MMLOC: Multi-Mode Indoor Localization System Based on Smart Access Points

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ABSTRACT

Indoor localization based on Wi-Fi fingerprints has been an active research topic for years. However, existing approaches do not consider the instability of access points (APs) which may be unreliable in practice, particularly the ones deployed by individual users. This instability impacts the localization accuracy severely, due to the unreliable or even wrong Wi-Fi fingerprints. Ideally, the localization should be done using only the well-deployed APs (e.g., deployed by facility teams). However, in many places the number of these APs is too few to achieve a good localization accuracy. To solve this problem, we leverage emerging smart APs equipped with multi-mode antennas, and build a new indoor localization system called MMLOC to reduce the number of necessary APs. The key idea is controlling the modes of AP antennas to generate more fingerprints with fewer APs. A clustering based localization strategy is designed to enable a mobile terminal to figure out the RSSI (Received Signal Strength Indicator) for different antenna modes without requiring any synchronization. We have implemented a prototype system using smart APs and commercial smartphones. Experimental results demonstrate that MMLOC can reduce the number of necessary APs by 50%, and achieve the same or even better localization accuracy.

CCS CONCEPTS

• Human-centered computing → Ubiquitous and mobile computing systems and tools; **• Computer systems organization** → Special purpose systems.

KEYWORDS

Indoor Localization, Smart Access Point, Clustering

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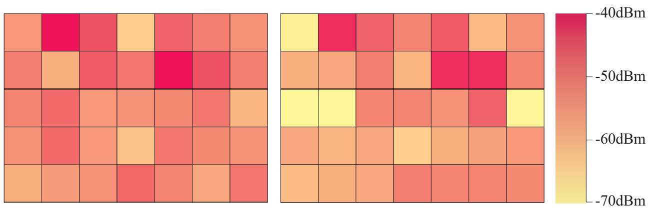
1 INTRODUCTION

With the rapid evolution of mobile terminals such as smartphones and laptops, indoor localization service has been increasingly important in the past ten years. A large number of indoor localization systems have been proposed, and one of the most widely-used technologies is the Wi-Fi fingerprint-based method [2, 7, 13, 14, 20, 40]. The main idea is leveraging the diversity of received signal strength (RSS) from WLAN access points (APs) to create a RSSI fingerprint for each location. This method is able to achieve acceptable localization accuracy (about 3 meters [23]), requires no additional infrastructure besides fingerprint database, and thus is easy to be deployed in various places such as airports and cleanrooms.

However, existing Wi-Fi fingerprint-based indoor localization systems largely ignore a very important *practical* issue: the instability of APs. They assume that the RSSI fingerprint measured by a mobile device does not change with time. This is often not true or even totally wrong in practice. First, many APs are privately deployed by individual users and thus are not reliable. For example, in a big shopping mall, besides the APs centrally deployed and managed by the facility team, the owners of small stores may also deploy their own private APs. Those private APs are usually not installed on the ceilings and thus the signal strength from them will oscillate severely because of the moving barriers. Furthermore, they may be moved from one location to another and turned on/off from time to time, depending on the needs of the owners. As a result, the RSSI fingerprints of those APs are highly dynamic and unreliable. Second, using techniques of virtual Wi-Fi [26] and Wi-Fi tethering [12], users may turn a laptop or smartphone into a mobile software AP. Those software APs come and go on-the-fly and thus their RSSI fingerprints are not stable at all. Because Wi-Fi fingerprint-based localization systems fundamentally rely on the stability of RSSI fingerprints, the instability of those unreliable private and software APs severely impacts the localization accuracy of the Wi-Fi fingerprint-based localization systems, making them inaccurate in practice.

Ideally, we should only use reliable APs for localization purpose, for example, the APs deployed by the facility team of a building or by the IT team of a company. Unfortunately, in many places the number of these reliable APs is limited. In some large-scale indoor spaces such as shopping malls and airports, the number of Wi-Fi access points that cover each location is often small, because they are deployed to provide network access instead of localization service [45]. For instance, according to our survey in Shanghai Jiao Tong University in China, there are only 5 to 8 fixed APs in each three-story mess hall, and usually only 2 or 3 of them can be scanned at each location, which can hardly meet the requirement of indoor localization. In other large indoor places such as stadiums and plants, the AP number is even smaller. For those places, it is also not practical to install more APs just for indoor localization purpose. Therefore, this lack of reliable APs is a big problem in practice because it has been shown that the accuracy of localization decreases severely when the number of APs is no larger than 5 to 6 [18, 41].



(a) Mode 1 (b) Mode 2

Figure 1: One example for the RSSI fingerprint maps generated by one two-mode smart AP. The measurement is performed in a 7×9 m^2 meeting room.

In this paper we propose to address the above practical problem by leveraging emerging *smart APs*. Unlike normal APs which are dumb and not programmable, smart APs run their own operating system and provide interfaces to control their configurations and behaviors, e.g., executing more complex tasks such as smart traffic scheduling [4]. Furthermore, as 802.11n and 802.11ac become increasingly popular, Multi-input Multi-output (MIMO) has been widely used. As a result, equipping an AP with more than one antenna is the mainstream of industry. In addition, there are also techniques to equip APs with the antennas that support multiple configurable operating modes (sometimes are called as smart antennas) [9]. With the production of smart APs, there is a trend that smart APs will supersede normal dumb APs and be widely installed in various places.

We design MMLOC, a multi-mode indoor localization system based on smart APs with multiple antennas. The main idea is that, since a change of antennas' mode also changes the distribution of RSSI, we can generate more RSSI fingerprints via only one smart AP by switching the operating modes of its antennas, as shown in Fig. 1. Thus, MMLOC can reduce the total number of APs required for indoor localization, making it a practical solution for many places with few APs.

