Accuracy Improvement in Sensor Localization System utilizing Heterogeneous Wireless Technologies

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***Abstract*—Sensor localization is one of the big problems when building large scale indoor sensor networks because GPS (Global Positioning System) is unavailable in indoor environments. We are developing ZigLoc, a sensor localization system using WiFi APs (access points) as references, which requires no additional infrastructure [1, 2]. In ZigLoc, a sensor node measures RSS (received signal strength) of WiFi AP signals using a ZigBee (IEEE 802.15.4) module. Location of a sensor node is then estimated using fingerprints collected for a WiFi localization system. However, ZigLoc exhibits low accuracy due to the RSS offset derived by ZigBee and WiFi modules. The RSS offset is mainly caused by the channel bandwidth difference.**

In this paper, we present a differential fingerprinting method to improve localization accuracy. Our key idea is that we focus on RSS difference between WiFi APs. RSS difference between APs should be the same when we measure RSS using either ZigBee or WiFi modules. Differential fingerprinting only relies on RSS difference in fingerprint similarity calculation. We conducted experimental evaluations in a practical environment. The experimental evaluations reveal that ZigLoc accuracy was improved by approximately 26 % using the differential fingerprinting method.

***Index Terms*—Sensor localization, localization system without anchor nodes, fingerprinting.**

I. Introduction

Sensor network is gaining its importance due to its low-cost and low-power features in IoT (Internet of Things). In sensor networks, sensor location is important information used for recognizing sensing area, target tracking, and network building. Large scale indoor sensor network faces the sensor localization problem; we need to manually localize a huge number of sensor nodes because GPS (Global Positioning System) is unavailable in indoor environments.

To address the sensor localization problem, previous studies have reported sensor localization systems [3–5]. Although these studies have successfully reduced deployment costs [6–11] or improved accuracy [12–18], they require user cooperation or anchor nodes whose location is manually measured.

We are developing ZigLoc, an indoor sensor localization system using WiFi APs as references, which requires no anchor deployments [1, 2]. We send specific beacon signals from multiple WiFi APs. Sensor nodes detect the beacon signals using cross-technology signal extraction scheme and measure RSS (received signal strength) of the signals. Location of a sensor node is then estimated using a fingerprinting method. We use WiFi fingerprints collected for a WiFi localization system to localize sensor node without site-survey that collects fingerprints at everywhere in a localization target area.

However, ZigLoc exhibits low accuracy because of difference between RSS measured on sensor nodes and on WiFi modules. The channel bandwidth of ZigBee and WiFi is different; ZigBee is using 2 MHz band while WiFi is using 22 MHz band. Sensor nodes receive part of WiFi signals resulting in smaller RSS compared to RSS measured on WiFi devices. ZigLoc estimates the distance between the sensor node and WiFi APs longer than the actual distance because of this RSS offset.

This paper presents a differential fingerprinting method to reduce the influence of the RSS offset, which improves localization accuracy. In fingerprinting, location is estimated by searching for fingerprints similar to RSS derived by a target device. The differential fingerprinting calculates fingerprint similarity based on RSS difference between APs. RSS difference between APs should be the same when we measure RSS using either ZigBee or WiFi modules, which minimizes the influence of the RSS offset. We conducted experiments in our university building and confirmed that the differential fingerprinting improved localization accuracy by approximately 26 %.

The remainder of this paper is organized as follows. Section II briefly describes the design of ZigLoc and Section III presents the design of a differential fingerprinting method. Section IV describes the implementation of a sensor localization system utilizing the differential fingerprinting and conducted experimental evaluations. Section V shows related works on indoor sensor localization. Finally, Section VI concludes the paper.

II. ZigLoc

A. Overview

Figure 1 depicts an overview of a sensor localization system ZigLoc. WiFi APs are transmitting periodic beacon signals. Sensor nodes detect the beacon signals from multiple APs and measure their RSS (received signal strength), which is sent to a localization server. The localization server performs fingerprinting localization [19] with the RSS data to estimate the location of sensor nodes. We can use WiFi APs already installed in the environment to minimize deployment costs.

