Calibration-free Approaches for Robust Wi-Fi Positioning Against Device Diversity: A Performance Comparison

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***Abstract*—Received signal strength (RSS) in Wi-Fi networks is commonly employed in indoor positioning systems; however, device diversity is a fundamental problem in such systems. This problem becomes more important in recent years due to the tremendous growth of new Wi-Fi devices, which perform differently in respect to the RSS values and degrade localization performance significantly. Several studies have proposed methods to improve the robustness of positioning systems against device diversity. This paper is primarily concerned with the performance of calibration-free approaches, including signal strength difference (SSD), hyperbolic location fingerprinting (HLF), and DIFF. The performance comparison is based on two Wi-Fi positioning systems in a 3-D indoor building, including a zero-configuration and a fingerprinting-based system. The results show that these calibration-free techniques perform much better than the original RSS with heterogeneous devices. However, the improvement in robustness is gained at the expense of losing some discriminative information. When the testing and training data are both measured from the same device, the performance of HLF and SSD is clearly below that of RSS in both systems. Although DIFF performs the best, it has to suffer from dealing with a space of large dimensions.**

***Index Terms*—Device diversity, robust Positioning, location fingerprinting, calibration-free system, heterogeneity.**

I. INTRODUCTION

Indoor location estimation has attracted considerable attention in the last few years due to the increasing demand for location-based services [1]. Because of recent advancements in wireless technology, considerable studies have been tackling this problem through existing wireless infrastructure. In a GPS-less environment, the massive deployment of Wi-Fi access points (APs) makes Wi-Fi a suitable technology for developing such indoor location systems [2], [3]. Among the variety of positioning characteristics in Wi-Fi networks, received signal strength (RSS) is the most popular approach, because the sensing function is available on all Wi-Fi-enabled devices [4]. A typical indoor Wi-Fi positioning system measures RSS from APs, and then estimates the location of user by triangulation or fingerprinting methods. The former relies on a power-distance mapping while the latter uses a previously-stored database [5], [6]. Each approach has both advantages and limitations [7]. For example, the advantage of the fingerprinting-based approach is a high positioning accuracy; however, constructing database for the target areas is time consuming and requires a previous calibration stage [8].

Although the Wi-Fi positioning is a promising technology, a key problem for RSS-based approaches is that device diversity introduces a new variable [9]. This problem occurs when a user's device and a system-configured device are different, which is commonly encountered in Wi-Fi positioning systems [9]. Unfortunately, different Wi-Fi devices performed differently in respect to the RSS values, thus degrading localization performance significantly [10]. Previous works have acknowledged the problem of cross-device positioning [9]. For example, [11]–[13] showed that RSS variation between diverse Wi-Fi devices may exceed 25 dBm even in the same location and [10] showed the similar results, even the diverse devices come from the same vendor. Common approaches for handling variations in hardware fall into two categories: device mapping [14]–[16] and robust location features [17]–[21]. The first method attempts to transform the measurement from user devices to trainings device through a mapping function. For example, the works in [15] suggested a linear transformation approaches to overcome this problem. However, determining mapping functions for every possible device is time consuming and unfeasible due to the enormous number of products on the market.

The second method extracts robust location features to mitigate the effects of heterogeneous devices. For example, Dong et al. used signal strength difference between pairwise APs, called DIFF [22], to reduce the impact of diverse devices. Similarly, Kjærgaard et al. utilized signal strength ratios as fingerprints, namely hyperbolic location fingerprinting (HLF), to overcome the hardware variance problem [17]. The work in [20] proposed an enhanced method namely SSD, which selects an independent subset of DIFF to reduce the computational overhead. These approaches, including SSD, HLF, and DIFF, are calibration-free because they do not require the manually collection of measurements from various devices. However, there is a literature gap in performance comparison between these calibration-free techniques used for robust Wi-Fi positioning against device diversity.