The main challenge is that, the mobile terminal needs to know the exact current mode of smart APs so that it can map the RSSI measurement to the corresponding fingerprint. One way to do it is to introduce time synchronization between the mobile terminal and the smart APs. However, this can make the system very complicated and hard to deploy in practice. It is even harder to maintain synchronization if more than one user need to be served by the localization system at the same time. Therefore, we design the *clustering-based localization strategy* and the *sliding window-based clustering mechanism* to enable the mobile terminal to differentiate different modes of smart APs. The intuition is that, since the mean value of RSSI at a given location changes with different AP modes, we can distinguish the RSSI values from different modes with the algorithm of clustering. Moreover, by assigning different durations to different AP modes, it is possible for the mobile terminal to recognize the AP modes.

In this work, we have made the following contributions:

- We propose an indoor localization system based on smart APs. By switching the modes of antennas, we can double the RSSI fingerprints of each AP and thus reduce the number of necessary APs by half while the localization accuracy is maintained. (Section 3)
- To allow mobile terminals to identify the modes of smart APs, we design the clustering-based localization strategy and the sliding window-based clustering mechanism to map RSSI fingerprint measurements to different modes of smart APs. (Section 4.2)
- We design a modified probability-based localization algorithm to utilize the additional fingerprint maps generated by smart APs. (Section 5)
- We have implemented a prototype system of MMLOC on Android platform and conduct comprehensive evaluations. (Section 7)

We organize the rest of the paper as follows. Section 2 surveys related work. Section 3 illustrates the system architecture. Section 4 introduces the process of localization and the proposed strategies in detail. Section 5 presents the algorithm of location estimation. Section 6 describes the implementation details of the system. Section 7 evaluates the performance of MMLOC and analyzes the results of experiments and simulations. We discuss the limitation of MMLOC and our future work in Section 8. Section 9 concludes our work.

2 RELATED WORK

Indoor localization system: Indoor location sensing systems have become extremely popular. There are multiple technologies that have been applied in this field. For instance, there are indoor localization systems based on RFID [16, 17], UWB [19, 36], Bluetooth [1, 6] and ultrasonic [32, 34]. Among the typical indoor localization technologies, we are mostly interested in the WLAN positioning systems using RSSI fingerprints. Unlike the other technologies such as AoA (Angle of Arrival) or TDoA (Time Difference of Arrival)-based approaches [3, 38, 39, 44], the Wi-Fi RSSI fingerprints-based indoor localization does not need additional infrastructures except pre-existing commercial WLAN APs. RADAR [2], an in-building user location and tracking system, adopts the method of kNN to achieve an accuracy of $2-3$ meters. Yang *et al.* in [40] leverage user motions to construct the radio map of a floor, which is previously obtained only by site survey. Laoudias *et al.* in [20] adopt Artificial Neural Networks (ANN) as a function approximation approach to map vectors of RSSI fingerprints.

However, most of the previous works do not consider the case where the number of available APs is limited and some of the APs are unreliable. When a user is covered by only a few APs, the accuracy of localization is limited [18, 41]. In [35], a single AP is used to locate users based on the AoA and ToA (Time of Arrival) information. However, the AP needs to conduct AoA and ToA measurement, which is less practical for commercial APs. SAIL [25] also utilizes a single AP to locate the user. However, it requires the assistance of the inertial sensors in the user's device, which makes the system impractical for the devices that are not equipped with the extra sensors. Moreover, the inertial sensor-based localization methods [21, 29] are vulnerable to magnetic interference [11, 27], because the magnetometer can be easily interfered, especially for the places where the magnetic field changes significantly [5, 24, 33, 43]. In our system, we reduce the demanded quantity of APs by using the smart APs equipped with two-mode antennas, and no measurement is required at the APs. The user's device needs to have the Wi-Fi module only. Meanwhile, the accuracy is still maintained and comparable to the previous systems based on RSSI fingerprints.

Smart access point: The usage of programmable smart APs in wireless technologies have also received great attention. Applying smart APs, SAP in [8] provides seamless handoff experience to users, while smartly balancing the network load across multiple interfaces based on users' time-varying traffic load conditions. Bottigliengo *et al.* in [4] propose an LLC-layer algorithm implemented at both AP and WSs to guarantee fair access to the medium to every user. OpenWrt [28] provides tools to make the channel or antenna selection on Wi-Fi devices, which enables the programmable control on APs. In this paper, we leverage programmable APs with multi-mode antennas to act as the smart APs, and apply the concept of smart APs in the field of indoor localizations.

Multi-mode antenna: The antennas with more than one work pattern have already been used in indoor localization systems. The work in [10] proposes an RF-based localization system that works using a single anchor node. The anchor is equipped with a switched-beam directional antenna that collects signal strength information sufficient for absolute 2D target positioning. However, the designed antenna can hardly be adopted in commercial APs. The system in [22] utilizes smart antennas to receive signal from a mobile target. The signal strength information is combined to find the direction of arrival of the signal and triangulate the mobile target position. FIFS [37] applies multiple antennas with spatial diversity to reduce signal strength variability and improve the accuracy of indoor localization. However, both the works have not considered the switch of antennas' modes. In our system each smart AP is equipped with two-mode antennas, and the radiation pattern is changeable. Thus more than one RSSI fingerprint map can be generated by each smart AP, and the accuracy of localization is also improved.

3 MMLOC SYSTEM ARCHITECTURE

3.1 System Overview

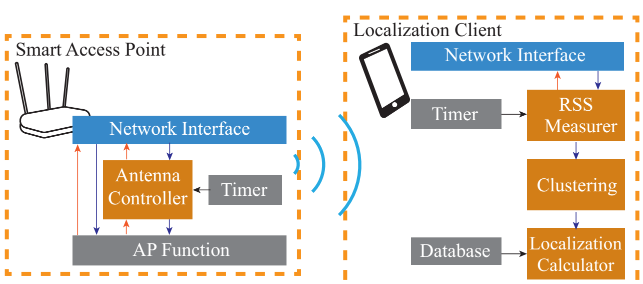


Figure 2: Architecture of MMLOC.