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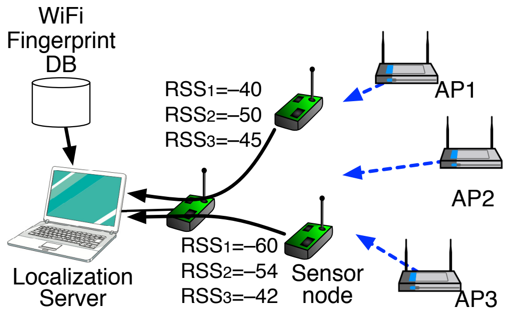

Fig. 1. Overview of ZigLoc

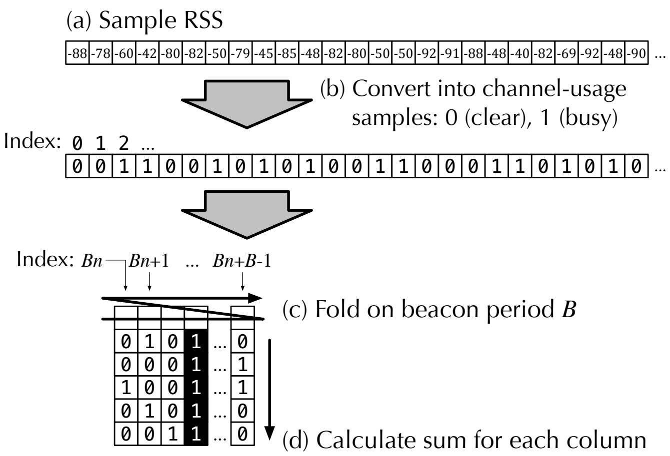

Fig. 2. Overview of AP signal detection. (a) A sensor node samples RSS and (b) converts the RSS samples into channel-usage samples. (c) The sensor node folds the channel-usage samples on beacon period, and (d) calculates the sum for each column to get channel-usage sums. Periodic beacon signals appear in a specific column, resulting in a large channel-usage sum.

The design of ZigLoc is divided into two components: an AP detector and location estimator utilizing WiFi fingerprints. Following subsections describe details of the each component.

B. AP Detector

The AP detector detects AP signals on a sensor node based on periodicity of beacon signals. Figure 2 shows an overview of AP signal detection. A sensor node periodically samples RSS in a specific ZigBee channel (Fig. 2a). Note that a ZigBee (IEEE 802.15.4) module on a sensor node has an RSS measurement function defined in the standard [20]. A sensor node is capable of WiFi signal detection because both WiFi and ZigBee are using the same 2.4-GHz band.

The collected RSS samples are converted into channel-usage samples: `0` for clear and `1` for busy (Fig. 2b). We use a threshold of -77 dBm for channel-usage determination, which follows after the default threshold of clear channel assessment on a CC2420 IEEE 802.15.4 module.

The channel-usage samples are folded on AP beacon period, resulting in a channel-usage matrix (Fig. 2c). We calculate the sum for each column in a channel-usage matrix (Fig. 2d). The sum is named a channel-usage sum.

We can identify AP signals by finding a column whose channel-usage sum is sufficiently large. AP beacon signals of the same interval as the folding period appear in a specific column. The large channel-usage sum therefore indicates that there are periodic beacon signals. The RSS samples corresponding to the detected AP signals are averaged to derive AP-RSS. We apply a simple filter prior to the averaging to reduce RSS measurement error [21].

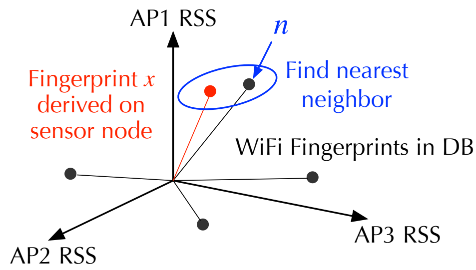

Fig. 3. Basics of ZigLoc fingerprinting localization

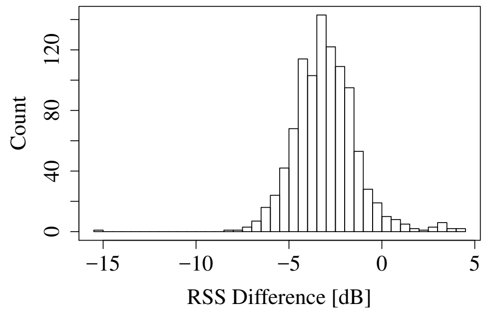

Fig. 4. Distribution of RSS difference

C. Location Estimator utilizing WiFi Fingerprints

The location estimator compares a set of AP-RSS measured on a sensor node with fingerprints in a WiFi fingerprint database to estimate sensor location. We assume that a WiFi fingerprint database is constructed prior to sensor deployment. This assumption is natural because WiFi localization systems utilizing fingerprinting are becoming prevalent nowadays.