In this paper, we present experimental results that demonstrate a comparison between these three RSS-variation techniques in two different realistic Wi-Fi positioning systems, including a zero-configuration-based and a fingerprinting-based system. The first system was implemented in a 3-floor building, using an Asus laptop and HTC Android phone as heterogeneous devices to locate a user in a 3-D environment. In this system, the mutual RSS between APs are used to create a RSS-distance mapping, thus requires zero-configuration. Onsite experimental results demonstrate that these calibration-free techniques, such as SSD, HLF, and DIFF, perform much better than the original RSS with heterogeneous devices. However, when the testing and training data are both measured from a laptop, the performance of HLF and SSD is clearly below that of RSS in this system. These results show that the improvement of these methods may be gained at the expense of discriminative information related to homogeneous devices. We can obverse the similar results in the second positioning system, which is implemented using a fingerprinting-based approach by collecting real RSS values at different reference locations in a 2-D plane. The measured RSS values clearly examine the effects of device diversity on Wi-Fi fingerprints. The experiment in this fingerprinting-based positioning system shows a consistent result and verifies our observations.

The rest of the paper is structured as follows. Section II illustrates the three robust and calibration-free positioning features against device diversity. Section III describes two Wi-Fi positioning systems. In Section IV, we explain the experimental setup and results. Finally, the conclusion is given in Section V.

II. Positioning Features Against Device Diversity

In this section, the three different robust positioning features, including DIFF, HLF and SSD, are described as follows.

A. Difference of Signal Strength (DIFF)

The difference of signal strength between pairs of APs, namely DIFF, was proposed in [22] to reduce the effect of diversity in devices. Assuming an observation o consists of a set of RSS from N APs, each observation o is represented as a vector as:

$$o = \{(b_1, x_1), ..., (b_N, x_N)\} \quad (1)$$

where b_N represents the N-th AP and x_N is the RSS values received from b_N. The difference of signal strength can be computed from two observations $o_i = (b_i, x_i)$ and $o_j = (b_j, x_j)$ as

$$\Delta x_{ij} = x_i - x_j \qquad i, j \in (1, N) \ \ , i < j \quad (2)$$

The set of DIFF positioning feature vector can be expressed as:

$$DIFF = \{\Delta x_{12}, ..., \Delta x_{(N-1)N}\} \quad (3)$$

If there are N APs, DIFF has C_2^N features in a positioning system. Note that it increases the dimensions from N to C_2^N, as compared to RSS.

B. Hyperbolic Location Fingerprinting (HLF)

The hyperbolic location fingerprinting (HLF) was proposed in [17], [23], using signal strength ratios between pairs of RSSs as fingerprints instead of absolute signal strength values. The main difference between DIFF and HLF is that the latter used normalized log signal strength ratios. HLF first transforms the received signal strength in dBm to integer values between 0 to 255 as

$$\{x_1, ..., x_N\} \rightarrow \{y_1, ..., y_N\} \qquad y \ \in (0, 255) \quad (4)$$

where y_i is the integer value from x_i according to [24]. The o being a pair of each AP b and a integer value y. The normalized log signal strength ratio nlr is defined from two observations o_i=(b_i, y_i) and o_j=(b_j, y_j) as

$$nlr(o_i, o_j) = \log(\frac{y_i}{y_j}) - \log(\frac{1}{y_{\max}}) \qquad i < j \quad (5)$$

where $y_{\max} = \max\{y_1, ..., y_N\}$ and the last term normalizes the ratios to keep the positive scale. The set of HLF positioning feature can be expressed as:

$$HLF = \{nlr(o_1, o_2), ..., nlr(o_{(N-1)}, o_N)\} \quad (6)$$

C. Signal Strength Difference (SSD)

The signal strength difference (SSD) method also takes the advantages of the difference of signal strength between pairs of APs as a robust location fingerprint [20], [25]. This method selects an independent subset of DIFF to reduce the computational overhead. For example, if 4 APs produces 6 DIFF values, SSD selects only Δx_{12}, Δx_{23} and Δx_{34} as positioning features since these components are independent with each other. In this example, the set of SSD positioning feature can be expressed as $SSD = \{\Delta x_{12}, \Delta x_{23}, \Delta x_{34}\}$. Note that this method decreases the dimensions from C_2^N to $N - 1$, thus saving the computational power as compared to DIFF.

