Infrastructureless Signal Source Localization using Crowdsourced Data for Smart-City Applications

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***Abstract*—As mobile crowdsourcing techniques are steering many smart-city and Internet-of-Things applications, a new challenge of *signal source localization* problem arises, which is to infer the locations of signal sources based on crowdsourced data. It will benefit real-world applications such as WiFi advisory systems by locating WiFi access points and urban noise monitoring systems by locating noise sources. However, crowdsourced data collected from diverse mobile devices are often sparse, fluctuating, and inconsistent. In this paper, we propose a source localization scheme to solve this problem, without the need of prior localization infrastructure or reference (anchor) nodes. We also implement a crowdsourcing WiFi advisory system and conduct real-world experiments to evaluate the performance of the proposed scheme. The results show that our scheme can locate the WiFi access points within a small error of $1 \sim 16$ meters, and improve the accuracy of a conventional method by up to 50%.**

***Index Terms*—Crowdsourcing, cyber-physical systems, mobile computing, participatory sensing, pervasive computing.**

I. Introduction

Mobile crowdsourcing techniques have spurred a wealth of smart-city applications such as air quality monitoring [1], transportation services [2][3], noise monitoring [4], and WiFi advisory systems [5]. Such systems need to deal with crowdsourced data generated from diverse mobile devices, interpret them properly, and produce useful information services such as noise heat maps or WiFi network quality maps.

Such smart-city applications face a challenge called *signal source localization*, which is to infer the locations of signal sources such as WiFi access points or noise sources in urban areas. For instance, in a crowdsourcing WiFi advisory system, citizens and tourists may share their experience of using public WiFi networks at various locations through their smartphones, and be guided to connect to a WiFi network of good quality. In such applications, location information of signal sources is essential for decision making and service provisioning, but the signal sources themselves are either not capable of providing this information, or the information provided is very coarse-grained (e.g., only indicating a region code) or erroneous due to misconfiguration. In view of this, one potential and cheap solution is to leverage crowdsourcing through WiFi user devices such as smartphones to help locate the signal sources. Performing such tasks is useful to improve the accuracy of contributed data and hence the *Quality of Contributed Service* [6] which is provisioned using user-contributed data. However, doing so is challenged by the following factors:

1) *Lack of infrastructure*: User locations contributed via users' smartphones are often erroneous and inaccurate, and there is usually no prior localization infrastructure or reference nodes [7] in the real environment to conduct calibration for public users' smartphones.
2) *Fluctuating and sparse data*: Crowdsourced WiFi locations may vary dramatically over time, even in the case that the data are collected by the same smartphone. In addition, crowdsourced data can be sparse due to the intermittent data-collection pattern.
3) *Inconsistent data*: WiFi locations collected by different smartphones are inconsistent even if they are connected to the same WiFi access point and are put side-by-side. This makes data aggregation difficult.

To meet these challenges, we propose a probabilistic source localization scheme to infer the location of signal sources using the crowdsourced data. The proposed scheme does not require prior localization infrastructure or reference points, but rather incrementally utilize the crowdsourced data to refine the localization results for increasingly higher accuracy. We also implement a mobile crowdsourcing WiFi advisory system to collect WiFi-quality data citywide, and conduct experiments to evaluate the performance of our proposed scheme. The experimental results show that our scheme can locate WiFi access points within a small error of $1 \sim 16$ meters, and improve the accuracy of a conventional method by up to 50%.

The rest of this paper is organized as follows. We discuss the existing work in Section II, and explain our system design in Section III. Section IV presents our system implementation and experimental results. Section V concludes this paper.

