Robust Wi-Fi Location Fingerprinting Against Device Diversity Based on Spatial Mean Normalization

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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 RSS-based systems. The variation in hardware is inevitable in the real world due to the tremendous growth in recent years of new Wi-Fi devices, such as iPhones, iPads, and Android devices, which is expected to continue. Different Wi-Fi devices performed differently in respect to the RSS values even at a fixed location, thus degrading localization performance significantly. This study proposes an enhanced approach, called spatial mean normalization (SMN), to design localization systems that are robust against heterogeneous devices. The main idea of SMN is to remove the spatial mean of RSS to compensate for the shift effect resulted from device diversity. The proposed algorithm was evaluated on an indoor Wi-Fi environment, where realistic RSS measurements were collected through heterogeneous laptops and smart phones. Experimental results demonstrate the effectiveness of SMN. Results show that SMN outperforms previous positioning features for heterogeneous devices.**

***Index Terms*—mobile positioning, hardware variation, positioning feature, location fingerprinting, and heterogeneity.**

I. Introduction

Because of recent advancements in wireless technology, considerable studies have been tackling indoor location estimation through existing wireless infrastructure [1]. In a GPS-less indoor environment, the massive deployment of Wi-Fi access points (APs) makes Wi-Fi a suitable technology for developing such indoor location systems [2], [3]. Many indoor positioning systems were developed based on various location metrics in Wi-Fi infrastructure, such as the time of arrival, angle of arrival and received signal strength (RSS). Among the variety of positioning characteristics in Wi-Fi networks, RSS is the most popular approach, because the sensing function is available on all Wi-Fi-enabled devices [4], [5]. A typical indoor Wi-Fi positioning system measures RSS from APs, and then estimates the location of user by fingerprinting methods [6], [7].

The location fingerprinting system design involves a database, called radio map that stores pre-recorded RSS at reference positions [8]. Then, the location is inferred by comparing a new RSS with the offline-constructed radio fingerprints. When a mobile device requests services, it compares the online RSS from nearby Wi-Fi APs with values stored in the database to determine its location. This approach does not need the locations of AP; however, it requires a prior data collection to build the radio map. Several pattern matching theories have been applied to this problem such as neural networks [9], kernel-based methods, and probabilistic approaches [10], [11]. The advantage of this approach is a high positioning accuracy; Nevertheless, constructing database for the target areas is time consuming and requires a previous calibration stage. In addition, although location fingerprinting shows great promise, a key challenge in RSS-based approaches is handling the heterogeneity in the hardware of devices.

The problem of device diversity occurs when a user's device and a system-configured device are different, which is commonly encountered in Wi-Fi positioning systems [12]. Such heterogeneity may result from using different chipsets or a lack consistency in the various standards. The variation in hardware is inevitable in the real world due to the tremendous growth in recent years of new Wi-Fi devices, such as iPhones, iPads, and Android devices, which is expected to continue. Previous works have acknowledged the problem of cross-device positioning. For example, Variation in RSS resulting from heterogeneous devices causes large bias error in localization systems [13], [14]. [15]–[17] showed that RSS variation between diverse Wi-Fi devices may exceed 25 dBm even in the same location and [13], [14] showed the similar results, even the diverse devices come from the same vendor. Thus, the works in [18] suggested a linear transformation approaches to overcome this problem. Kjærgaard et al. utilized signal strength ratios as fingerprints, namely hyperbolic location fingerprinting (HLF), to overcome the hardware variance problem [19], [20].

This study proposes an enhanced approach, called spatial mean normalization (SMN), to design localization systems that are robust against heterogeneous devices. The variation in hardware is usually considered additive bias with respect to the RSS values. The intention of SMN is to eliminate difference between heterogeneous devices through the calculation of the spatially average RSS. By removing the spatial mean, it compensates for the global shift of the RSS distributions caused by the heterogeneity. This makes SMN more appropriate than RSS when dealing with device diversity. The analysis shows that the SMN-based approach is independent of device gains, which somehow reduces problem associated with hardware variation. The proposed SMN algorithm was applied in an actual Wi-Fi environment at Yuan-Ze University, using an Asus laptop and HTC Android phone as heterogeneous devices. The results show that SMN performs better than the original RSS and previous HLF method with heterogeneous devices.

