, such as rooms, hallways, and corridors. Furthermore, Molé suggests using a hierarchical name space for organizing different indoor environments. For this kind of semantic location labeling, in the online positioning phase a smartphone will be assigned to the semantic location.

Unlike most fingerprints using RSS measurements, GROPING [10] uses geomagnetism for fingerprints, which can be measured by the magnetometer of a smartphone. GROPING also does not require a floor map; instead, it can construct a semantic one via annotated walking trajectories. For example, Fig. 1 illustrates using walking trajectories for fingerprint annotation. For the walking trajectory $\overset{\frown}{ACDG}$, a user can annotate the starting point A, turning points C and D, and ending point G. With many such trajectories, GROPING extracts unique segments, and then links them to form a semantic navigation map.

A unique challenge of active crowdsourcing is that a user may bind a wrong location with her/his measurements, either intentionally or unintentionally. Park *et al.* [5] summarize three categories of mistaken contributions: selecting a wrong room or floor, typing a wrong semantic name, and polluting a bind with measurements from distinct places due to movement. In OIL [5], based on the assumption that most users would like to provide a correct contribution, the problem of wrong selection is approached by

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[1] http://www.google.com/maps/about/partners/indoormaps/

[2] http://www.openstreetmap.org/

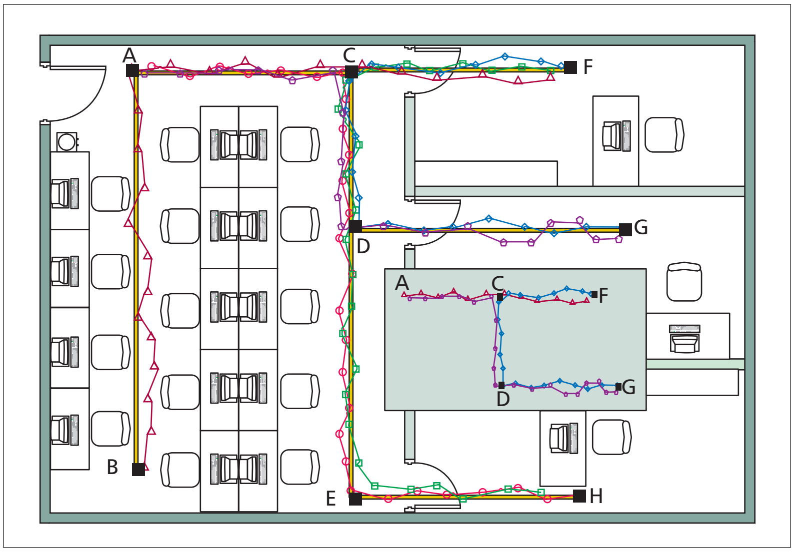

Figure 1. Illustration of using walking trajectories for fingerprint annotation. A walking trajectory along with its start point, turning point(s), and endpoint can be deduced from smartphone sensors' measurements. From crowdsourced walking trajectories, multiple segments can be obtained via some data mining technique. A segment can provide either semantic location information or physical coordinate information with the aid of a floor plan, by which the fingerprints of a walking trajectory can be annotated. In the smaller figure, from crowdsourced three walking trajectories, $\overset{\frown}{ACF}$, $\overset{\frown}{ACDG}$, and $\overset{\frown}{FCDG}$, four segments, $\overline{AC}$, $\overline{CD}$, $\overline{CF}$, and $\overline{DG}$, can be obtained.

using a clustering algorithm to group similar fingerprints and to detect fingerprint outliers.

Passive Fingerprint Crowdsourcing

Although prompting users to actively annotate fingerprints is the most straightforward way, it may be too intrusive to some users with undesired interruptions. Passive crowdsourcing, on the other hand, performs location annotation without user intervention, which can be realized with the help of smartphone inertial sensors. Typical built-in sensors include accelerometers, gyroscopes, magnetometers, and barometers, and they can provide measurements of acceleration, rotational velocity, direction, and altitude.

As a background process, passive crowdsourcing records a period of RSS and sensors' measurements with timestamps to create a user movement trajectory in the fingerprint space. Three components can be extracted from a movement trajectory: walking steps, heading directions, and stride length. The first two can be derived from measurements by the accelerometer and magnetometer, and the stride length can use an empirical value or extract from a fitted Gaussian distribution. If we can match a movement trajectory from the fingerprint space to the physical space, fingerprint annotation is simultaneously done. Several algorithms have been proposed for this matching, with the aid of a floor plan [11, 12] or without [13, 14].