II. Related Work

Crowdsourcing WiFi localization systems have attracted substantial attention to reducing the cost of radio map construction [8][9][7][10]. The radio map construction in [8] relies on data contribution from a group of people who are willing to contribute WiFi fingerprints, while [9] proposes an algorithm to know whether further user input will improve the fingerprint database in terms of system coverage and accuracy. To reduce human intervention for measuring site-specific WiFi fingerprints, [7] incorporates inertial sensors to collect WiFi measurements along users' moving paths and infer users' locations by matching with a known floor map. In addition to moving path, [10] considers the distances between walking steps to match the floor plan for reducing costs on

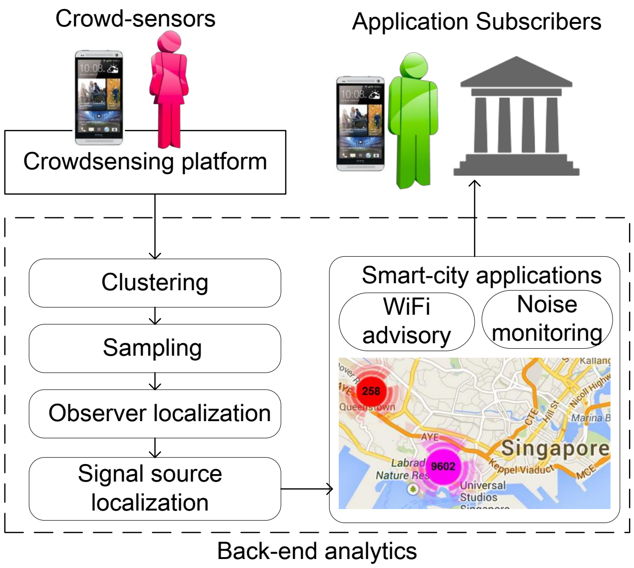


Fig. 1. System architecture of our signal source locator.

manpower and time for radio map construction. Work [11][12] considers modeling indoor space based on WiFi fingerprints of a few given locations instead of such a heavy collecting and training process. To improve the localization accuracy, [13] incorporates received signal strength (RSS) to extract WiFi fingerprints from crowdsourced data for relieving the influence of RSS variation on localization, while [14] incorporates not only WiFi fingerprints but also Bluetooth beacons together to address the issue of space uncertainty. In addition to indoor localization services, [15] designs an indoor WiFi monitoring system to provide WiFi coverage map in indoor places, where crowdsourced data is considered instead of manual site survey. [16] extends [15] to incorporate human activity detection for improving the localization accuracy. Instead of RF signals, [17] considers the physical objects in the environment (e.g. paintings and shops' logos) as reference points to conduct localization, where the user takes photos and sends to a server to identify those physical reference points. Since the above require a prior knowledge of floor map, [18] considers patterns of walking trajectories captured by inertial sensors and WiFi networks, that consists of walking steps, distance, and direction, and WiFi fingerprints along these steps, to construct a floor map for the indoor localization purpose.

Compared to the existing work, our work addresses a different challenge from indoor localization, which is source localization using crowdsourced data for smart-city applications. Second, our approach is calibration-free in the sense that no prior infrastructure and reference nodes are needed. Third, we design and implement a real smart-city application to verify and demonstrate how we bridge the theoretical techniques and practical applications in the real world.

III. System Design

The system architecture of our signal source locator is illustrated in Fig. 1. It consists of three components: crowd-sensors, backend analytics, and application subscribers. Crowd-sensors incorporate human and smartphone with various built-in sensors into the sensing loop in the sense that both human and sensor inputs can be treated as data contributions. The backend analytics runs our algorithm to infer the the locations of signal sources such as wireless access points in a WiFi advisory system or noise sources in a noise monitoring system. The application subscribers (e.g., citizens, tourists, government agencies) can access the crowdsourced data in the form of refined and more accurate location information to find out the signal sources. For example, a tourist may want to know the exact location of a WiFi access point, and national environment agency may want to locate intense noise sources in urban areas.

