Evaluation of MultiZigLoc: Indoor ZigBee Localization System Using Inter-Channel Characteristics

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***Abstract*—Sensor localization is one of the big problems when building large scale indoor sensor networks. We are developing ZigLoc, a sensor localization system using Wi-Fi (IEEE 802.11) APs (access points) as references [1, 2]. ZigLoc measures RSS (received signal strength) of Wi-Fi AP signals to localize ZigBee (IEEE 802.15.4) sensor nodes. However, ZigLoc exhibits low accuracy because of inaccurate RSS measured on a single narrow-band ZigBee channel. In this paper, we present a highly accurate sensor localization system *MultiZigLoc*, which is an extended system of ZigLoc. Our key idea is to employ RSS measured in multiple ZigBee channels in fingerprinting localization. The RSS in multiple channels is dependent on the measured location because ZigBee uses narrow-band channels. Narrow-band ZigBee communication is highly affected by frequency selective fading, whose influence is dependent on channels and locations of both Wi-Fi APs and a sensor. We utilize fingerprints that separately handles RSS in multiple ZigBee channels to employ channel specific features. We conducted initial evaluations using RSS measured in a practical environment. The evaluations reveal that MultiZigLoc improved the localization accuracy by more than 10 points.**

***Index Terms*—sensor network, localization, ZigBee, Wi-Fi, multi-channel**

I. Introduction

Wireless sensor network is gaining its importance due to its low-cost and low-power features in the fields of IoT (Internet of Things) and M2M (Machine-to-Machine). In sensor networks, sensor location is important for recognizing sensing area, target tracking, and a network routing. Sensor location is usually derived by using GPS (Global Positioning System) or manual measurements. We face a sensor localization problem when we build a large scale sensor network in indoor environments where GPS is unavailable.

To address the sensor localization problem, previous studies have reported sensor localization systems [3–5]. Although these studies have successfully reduced deployment costs [6–20] or improved accuracy [21–26], they require user cooperation or anchor nodes whose location is manually measured.

We also have developed ZigLoc, a sensor localization system using Wi-Fi (IEEE 802.11) APs (access points) as references [1, 2]. ZigBee (IEEE 802.15.4) sensor nodes detect specific beacon signals from multiple Wi-Fi APs installed in an indoor environment and measure RSS (received signal strength) of the signals. Location of sensor nodes is then estimated by using fingerprinting or multilateration methods.

However, ZigLoc exhibits low accuracy because of inaccurate RSS measured in a single narrow-band ZigBee channel. ZigBee uses narrow-band channels compared to Wi-Fi, which greatly affected by frequency selective fading. When we measure RSS of signals from an identical Wi-Fi AP in different channels, the channel responses are dependent on the channel. We observe different RSS values in different ZigBee channels.

In this paper, we present a high accuracy sensor localization system *MultiZigLoc*, which is an extended system of ZigLoc. Our key idea is to employ RSS measured in multiple ZigBee channels as location-specific features in fingerprinting localization. The RSS in multiple channels is dependent on the measured location because of frequency selective fading. We build a fingerprint database that separately stores RSS in multiple ZigBee channels to employ channel specific features.

We conducted RSS measurement experiments in our university building and analyze data by leave-one-out 10-fold cross validation as an initial evaluation of MultiZigLoc. As a result of classifying the location of sensor nodes into 3 locations and calculating the localization accuracy, MultiZigLoc improved the localization accuracy by more than 10 points from ZigLoc.

Specifically, our main contributions are twofold:

- We present the design of MultiZigLoc, high accuracy indoor localization system. MultiZigLoc employs Wi-Fi AP RSS measured on multiple ZigBee channels in fingerprinting localization to enhance location-specific features improving localization accuracy.
- We conduct initial evaluations of MultiZigLoc using an actual sensor node and Wi-Fi APs. We experimentally show that MultiZigLoc improves localization accuracy.

The remainder of this paper is organized as follows. Section II explains about ZigLoc and points out a problem of ZigLoc. Section III presents the design of MultiZigLoc and Section IV conducts an initial evaluation. Section V shows related work on indoor sensor localization. Finally, Section VI concludes the paper.