III. Wi-Fi Localization System

We implemented two Wi-Fi positioning systems, including a zero-configuration and a fingerprinting-based system, to evaluate the performance of different robust positioning features. The details of these two system are described as follows.

A. Zero-Configuration System

We develop a zero-configuration positioning system according to the procedures in [26]. The system contains two main stages: signal-distance mapping and distance-based location search. The system takes as input the mutual power measurements between APs and between a device and APs. In the first stage, the pairwise RSS measurements between APs are used to create a RSS-distance mapping using a linear regression method. Then, the RSS measurements between a device and APs are used to estimate device-APs distances based on the mapping. In the second stage, this system adopts a simple gradient-based method to find the device's location. Using the estimated distances obtained from the first stage, this method

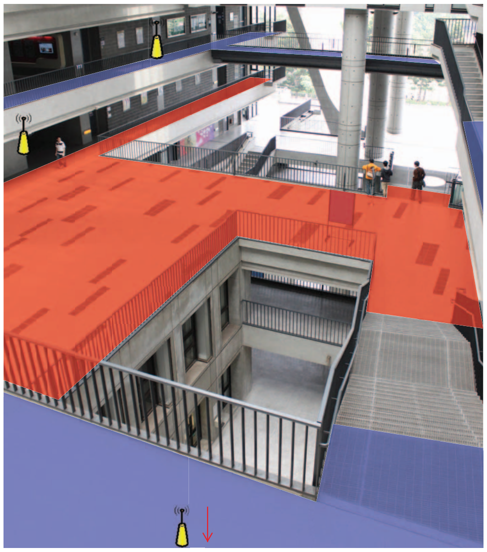


Fig. 1. Part of the FarEasTone Telecommunications Building, where we performed the experiment.

iteratively updates the location estimation by minimizing the mean square error objective function. Note that this system requires zero-configuration because a time-consuming site survey or a massive RSS collection is not required and the mapping based on pairwise RSS measurements is automated.

B. *Fingerprinting-based System*

The fingerprinting-based system [5] has two stages: offline and online. It collects radio fingerprints in the target environment and stores them in the database called *radio map* during the offline stage. When the device requests location-based services, the measured RSS is compared with the fingerprints in the radio map and the best matched location is estimated during the online stage. In this system, the positions of APs are not needed to know whereas a site survey is required. Several algorithms have been applied to the fingerprinting-based positioning systems such as k-nearest-neighbor, neural networks, kernel-based and probability-based approaches. We implement this fingerprinting-based system using the probability-based approaches. During the offline stage, we model the RSS distributions for each reference location. During positioning, we compute the likelihood function that indicates indicating how similar between the online measured RSS and that stored in the database. The likelihood values are then used to interpolate the location of device.

IV. Experimental Setup and Result

A. *System Setup*

In the first experiment, we built the zero-configuration-based system according to [26] which uses the information between APs to estimate the location. The experiments are conducted in the part of the FarEasTone Telecommunications Building (from the fourth to the sixth floor) at Yuan-Ze University, as shown in Fig. 1. This system has the capability to localize a device in a 3-D space since the height is taken into consideration. We set up 2 APs for each floor and collect mutual RSS between six APs to construct the RSS-distance mapping. In Fig. 1, we marked the locations of only three APs due to the limited range of this figure. The size of the test-bed was 63.5 $\times$ 36.5 $\times$ 10.5 meters and each AP is separated by 30 meters on average. We collected 200 testing samples at 42 different locations in this 3-D test field. Note that the dimension of RSS is 6 and that of HLF and DIFF increase from 6 to 21 due to the extended signal strength difference. SSD reduces the dimension from 7 to 6 by choosing an independent subset of DIFF.

