Evaluation of BLE Separate Channel Fingerprinting in Practical Environment

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***Abstract*—This paper presents an actual BLE-based indoor localization system utilizing separate channel fingerprinting. Separate channel fingerprinting measures RSS (received signal strength) of BLE signals in three advertising channels to enhance location-specific features for accuracy improvement. The basic ideas of separate channel fingerprinting was presented in our previous work lacking evaluation of localization accuracy in a practical environment. We therefore present design and implementation of a localization system utilizing separate channel fingerprinting. We conducted experimental evaluation and demonstrated that the separate channel fingerprinting successfully reduced localization accuracy by approximately 28.5 %.**

***Index Terms*—Bluetooth Low Energy, indoor localization, fingerprint, channel specific features**

I. Introduction

As smartphones become more prevalent, indoor localization technologies are more required to extend location-based services to indoor environments. The literature have reported many kinds of indoor localization methods using ultrasound, infrared light, and wireless signals. A BLE (Bluetooth Low Energy) based localization method, especially, attracts attention as a low-power localization method. BLE is a low power wireless technology suitable for battery-powered mobile devices. BLE is now prevalent on smartphones equipped with Bluetooth modules that also receive BLE signals.

BLE-based localization methods, however, exhibit low accuracy mainly because of frequency separation of communication channels. The BLE-based localization methods utilize three advertising channels to measure RSS (received signal strength) for localization. The advertising channels are separated by up to 78 MHz; channel responses of these channels are completely different, resulting in RSS difference. In fact, BLE-based iBeacon technology estimates proximity to a BLE beacon in three levels: within 10 centimeters as *immediate*, within one meter as *near*, no less than one meter as *far*. There is another *unknown* status for localization failure.

There are several studies working on BLE localization [1–4]. In these studies, BLE beacons sending advertising packets are installed in an indoor environment. A user BLE device receives the advertising packets and measures the RSS of the signal to estimate own location. These methods suffer from low localization accuracy of approximately five-meter error because of unstable RSS of BLE signals. The unstable RSS is mainly caused by channel response difference of three advertising channels.

We also have reported a BLE-based fingerprinting localization method utilizing channel specific features [5]. In our previous study, we proposed a separate channel fingerprinting that measures RSS of BLE signals in three advertising channels to enhance location-specific features for accuracy improvement. Initial experimental evaluations were conducted to confirm the feasibility of the separate channel fingerprinting and demonstrated improvement of location estimation accuracy by approximately 12 %.

Our previous work lacks evaluation of localization error in a practical environment. This paper therefore presents design and implementation of a localization system utilizing separate channel fingerprinting. We conducted experiments in our university building to demonstrate the actual performance of the separate channel fingerprinting. Specifically, our key contributions are two-fold:

- We propose an actual localization system utilizing separate channel fingerprinting presented in our previous work.
- We evaluated basic performance of separate channel fingerprinting localization to demonstrate the effectiveness of separate channel fingerprinting.

Remainder of this paper is organized as follows. Section II reviews related works on BLE localization methods. Section III the design of localization method utilizing separate channel fingerprinting. Section IV conducts experimental evaluation, and Section V summarize the paper.

II. Related Works

In this section, we review indoor localization studies using wireless signals.

Fingerprinting is a popular method in localization using wireless signals due to its high accuracy [6]. Fingerprinting consists of two phases: a *learning phase* to construct a fingerprint database by collecting RSS (Received Signal Strength) data at each location, and an *estimating phase* to estimate device location by comparing the RSS measured at the location with the fingerprints. The high accuracy of the fingerprinting is supported by a site survey that collects enormous amounts of RSS data.

Much literature on fingerprinting reports accuracy improvement [7–12]. These studies primarily uses Wi-Fi but are applicable to other wireless technologies including ZigBee, UWB (Ultra Wide Band), and Bluetooth.