II. ZigLoc

Figure 1 depicts an overview of a sensor localization system ZigLoc. ZigLoc consists of sensor nodes, a localization

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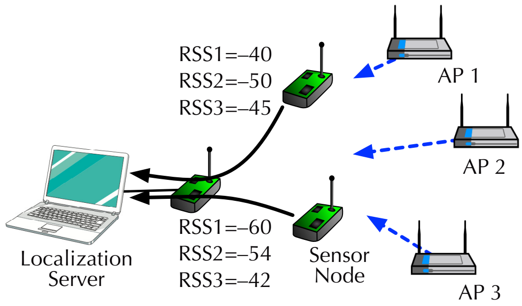

Fig. 1. Overview of ZigLoc

server, and multiple Wi-Fi APs installed in an environment. Each Wi-Fi AP is transmitting periodic beacon signals. The sensor nodes detect the beacon signals from multiple APs and measure their RSS (received signal strength) in a single ZigBee channel. The sensor nodes then send all the RSS data to a localization server. The localization server estimates the location of the sensor nodes from the RSS data by using a localization method such as fingerprinting or multilateration.

When ZigBee sensor nodes measure RSS of signals from a Wi-Fi AP, the RSS value is dependent on the measurement channel. ZigBee uses 2-MHz channel, while Wi-Fi uses 22-MHz channel. We observe different Wi-Fi AP RSS in each ZigBee channel because narrow-band ZigBee channels tend to be affected by frequency selective fading. The RSS difference degrades localization accuracy.

III. MultiZigLoc

A. Key Idea

Our key idea is to employ RSS (received signal strength) measured in multiple ZigBee channels in fingerprinting localization. ZigBee uses narrow-band channels, so the RSS in multiple channels is dependent on the measured location, as mentioned in Section II. Also, because of narrow-band channels, four ZigBee channels overlap a single Wi-Fi channel in the same frequency band. The channel response of four ZigBee channels are different from each other because of the difference of channel frequency. Then, we observe different RSS depending on the channels despite measuring an identical Wi-Fi signal. The difference of RSS shows different characteristics depending on location. MultiZigLoc improves localization accuracy by using RSS measured in multiple ZigBee channels in fingerprinting localization.

B. Design Overview

Figure 2 depicts an overview of MultiZigLoc. MultiZigLoc consists of a multi-ch-RSS measurement and fingerprint localization blocks. In a multi-ch-RSS measurement block, sensor nodes measure RSS while switching ZigBee channels. Fingerprint localization block estimates sensor location by using a fingerprinting localization method.

Following subsections present design details of the each block.

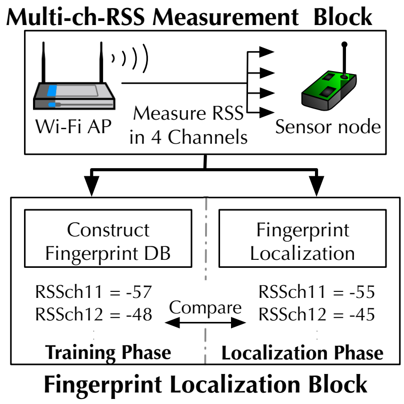

Fig. 2. Overview of MultiZigLoc

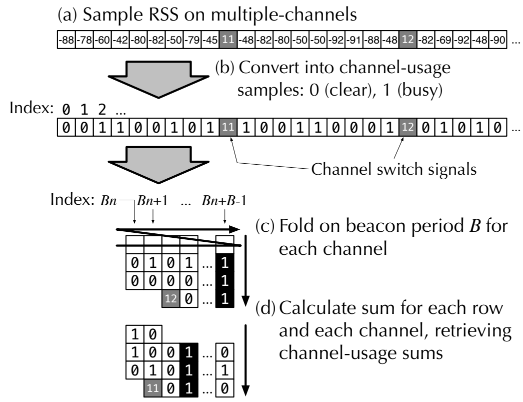

Fig. 3. Overview of AP signal detection in multi-ch-RSS measurement block

C. Multi-ch-RSS Measurement Block

In a multi-ch-RSS measurement block, sensor nodes detect beacon signals sent from Wi-Fi APs based on periodicity of beacon signals. Fig. 3 shows an overview of AP signal detection. A sensor node periodically samples RSS in a ZigBee channel (Fig. 3a). Note that a ZigBee module on a sensor node has an RSS measurement function defined in the standard [27]. A sensor node is capable of Wi-Fi signal detection because both Wi-Fi and ZigBee are using the same 2.4-GHz ISM band.