Figure 3 shows the basics of a fingerprinting localization in ZigLoc. A fingerprint is a vector of AP-RSS. In Fig. 3, a fingerprint is a vector in a three dimensional space because the number of APs is three. Let x be a fingerprint derived on a sensor node. The location estimator finds a WiFi fingerprint n nearest to x. We repeat this search for k times and calculate weighted average of the locations of k nearest fingerprints to estimate sensor location.

D. RSS Offset Problem

In existing fingerprinting localization methods, a localization target device and devices for fingerprint collection are employing the same wireless technology. In ZigLoc, however, a target device and fingerprint collection are conducted by devices having different wireless technologies. A target device, i.e., a sensor node uses ZigBee (IEEE 802.15.4) while fingerprints are collected using WiFi (IEEE 802.11).

The RSS of an identical AP measured on ZigBee and WiFi modules are different, which degrades localization accuracy.

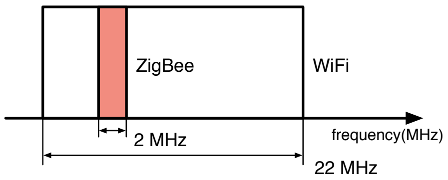

Fig. 5. Channel bandwidth of ZigBee and WiFi

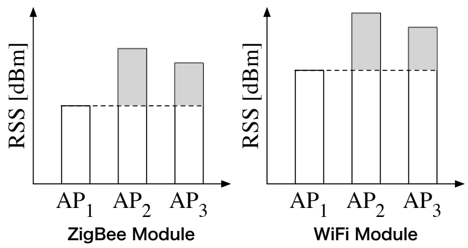

Fig. 6. RSS offset between ZigBee and WiFi modules

Figure 4 shows the distribution of RSS difference measured on a sensor node and WiFi device. The RSS measured on a sensor node is smaller than that measured on a WiFi device by $-3.15\,\mathrm{dB}$ on average.

The RSS difference originates from channel bandwidth difference between ZigBee and WiFi. Figure 5 illustrates the channel bandwidth of ZigLoc and WiFi. Bandwidth of ZigBee is $2\,\mathrm{MHz}$, whereas bandwidth of WiFi is $22\,\mathrm{MHz}$. A sensor node detects part of a WiFi signal and measures RSS of the partial WiFi signal. The RSS difference would be constant because the RSS difference is mainly caused by unchanging bandwidth difference. Antenna and amplifier gains might be other sources of the RSS offset.

The constant RSS difference, i.e., RSS offset seems to be compensated by adding a constant value to measured RSS. Radio circuit characteristics including antenna and amplifier gains on sensor nodes are different. Manual calibration is therefore required at each sensor node to apply the compensation.

III. Differential Fingerprinting

To address the RSS (received signal strength) offset problem, we develop differential fingerprinting. The key idea of the differential fingerprinting is to calculate fingerprint similarity based on RSS difference between APs. Figure 6 illustrates RSS derived by ZigBee and WiFi modules at the same location. Grayed boxes in Fig. 6 indicate RSS difference of AP_2 and AP_3 compared to the RSS of AP_1. We can assume that the RSS difference between APs measured by ZigBee and WiFi modules should be the same because bandwidth difference, which is a main cause of the RSS offset, between ZigBee and WiFi is unchanging. We utilize the RSS difference to estimate sensor location, removing the influence of the RSS offset.

Figure 7 shows an overview of differential fingerprinting. The differential fingerprinting consists of learning and estimating phases. The learning phase constructs a WiFi fingerprint database by collecting RSS of WiFi APs in a target area using a WiFi device. The estimating phase estimates sensor

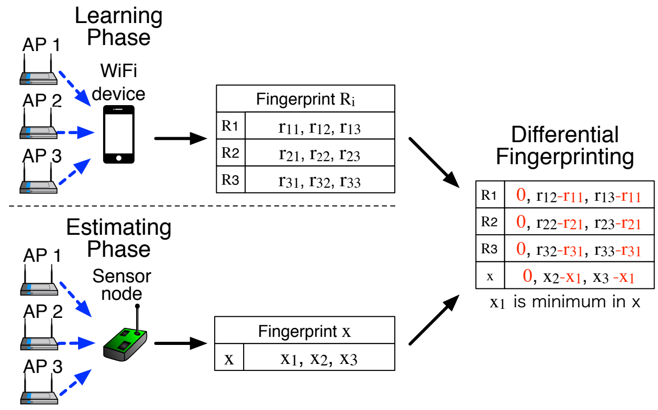

Fig. 7. Overview of differential fingerprinting

location by comparing the RSS measured at the location with the fingerprints. The following subsections describe the each phase in more detail.