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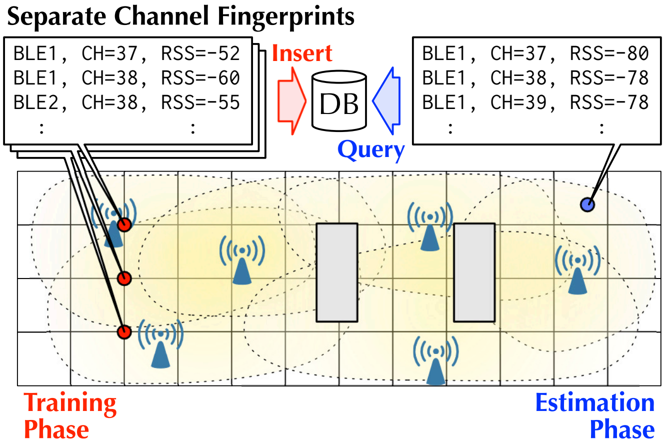


Fig. 1. Overview of separate channel fingerprinting localization system. BLE beacons installed in an environment are sending advertising packets separately in each advertising channel. In a training phase, separate channel fingerprints are collected everywhere in the environment. The fingerprints are stored in a fingerprint database. In an estimation phase, separate channel fingerprint is collected at a target location. The fingerprint is compared with fingerprints in the fingerprint database to estimate the target location.

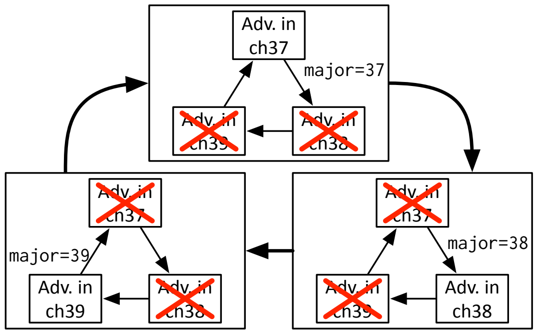


Fig. 2. Overview of separate channel advertising. A BLE beacon periodically switches a mask to restrict advertising channels. BLE defines no API to retrieve channel information of received packets. Instead, we embed transmission channel information in a `major` field of advertising packets.

Fingerprinting using Bluetooth Classic utilizes inquiry process to measure RSS [13, 14]. Bluetooth inquiry takes 5.12 seconds to discover 99 percent of scanning devices [15], which makes difficult to realize practical Bluetooth localization systems in mobile scenarios.

Recent Bluetooth 4.0, i.e., BLE (Bluetooth Low Energy), addresses the slow discovery problem by employing a small number of channels for discovery [16]. BLE uses only three advertising channels to broadcast existence of BLE devices, resulting in quick discovery.

Maximizing an advantage of the short discovery time, BLE fingerprinting was recently proposed [4]. The study experimentally demonstrated RSS variations in three advertising channels. The variations are mainly caused by frequency selective fading and different channel gains. The study therefore constructs location fingerprints including all the three advertising channels while excluding frequency selective fading effect to mitigate the variation problem. We are developing a fingerprinting scheme extending this study to utilize channel-specific information to improve accuracy.

III. Separate Channel Fingerprinting Localization System

A. System Overview

Figure 1 shows an overview of a localization system utilizing separate channel fingerprinting. The localization system consists of training and estimation phases. In a training phase, a fingerprint database that stores separate channel fingerprints is constructed by measuring RSS (received signal strength) of advertising packets everywhere in three advertising channels. An estimation phase estimates the target location by comparing RSS measured at a target location with separate channel fingerprints in the fingerprint database.

The following subsections describe training and estimation phases in details.

B. Training Phase

Training phase constructs a fingerprint database by measuring RSS of BLE advertising packets. BLE beacons are installed in an environment and are transmitting advertising packets including transmission channel information in three advertising channels. We measure RSS of advertising packets at sub-areas in a target area using a BLE device. Let $\mathbf{S}$ denote a set of sub-areas and n denote the number of BLE beacons. A separate channel fingerprint S_i on a point $i \in \mathbf{S}$ is an $3n$-th vector as advertising packets are sent in three advertising channels 37, 38, and 39. A separate channel fingerprint S_i is defined as

$$S_i = \{\overline{s_{i1,37}}, \overline{s_{i1,38}}, \overline{s_{i1,39}}, \overline{s_{i2,37}}, \dots, \overline{s_{in,39}}\}, \qquad (1)$$

where $\overline{s_{ij,c}}$ $(j \in \{1, 2, \dots, n\},\ c \in \{37, 38, 39\})$ is a median RSS of BLE beacon m in a channel c. We collect a separate channel fingerprint S_i in all sub-areas $i \in \mathbf{S}$ and store the separate channel fingerprints in a fingerprint database.