Based on the exact floor layout, Zee [11] leverages underlying physical constraints, such as walls, pathways, and partitions, to obtain possible walking routes for matching. If the analysis from sensors' measurements indicates a zigzag path in the fingerprint space, while the map suggests that only one physical route can accommodate this kind of a zigzag path, some physical locations can be identified to annotate fingerprints on this trajectory. For example, in Fig. 1, if a walking trajectory is identified with a zigzag path like <A, C, D, E, H>, it can be linked to this physical route, as there is only one such physical trajectory in the floor plan. LiFS [12] proposes to reform the physical floor map to a new stress-free floor plan, in which the distance between two locations in the new map represents the practical walking distance in the physical map. In the fingerprint space, the moving distances in a walking trajectory are derived from accelerometer readings, and trajectories are matched to the stress-free map, by which fingerprints can be annotated with physical locations in the original floor map.

ARIEL [13] does not need a floor plan, but it only provides room-level localization. Thus, its objective is to distinguish rooms in the fingerprint space and extract their fingerprints from crowdsourced measurements. Since RSS and sensors' measurements are obtained simultaneously, ARIEL [13] first determines those stationary RSS fingerprints according to the acceleration samplings and clusters them into several hotspot zones. It then applies another motion-based clustering algorithm to identify inter-zone correlation and groups hotspots into different rooms to obtain room fingerprints. PiLoc [14] seeks to construct a floor plan merely from walking trajectories in the fingerprint space instead of using an off-the-shelf map. In PiLoc, a walking trajectory is divided into several segments based on the analysis of sensors' measurements, like using a derived turning point to divide a trajectory into two or more segments. For example, the derived turning point C and D can help to divide the walking trajectory

$\overset{\frown}{ACDG}$

into segments of

$\overline{AC}$, $\overline{CD}$, and $\overline{DG}$.

Multiple walking segments from crowdsourced trajectories are then merged to represent the same piece of a physical route. A physical floor map can then be constructed from such derived routes, through which fingerprints on trajectories can be annotated by the derived locations.

Dealing with Device Diversity

Device diversity is an inherent characteristic of crowdsourcing, for users have various brands and types of smartphones. Different radio chips and antenna designs of diverse smartphones may lead to different values of RSS measurement of the same AP even at the same location and time. Several approaches have been proposed to address this problem, and can be categorized in two groups according to whether adopting fingerprint inter-device calibration [6–8] or intra-device transformation [9, 13].

The reason for using fingerprint inter-device calibration is based on the assumption that there is some linear relation between two different devices' RSS measurements. Elekspot [8] maintains an inter-device calibration matrix for all supported devices, in which an element $a_{ij} (i \neq j)$ describes the linear relation between the fingerprint from device i and the one from device j. It is

System	Year	Crowdsourcing	Floor plan	Assistant sensors*	Device diversity**	Localization	
						Point (m)***	Room (%)
Redpin [4]	2008	Active	With	None	–	–	90
OIL [5]	2010	Active	With	None–	5.3	–	
OIL ext. [6]	2011	Active	With	None	Inter-calib.	–	–
Molé [7]	2011	Active	Without	Acce.	Inter-calib.	–	90.7
Elekspot [8]	2012	Active	Without	None	Inter-calib.	–	56.15 ~ 100
FreeLoc [9]	2013	Active	Without	None	Intra-trans.	<3	–
GROPING [10]	2015	Active	Without	Acce., gyro., magn.	-	<5	–
Zee [11]	2012	Passive	With	Acce., gyro., magn.	–	1	-
LiFS [12]	2015	Passive	With	Acce.	–	1.5	–
ARIEL [13]	2012	Passive	Without	Acce.	Intra-trans.	–	95
PiLoc [14]	2014	Passive	Without	Acce., gyro., magn.	–	1.37	-

* Acce.: accelerometer; Magn: magnetometer; Gyro: gyroscope
** Inter-calib.: inter-device calibration; Intra-trans.: intra-device transformation
*** Average or median localization error

Table 1. Fingerprint crowdsourcing-based indoor localization systems.

updated by a linear regression function with the input of the two devices' fingerprints obtained at the same location. The extension of OIL [6] particularly studies the device diversity problem for the OIL localization system. As the measured RSS values from an AP at a particular location are kind of randomly distributed within a range, Park *et al*. [6] suggest taking this RSS dispersion into consideration for inter-device calibration. They propose using a kernel density estimator to model the RSS distribution, and apply the linear correlation in the mean value of RSS measurements for a pair of devices. Also, their experiments suggest that using a kernel width of 1.5~2 times the standard deviation of RSS measurements achieves higher cross-device localization accuracy. Molé [7] adopts the approach of OIL extension [6] to deal with device diversity.