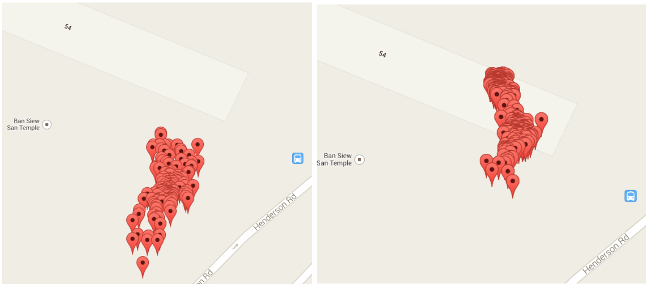
A. Model

In our system, we assume that each source is a static signal transmitter (e.g., a WiFi access point) in a given field F. Each smartphone is assumed as a static observer when it is measuring the signals from a particular source. For a given source w, let $M = \{m_1, m_2, \ldots, m_k\}$ denote the measurements observed by a smartphone b. Each measurement is denoted by $m_i = (t_i, l_i, a_i, s_i)$, where t_i is the timestamp, $l_i = (x_i, y_i)$ is a pair of latitude and longitude obtained via network-based positioning techniques, a_i is the localization accuracy of using the positioning technology[1], and s_i is the received signal strength. For each measurement m_i, the actual location of the smartphone b is $L_b = l_i + e_i$, where e_i is the localization error. The Euclidean distance $d(L_b, l_i) \leq a_i$, in the sense that the actual location of the observer b is assumed as the measured location shifted a small error distance. A critical issue is the *signal source localization* problem which refers to inferring the location of the observed sources in the monitored field F. Specifically, given a signal source w and a set of measurements M, the signal source localization problem is to infer the location with the maximal probability where w is located at. Section III-B, we address the source localization problem under a simple model incorporating observations from a single smartphone. Section III-C then extends it to a more complex model with multiple smartphones' observations.

B. Probability-based Source Localization scheme

To solve the source localization problem, we propose a *probability-based approach* that figures out the location with the highest probability where the signal source is located at. The key idea of our algorithm is to infer the location of the observer first and then infer the location of the source based on the probability distribution of the observer's location. The proposed scheme consists of four steps: (1) clustering, (2) sampling, (3) observer localization, and (4) source localization. The first two steps are to preprocess crowdsourcing data to figure out the input set M, while the latter two steps are to infer the location of the signal source.

[1]The android-based smartphones are able to capture the location of itself based on availability of cell towers and WiFi access points. Results are retrieved by a means of a network lookup.



(a) Measurements on a Sunday. (b) Measurements on a Friday.

Fig. 2. Measurements for a single source on two different days.

1) Clustering: As a smartphone may observe several different signal sources in F, this step is to group all the measurements into different clusters such that measurements in the smae cluster pertain to the same signal source. Each source is associated with a unique signature, which is an application-dependent identification. For instance, the BSSID of a WiFi access point can be the source signature in a WiFi advisory application, and fundamental frequency could be the source signature in a noise monitoring application. In this work, we consider a WiFi advisory application as the proof of concept for our proposed scheme. Thus, two measurements corresponding to the same WiFi access point (i.e, the same BSSID) will be grouped into the same cluster.

2) Sampling: This step is to select a representative subset of measurements from the collected measurements so as to reduce the computation overhead in estimating the location over the whole population of measurements. Here, we select the representative subset based on the quality of data since the collected measurements vary over time. To see this, we conduct an experiment to measure a single wireless access point for five minutes on two different days, where a single smartphone stays static to collect measurements every second. As it can be seen in Fig. 2, the locations measured on the two days have different patterns. Among all the measurements, we select those with the most accurate location information. Specifically, for a given cluster C, we will identify a subset $M \subseteq C$ to be the input of our scheme (i.e., $M = \{m_1, m_2, \ldots, m_k\}$) as follows. First, the measurements are sorted by the localization accuracy. Then, we consider a fixed window T to frame the sorted measurements for sampling, where the number of measurements within a frame is $r \times T$, where r denote the arrival rate of the crowdsourced data. Then, we randomly select k measurements from the first k frames to form the $M = \{m_1, m_2, \ldots, m_k\}$.

3) Observer Localization: This step is to find the observer's location using the sampling results, for which we take the maximum likelihood estimation (MLE) approach. Considering the observer's (true) location by θ_b, for a given the set of measurements $M = \{m_1, m_2, \ldots, m_k\}$, where the observed location values are $\tilde{l}_1 = l_1, \tilde{l}_2 = l_2, ..., \tilde{l}_k = l_k$, the joint density is

$$f(l_1, l_2, ..., l_k|\theta_b) \equiv E(\theta_b). \tag{1}$$

Here, let $E(\theta_b)$ denote the likelihood function of θ_b. Strictly speaking, $\tilde{l}_i$ is a two-dimensional random variable and we could more rigorously write the above as per x_i and y_i separately, in the form of two equations with exactly the same structure. However, for brevity we use a single equation here without compromising clarity. Assume that each $\tilde{l}_i$ is an independent normal random variable $\tilde{l}_i$ and follows the normal distribution $N(\theta_b, a_i^2)$. Thus, the likelihood function of θ_b, $E(\theta_b)$ is

$$E(\theta_b) = \prod_{i=1}^{k} f(l_i|\theta_b) = \prod_{i=1}^{k} \frac{1}{a_i\sqrt{2\pi}} \exp(-\frac{(l_i - \theta_b)^2}{2a_i^2}).$$