The BLE standard specification defines no API to retrieve channel information of received packets. We therefore use a separate channel advertising method. Figure 2 depicts an overview of separate channel advertising. In separate channel advertising, a BLE beacon periodically switches its transmission channel mask to transmit advertising packets from a specific channel, as shown in Fig. 2. We slightly change channel-switch period on every transmission to emulate BLE advertising with random delays.

We configured BLE beacons to send advertising packets compatible with Apple iBeacon. Transmission channel information is embedded in a `major` field of iBeacon advertising packets, as shown in Fig. 2.

Although advertising channel mask is one of the popular HCIs (host control interfaces), BLE standards specification defines no API to limit transmission channel. We need to use specific BLE beacon hardware that provides transmission channel mask, which is a main limitation of the separate channel advertising.

C. Estimation Phase

In an estimation phase, we estimate location of a target BLE device based on distance between a separate channel fingerprint measured at a target location and fingerprints in the database. A target BLE device measures RSS of advertising packets and calculate a separate channel fingerprint $R = \{\overline{r_{1,37}}, \overline{r_{1,38}}, \overline{r_{1,39}}, \overline{r_{2,37}}, \ldots, \overline{r_{n,39}}\}$ in the same manner as Eq. (1). Distance between the fingerprint R and the fingerprints S_i in the database is calculated using RSS difference. We use Euclidean distance $D(S_i, R)$ between fingerprint vectors defined as

$$D(S_i, R) = \sqrt{\sum_{j=1}^{n} \sum_{c \in \{37,38,39\}} (\overline{s_{ij,c}} - \overline{r_{j,c}})^2}. \quad (2)$$

Finally, device location is estimated using a k-nearest neighbor method. The k-nearest neighbor method chooses k sub-areas that have fingerprint nearest to the target fingerprint R. Let N_k denote a set of the selected nearest neighbor sub-areas. The location P of a target device is estimated as

$$P = \frac{\sum_{i \in N_k} \frac{1}{D(S_i,R)} X_i}{\sum_{i \in N_k} \frac{1}{D(S_i,R)}}, \quad (3)$$

where X_i is the coordinates of sub-area i.

IV. Evaluation

To demonstrate the effectiveness of our separate channel fingerprinting, we evaluated localization accuracy in our university building. Localization accuracy is the 90th percentile of localization error for all localization results [17], which is a popular metric in the field of localization.