As shown in Fig. 2, our system consists of two parts: *smart access point* (smart AP) and *localization client*. A mobile terminal which needs to use our system must have installed the localization client and be covered by at least one smart AP. Each smart AP switches its antenna modes independently and periodically. When the terminal needs to locate itself, its localization client starts a series of measurement, clustering and calculation. Multiple users can locate themselves at the same time, even if the same set of smart APs are occupied. It should be noted that the smart APs still retain the function of normal access point, and any mobile terminals can visit Internet through them.

Next, we introduce the architecture of smart AP and localization client in detail, respectively.

3.2 Architecture of Smart Access Point

Besides the function of normal access point, a smart AP has the following additional component.

Antenna Controller: It controls the switch of the two-mode antennas. Based on the predefined period lengths of the two modes, the antenna controller takes the timer as the time source and switches the mode of the antenna. Note that although all smart APs share the same two lengths of periods, their periods are not aligned. Therefore, there is no synchronization among the smart APs. Moreover, since we assign different period lengths for different modes to allow mobile terminals to differentiate the two kinds of RSSI measurements, no synchronization is needed between smart APs and mobile terminals either.

3.3 Architecture of localization client

The localization client is installed in mobile terminals and contains the following components mainly.

RSS Measurer: It measures the RSS from available APs for a certain predefined period of time. This period length is the sum of the period lengths of the two modes of the antennas. The returned values are RSSIs. Note that only the signal strength from the reliable smart APs that have been registered in our system is processed.

Clustering: It divides the measurement results into two clusters. Then based on the size of the clusters, it maps the two clusters to the two antenna modes.

Localization Calculator: It estimates the location of a user according to the mapped measurement results and the stored RSSI fingerprints. A localization algorithm based on probability distribution is followed.

Database: It stores the RSSI fingerprints of different smart APs in the localization region. Different from previous works, for each smart AP we store two different RSSI fingerprint maps.

4 PROCESS OF LOCALIZATION

4.1 Basic Process of MMLOC

As introduced before, to reduce the number of APs needed during the localization process, we make use of the smart APs with two-mode antennas. When the mode of the antenna is changed, the distribution of signal strength is also changed. Thus we can get two RSSI fingerprint maps for each smart AP. As other typical indoor location systems, the process of localization in our system consists of *offline data collection and training phase* and *online localization phase*.

In the offline data collection and training phase, we divide the localization region into grids with constant size, and measure the RSS from the smart APs at the center of each grid. Since each smart AP has two different modes, the RSS should be measured twice for each smart AP in each mode. All the fingerprint information collected will be uploaded to a server. The data processing for these measure results will be shown in Section 5. A mobile terminal needs to download the RSSI distribution map from the server before it can use our service. Note that the server is for data processing only and its operation can be easily implemented on the mobile terminal. So we does not include the server in the system architecture of MMLOC.

In the online localization phase, the basic process is that, a mobile terminal keeps measuring RSS for a certain duration when the mode of each smart AP has changed at least once. Then the terminal can estimate its position according to the results based on the RSSI distribution map. Considering the practicability, our system cannot require the synchronization between the mobile terminal and smart APs, and our system must be able to serve a large number of users at the same time. However, the mobile terminal need to measure the RSS for both the two modes of each smart AP, without knowing which signal is generated by which antenna mode. To avoid modifying the protocol followed by the wireless devices, we do not use the beacons of smart APs to carry antenna mode information. We design a clustering-based localization strategy to solve this problem.

4.2 Clustering-based Localization Strategy

For most of the previous works based on RSSI fingerprint, since only one-mode antennas are used in APs, the clients can measure the signal strength from these APs at any time for arbitrary duration. In our system however, every smart AP has two modes, and clients have no access to know each RSSI belongs to each mode. Two contiguous measurements may even get the results for two different modes. Although we find it impractical to synchronize smart APs and mobile terminals, it is still possible for them to reach certain consensus about the duration of mode changing, i.e., we can make the measurement duration of mobile terminal equal to the period of mode changing in smart APs. We propose the clustering based localization strategy to utilize this observation.

Strategy on smart APs: Each smart AP changes its antenna mode following a common period T_c. During the first slot T_1 in T_c, the AP's antenna works in *Mode 1*. During the second slot T_2, the AP's antenna works in *Mode 2*. Note that $T_1 + T_2 = T_c$, and $T_1 \neq T_2$. We assume $T_1 > T_2$ for convenience. Usually the difference $T_1 - T_2$ should be large enough. We set $T_1 = 2T_2$ in this paper. It is not necessary for the smart APs to be synchronized. We admit that changing of mode would lead to unpredictable delay, but that does not matter a lot, which will be discussed later.

Strategy on mobile device: Once a mobile device need to locate itself, it starts the RSS measurement. The duration is T_c, during which the device keeps sampling the RSS for multiple times. In practice, the sampling rate for RSS would vary with time. However, since the sampling rate is usually relatively stable during the measurement duration, the performance of the strategy is still maintained. The measured results will be processed by the clustering algorithm, which will be shown in Section 4.3.

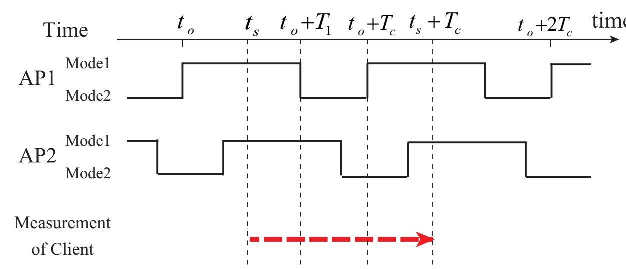


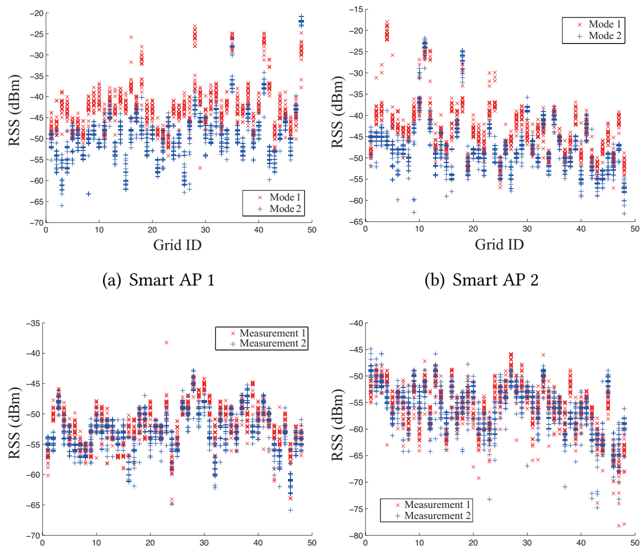
Figure 3: One example of a RSS measurement process.