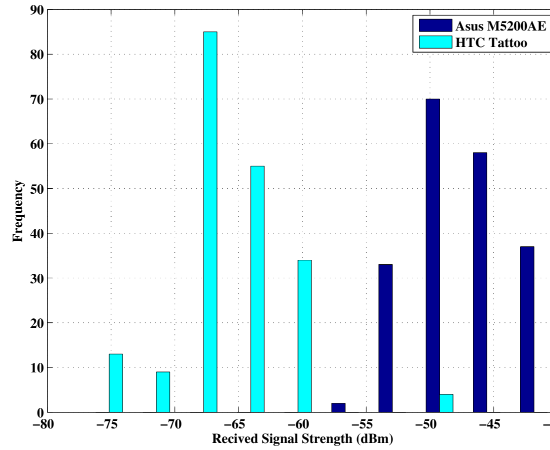


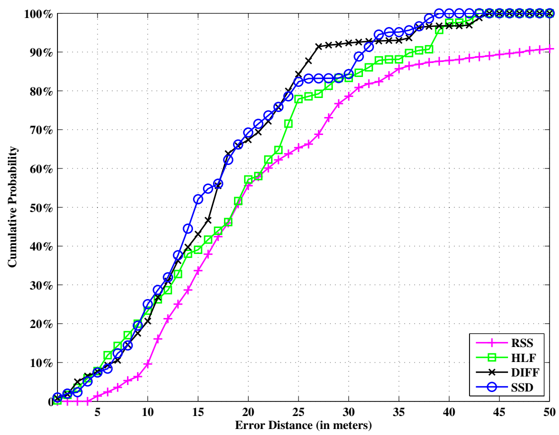
Fig. 2. The RSS Measurements using different devices at the fixed location from the same AP.

In the second experiment, we developed the fingerprinting-based system by collecting RSS data at different reference locations. We select 17 training locations at the same floor, separated by 2 meters on average, to measure RSS and construct the database. Every location in this environment is covered by seven APs on average. The dimension of RSS thus becomes 7 while that of DIFF, HLF, and SSD are 21, 21, and 6, respectively.

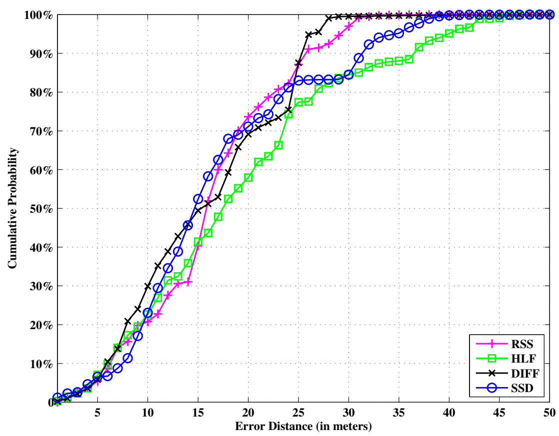
In both systems, we used an Asus M5200AE laptop to gather RSSs and to initialize the positioning systems. Then, we adopted HTC smart phone as a heterogeneous mobile device to simulate the device diversity. Figure 2 shows the RSS measurements at the fixed location from the same AP using the laptop and smart phone, respectively. The differences of RSS measurements form heterogeneous devices general exist and are larger than 30 dBm. This figure clearly reveals the device diversity problem since the RSS patterns could not match with heterogeneous devices.

B. *Performances*

This section compares the positioning performance of the SSD, HLF, DIFF and RSS on zero-configuration-based system and fingerprinting-based system, respectively. This study defines the positioning error as the Euclidean distance between the estimated results and the true coordinates. First, Fig. 3 reports the cumulative positioning error of different positioning features with heterogeneous and homogeneous devices in the zero-configuration system. Here the heterogeneous means that the testing data is measured using the smart phones

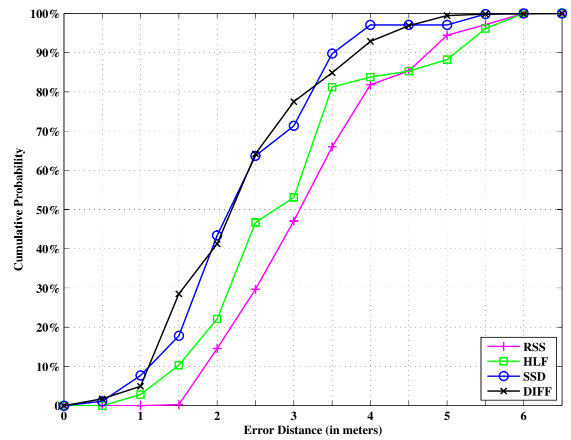


(a)