The sensor node changes its observation channel after the specific number of samples are collected. Channel switch takes some time to restart radio circuits. We embed channel switch signals instead of RSS samples during the channel switch period. Because ZigBee modules provide average RSS over 128 microseconds, which is defined in the standard, we set an RSS sampling period to 128 microseconds not to miss Wi-Fi signals while minimizing the sampling rate. The collected RSS samples are converted into channel-usage samples: `0` for clear and `1` for busy (Fig. 3b). We use a threshold of $-77\,\text{dBm}$ for channel-usage determination, which follows after the default threshold of a CC2420 IEEE 802.15.4 module for clear channel assessment [28].

The channel-usage samples are grouped by measurement

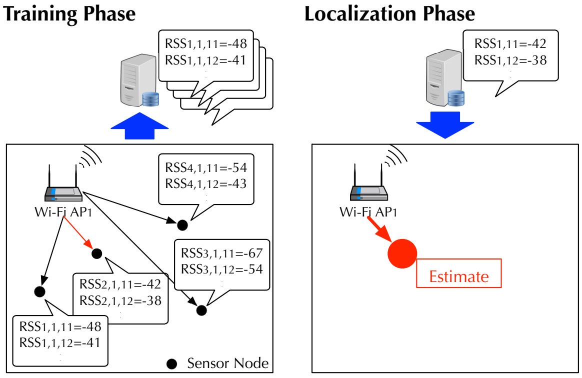

Fig. 4. Overview of fingerprint localization block

Fig. 5. Sensor node, Wi-Fi AP, and data processing laptop used in implementation

channels and are folded on the AP beacon period, resulting in channel-usage matrices (Fig. 3c). To preserve beacon timing information, a part of the each matrix might be missing, as shown in Fig. 3. We calculate the sum for each column in each channel-usage matrix (Fig. 3d). These sums are named channel-usage sums.

We can detect AP signals in each ZigBee channel by finding a column whose channel-usage sum is above a threshold. AP beacon signals whose interval matches to the folding period appear in a specific column. Large channel-usage sum therefore indicates that there are beacon signals whose interval matches to the folding period. AP signals from an identical AP have an identical beacon index. We configure APs with beacon intervals that are non-multiples each other to separately detect the APs [29].

AP-RSS is calculated by averaging RSS samples of the detected AP signal. RSS samples corresponding to the AP signal columns in a channel-usage matrix are extracted and averaged. Note that we employ a simple edge filter to reduce the RSS measurement error [30].

D. Fingerprint Localization Block

Figure 4 shows an overview of a fingerprinting localization block. Fingerprint localization block consists of training and localization phases.

In a training phase, fingerprinting localization block collects fingerprints at multiple locations in a localization target area and constructs a fingerprint database. Fingerprints made from RSS of multiple Wi-Fi APs are features representing the location. We name the set of fingerprints stored in the database as *database-fingerprints*. Let i denote the location where a sensor node measures RSS, n denote the number of Wi-Fi APs, and c denote a ZigBee channel. The database-fingerprint R_i at a location i is defined as

$$R_i = \{r_{i,1,1}, r_{i,1,2}, \dots, r_{i,2,1}, \dots, r_{i,n,c}\}, \tag{1}$$

where $r_{i,j,c}$ $(j = 1, 2, \dots, n)$ is an average RSS of AP$_j$ measured in a channel c at a location i.