In order to maximize $E(\theta_b)$, we instead maximize $F(\theta_b) \equiv \log E(\theta_b)$ equivalently, that is

$$\begin{aligned} F(\theta_b) &= \sum_{i=1}^{k} \log f(l_i|\theta_b) \\ &= -\frac{k}{2}\log(2\pi) - \sum_{i=1}^{k} \log a_i - \frac{1}{2}\sum_{i=1}^{k} \frac{(l_i - \theta_b)^2}{a_i^2} \end{aligned}$$

of which the first-order condition is

$$\frac{\partial F(\theta_b)}{\partial \theta_b} = \sum_{i=1}^{k} \frac{l_i - \theta_b}{a_i^2}$$

Setting it to zero leads to the maximum likelihood estimate of the observer's location

$$\hat{\theta}_b = \sum_{i=1}^{k} \frac{l_i}{a_i^2} \Bigg/ \sum_{i=1}^{k} \frac{1}{a_i^2} \tag{2}$$

In a coarse-grained system, we can simply assume that the observer's location is exactly the source's location. Then the source localization problem is degenerated to finding the observer's location. However, in a fine-grained application (e.g., a WiFi advisory system), this assumption is not well validated. Therefore, we explain the detailed source localization algorithm when the observer is considered not co-located with the source.

4) Source Localization: Below, we consider the probability distribution of the observer's location and the signal propagation model together to model the probability distribution of the source's location. We extend our prior work [19] by incorporating crowdsourced data to address the source localization issue. Given a set of measurements $M = \{m_1, m_2, \ldots, m_k\}$, for each m_i, we model the observer b's location as a random variable l_b with the probability distribution function

$$p_i(l_b) = \frac{1}{\sqrt{2\pi}a_i} \exp(-\frac{(l_b - l_i)^2}{2a_i^2}). \tag{3}$$

On the other hand, assume that the signal propagation model is a log-distance path loss model [20], where the path loss for a given distance d between a pair of transmitter and receiver is

$$\begin{aligned} PL(d) &= S_{tx} - S_{rx} \\ &= PL(d_0) + 10n\log(\frac{d}{d_0}), \end{aligned} \tag{4}$$

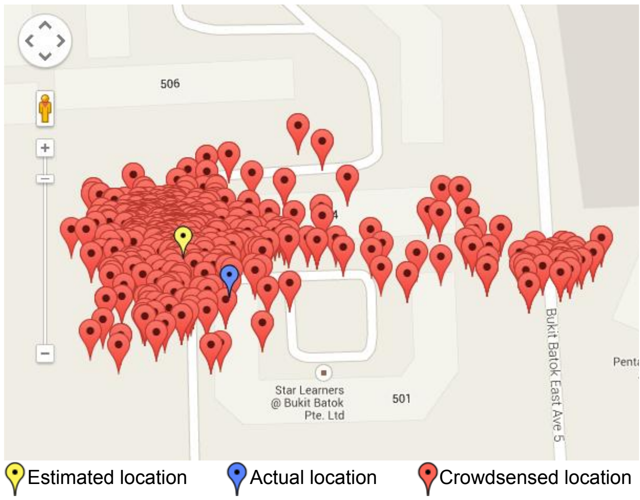


Fig. 3. The results of data analysis for a WiFi access point.