II. Related works

Although the Wi-Fi positioning is a promising technology, a key problem for RSS-based approaches is that device diversity introduces a new variable [21]. This problem occurs when a user's device and a system-configured device are different, which is commonly encountered in Wi-Fi positioning systems [21]. Unfortunately, different Wi-Fi devices performed differently in respect to the RSS values, thus degrading localization performance significantly [22]. Previous works have acknowledged the problem of cross-device positioning. For example, [15]–[17] showed that RSS variation between diverse Wi-Fi devices may exceed 25 dBm even in the same location and [22] 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 [18], [23], [24] and robust location features [13], [19], [25]–[27]. The first method attempts to transform the measurement from user devices to trainings device through a mapping function. For example, the works in [18] 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, Kjærgaard et al. utilized signal strength ratios as fingerprints, namely hyperbolic location fingerprinting (HLF), to overcome the hardware variance problem [19], [20]. The work in [28] proposed an enhanced method to reduce the computational overhead. These approaches are calibration-free because they do not require the manually collection of measurements from various devices. [29] provides a performance comparison between these calibration-free techniques.

III. Proposed Algorithm

In general, the log-normal RSS model can be expressed as [31]:

$$P_r\left(d\right) = P_t - PL\left(d\right) \tag{1}$$

where $P_r\left(d\right)$ refers to the received power at a particular distance d, P_t is the transmission power, and $PL\left(d\right)$ is the path loss at distance d as:

$$PL\left(d\right) = PL\left(d_0\right) + 10n\log\left(\frac{d}{d_0}\right) + X_\sigma \tag{2}$$

In Eq. 2, $PL\left(d_o\right)$ represents the path loss at reference distance d_o, n is an exponent that depends on the propagation environment, and X_σ is a random variable representing uncertainty in the model. Path loss $PL\left(d_o\right)$ is defined as the difference between the transmitted power and received power, which may include the effect of antenna gain as:

$$PL\left(d_o\right) = -10\log\left(\frac{G_t G_r \lambda_t^2}{\left(4\pi\right)^2 d_0^2}\right) \tag{3}$$

where G_t is the transmitter antenna gain, G_r is the receiver antenna gain, and λ is the wavelength of the transmitted radio signal. Substituting Eq. 2 and Eq. 3 into Eq. 1, we obtain

$$P_r\left(d\right) = P_t + 10\log\left(\frac{G_t G_r \lambda_t^2}{\left(4\pi\right)^2 d_0^2}\right) - 10n\log\left(\frac{d}{d_0}\right) - X_\sigma \tag{4}$$

Eq. 4 shows that two factors introduce variation into the measurements. The first factor is the random variable X_σ, which causes temporal variation in RSS due to the nature of radio propagation. The next factor is the receiver antenna gain G_r. Under heterogeneous conditions, variations in G_r lead to entirely different RSS values, even over a fixed distance. Thus, spatial mean normalization (SMN) is proposed to mitigate the effects of such variations in hardware. Assuming that RSSs (x_i) are measured from AP$_i$ at distances d_i, we write

$$x_i = P_i - 10\log\left(\frac{G_i G_d \lambda_i^2}{\left(4\pi\right)^2 d_0^2}\right) - 10n\log\left(\frac{d_i}{d_0}\right) \tag{5}$$

where P_i is the transmission power, G_i is the transmitter antenna gain, G_d is the receiver antenna gain from AP$_i$ at distances d_i, we ignore the temporal variation for simplifying the analysis. The intention of SMN is to eliminate difference between heterogeneous devices through the calculation of the spatially average RSS. SMN removes the spatial mean as:

$$\hat{x}_i = F(x_i|1,...,N)) = x_i - \bar{x} \tag{6}$$

where N is the number of APs, $\bar{x}$ is the spatial mean RSSs, and $\hat{x}_i$ are the processed features. The value of $\bar{x}$ is computed by

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{7}$$

The SMN method compensates for the global shift of the RSS distributions caused by the heterogeneity. This is because the term $\bar{x}$ contains the same component $-10\log\left(\frac{G_i G_d \lambda_i^2}{(4\pi)^2 d_0^2}\right)$ with different G_d. This indicates that after SMN, $\hat{x}_i$ is independent of antenna gains due to the cancellation, which reduces problem associated with hardware variation. Thus we use $\hat{x}_i$ instead of x_i as the input positioning features for a location fingerprinting task. We note that both the offline phase and online phase should perform the SMN method to make the pattern-matching consistent.