A. Learning Phase

In a learning phase, differential fingerprinting collects fingerprints at everywhere in a target area to construct a WiFi fingerprint database. A localization target area is divided into small sub-areas, in each of which we collect RSS of WiFi APs using a WiFi module. Let S denote a set of sub-areas and m denote the number of WiFi APs. The fingerprint R_i in a sub-area $i \in S$ is a m-th vector defined as

$$R_i = \{\overline{r_{i1}}, \overline{r_{i2}}, \ldots, \overline{r_{im}}\}, \tag{1}$$

where $\overline{r_{ij}}$ $(j = 1, 2, \ldots, m)$ is an average RSS of AP_j in a sub-area i. We collect fingerprints R_i at all the sub-areas $i \in S$ and store the fingerprints in a database constructing a WiFi fingerprint database.

B. Estimating phase

In an estimating phase, differential fingerprinting estimates sensor location based on distance between fingerprints. A sensor node measures RSS of WiFi APs and calculates a fingerprint $x = \{\overline{x_1}, \overline{x_2}, \ldots, \overline{x_m}\}$ in the same manner as in Eq. (1). Distance between the fingerprint x and the WiFi fingerprints R_i in a fingerprint database is calculated using RSS difference between APs.

We used ℓ^1 norm of RSS difference in distance calculation. Let v denote a WiFi AP with the minimum RSS in x. The distance $dist(R_i, x)$ between the fingerprints x and R_i is calculated as follows:

$$dist(R_i, x) = \sum_{j=1}^{m} |(\overline{r_{ij}} - \overline{r_{iv}}) - (\overline{x_j} - \overline{x_v})|. \tag{2}$$

Finally, differential fingerprinting estimates sensor location using a k-nearest neighbor method. The k-nearest neighbor method chooses k sub-areas that have fingerprints nearest to the fingerprint x. Let N_k denote a set of the selected nearest neighbor sub-areas. The location P of a target sensor node is estimated as

$$P = \frac{\sum_{i \in N_k} \frac{1}{dist(R_i, x)} X_i}{\sum_{i \in N_k} \frac{1}{dist(R_i, x)}}, \tag{3}$$

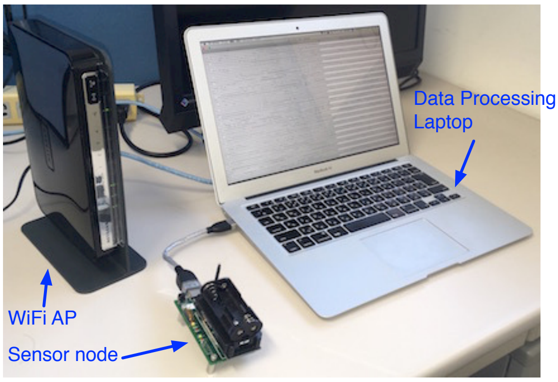

Fig. 8. Sensor node, WiFi AP, and data processing laptop used in implementation

where X_i is the coordinates of sub-area i.

IV. Evaluation

To validate the effectiveness of our differential fingerprinting presented in Section III, we evaluated localization accuracy. Localization accuracy is popular metrics first used in [22] and is the 90th percentile of localization error for all localizations.

A. Implementation

Figure 8 shows equipments used in our implementation. We used WNDR4300 WiFi APs from Netgear running OpenWrt and a MICAz sensor node from Crossbow that employs a CC2420 IEEE 802.15.4 module. A data processing laptop was MacBook Air running Mac OSX 10.10.5. We implemented a localization system as a Python program running on the data processing laptop and used MongoDB database as a fingerprint database.