We use an example to show how the clustering-based localization strategy works. In Fig. 3, there are two smart APs changing their modes with period T_c. Assume that a mobile terminal starts the measurement at time point t_s. The measurement continues until $t_s + T_c$. It is shown that during t_s to $t_o + T_1$ and $t_o + T_c$ to $t_s + T_c$, smart AP 1 works in Mode 1. During $t_o + T_1$ to $t_o + T_c$, smart AP 1 works in Mode 2. Thus if the sampling rate of mobile terminal is relatively stable during the measurement duration, the ratio r_M between the number of RSS measurements belonging to Mode 1 and those belonging to Mode 2 should be around T_1/T_2 (note that the mobile terminal has no idea about the values of $t_o + T_1$ and $t_o + T_c$). This gives us a chance to figure out which mode that each RSSI sample belongs to. The same principle also applies for smart AP 2 in the figure. Thus within a single measurement duration, it is possible for the mobile terminal to get the RSSI for each smart AP in each mode. This strategy also works for multiple mobile terminals at the same time.

Another key feature of our strategy is that, the error of timing system on each device does not impact the performance of the strategy. Since no synchronization is used, the timing error on smart APs is not cumulative. One extreme example is that, even if a smart AP is down for a short time and starts to work again later, the following measurements of mobile terminals are still not impacted. On the other hand, the joggling of a mobile terminal's sampling rate will not change r_M a lot, as long as the total number of sampling points in T_c is large enough. These ensure the robustness of our strategy.

4.3 Sliding Window-based Clustering Mechanism

We first show that the RSS measurements from each smart AP's two antenna modes are distinguishable. We collect RSS measurements from smart AP 1-2 in both modes. For comparison, we also collect measurements from normal AP 1-2 at the same time. When the smart APs are working in Mode 1, the RSS measurements in each grid are shown in red in Fig. 4. We then turn all smart APs to Mode 2 and the RSS measurements are shown in blue. Fig. 4(c) and Fig. 4(d) show that, for the normal APs, the blue and red points are mixed with each other and cannot be separated easily, which is expected. In contrast, from Fig. 4(a) and Fig. 4(b), we can see that measurements from each smart AP's two modes are not mixed up and thus can be separated by clustering mechanisms.



(a) Smart AP 1 (b) Smart AP 2

(c) Normal AP 1 (d) Normal AP 2

Figure 4: RSS measurements in different smart AP modes at different grids.

The problem of clustering RSS measurements from smart APs to two modes is actually easier than the common clustering problem. Notice that we have $T_c = T_1 + T_2$ and the measurements are aligned according to their timestamps. Therefore at least the measurements of one mode are consecutive within one measurement duration. This allows us to use a sliding window-based clustering mechanism.

As Fig. 5 shows, the sliding window based clustering algorithm can be described in the following 5 steps:

(1) We first remove the bad measurements which are outliers to other measurements. Assume the number of the remaining measurements is K.
(2) We then form a circle by concatenating the last measurement with the first one.
(3) A window of length KT_1/T_c is moved to find the position where the absolute difference of the averages inside and outside the window is maximized. After this position is found, we consider the measurements inside the window corresponding to Mode 1 and the others corresponding to Mode 2.
(4) Then we sort the two sets of data respectively.
(5) Finally, we select several measurements around the median of each set as its representatives to further cancel the effect of bad or noisy data.

Note that it is possible that the mechanism identifies wrong window positions for some grids. But this means the RSS measurements of the two modes in those grids are originally very close so that the wrong representatives selected will not affect the final localization results a lot.

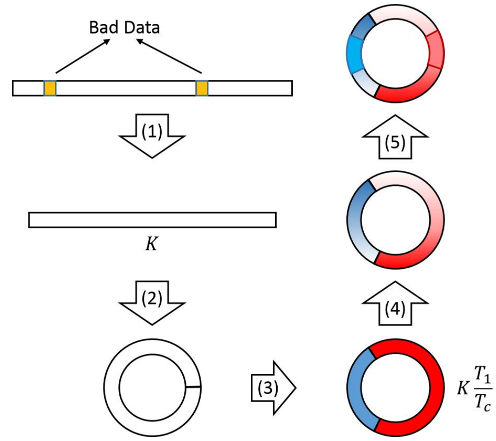


Figure 5: Sliding window-based clustering mechanism.

5 LOCALIZATION ALGORITHM

In this section, we present an accurate and scalable algorithm for determining the user location in an 802.11 WLAN framework. Unlike that used by normal fingerprint-based localization systems, our algorithm has been modified to utilize the additional fingerprint maps generated by smart APs.

5.1 Theoretical Basis

Our algorithm uses probability distributions to enhance accuracy and tackle the noisy nature of wireless channels.

Location Estimation: Generally, we use l to denote a location in the indoor localization region, o to denote a training datum of RSSI from a smart AP, and $\bar{o}$ to denote an observation variable of RSSI.