In a localization phase, fingerprinting localization block estimates sensor location based on distance between fingerprints. A target sensor node measures RSS of Wi-Fi APs and calculates a *target-fingerprint*. A target-fingerprint $\bar{t}$ is defined as

$$\bar{t} = \{t_{1,1}, t_{1,2}, \dots, t_{2,1}, \dots, t_{n,c}\}, \tag{2}$$

in the same manner as in Eq. 1. Distance between the target-fingerprint $\bar{t}$ and the each database-fingerprint R_i is calculated as follows:

$$\begin{aligned} dist(R_i, \bar{t}) &= \sqrt{(R_i - \bar{t})^2} \\ &= \sqrt{\sum_{n,c} (r_{i,n,c} - t_{n,c})^2}. \end{aligned} \tag{3}$$

Finally, fingerprinting localization block estimates sensor location. Fingerprinting localization block selects a target sensor location $\hat{\imath}$ that have the nearest database-fingerprint to the target-fingerprint, as following formula.

$$\hat{\imath} = \arg\min_i dist(R_i, \bar{t}). \tag{4}$$

IV. Initial Evaluation of MultiZigLoc

In order to evaluate the effectiveness of MultiZigLoc, we implemented MultiZigLoc system and conducted the evaluation experiment of the localization accuracy.

A. Initial Implementation

Figure 5 shows equipments used in our implementation. We used WNDR4300 Wi-Fi APs from Netgear running OpenWrt and a MICAz sensor node from Crossbow that employs a CC2420 IEEE 802.15.4 module [28]. A data processing laptop was MacBook Air running Mac OSX 10.11.4. The sensor node connected with the laptop. We implemented a localization system as a Python program running on the data processing laptop.

The sensor node periodically retrieved RSS samples and send the RSS samples to the data processing laptop. The data processing laptop applied the technique described in Section III-C and obtained RSS on each ZigBee channel.

B. Experiment Setup

Figure 6 shows an experiment setup. We installed a Wi-Fi AP in our laboratory. We measured RSS (received signal strength) of the Wi-Fi AP signals in four ZigBee channels using a sensor node at three locations a, b, and c, as shown

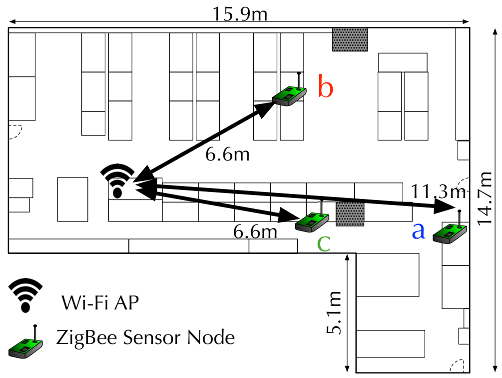

Fig. 6. Experiment setup

in Fig. 6. The locations a, b, and c are 11.3, 6.6, 6.6 meters away from the Wi-Fi AP, respectively. The beacon interval of our AP was set to 109 TU to safely distinguish our AP from other APs whose beacon interval is 100 TU. We used channel 11, where small number of Wi-Fi APs were operating in our experiment environment. The sensor node periodically switched its ZigBee channel from 21 to 24, which overlap with Wi-Fi channel 11. The RSS samples were collected for four seconds in each ZigBee channel. We repeated the RSS sampling for 1500 trials. Trials with successful AP detection on all the four ZigBee channels were used in our evaluation.

We evaluated localization accuracy by leave-one-out 10-fold cross validation. In 10-fold cross validation, RSS samples are divided into ten chunks, nine of the chunks were used for learning in the training phase and the remaining one chunk was used for localization in the localization phase. We estimated the location of the sensor node from the 3 locations a, b, and c in Fig. 6. The estimation was performed on all combinations of test data. The total number of estimation trials is $3 \times 10^3 = 3000$ times. The estimation result was compared with the location where the test data was actually measured, and the correct answer rate was evaluated as the localization accuracy. Distance between a target-fingerprint and database-fingerprints in each trial was also evaluated to show the effectiveness of MultiZigLoc.

To demonstrate relative performance of MultiZigLoc, we compared the localization accuracy of MultiZigLoc and ZigLoc. MultiZigLoc uses RSS measured in four ZigBee channels as features, as shown in Section III. ZigLoc method uses RSS measured in a single ZigBee channel as a feature.

C. Localization Accuracy

Table I shows the localization accuracies of MultiZigLoc and ZigLoc. Table I indicates that MultiZigLoc improved the accuracy by more than 10 points.