Sensor node periodically retrieves RSS samples and send the RSS samples to the data processing laptop. The data processing laptop applies the technique presented in Section II-B and measures RSS of each APs to estimate sensor location.

B. Experiment Setup

Figure 9 shows an experiment setup. A localization target area was a $4 \times 9\,\mathrm{m}^2$ area in our laboratory. Eight APs were installed on desks in and around the target area.

In a learning phase, we constructed a WiFi fingerprint database. We measured RSS of AP beacon signals using a WiFi module on a MacBook Air laptop at 50 reference locations with 1-meter grid in the target area. At the each location, RSS samples were collected for 60 seconds and averaged out to generate a WiFi fingerprint.

In an estimating phase, we collected RSS samples for four seconds at seven locations using a sensor node and estimated the sensor location. The RSS collection was repeated for 15 times at the each location. The value of k in a k-nearest neighbor method was set to 3, which is the same as an existing localization method presented in [23]. We also measured RSS using a WiFi device for performance comparison.

In order to show the relative performance, we compared the performance of following three localization methods:

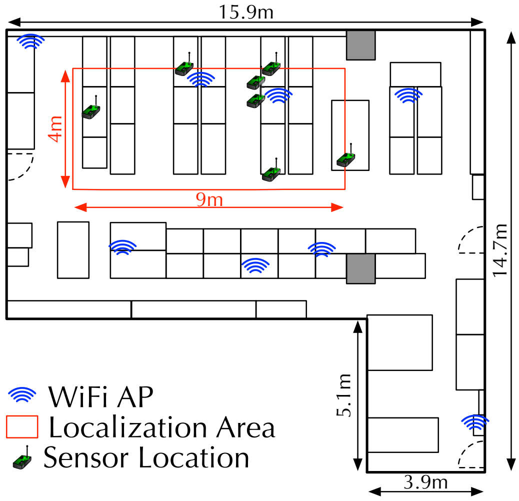

Fig. 9. Experiment setup

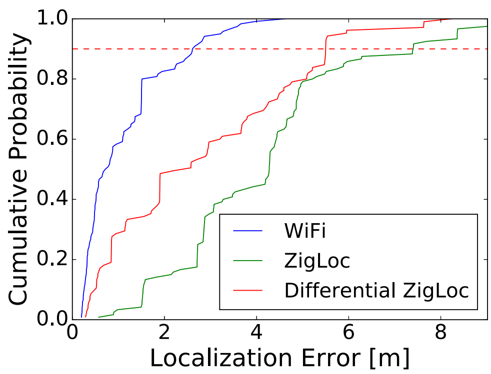

Fig. 10. Empirical cumulative distribution function of localization errors

1) *WiFi fingerprinting*: The WiFi fingerprinting estimates location of a WiFi device using WiFi fingerprints. This method is widely used in WiFi localization systems and its performance is a baseline for comparison with other methods.
2) *ZigLoc*: ZigLoc is the localization method that we have reported in [24]. This method compares WiFi AP-RSS measured on a sensor node with WiFi fingerprints to estimate sensor location.
3) *Differential ZigLoc (proposed)*: Differential ZigLoc is a ZigLoc localization method utilizing differential fingerprinting described in Section III. This method compares WiFi AP-RSS measured on a sensor node with WiFi fingerprints using differential fingerprinting.

C. Localization Accuracy

Figure 10 shows an ECDF (empirical cumulative distribution function) of the localization errors. Figure 10 indicates the following:

1) Localization accuracy of WiFi localization, ZigLoc, and differential ZigLoc was 2.70, 7.41, and 5.50 meters, re-

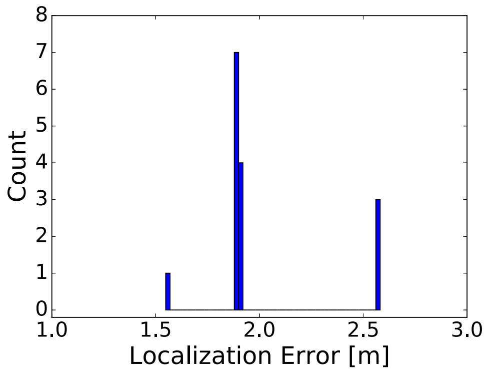

Fig. 11. Distribution of localization errors at (3.5, 4.0) in differential ZigLoc

spectively. Differential fingerprinting improved ZigLoc localization accuracy by $(7.41 - 5.50)/7.41 \times 100 \simeq 26\,\%$. The probability of small localization errors in differential ZigLoc was higher than that in ZigLoc. With neither additional equipment nor high additional computation, differential fingerprinting successfully reduced localization errors.