Our algorithm is based on a frequently-used probabilistic model [42] for the location estimation problem. For any given location l, we can obtain a distribution of signal strength $p(\bar{o}|l)$ via measurement and estimation. In *kernel method*, the $p(\bar{o}|l)$ can be calculated as

$$p(\bar{o}|l) = \frac{1}{n}\sum_{i=1}^{n} K(\bar{o}; o_i), \tag{1}$$

where $K(\bar{o}; o_i)$ is the *kernel function*, o_i is the i_{th} RSSI training datum measured at l, and the total number of o_i is n. In our system we use the Gaussian kernel, which is a widely used kernel function:

$$K(\bar{o}; o_i) = \frac{1}{\sqrt{2\pi}\sigma}\exp(-\frac{(\bar{o} - o_i)^2}{2\sigma^2}), \tag{2}$$

where σ is an adjustable parameter that determines the width of the kernel. Thus we can get a estimate of $p(\bar{o}|l)$ by Equation (1).

Following the Bayes rule, we can obtain the posterior distribution of the location:

$$p(l|\bar{o}) = \frac{p(\bar{o}|l)p(l)}{p(\bar{o})}, \tag{3}$$

where $p(l)$ is the prior probability of being at location l before knowing the value of observation variable. In our algorithm we assume $p(l)$ as a constant for all grids. $p(\bar{o})$ is also treated as a constant since it does not depend on the location variable l. Thus with Equation (3) we can get the probability that $\bar{o}$ is measured at location l when $\bar{o}$ is known.

Most probable location: With the posterior distributions calculated for each location, when an observation vector $\bar{O} = \{\bar{o}_1, ..., \bar{o}_k\}$ is given, we need to find l such that $P(l|\bar{O})$ is maximized, i.e., we want $\text{argmax}_l[P(l|\bar{O})]$. According to Equation (3), and since $P(\bar{O})$ and $p(l)$ are constant for all l, this can be rewritten as:

$$\text{argmax}_l[P(l|\bar{O})] = \text{argmax}_l[P(\bar{O}|l)]. \tag{4}$$

Assuming that the access points are independent, $P(\bar{O}|l)$ is calculated by using:

$$P(\bar{O}|l) = \prod_{i=1}^{k} p(\bar{o}_i|l), \tag{5}$$

where $p(\bar{o}_i|l)$ is estimated by Equation (1).

5.2 Data Processing in Offline Data Collection and Training Phase

Assume that we have a room with $X \cdot Y$ grids, where X denotes the units in length direction and Y denotes the units in width direction. We use G_{ij} to denote a grid with coordinate (i, j), $i = 1, ..., X$, $j = 1, ..., Y$.

In our smart AP localization algorithm, each mode of each smart AP will be assigned a fingerprint map denoted by F_s^m, where $s = 1, ..., M$ and M is the number of smart APs in our system. We use $m \in \{1, 2\}$ to label the two modes of the AP. For each fingerprint map, we use G_{ij}^{sm} to represent a specific grid in it. Each fingerprint map will be initialized using the fundamental machine learning mechanism. First, we collect training data using Android smartphones, and for each fingerprint map, we have a set of training data:

$$O_s^m = \{O_{ij}^{sm} | i = 1, 2, ..., X, \ \ j = 1, 2, ..., Y\}, \tag{6}$$

where

$$O_{ij}^{sm} = \{o_{ijq}^{sm} | q = 1, 2, ..., N\}. \tag{7}$$

Here, each O_{ij}^{sm} includes N RSSI signals that we will later utilize to calculate the probability distribution of RSSI in G_{ij}^{sm}, and o_{ijq}^{sm} is the q_{th} training observation in G_{ij}^{sm}.

According to Equation (1) and (2), for each grid G_{ij}^{sm} the resulting density estimate for an observation $\bar{o}$ is a mixture of N equally weighted density functions

$$p(\bar{o}|G_{ij}^{sm}) = \frac{1}{N} \sum_{q=1}^{N} \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(\bar{o} - o_{ijq}^{sm})^2}{2\sigma^2}\right), \tag{8}$$

where σ is an adjustable parameter that determines the width of the kernel. Specifically, according to [31], to get a smoother estimation for RSSI distribution, we use $\sigma = 10$.

We iterate the observation $\bar{o}$ from its lower bound to upper bound to calculate the density distribution in each G_{ij}^{sm}. Specifically, we traverse $\bar{o}$ from −150 dBm to 0 dBm and then normalize the density distribution to probability distribution for each G_{ij}^{sm}.

Finally, we train each G_{ij}^{sm} in each fingerprint map F_s^m with training data O_s^m. Since the value of RSSI measured by smartphones is discrete, we can previously store $p(\bar{o}|G_{ij}^{sm})$ for each integral value of $\bar{o}$. Thus for each F_s^m we get a probability distribution database denoted by

$$D_s^m = \{D_{ij}^{sm} | i = 1, 2...X, \ \ j = 1, 2...Y\}, \tag{9}$$

where D_{ij}^{sm} is the probability distribution database for the G_{ij}^{sm} in F_s^m. We store D_s^m in our localization server.

5.3 Location Estimation in Online Localization Phase

We assume that the client has downloaded D_s^m from the server. When the client starts the localization process, it has to measure the RSSI from the smart APs following the strategy in Section 4.2 and 4.3, and the result is denoted by

$$\bar{O} = \{\bar{o}_k^{sm} | k = 1, ..., K, \ \ s = 1, ..., M, \ \ m \in \{1, 2\}\}, \tag{10}$$

where K is the number of times the client has measured for the same AP. Note that if the client is not covered by the s_{th} AP, $\bar{o}_k^{sm}$ will be labeled by NaN and thus does not impact the following calculation.

For each $\bar{o}_k^{sm}$, according to Equation (8) we can calculate the conditional probability $p(\bar{o}_k^{sm}|G_{ij}^{sm})$. Since $p(\bar{o}|G_{ij}^{sm})$ has already been stored in D_s^m, we can get $p(\bar{o}_k^{sm}|G_{ij}^{sm})$ directly by accessing the database stored in the client. Therefore, there is no need to calculate the probability again, which reduces our system's energy consumption and computation complexity.