All false answers in ZigLoc were caused by RSS fluctuations of test data at location a. The false answers in MultiZigLoc were caused at location b, which were estimated as location c. These false estimation occurred for test data taken from the head of collected RSS data, which were highly affected by environmental changes mainly due to an experiment operator. RSS measurement was conducted mainly at night to minimize the influence of environmental changes. However, at the head of measurement, some people who affected the radio propagation environment were in the experiment environment, which resulted in RSS fluctuations. When we retrieve test data from the head of measurement, database-fingerprints were built from RSS samples in an almost stable environment, resulting in the high false answer rate.

TABLE I
LOCALIZATION ACCURACY OF MULTIZIGLOC AND ZIGLOC

	MultiZigLoc	ZigLoc
True	2940	2600
False	60	400
Accuracy	98.0 %	86.7 %

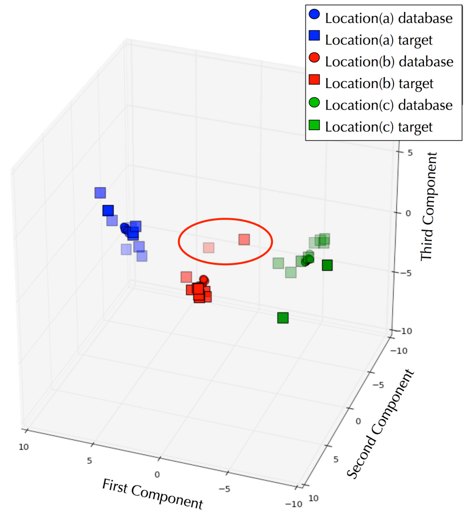

Fig. 7. Fingerprints of MultiZigLoc

To demonstrate that MultiZigLoc approach, i.e., utilizing RSS in multiple channels in fingerprinting, is effective for accuracy improvement, we analyze distance between fingerprints. Fingerprints are 4-dimensional vector in MultiZigLoc, which is difficult to show in a plot. We therefore compress fingerprints into 3-dimensional vector by PCA (principal component analysis).

Figure 7 shows the converted 3-dimensional fingerprints. Circles and squares in the figure represent database-fingerprints (database) and target-fingerprints (target), respectively, and their color represents the measurement location. Figure 7 shows that the distance between target-fingerprints and database-fingerprints was shorter than the distance between database-fingerprints at different locations. The database-fingerprints at different locations had bigger separation compared to database-fingerprints at the same location. The target-fingerprints distributed near the database-fingerprints at the same location, which resulted in high estimation accuracy.

The target-fingerprints in a red ellipse in Fig. 7 caused false answers of estimation. These target-fingerprints at location b are distant from the database-fingerprints at the same location

TABLE II
FINGERPRINT DISTANCE RATIO

(a) MultiZigLoc

		Location j a	b	c
Location i	a	1	0.312	0.212
	b	0.266	1	0.304
	c	0.164	0.277	1

(b) ZigLoc

		Location j a	b	c
Location i	a	1	0.789	0.290
	b	0.328	1	0.167
	c	0.057	0.087	1

b and are more close to database-fingerprints at the different location c.

D. Fingerprint Distance Ratio

To accurately estimate sensor location, target-fingerprints should be located close to database-fingerprints at the same location compared to database-fingerprints at the different locations. In other words, the distance ratio of the fingerprints at the same location to the fingerprints at the different location should be small.

In MultiZigLoc, distance between fingerprints at the same location is smaller than distance between fingerprints at different locations, which improves location estimation accuracy. To confirm that fingerprints at different locations are distant, we evaluated a fingerprint distance ratio. The fingerprint distance ratio $\eta_{i,j}$ between locations i and j is defined by mean distances between fingerprints as:

$$\eta_{i,j} = \frac{\frac{1}{|\mathbf{T}_i|}\sum_{\bar{t}\in\mathbf{T}_i} dist(R_i, \bar{t})}{\frac{1}{|\mathbf{T}_i|}\sum_{\bar{t}\in\mathbf{T}_i} dist(R_j, \bar{t})}, \tag{5}$$

where $\mathbf{T}_i$ is a set of target-fingerprints at location i for all estimation trials.

Table II shows the fingerprint distance ratio $\eta_{i,j}$. Most of the $\eta_{i,j}$ in ZigLoc is greater than that in MultiZigLoc, which caused false answers in location estimation in ZigLoc. ZigLoc includes an outlier, i.e., a remarkably high fingerprint distance ratio $\eta_{a,b}$, while MultiZigLoc includes no outlier. The fingerprint distance ratios in MultiZigLoc were small enough to accurately estimate sensor locations, which improved over all estimation performance.