2) Localization accuracy of differential ZigLoc was lower than that of WiFi localization. Differential ZigLoc exhibited lower localization performance because the differential ZigLoc highly suffered from frequency selective fading caused by a narrow bandwidth compared to that of WiFi.
3) Cumulative probability of localization errors in differential ZigLoc significantly increased at 0.8, 1.9, and 5.5 meters, which indicates that localization errors were concentrated at these values. This was mainly caused by the small number of localization samples, i.e., 15 samples at each seven target locations. At a specific location, localization errors tend to be concentrated at a single value. Figure 11 shows an example of the distribution of localization errors at location $(x, y) = (3.5, 4.0)$. At (3.5, 4.0), localization errors were concentrated at around 1.9 meters. The remaining localization error might be caused by a location-specific factor such as frequency selective fading as described above.

The above results confirm that the differential fingerprinting improved ZigLoc localization accuracy. Tackling the effect of frequency selective fading might be required to further improve localization accuracy in ZigLoc.

D. Localization Results

Figure 12 shows the localization results of ZigLoc and differential ZigLoc. Stars in the figure are true target locations. Circles are localization results and the color represents the corresponding true location. Figure 12 indicates the following:

1) All the localization results of ZigLoc were concentrated in the left half side of a localization target area. This was mainly caused by constant RSS offset between WiFi and ZigBee modules. Distance between a WiFi AP and sensor node is estimated more longer as the sensor node is distant from the AP because the RSS offset is independent on the distance between a sensor node and WiFi AP. The localization results concentrated in the left side because the farthest AP was installed at the right bottom in the environment as shown in Fig. 9.
2) Localization results of differential ZigLoc moved to the right side compared to ZigLoc. Differential fingerprinting successfully reduced the influence of the RSS offset and distance between a WiFi AP and sensor node was more accurately estimated.
3) Localization results at $A = (6.0, 3.5)$ and $B = (6.0, 3.0)$ were significantly different, although A and B were separated by only 0.5 meters. At location A, location of a sensor node was almost accurately estimated because differential ZigLoc successfully reduced the influence of RSS offset. At location B, however, localization results in differential ZigLoc were very similar to those in ZigLoc. This implies that there should be other issues that greatly affected the localization accuracy.

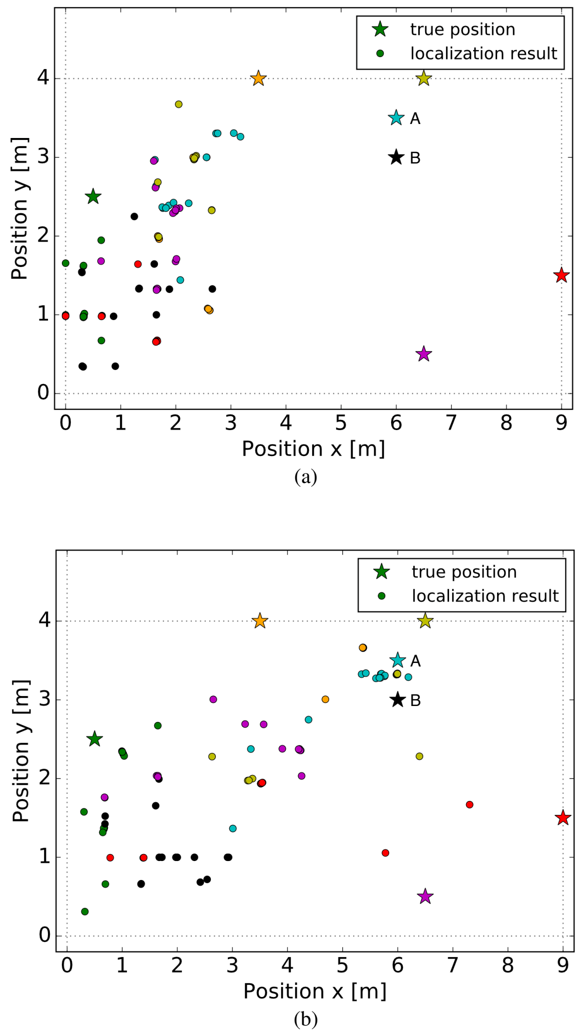

Fig. 12. Localization results of ZigLoc (a) without and (b) with differential fingerprinting. Stars are true target locations. Circles indicate localization results and the color represents the corresponding true location.