In this paper we assume that the signal strengths from the smart APs are independent. This assumption is justifiable for a well designed 802.11 network, where each AP runs on a non-overlapping channel. Therefore, we could estimate the joint probability using the marginal probability. According to Equation (5), we get the probability for that the client observes $\bar{O}$ when it is in G_{ij}:

$$P(\bar{O}|G_{ij}) = \prod_{s=1}^{M} \prod_{k=1}^{K} [p(\bar{o}_k^{s1}|G_{ij}^{s1}) \cdot p(\bar{o}_k^{s2}|G_{ij}^{s2})]. \tag{11}$$

Thus based on Equation (11), we get the estimated probability for the client to be in the G_{ij} when $\bar{O}$ is observed:

$$P(G_{ij}|\bar{O}) = P(\bar{O}|G_{ij}). \tag{12}$$

Finally, the joint probability matrix can be denoted by

$$P_{joint} = \{P(G_{ij}|\bar{O}) | i = 1, ..., X, \ \ j = 1, ..., Y\}. \tag{13}$$

We then simply find the largest $P(G_{ij}|\bar{O})$ in P_{joint} and its corresponding G_{ij} denotes the estimated location for the user.

6 IMPLEMENTATION DETAILS

In this section we describe the implementation details of MMLOC.

The usage of two-mode antenna: In our system, we use 802.11n-based TP-LINK TL-WN951N to act as a smart AP equipped with two-mode antennas. Since the network card allows users to change the antenna mode via software settings, we make no hardware change and keep a java program running as the antenna controller. TL-WN951N has three antennas, and the diversity technique of MIMO is applied. Typically there are two different modes of MIMO: diversity mode and multiplexing mode [15]. For multiplexing mode, without refitting the wireless devices in mobile terminals, it is hard to maintain the connections between mobile terminals and APs when we change the power of antennas. Thus we use the diversity mode to avoid disconnections. In Mode 1 of the smart AP, all of the three antennas are used, while in Mode 2, we turn off the power of one antenna, and only two antennas are working in normal state. Since the three antennas are set in different directions, the distribution of RSSI fingerprints varies with the two modes.

The expandability of MMLOC: MMLOC can be viewed as a framework of indoor localization systems. For example, although we use the localization algorithm based on probability alone in this paper, it is still easy to apply other algorithms such as kNN [2] in the system. Moreover, other techniques such as crowdsourcing-based fingerprint collection [30] can also be employed in MMLOC. Thus MMLOC has good expansibility and other possible advantages can be achieved in addition to the reduction of necessary APs.

7 MEASUREMENT AND EVALUATION

In this section, we evaluate the performance of our indoor localization system by conducting experiments on the testbed consisting of Android smartphones. We set our test environment at one laboratory in a building of a university, which is shown in Fig. 6. The total area covered is more than 70 m^2, and there exist lots of obstacles and the indoor environments are complex. During the test we use TP-LINK TL-WN951N to act as the two-mode smart AP, and use the APs installed in the building to act as the normal APs. Altogether 4 smart APs are deployed in the test region. To ensure the fairness of comparison, all the 8 normal APs used have the similar RSSI levels as those of smart APs. The smart APs are deployed at the four corners of the room. We divide the experiment field into 48 girds and collect the RSSI fingerprints of them using 3 Android smartphones. All of the smartphones are Nexus S with Android Jelly Bean (4.2.2) as their operation systems. Each of these smartphones is equipped with a 1.5GHz CPU and 2G RAM. The size of each grid is 1.2 m ×1.2 m, and for each grid we collect 20 RSSI samples from each AP in each mode. During the online localization phase, we set $T_1 = 20$ s for Mode 1, $T_2 = 10$ s for Mode 2, and thus $T_c = 30$ s. As described before, following the cluster based localization strategy, the smart APs will change the modes with period T_c, and the measurement duration of each smartphone is also T_c. Since the average time needed by a RSSI scan is about 1 s, usually around 30 RSSI points can be measured during T_c. As described in Section 4.3, for each mode, 10 RSSI points are selected for localization. We admit that $T_c = 30$ s is quite long in practice, and we will discuss this in Section 8.

Figure 6: Photo of the experiment field.

7.1 Diversity between the Fingerprint Maps Generated by One Smart AP

Before we evaluate the performance of MMLOC, we prove that the diversity between the two fingerprint maps generated by a smart AP is obvious enough, so that the two maps can be regarded as those generated by two different APs.

Table 1: Number of the grids that have similar average RSSI in two fingerprint maps.

	AP1/2	AP2/1	AP2/2	AP3/1	AP3/2	AP4/1	AP4/2
AP1/1	15	17	11	12	7	14	11
AP1/2		17	12	12	14	14	13
AP2/1			18	10	10	13	11
AP2/2				11	10	12	10
AP3/1					17	19	13
AP3/2						18	14
AP4/1							16

Note: AP1/2 denotes the map generated by AP1 working in Mode 2, and so on. The gray cells mark the comparison between the two modes of the same smart AP.

As mentioned before, the laboratory is divided into 48 grids and at each grid we measure the average RSSI based on 30 observed values from each smart AP working in each mode. After the measurement, for each couple of maps, we calculate the number of the grids that satisfy the following condition: for a grid, there exist at least one other grid whose average RSSI is within ±5 dBm from that of this grid in both the two maps.

The result is shown in Table 1. It can be seen that, for the two maps generated by one smart AP, the number of the grids with similar RSSI in both the maps is comparable to that of the grids in the maps from different APs. Thus it is proved that, compared with the overlap between the normal maps generated by disparate APs, the extra overlap between the maps from the same smart AP is negligible.

7.2 Comparison between MMLOC and Normal AP-based Localization System

In this subsection we compare the performance of MMLOC and a normal AP-based localization system. To ensure the fairness of the comparison, all the test girds must have been covered by multiple smart APs and normal APs at the same time, i.e., at each grid in the room, the signal from all the 4 smart APs and 8 normal APs can be received.