IV. Experimental Results

A. Experimental Setup

The Wi-Fi measurements are collected in the Wireless Mobile Computing Lab 70639 of the FarEasTone Telecommunications Building at Yuan-Ze University. We use an Asus M5200AE laptop with Windows XP, and NetStumbler network software to gather RSSs from APs. We also used HTC

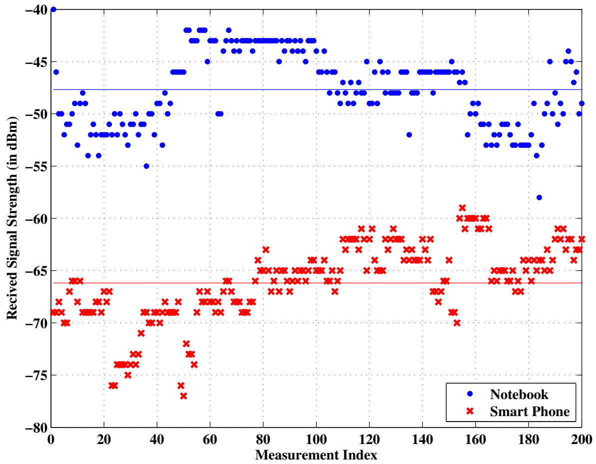

Fig. 1. The RSS distributions using diverse devices from the same AP and at the fixed location.

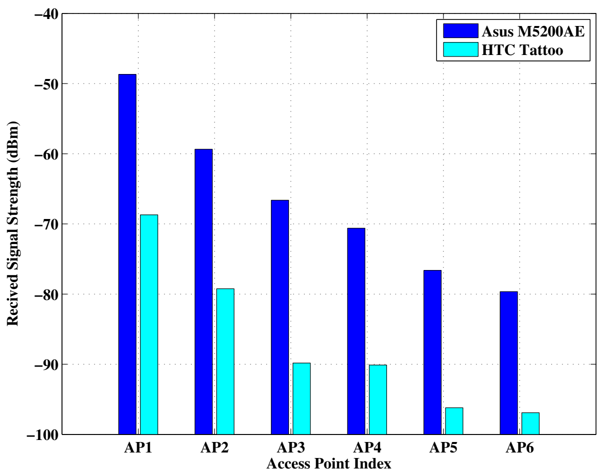

Fig. 2. The average RSS using diverse devices from six APs at the fixed location.

Android smart phone as heterogeneous mobile devices in the meantime. The size of the test-bed was 8.6 $\times$ 5.2 meters. We collected Wi-Fi RSS measurements every 50 times for each four different user orientation at 17 different reference locations. The locations separated by a distance of 1.2 to 2 meters. Fig. 1 shows the distribution of RSS measurements at the same location and from the same AP, using the laptop and smart phone, respectively. The lines represent that the average RSS value from laptop is -47.6 dBm whereas that from the smart phone is -66.2 dBm. This figure clearly reveals the hardware variation problem since the RSS patterns could not match with heterogeneous devices. Figure 2 shows the average RSS using diverse devices from six APs at the fixed location. This figure again shows that the RSS patterns could not be matched with heterogeneous devices.

B. Experimental Results

In this section, the performances are evaluated by a fingerprinting-based system and compared between three different spaces, including SMN, HLF and RSS. We adopt a maximum likelihood approach to implement the fingerprinting-based location system. This approach models the collected data as probabilistic distributions. Then, it calculates the likelihood of all reference positions and selects the position with the largest likelihood values as the estimated result. Figure 3 reports the cumulative error distribution of different approaches with heterogeneous and homogeneous devices. Figure 3(a) shows that the positioning features, HLF and SMN perform better than the original RSS with heterogeneous devices. The 3 meters accuracy of our approach achieves 74.06%, while those of HLF and RSS are 60.50% and 49.58%, respectively. This figure clearly shows that SMN outperforms the existing method, because our proposed approach reduces the effects of heterogeneous hardware and this can observed from Fig. 4. After the normalization, the RSS distributions become similar at a fixed location, thus making a larger probability at a correct match. However, the side effect is that the original RSS performs better than the robust approaches with homogeneous devices, as shown in Fig. 3(b). This can be explained by that the effective positioning features are better characterized by RSS values. The normalization may lose some discriminative information like G_d.