The above results implies that there are other issues that degrade localization performance in ZigLoc. Differential ZigLoc currently exhibited insufficient localization accuracy for practical use. We believe that there is a room for accuracy improvement.

V. Related Works

To the best of our knowledge, fingerprinting localization relying on different radio technologies is novel in the field of localization. In this section, we look through related works on fingerprinting localization in terms of deployment cost reduction, accuracy improvement, and ZigBee fingerprinting.

Crowdsourcing combined with fingerprinting localization greatly reduces deployment costs. In a learning phase, crowdsourcing conducts a site-survey, i.e., fingerprint collection, by user cooperation [8–11]. For example, WILL [10] combines measured RSS with user location estimated from acceleration derived on a user device to construct a fingerprint database without bothering users. User collaborative Redpin [25] shares fingerprint information between users to reduce the site-survey costs. In our ZigLoc system, crowdsourcing is a useful approach to collect WiFi fingerprints.

There is much literature working on localization accuracy improvement [12–18]. As shown in Section IV-D, issues other than RSS offset degrade ZigLoc localization accuracy. We believe that these previous works on accuracy improvement are therefore useful for more accuracy improvement in ZigLoc.

There is another fingerprinting method named ZiFind that utilizes WiFi AP signals for sensor localization [26]. ZiFind, however, requires WiFi devices called ZiFind mappers to collect fingerprints installed at a known location.

VI. Conclusion

In this paper, we present a differential fingerprinting method to improve localization accuracy in a sensor localization system ZigLoc. The differential fingerprinting focuses on RSS difference between APs in fingerprinting localization to minimize the influence of RSS offset caused by bandwidth difference between ZigBee and WiFi. We implemented a localization system utilizing the differential fingerprinting. Experimental evaluations showed that the ZigLoc localization accuracy was improved by approximately 26 % by applying a differential fingerprinting method.

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References

[1] K. Izumi, S. Ishida, S. Tagashira *et al.*, "Design of WiFi AP-RSS monitoring system using sensor nodes," in *Proc. Int. Symp. on Computing and Networking (CANDAR)*, Dec. 2015, pp. 115–121.

[2] S. Ishida, Y. Kunihiro, K. Izumi *et al.*, "Design of WiFi-AP operating channel estimation scheme for sensor node," in *Proc. Int. Conf. on Mobile Computing and Ubiquitous Networking (ICMU)*, Oct. 2016, pp. 13–18.

[3] J. Wang, R. K. Ghosh, and S. K. Das, "A survey on sensor localization," *J. Control Theory Applications*, vol. 8, no. 1, pp. 2–11, Feb. 2010.

[4] L. Cheng, C. Wu, Y. Zhang *et al.*, "A survey of localization in wireless sensor network," *Int. J. Distributed Sensor Networks*, vol. 2012, pp. 1–12, Nov. 2012, article ID 962523.

[5] A. Lédeczi and M. Maróti, "Wireless sensor node localization," *Philosophical Trans. Royal Society A*, vol. 2012, no. 370, pp. 85–99, Jan. 2012.

[6] M. Minami, Y. Fukuju, K. Hirasawa *et al.*, "DOLPHIN: A practical approach for implementing a fully distributed indoor ultrasonic positioning system," in *LNCS*, vol. 3205, Sep. 2004, pp. 437–365, proc. ACM Conf. Ubiquitous Computing (Ubicomp).

[7] L. Huang, F. Wang, C. Ma *et al.*, "The analysis of anchor placement for self-localization algorithm in wireless sensor networks," in *Advances Wireless Sensor Networks, Communications in Computer and Info. Science*, vol. 334, 2013, pp. 117–126.

[8] H. Wang, S. Sen, A. Elgohary *et al.*, "No need to war-drive: Unsupervised indoor localization," in *Proc. ACM MobiSys*, Jun. 2012, pp. 197–210.

[9] Z. Yang, C. Wu, and Y. Liu, "Locating in fingerprint space: Wireless indoor localization with little human intervention," in *Proc. ACM MobiCom*, Aug. 2012, pp. 269–280.