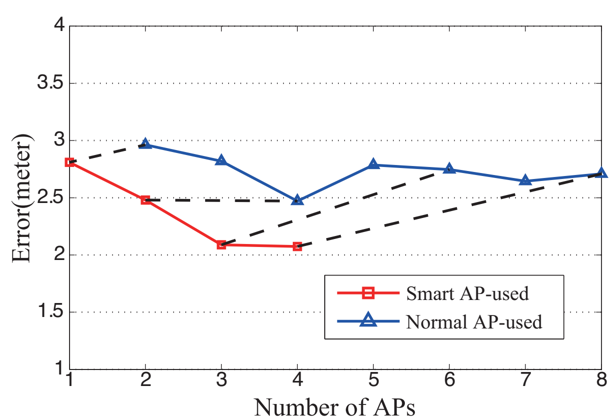
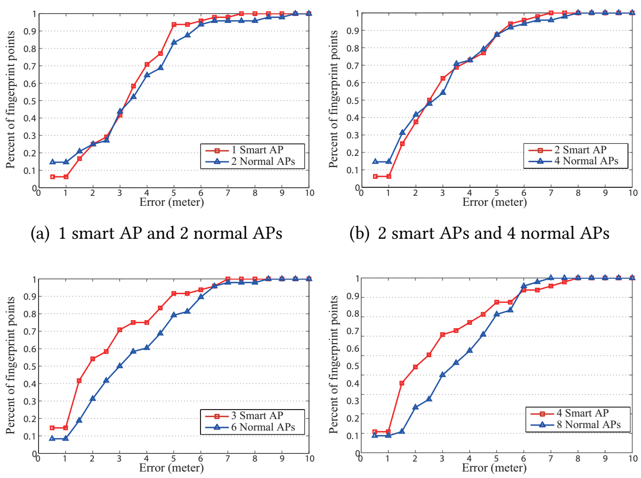


Figure 7: Comparison of average location errors of the two localization systems.

The normal AP-based localization system used in this test makes use of normal APs only. The algorithm it uses to estimate the location of users is similar to that used by MMLOC, and the only difference is that there is only one RSSI fingerprint map for each AP.

The experiment consists of two stages. For the first stage, we test the performance of MMLOC and the number of smart APs used ranges from 1 to 4. For the second stage, we test the performance of the normal AP-based localization system with 2 to 8 normal APs, respectively. To select the APs from the AP set, we enumerate all the possible subsets of APs and select the subset which provides the best accuracy. This method is applied to both the smart AP and normal AP selection for fairness. For each stage more than 1440 RSSI points have been sampled, and the errors of localization are recorded.



(a) 1 smart AP and 2 normal APs

(b) 2 smart APs and 4 normal APs

(c) 3 smart APs and 6 normal APs

(d) 4 smart APs and 8 normal APs

Figure 8: CDF of location errors in different cases.

The average errors of different cases in the two stages are shown in Fig. 7. It can be seen that, the average error of MMLOC is less than that of the normal AP-based localization system when same number of smart APs and normal APs are used. With 4 smart APs covering the experiment field, the average error can be reduced to 2.07 m, while that of the 4 normal AP case is 2.47 m. We should also respectively compare the system performance using 1, 2, 3, 4 smart APs with that using 2, 4, 6, 8 normal APs, as shown by the dash lines in Fig. 7. It is shown that MMLOC can even achieve equivalent or better accuracy compared with the normal AP-based localization system but with only half number of APs. In the figure, we can see that the average error of the normal AP-based localization system does not always decrease with the increase of AP number. One major reason is that, given the fact that the number of stable APs are limited, some unstable APs are included in the selected AP set when we increase the number of APs. As a result, the accuracy of the entire system suffers from the use of less-qualified RSS measurements from unstable APs. However, MMLOC does not have this problem since less APs are required to achieve equivalent or better accuracy so that the including of unstable APs can be avoided.

To better compare the performance of the two systems, we also plot the cumulative distribution (CDF) of location errors in Fig. 8. As shown in the Fig. 8(a) and Fig. 8(b), in the cases of 1 smart AP v.s. 2 normal APs and 2 smart APs v.s. 4 normal APs, the distributions of location errors in the two systems similarly match each other. Moreover, Fig. 8(c) and Fig. 8(d) show that MMLOC outperforms the normal AP-based system in cases of 3 smart APs v.s. 6 normal APs and 4 smart APs v.s. 8 normal APs.

Thus we can draw the conclusion that with limited number of reliable APs, MMLOC can achieve equivalent or better accuracy compared with normal RSSI-based systems but with only half number of APs.

7.3 Impact of RSSI Sampling Number

In this section we evaluate the relationship between the number of RSSI sampling made during the test phase and the accuracy of localization. Note that the number of sampling is related to the duration of measurement as well as the mode changing period T_c. The longer T_c is, the more RSSI sampling points are available. Since the ratio $T_1/T_2 = 2$, if $T_c = 30$ s, after clustering usually Mode 1 gets around 20 RSSI points and Mode 2 gets around 10 RSSI points. To assign a same weight for the two modes, during the previous test we select 10 points from the 20 points in Mode 1, as mentioned in Section 4.3. The same rule applies for the following experiments.

We change the number of RSSI points used for localization from 1 to 10, and recalculate the average error for the case "2 smart APs / 4 normal APs" and "4 smart APs / 8 normal APs". The results are illustrated in Fig. 9. Although theoretically more sampling points should lead to higher localization accuracy, it is shown that the average error is not highly impacted by the number of sampling points. This would be caused by the phenomenon that two contiguous samplings for RSSI usually get the same value.

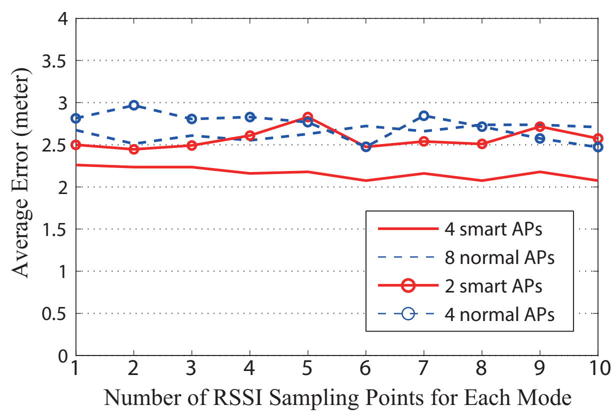


Figure 9: Average location errors when the number of RSSI sampling points changes.