However, inter-device calibration increases the complexity of fingerprint database. Both FreeLoc [9] and ARIEL [13] propose to transform the RSS measurement vectors to relative RSS orderings as fingerprints. Let (ap_1, …ap_i, …, ap_N) denote the AP index vector sorted according to the decreasing order of their respective RSS value. FreeLoc [9] uses a *Key-Value* mechanism to construct a fingerprint. Each ap_i is seen as a key, and its value is a set of other APs with RSS values smaller over δ. ARIEL [13] proposes to use a subsequence of an ordered AP index vector with length $n < N$ as the room fingerprint to achieve room-level localization, which is based on the assumption that each room would have a unique fingerprint of such a truncated and reordered RSS vector. Notice that this intra-device transformation loses exact RSS values for APs. Therefore, they might not be able to realize fine point localization, but they are shown to be good enough for room-level localization.

Comparison

Table 1 summarizes all the surveyed fingerprint crowdsourcing-based indoor localization systems. Notice that the accuracy attributes are extracted from each published paper, but are obtained in much different experiment environments. The point-level accuracy is the mean or median error between estimated and actual place, while the room-level accuracy is the hitting rate when locating a user in a correct room. Note that Elekspot [8] conducts experiments in three scenarios with four algorithms. Thus, their room-level hitting rate varies from 56.15 to 100 percent. As commented by Harle [2] and Subbu *et al.* [3], it is difficult to make a fair comparison of their localization performance due to the lack of uniform test methodologies and environments. However, their results still provide insights about how an indoor localization system could perform for practical applications. Also, we notice that a public competition was just conducted (Microsoft Indoor Localization Competition-IPSN 2014[3]), which could provide a valuable platform for validating various indoor localization schemes.

A New Indoor Subarea Localization Scheme

We next propose a new indoor subarea localization scheme based on passive fingerprint crowdsourcing. In some scenarios and applications, it may be enough to locate a smartphone in some subarea of a large indoor environment, as the exact location within the subarea can be revealed

[3] http://research.microsoft.com/en-us/events/ipsn2014indoorlocalizationcompetition

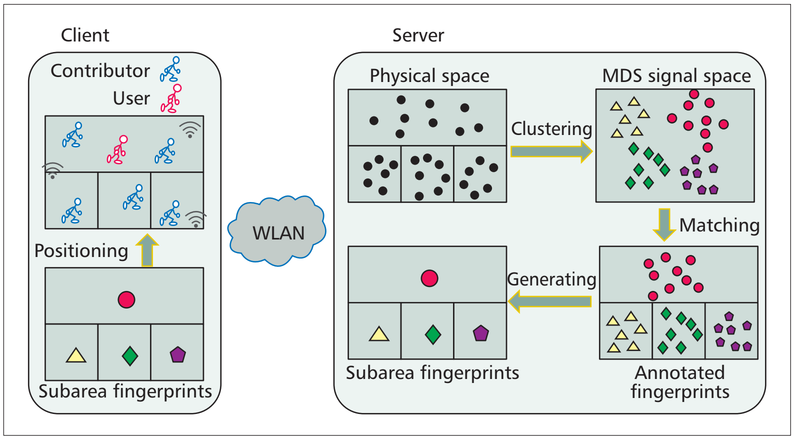

Figure 2. Illustration of the proposed system architecture. The server clusters the crowdsourced fingerprints, matches each cluster to one subarea to generate a subarea fingerprint, and constructs the indoor subarea fingerprint database. A client can download the subarea fingerprint database for its online subarea localization.

in sight by the smartphone holder. For example, in a large shopping mall, if a person can obtain the subarea information about within which store she/he is now staying, he can use a floor layout map to decide the route to walk to her/his next destination store. Usually, subareas can be obtained as the inherent functional division for an indoor environment, such as an office room, or a part of corridor between two office rooms.