[10] C. Wu, Z. Yang, Y. Liu *et al.*, "WILL: Wireless indoor localization without site survey," *IEEE Trans. Parallel Distrib. Syst.*, vol. 24, no. 4, pp. 839–848, Apr. 2013.

[11] Z. Jiang, J. Zhao, J. Han *et al.*, "Wi-Fi fingerprint based indoor localization without indoor space measurement," in *Proc. IEEE Int. Conf. on Mobile Ad-Hoc and Sensor Systems (MASS)*, Oct. 2013, pp. 384–392.

[12] A. Taok, N. Kandil, and S. Affes, "Neural networks for fingerprinting-based indoor localization using ultra-wideband," *J. Communications*, vol. 4, no. 4, pp. 267–275, May 2009.

[13] G. S. Kuruoglu, M. Erol, and S. Oktug, "Three dimensional localization in wireless sensor networks using the adapted multi-lateration technique considering range measurement errors," in *Proc. IEEE GLOBECOM Workshops*, Nov.–Dec. 2009, pp. 1–5.

[14] A. W. Tsui, Y.-H. Chuang, and H.-H. Chu, "Unsupervised learning for solving RSS hardware variance problem in WiFi localization," *Mobile Networks and Applications*, vol. 12, no. 5, pp. 677–691, Oct. 2009.

[15] A. Kushki, K. N. Plataniotis, and A. N. Venetsanopoulos, "Intelligent dynamic radio tracking in indoor wireless local area networks," *IEEE Trans. Mobile Comput.*, vol. 9, no. 1, pp. 405–419, Mar. 2010.

[16] K. Kaemarungsi and P. Krishnamurthy, "Analysis of WLAN's received signal strength indication for indoor location fingerprinting," *Pervasive and Mobile Computing*, vol. 8, no. 2, pp. 292–316, Apr. 2012.

[17] S. Sen, B. Radunović, R. R. Choudhury *et al.*, "You are facing the Mona Lisa: Spot localization using PHY layer information," in *Proc. ACM MobiSys*, Jun. 2012, pp. 183–196.

[18] N. Wirström, P. Misra, and T. Voigt, "Spray: A multi-modal localization system for stationary sensor network deployment," in *Proc. Annual Conf. Wireless On-demand Network Systems Services (WONS)*, Apr. 2014, pp. 25–32.

[19] K. Kaemarungsi and P. Krishnamurthy, "Modeling of indoor positioning systems based on location fingerprinting," in *Proc. IEEE Int. Conf. on Computer Communications (INFOCOM)*, Mar. 2004, pp. 1012–1022.

[20] IEEE Standards Association, "IEEE Std 802.15.4-2011, IEEE standard for local and metropolitan area networks — part 15.4: Low-rate wireless personal area networks (LR-WPANs)," Sep. 2011, http://standards.ieee.org/.

[21] S. Ishida, K. Izumi, S. Tagashira *et al.*, "WiFi AP-RSS monitoring using sensor nodes toward anchor-free sensor localization," in *Proc. IEEE Vehicular Technology Conf. (VTC-Fall)*, Sep. 2015, pp. 1–5.

[22] M. Youssef and A. Agrawala, "The Horus WLAN location determination system," in *Proc. ACM MobiSys*, Jun. 2005, pp. 205–218.

[23] P. Bahl and V. N. Padmanabhan, "RADAR: An in-building RF-based user location and tracking system," in *Proc. IEEE Int. Conf. on Computer Communications (INFOCOM)*, Mar. 2000, pp. 775–784.

[24] S. Ishida, K. Izumi, T. Yamamoto *et al.*, "Initial evaluation of ZigLoc: Anchor-free sensor localization system using WiFi fingerprints," in *Proc. ACM HotMobile, Demo*, Feb. 2017, p. 1.

[25] P. Bolliger, "Redpin – adaptive, zero-configuration indoor localization through user collaboration," in *Proc. ACM Int. Workshop on Mobile Entity Localization Tracking GPS-less Environments (MELT)*, Sep. 2008, pp. 55–60.

[26] Y. Gao, J. Niu, R. Zhou *et al.*, "ZiFind: Exploiting cross-technology interference signatures for energy-efficient indoor localization," in *Proc. IEEE Int. Conf. on Computer Communications (INFOCOM)*, Apr. 2013, pp. 2940–2948.