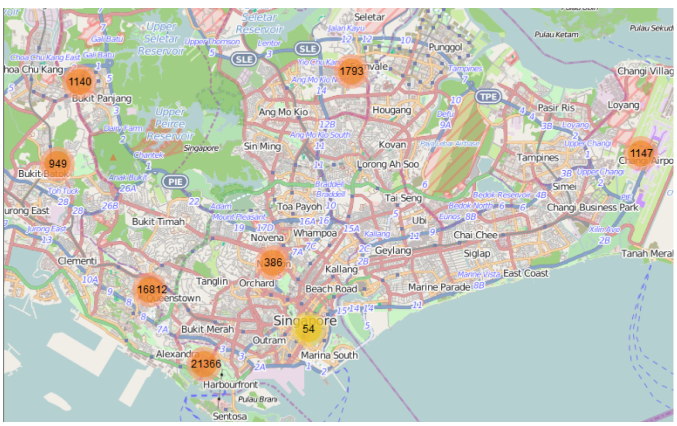


Fig. 4. Visualization of crowdsourced data.

where S_{tx} and S_{rx} are transmitted power and received power, respectively, n is the path loss exponent for a given environment (e.g., $n = 2$ for free space), and d_0 is a reference distance close to the transmitter. When the shadowing effect is considered, the path loss is modeled as a random variable

$$\begin{aligned}\widetilde{PL(d)} &= PL(d_0) + 10n\log(\frac{d}{d_0}) + N(0,\sigma)\\ &= N(PL(d),\sigma),\end{aligned}$$

which is a normal distribution with a mean of $PL(d)$ and a standard deviation of σ. Here, $N(0, \sigma)$ is a normal distribution with a zero-mean and a standard deviation of σ that stands for the signal shadowing effect. Note that we use $\widetilde{PL(d)}$ to distinguish from $PL(d)$ where the latter stands for the case without shadowing effects. Thus, for a given actual distance d between a pair of source and observer, the path loss μ can be modeled as a random variable with the probability distribution function

$$q(\mu) = \frac{1}{\sqrt{2\pi}\sigma}\exp(-\frac{(\mu - PL(d))^2}{2\sigma^2}). \tag{5}$$

Thus, we can model the distance d between the source and the observer as a random variable and let $g_i(d)$ denote the probability distribution function of d. Since μ is a random variable and $\mu = PL(d)$ (i.e., μ is a function of the random variable d), we have

$$q(\mu) = g_i(d)\frac{\partial PL^{-1}(\mu)}{\partial \mu}, \tag{6}$$

where $PL^{-1}(\mu) = (10^{\frac{\mu - PL(d_0)}{10n}})d_0$ based on Eq. (4). Since the probability distribution function of μ is known in Eq. (5), we have

$$g_i(d) = \frac{q(\mu)}{\frac{\partial PL^{-1}(\mu)}{\partial \mu}}. \tag{7}$$

However, $g_i(d)$ states the distance relationship between the source and the observer in an one-dimensional domain. We can extend it to a 2-dimensional domain to model the the probability distribution of the source's location. For a given measurement m_i obtained by the observer at the (known) location of l_b, based on the received signal strength, we can model the source's location l as a random variable with the probability distribution function

$$h_i(l|l_b) = \frac{1}{2\pi} \times g_i(D(l, l_b)), \tag{8}$$

where $D(l, l_b)$ is the distance between location l and location l_b. Furthermore, for a given measurement m_i, we recall the observer's location is a random variable following Eq. (3). Thus, we define the normalized probability that the source is at location l is

$$H_i(l) = \frac{\int_{l_b \in F} h_i(l|l_b) \times p_i(l_b)dl_b}{\int_{l \in F}\int_{l_b \in F} h_i(l|l_b) \times p_i(l_b)dl_b dl}.$$

Finally, we consider all of measurements in M to infer the source's location. By giving equal weight to each measurement, the normalized probability that the source's location at l is

$$\Omega(l) = \frac{1}{k}\sum_{i=1}^{k} H_i(l), \tag{9}$$

where $\Omega(l)$ aggregates the crowdsensing evidences. Therefore, we can infer the location of the source w by

$$\widehat{L_w} = \arg\max_{l \in F} \Omega(l), \tag{10}$$

where $\widehat{L_w}$ denotes the estimated location of the source based on the set of measurements M selected from the whole measurements contributed by the observer b. Here, we use $\widehat{L_w}$ to distinguish from the actual location L_w.