The system architecture is illustrated in Fig. 2. In the offline phase, the server collects unlabeled RSS fingerprints via passive crowdsourcing and applies a clustering algorithm to group them into several clusters, each of which is matched to one subarea in order to generate a subarea fingerprint. The sever then constructs a subarea fingerprint database, which can be downloaded by a client for its online subarea localization. The subarea fingerprint database can be easily updated, after a new batch of unlabeled RSS measurements has been collected.

Besides fingerprint crowdsourcing, our scheme can be further divided into fingerprint clustering, cluster-subarea matching and subarea positioning. Assuming that N APs are located within an indoor environment that is divided into K subareas. Let M denote the number of *sampling points* (SPs) within the indoor environment. Note that a sampling point can be as simple as one RSS measurement yet with unknown location. Let $\mathbf{r}_i = (r_{i1}, \ldots, r_{in}, \ldots, r_{iN})$ denote the RSS fingerprint of the ith SP, where r_{in} is the RSS from the nth AP.

Fingerprint Clustering

To cluster crowdsourced fingerprints into different subareas, we adopt the new clustering algorithm which is published in Science [15] recently. As the authors do not name their algorithm, we use their family initials to call it s the *RL-clustering* algorithm here. The RL-clustering algorithm combines the advantages of several classical clustering strategies like K-medoids and DBSCAN [15]. The basic idea of this algorithm is that *cluster centers are surrounded by neighbors with lower local density, and they are at a relatively large distance from any points with higher local density*. Furthermore, RL-clustering can detect non-spherical clusters well and produce any given number of clusters.

For a given SP fingerprint $\mathbf{r}_i$, two quantities are considered: its local density ρ_i and its difference distance δ_i. The local density ρ_i is defined as the number of SP fingerprints $\mathbf{r}_j$ ($j = 1, 2, \ldots, M$) with Euclidean distance between $\mathbf{r}_i$ smaller than a *cutoff distance* d_c. Let d_{ij} denote the Euclidean distance between the ith and jth SP fingerprint. Let Ω_i denote the set of fingerprints with local density higher than $\mathbf{r}_i$. If $\mathbf{r}_f \in \Omega_i$ is the fingerprint with the minimum distance d_{if} among any other fingerprint in Ω_i, this minimum distance value d_{if} is defined as the *difference distance* δ_i for $\mathbf{r}_i$. We say that the $\mathbf{r}_f$ is the father of $\mathbf{r}_i$, and $\mathbf{r}_i$ is in turn the child of $\mathbf{r}_f$. If more than one $\mathbf{r}_f$ have the same minimum distance between $\mathbf{r}_i$ in Ω_i, we randomly choose one of them as the father of $\mathbf{r}_i$. For the highest density SP fingerprint $\mathbf{r}_i$, its difference distance is chosen as the maximum value of $\delta_j(\rho_j \neq \max(\rho_i))$.

$$\delta_i = \begin{cases} \min_{j:\rho_j > \rho_i} d_{ij}, & \rho_i \neq \max(\rho_j) \\ \max_{j \neq i} \delta_j, & \rho_i = \max(\rho_j) \end{cases} \quad i, j = 1, 2, \ldots M. \tag{1}$$

In the fingerprint clustering process, we need to consider how to select cluster centers, denoted by C_k, $k = 1, 2, \ldots, K$. After obtaining ρ_i and δ_i, a *decision graph* can be plotted to facilitate cluster center selection. A decision graph from one of our experiments is plotted in Fig. 3, where each dot represents an SP fingerprint. We label six points in Fig. 3. The RL-clustering algorithm suggests choosing K cluster centers according to the value of $\rho_i \times \delta_i$ from the largest in descending order. For $K = 4$, it would result in points {1, 2, 3, 4} being selected. According to the definition of difference distance, we know that only local or global maxima density fingerprints with very large value of δ are good candidates for cluster centers. As shown in Fig. 3, as $\mathbf{r}_2$ ($\mathbf{r}_4$) has relatively small value of δ, it is not likely to be a local maxima or global maxima density fingerprint. Thus, it is not an appropriate choice for a cluster center. Therefore, we suggest that it is better to not only consider the value of $\delta \times \rho$, but also avoid choosing too small δ.