V. Conclusion

This study proposes a novel spatial mean normalization (SMN) approach to design localization systems that are robust against heterogeneous devices. The main idea of SMN is to remove the spatial mean of RSS to compensate for the shift effect resulted from device diversity. The proposed algorithm was evaluated on an indoor Wi-Fi environment, where realistic RSS measurements were collected through heterogeneous laptops and smart phones. Experimental results demonstrate the effectiveness of SMN. Results show that SMN outperforms previous positioning features for heterogeneous devices.

Acknowledgment

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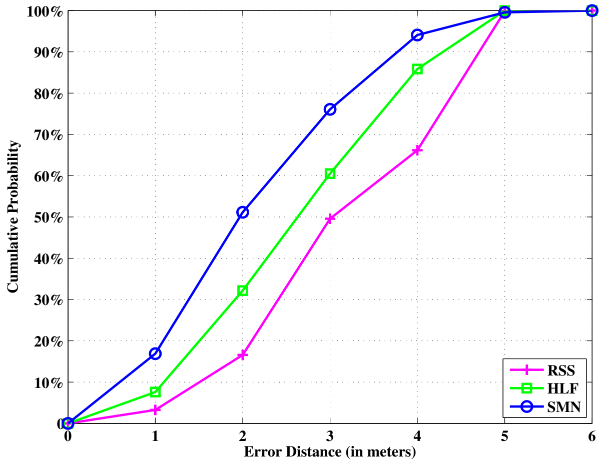
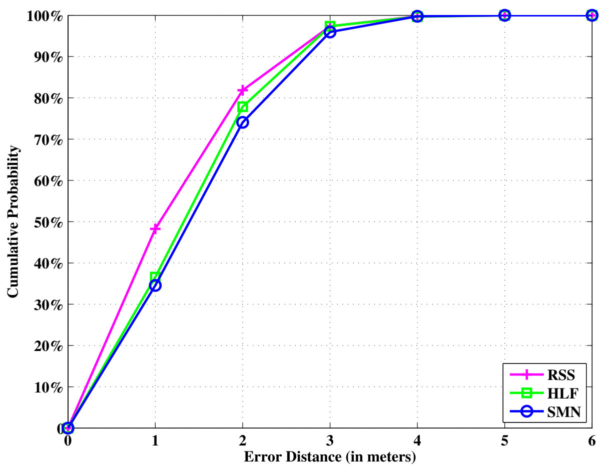


(a)



(b)

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

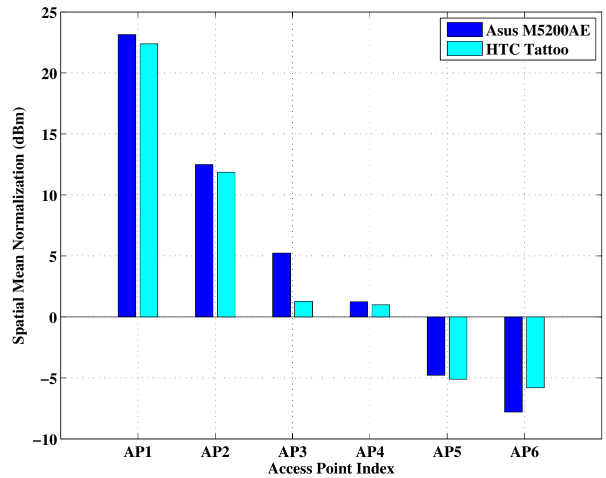


Fig. 4. The spatially normalized RSSs using the heterogeneous devices (HTC Smartphone and Asus Laptop) at the fixed location

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