C. Cross-Device Signal Source Localization

Since the measurements for a particular source are from different observers (i.e., smartphones), we then explain how to infer the source location based on cross-device measurements. Let $\widehat{L_w}(b_1)$, $\widehat{L_w}(b_2)$, ... $\widehat{L_w}(b_N)$ denote the estimated location of a particular source w based on the measurements by N

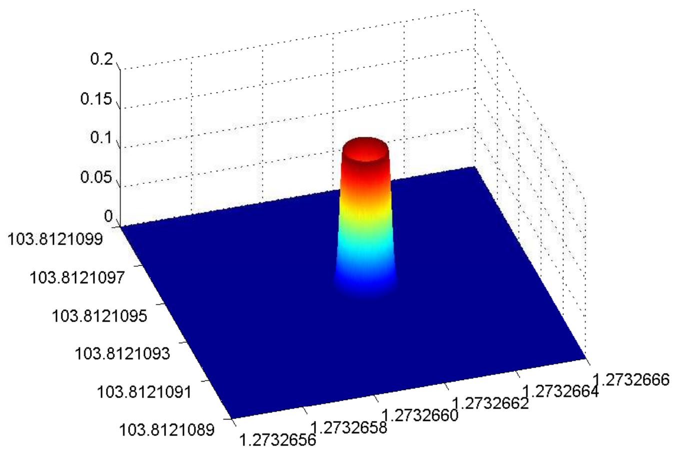
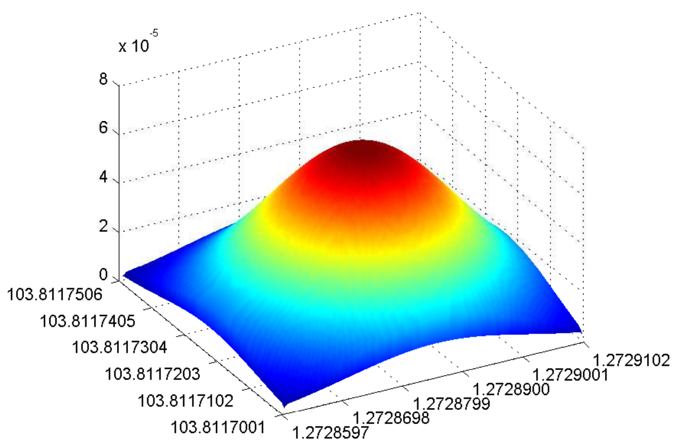


Fig. 5. The probability distribution function $h_i(l|l_b)$ for a measurement with $l_b = (1.2733656, 103.8122089)$.



(a)

Fig. 6. The probability distribution of the WiFi access point's location.

observers $b_1, b_2, \ldots, b_N$, respectively. Based on the amount of data contributed observers, we can estimate the location of the source w by

$$\sum_{i=1}^{N} \frac{R_i}{\sum_{i=j}^{N} R_j} \cdot \widehat{L_w}(b_i), \tag{11}$$

where R_i is the number of measurements contributed by observer b_i, and $\widehat{L_w}(b_i)$ is estimated location using Eq. (10). The weights assigned to the estimated locations imply that an observer who contributes more data will be trusted more by the system.

IV. Experiments on a Crowdsourcing WiFi Advisory System

We extend a crowdsourcing WiFi advisory system [5] to evaluate the performance of our signal source localization scheme. The WiFi advisory system aims to serve two types of application subscribers: normal users (citizens and tourists) and WiFi service providers. When a normal user visits a place, the WiFi advisory system can help him/her to find available WiFi access points within a queried area. For WiFi service providers, the system provides an overview and details of the coverage, connectivity, and user experience of using WiFi hotspots, thereby facilitating urban planning and infrastructure maintenance. In either case, locating WiFi signal sources (i.e., access points) is important for such smart-city applications. Below, we explain the implementation details of the WiFi advisory system and conduct experiments to study the performance of the proposed signal source localization scheme.