We next propose a modified method with two selection thresholds ρ^{th} and δ^{th}: ρ^{th} is defined as the β percentile of all ρ_is in descending order, and ρ^{th} the γ percentile of all δ_is, also in descending order. Let Φ denote the set of SP fingerprints with both $\rho_i > \rho^{th}$ and $\delta_i > \delta^{th}$. Cluster centers are then selected as the K SP fingerprints in Φ with the value of $\rho_i \times \delta_i$ from the largest to the Kth largest. If there are less than K such fingerprints in Φ, we enlarge the search zone by simultaneously increasing β and γ with a fixed step. Note that the initial value of β is larger than γ. This is because δ_is are much larger than the typical nearest neighbor distance only for points that are local or the global maxima in density.

Take Fig. 3 as an example. In the first loop, there are only two candidate points in Φ. Then we increase the search zone until there are no less than K points. In this example, points {1, 2, 3, 4} are the four points with largest $\rho \times \delta$. However, our method selects Φ = {1, 3, 5, 6} finally.

[3] http://research.microsoft.com/en-us/events/ipsn2014indoorlocalizatinocompetition

Note that point 5 is not the fifth largest $\rho \times \delta$; that is point 6.

After selecting K cluster centers $C_k(k = 1, \ldots, K)$, all the offspring of C_k are grouped into the kth cluster, denoted by $\mathcal{R}_k$, $k = 1, \ldots, K$.

Cluster-Subarea Matching

After fingerprint clustering, we need to further match each cluster to one subarea. We first propose to apply the *multi-dimensional scaling* (MDS) method to transform each N-dimensional SP fingerprint to a two-dimensional MDS location. To match each cluster to one subarea, we propose to exploit the geometric relation of subarea centers. We argue that if the Euclidean distance between a subarea center S_1 and S_2 is smaller than that of S_1 and S_3, the fingerprint distance between S_1 and S_2 is also likely to be smaller than that of S_1 and S_3. As we assume knowledge of the indoor layout, we also know the Euclidean coordinate of a subarea center point. Let (x_k, y_k) denote the Euclidean coordinate of the kth subarea center, and let $\mathbf{D}_s = [s_{ij}]_{K\times K}$ denote the normalized distance matrix of subarea centers. Similarly, we let (x_k^m, y_k^m) denote the MDS location of the kth cluster center, and $\mathbf{D}_m = [s_{ij}^{(m)}]_{K\times K}$ the normalized distance matrix of cluster centers. Note that we can arrange the index of K clusters to generate in total $K! = K \times (K-1) \cdots \times 1$ different cluster-subarea matching schemes. We propose to select one matching scheme that can minimize the total pairwise distance difference of all cluster centers and subarea centers, that is,

$$\arg\min_{\mathbf{D}_m} \sum_{i=1}^{K}\sum_{j=1}^{K}\left|s_{ij} - s_{ij}^{(m)}\right|, m = 1, 2, \ldots K!, \tag{2}$$

Subarea Positioning

For each cluster $\mathcal{R}_k$, we define its cluster fingerprint $\mathbf{R}_k = (R_{k1}, \ldots, R_{kN})$ as the average RSS of the SPs in $\mathcal{R}_k$. The cluster fingerprint is also used as its corresponding subarea fingerprint. To deal with the device diversity issue, we propose a novel online subarea localization algorithm, called VAR, to locate a fingerprint $\mathbf{r}^o = (r_1^o, \ldots, r_N^o)$ into a subarea k. The basic idea is that the RSS measurements from different smartphones often show an inherent bias due to device diversity, which means the RSS differences between different smartphones among APs in the same position are more stable than other positions. Hence, the observed fingerprint can be located in the subarea with the least variance of RSS differences among APs, which can be computed by

$$\hat{s} = \arg\min_k \frac{1}{N}\sum_{n=1}^{N}\left((r_n^o - R_{kn}) - \bar{r}_k\right)^2, \quad k = 1, \ldots K. \tag{3}$$

where $\bar{r}_k$ is the average of $((r_1^o - R_{k1}), \ldots, (r_n^o - R_{kn}))$.

Experiment Results

The experiment site is a typical office scenario, with the floor layout illustrated in Fig. 1. It has an area of 10.7×7.5 m^2, and four functional subareas are divided by frosted glass walls.