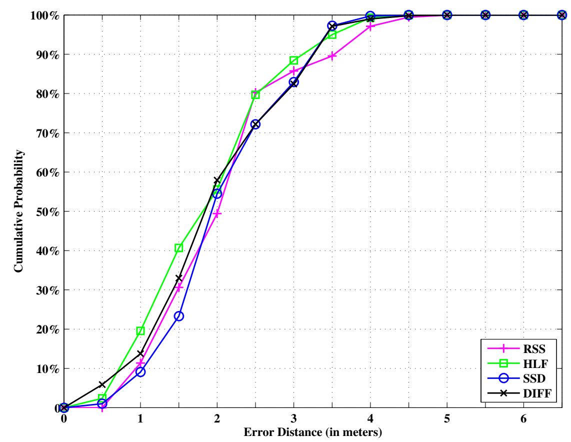


(b)

Fig. 3. The cumulative error distribution on zero-configuration-based system using (a) the heterogeneous devices, (b) the homogeneous devices.



(a)



(b)

Fig. 4. The cumulative error distribution on fingerprinting-based system using (a) the heterogeneous devices, (b) the homogeneous devices.

while the training data is obtained by the laptop. Figure 3(a) compares the performance in this scenario. This figure shows that the enhanced positioning features, such as SSD, HLF, and DIFF, perform much better than the original RSS with heterogeneous devices. The 20 meters accuracy of RSS achieves 56.02%, while those of DIFF, SSD and HLF are 67.50%, 69.31% and 57.06%, respectively. These positioning features are more robust than RSS. Next, Fig. 3(b) compares the positioning results with homogeneous devices, where the testing and training data are both measured from the laptop. This figure shows that, DIFF performs slightly better than SSD and HLF. More importantly, we can observe that the performance of HLF and SSD is clearly below that of RSS in this system. These results show that the improvement of these methods may be gained at the expense of discriminative information related to homogeneous devices. In other words, the side effect of these approaches is that the performances is not always better than the original RSS or even worse with homogeneous devices. Although DIFF performs the best among the compared methods, it has to suffer from dealing with a space of large dimensions. Incorporating some selection mechanisms may overcome this problem.

Figure 4 reports the cumulative positioning error of different positioning features in the fingerprinting-based system. With heterogeneous devices, Fig. 4(a) shows that the three meters accuracy of RSS 47.06%, while those of DIFF, SSD and HLF are 77.50%, 71.31% and 53.26%, respectively. Figure 4(b) shows the performance under homogeneous devices. The experiment in this fingerprinting-based positioning system shows a consistent result and verifies our observations. Based on the experiments, it has been concluded that although these methods perform much better than the original RSS with heterogeneous devices, the improvement in robustness is gained at the expense of losing some discriminative information. Note that the performance of a fingerprinting-based system is much better than a zero-configuration system for two reasons. First, the former is performed on a small and 2D plane while the latter is performed in a large 3-D building. Second, fingerprinting-based system uses the massive RSS training data to avoid the the uncertainties in power-distance mapping. Although fingerprinting-based system achieves a higher accuracy, it requires a time-consuming site survey, a previous calibration stage and may not be scalable to large environments.

V. Conclusion

In this paper, the three of the popular calibration-free techniques algorithms for handling variations in Wi-Fi hardware, including SSD, HLF, and DIFF, have been implemented. Their performance is compared on two Wi-Fi positioning systems, including a zero-configuration-based and a fingerprinting-based system in a 3-D indoor building. The performance results have been summarized and a conclusion has been presented. Based on the experiments, it has been concluded that although these methods perform much better than the original RSS with heterogeneous devices, the improvement in robustness is gained at the expense of losing some discriminative information. When the testing and training data are both measured from the same device, the performance of HLF and SSD is clearly below that of RSS in both systems. In two scenarios, the DIFF method performs the best. However, it has to suffer from having to deal with a space of large dimensions. Incorporating some selection mechanisms may overcome this problem.

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