A. Implementation

There are 4 main components in our WiFi advisory system: (1) background data collection, (2) foreground interface, (3) data analysis, and (4) data visualization. The first component collects ambient WiFi-related information every 30 seconds through an Android background program. The information includes the latitude and longitude location (measured by network-based positioning technology), received signal strength, and link speed, all associated with the WiFi access point that the smartphone is connected to. The collected data will be uploaded to the backend server when the Internet is available. The second one is a mobile application that provides users with an interactive interface to contribute their user experience of using WiFi networks and guides them to choose a good WiFi network. The third component runs our signal source localization algorithm to determine the locations of those collected WiFi access points. Fig. 3 shows the localization results for a WiFi access point based on crowdsourced data. The fourth component provides different data representations for application subscribers. Fig. 4 visualizes the distribution of crowdsourced data.

B. Experimental Results

We conduct two experiments to study how our algorithm localizes WiFi access points using real-world crowdsourced data and the associated localization errors. In our experiments, we obtain the actual location of WiFi access points from the Google Map with human engagement. For parameters, we set $\sigma = 14.6$ dB, $n = 25.8$, $d_0 = 1$ meter, and $PL(d_0) = 53.2$ dBm as the default parameters in the log-distance path loss model which are suggested by [21].

In the first experiment, we use MATLAB to study the probability distribution functions of our algorithm when real-world data is incorporated. We use a single smartphone (a Redmi smartphone) to measure a single WiFi access point for 1 hour. The fixed window $T = 36$ is considered in the sampling step, and a total $k = 100$ measurements are randomly selected. Fig. 5 shows the probability distribution function $h_i(l|l_b)$ in Eq. (8) for a measurement with $l_b = (1.2733656, 103.8122089)$, $a_i = 43.5$, and $s_i = -71$. Fig. 6 shows the probability distribution function $\Omega(l)$ in Eq. (9),

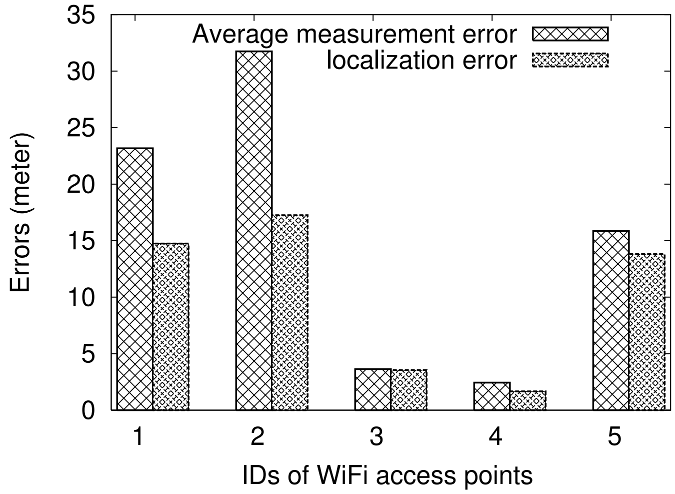


Fig. 7. Evaluating localization accuracy for 5 WiFi access points.

where the location of the WiFi access point was inferred to be $\widehat{L_w} = (1.2733950710421, 103.8122556990361)$.

In the second experiment, we consider crowdsourcing measurements for multiple (five) WiFi access points. We compare the localization errors of our algorithm against the average measurement errors, where the localization error is the distance between the actual location of a WiFi access point and the estimated location by Eq. (10), and the average measurement error is the average of the distance between each measured location and the actual location of the the WiFi access point, i.e., $\sum_{i=1}^{k} |l - l_i|/k$. The experimental results are shown in Fig. 7, and it indicates that our algorithm achieves an localization error between $1 \sim 16$ meters which amounts to an accuracy improvement over the average measurement errors by 36.41%, 45.65%, 2.20%, 31.63%, and 12.81% for the five WiFi access points, respectively.

V. Conclusion

This paper addresses the challenge of signal source localization in a newly emerged data collection paradigm, crowdsourcing, for smart-city applications. We propose a probabilistic algorithm to process the fluctuating, sparse, and inconsistent crowdsourcing data without prior infrastructure. Furthermore, we have implemented a crowdsourcing WiFi advisory system and conducted experiments in the real world to evaluate the performance of our algorithm. The experimental results indicate our proposed scheme can determine the locations of signal sources (i.e. WiFi access points) with an error of only $1 \sim 16$ meters and improve the conventional measurement method by up to 50% in terms of accuracy.

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