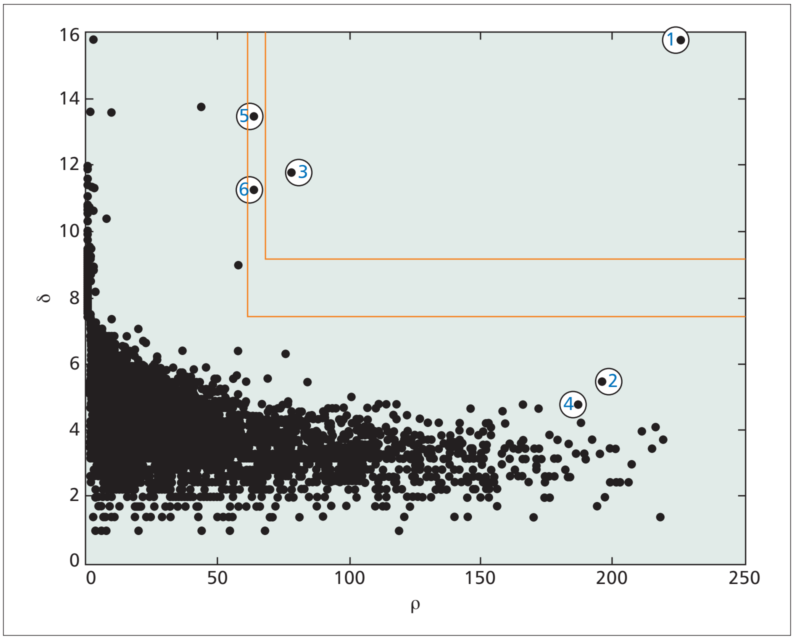

Figure 3. Decision graph from one of our experiments with in total 5000 sampling points.

The largest one is for students, and the three smaller ones are for staff. In our experiments, six TP-Link TL-WR740N wireless routers were used as APs, and three types of smartphones — Lenovo A820T, Huawei Hol T00, and Samsung GT-I9050 — were used to collect RSS measurements at random locations. We did not control the indoor environment during our measurement process: RSS measurements were collected on different days; people walked around and into/out of the rooms arbitrarily. In our data collection, we recorded the true subarea for each RSS fingerprint, and collected in total 17,800 fingerprints. In our selection method, we initialize $K = 4$, $\beta = 15$, and $\gamma = 1$ at first. Each time the number in Φ is smaller than K, we increase both β and γ by one.

We consider two performance metrics. The cluster-subarea matching rate P_m is defined as the ratio of the number of correctly locating a cluster center in a subarea to the subarea number K, and the fingerprint-subarea hitting rate P_h is defined as the ratio of the number of correct subarea localization fingerprints to the total number of testing fingerprints. The results also compare the proposed VAR localization algorithm with the classical NN algorithm.

In Fig. 4, we use mixed SPs from different smartphones to generate the subarea fingerprints. As using mixed SPs does not differentiate the RSS measurement bias due to using different smartphones, it is observed that different smartphones exhibit similar localization performance. However, the performance of both P_m and P_h are not very satisfactory, with the best performance no larger than 70 percent. This is because the bias of RSS measurements caused by diverse radio chips in different smartphones will degrade the clustering performance.

An alternative is to use RSS measurements from only one type of smartphone for clustering and generating subarea fingerprints. Figure 5 plots the localization performance against the number of SP fingerprints M using RSS measurements only from Lenovo A820T. It is first observed that both P_m and P_h increase with the increase of M, and become stable when M is large enough. Due to the device diversity issue, the localization results using other smartphone types are inferior to those using Lenovo A820T. However, compared to the NN algorithm, our proposed VAR improves the hitting rate from 91.8 to 94.7 percent for Huawei Hol T00 and 83.1 to 91.2 percent for Samsung GT-I9050, without degrading the performance for the homogeneous devices when $M = 6000$, which validates its effectiveness in dealing with device diversity.