The test result also implies that we can reduce the number of RSSI samplings to reduce the measurement duration. However, we cannot simply reduce the number of samplings to 1 because we need to keep the performance of clustering. To figure out which sampling point belongs to which mode, the number of sampling points cannot be too small. During our experiments we set $T_c = 30$

s to get around 30 RSSI points, so that for each mode clustering algorithm outputs 10 points for localization. It is still possible to reduce the number of points, and T_c can also be shortened by using higher sampling rate, which will be discussed in Section 8.

7.4 Transmission Stability for Normal Users

As discussed in Section 6, it is important to ensure the stable transmission of users. In this subsection we will show that the problem of possible coverage holes caused by changeable antenna modes is not serious, and the transmission rate of normal users are not obviously influenced when the modes are switched.

Stability of Wi-Fi Connection: During the test in Section 7.2, at each position we make our smartphones connect to each smart AP. For all the 48 grids in the experiment field, we check the state of Wi-Fi connection for each smartphone during the whole localization process, and the result shows that none of the links between the smart APs and the smartphones is broken. The reason is that we use the diversity mode of MIMO instead of the multiplexing mode, and thus the wireless links for smartphones can be maintained. Therefore, in most cases the links between mobile terminals and smart APs are maintained.

Stability of Wi-Fi Transmission Rate: We have made several measurements to confirm that the switch of antenna mode does not impact the transmission rate of normal users connected to the smart APs in our system. Firstly we measure the transmission rate of Wi-Fi in WLAN when the mode is changed. To exclude the factor of unstable data rate caused by the Internet, we set a FTP server on a computer, which is directly connected to a smart AP. Then a file with size 485 MB is transmitted between a smartphone and the computer via the smart AP.

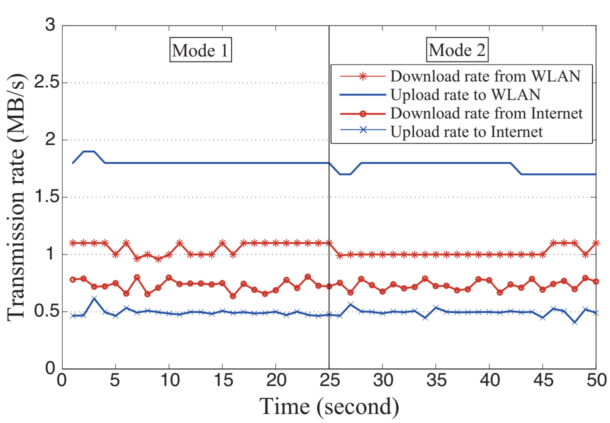


Figure 10: Transmission rate before and after the switch of antenna mode. The data rates are measured 5 meters away from a smart AP with sampling frequency 1 Hz.

As shown by the case of WLAN in Fig. 10, the average download and upload rate in Mode 1 are 1.06 MB/s and 1.80 MB/s, respectively. The phenomenon that the latter is higher than the former is caused by the performance difference between the AP's and cellphone's antennas. At the 25th second the mode is switched to Mode 2 and it can be seen that the data rates are not obviously influenced, and the swing range is less than 0.1 MB/s. Therefore the download/upload rate of Wi-Fi in WLAN is not impacted severely by the change of mode.

Moreover, we also find that, because of the bandwidth limitation of the Internet, the data rate via the Internet does not necessarily reach that of Wi-Fi in WLAN, and thus the actually transmission rate is also not obviously impacted by the switch of antenna mode. During our measurement we let the smartphone download/upload the same file via the Internet, and then change the mode of the smart AP. The case of download/upload rate through the Internet in Fig. 10 also shows that although the transmission rate keeps fluctuating, it is not influenced at the 25th second.

Thus it is confirmed that the quality of transmission for normal users are not impacted during our system's operation.

8 LIMITATION AND FUTURE WORK

We admit that the duration of $T_c = 30$ s in our prototype is quite long. We also observe that for different mobile devices the time needed to get the same number of RSSI samples is also different. For instance, with Nexus S we need around 30 s to get 30 RSSI points, while only around 20 s is needed with Nexus 5. So the measurement duration can be reduced with more powerful devices. Moreover, this value can be easily reduced by increasing the sampling rate for RSSI on the mobile terminal. Currently since we use the API of Android (WifiManager) directly, the sampling rate is limited. We believe a much higher sampling rate can be achieved if the support of driver layer is available. Since this is only a technical problem, we omit it in our paper.

On the other hand, the test result in Section 7.3 show that it is also possible to reduce the number of required RSSI points, so that the duration of measurement can also be shortened. While this method is promising, too short measurement duration will lead to the lack of points for clustering. In our paper $T_c = 30$ s maintains the good performance of clustering. There exists a trade-off between the measurement duration and the performance of clustering, and we leave the further exploration to our future work.

Currently we use only two modes on each smart AP. With three available antennas, potentially more modes are available, and the number of required smart APs can be further reduced. However, more antenna modes also increase the complexity of clustering, which would in turn reduce localization accuracy. We leave it to our future work to utilize more antenna modes.

9 CONCLUSION

In this paper we proposed MMLOC, an indoor localization system based on smart APs. The smart APs are equipped with two-mode antennas, and by switching the modes, two RSSI fingerprint maps can be generated by each smart AP. We design the clustering-based localization strategy and the sliding window-based clustering mechanism to allow mobile terminals to recognize the modes of APs, without any complex synchronization. The experiment results show that MMLOC can reduce the number of necessary APs by half while achieving the same or even better accuracy. The main benefit of our system is that, it enables us to rely on only a small number of well-deployed smart APs instead of unreliable private APs, and thus improves the stability and accuracy of the localization system.

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