V. RELATED WORK

To the best of our knowledge, fingerprinting localization measuring RSS of Wi-Fi wide-band signal in multiple ZigBee channels is novel in the field of indoor localization. In this section, we look through related work on the indoor sensor localization, and the improvement of localization accuracy using frequency difference.

A. Indoor Localization Method

Indoor localization methods using wireless communication are roughly divided into two methods: range-based and range-free methods.

Range-based localization methods perform localization by estimating the distance between a target sensor node and reference nodes. The target sensor node measures RSS of wireless signals of reference nodes to estimate distance from the references. Then, the location of the target is estimated by multilateration using the distance from multiple references.

In the field of range-based localization, previous studies have primarily investigated reduction in deployment costs. Iterative Multilateration [6] is a method that uses a localized target node as a new reference. Because the number of references increases as node localization proceeds, the number of references initially deployed can be reduced. A method of reducing the number of references by optimizing the arrangement of references has also been reported [7]. MultiZigLoc can reduce the number of manually deployed references by adopting these methods.

Range-free localization does not depend on physical information such as the distance from a localization reference. Range-free localization has been studied in the fields of wireless sensor networks and ad hoc networks with limited computing resources. Centroid [14], DV-Hop [15, 16], Amorphous [25], APIT [17, 18] are localization methods based on the network connectivity. These methods have low calculation load but it is difficult to realize high accuracy.

Fingerprinting localization, which is a kind of range-free localization, is a widely used indoor localization method because it can realize high accuracy [26]. Fingerprinting localization consists of learning and localization phases. In a learning phase, fingerprinting method collects fingerprints at everywhere in a target area. Fingerprint, which is a vector of RSS of signals from multiple references, is dependent on measurement location. In a localization phase, target sensor nodes measure the RSS, and estimate the location by searching for the most similar fingerprint from the fingerprints collected in the learning phase. MultiZigLoc shown in this paper is a method that improves sensor localization accuracy of fingerprinting.

In order to perform fingerprinting localization with high accuracy, it is essential to collect huge amount of fingerprints. For this reason, there is much literature working on deployment cost reduction. For example, ZiFind utilizes Wi-Fi AP signals for sensor localization [19]. ZiFind localizes sensor nodes using transmission timing of Wi-Fi beacon signals as location-specific features. ZiFind, however, requires Wi-Fi devices called ZiFind mappers installed at known locations to collect fingerprints.

ZIL [20] performs fingerprinting localization using Wi-Fi signal RSS and transmission timing of Wi-Fi beacon signals. We also proposed ZigLoc [1, 2], a sensor localization system using Wi-Fi APs as references. MultiZigLoc shown in this paper can be combined with these methods. We believe that there is a room for accuracy improvement by taking advantage of these methods.

B. Accuracy Improvement Using Frequency Difference

There are studies improving localization accuracy by using frequency difference of multiple channels. These studies utilize Wi-Fi OFDM (orthogonal frequency division multiplexing) modulation. CSI fingerprinting [31] extracts radio wave propagation characteristics from each Wi-Fi subcarrier and performs fingerprinting localization. Also, there are studies that generate virtual wide-band signals by connecting multiple Wi-Fi channels to perform localization based on time of arrival [32, 33]. These methods, however, depend on the Wi-Fi OFDM modulation. We cannot use them in sensor localization.

There is a ranging method combining multiple ZigBee channels [34]. This method improves accuracy by using the averaged RSS measured in multiple ZigBee channels. MultiZigLoc improves accuracy by applying this method, without averaging RSS measured in multiple channels.

VI. Conclusion

In this paper, we present a sensor localization system MultiZigLoc, which is an extended system of ZigLoc to improve localization accuracy. Because ZigBee channel is narrow and highly influenced by frequency selective fading, MultiZigLoc performs fingerprinting localization using RSS measured in multiple ZigBee channels as location-specific features. We conducted initial evaluations using RSS measured in a practical environment. The evaluations demonstrated that MultiZigLoc improved localization accuracy by more than 10 points compared to that of ZigLoc.

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