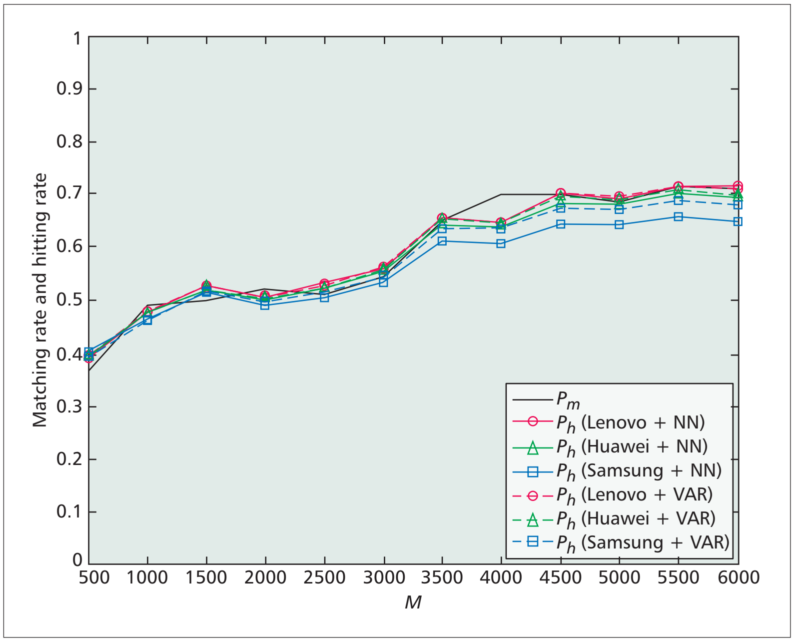

Figure 4. Experiment performance using mixed SPs.

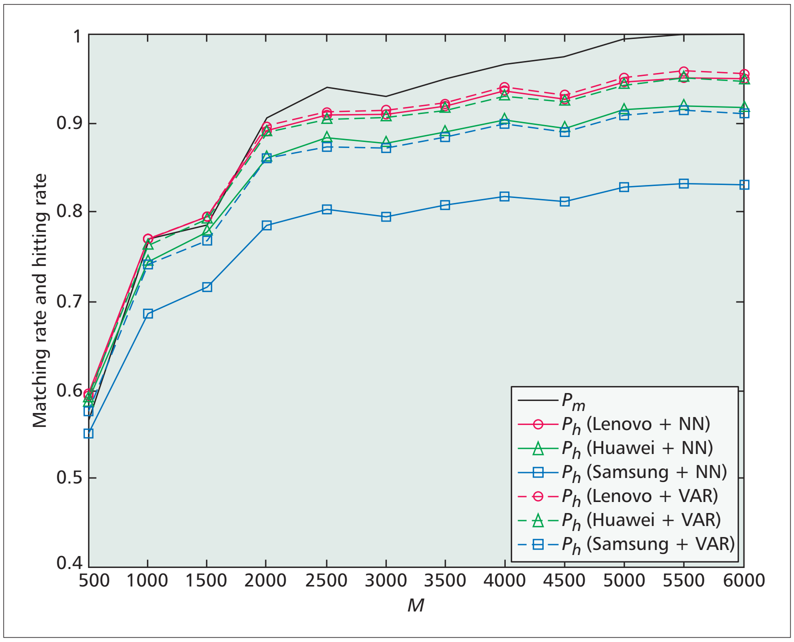

Figure 5. Experiment performance vs. the number of sampling points.

Concluding Remarks

To enable ever increasing location-based services, many indoor localization schemes have been proposed. Among them, we believe that RSS fingerprinting is the most promising approach, as it has the lowest hardware requirement and can exploit ubiquitous WLANs. To eliminate time-consuming and labor-intensive site survey, fingerprint crowdsourcing has been promoted for radio map construction. To successfully apply crowdsourcing, two challenges need to be addressed first: fingerprint annotation and device diversity. This article has reviewed recent approaches to cope with the two challenges, and proposes fingerprint passive crowdsourcing and unsupervised clustering for indoor subarea localization. In our future work, more experiments in large-scale indoor environments will be conducted. How to dynamically update the fingerprint database will also be further investigated.

We would like to close the article with some comments from the viewpoint of users. The location information could be explicitly used by a user, or implicitly exploited by a smartphone app. For both cases, we consider that passive crowdsourcing would be a better choice due to its nonaggressive implementation. On the other hand, as active crowdsourcing is more efficient for annotation, its integration may still be necessary, but its execution should be designed in a non-intrusive manner. As for the floor plan, albeit not cheap, we believe that it is still very necessary to integrate one into a localization system, as it could greatly improve users' quality of experience by offering a panoramic view of the ambient environment.

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