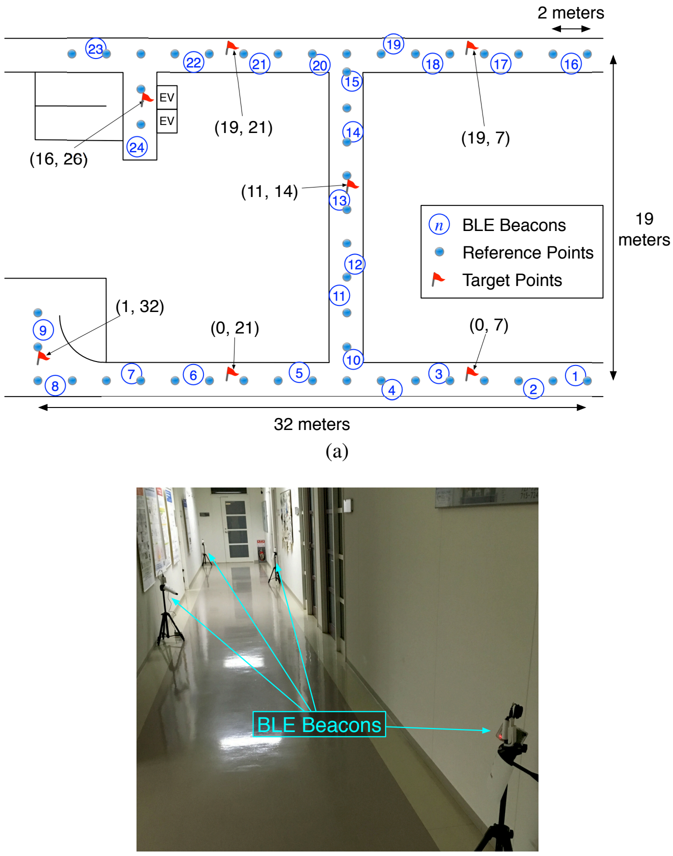
A. Experiment Setup

Figure 3 shows an experiment setup. A localization target area is H-shaped corridors in a $19{\times}32$-m^2 area in our university building. We installed 24 BLE beacons operated by mobile batteries at a height of approximately 1 meter in the target area using tripods, as shown in Fig. 3b. Each BLE beacon transmitted advertising packets with intervals of 30 to 32.5 milliseconds and switched an advertising channel after five packet transmissions. Note that there were 20 Wi-Fi APs operating in the same 2.4-GHz band in and around the evaluation environment.

In a training phase, we measured RSS (received signal strength) of BLE beacons at 46 reference points with 2-meter grid in the localization target area to construct a fingerprint database. At each reference point, we collected RSS samples for 120 seconds and calculate a median value $\overline{s_{ij,c}}$ described in Section III-B. We used Silicon Labs BLED112 beacons and a MacBook Pro receiver.

In an estimation phase, we collected RSS samples at each of eight target points for 120 seconds and estimated the target location. The 120-second data is divided with 10-second sliding window and performed location estimation for the each windowed data.

In order to confirm the relative performance, we compared the performance of following two localization methods.



(a)

(b)

Fig. 3. Experiment setup. (a) Locations of BLE beacons, reference points, and target in a localization target area. (b) Actual setup. BLE beacons were installed at a height of approximately 1 meter using tripods.

1) *Separate channel fingerprinting (proposed)*: The separate channel fingerprinting is a localization method presented in this paper. A BLE receiver separately measures RSS on each advertising channel.
2) *Unified channel fingerprinting*: The unified channel fingerprinting is a conventional fingerprinting method. A BLE receiver retrieves no channel information: fingerprints consist of one RSS value for each BLE beacon regardless of advertising channel.

B. Localization Accuracy

Figure 4 shows an ECDF (empirical cumulative distribution function) of localization errors. A red line indicates cumulative probability of 0.9. Figure. 4 indicates the following:

1) Localization accuracies in separate and unified channel fingerprinting were 2.01 and 2.81, respectively. Separate channel fingerprinting successfully reduced localization errors by utilizing channel specific features in fingerprints. The localization accuracy was improved by approximately $(2.81 - 2.01)/2.81 * 100 = 28.5\,\%$.
2) In both separate and unified channel fingerprinting, ECDF of localization errors abruptly increases at some localization-error points. Cumulative probability of localization errors in separate channel fingerprinting, for

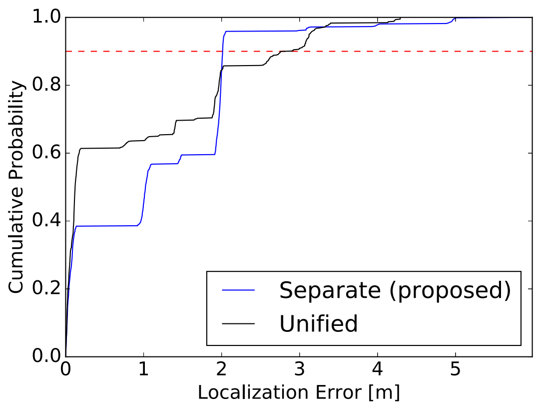


Fig. 4. ECDF (empirical cumulative distribution function) of localization errors. A red line indicates cumulative probability of 0.9. Localization accuracies, i.e., 90th percentile points, in separate and unified channel fingerprinting were 2.01 and 2.81, respectively.

TABLE I
LOCALIZATION ACCURACY AT EACH TARGET LOCATION

Target location	Separate channel fingerprinting [meter]	Unified channel fingerprinting [meter]
$(0, 7)$	2.03	2.65
$(0, 21)$	0.05	0.06
$(1, 32)$	1.48	4.14
$(11, 14)$	1.99	1.91
$(16, 26)$	0.12	0.13
$(19, 7)$	2.01	1.99
$(19, 21)$	3.99	1.07

example, significantly increased at localization errors of 0, 1, and 2 meters. This indicates that the localization errors concentrated on these specific values. This was mainly caused by the small number of target locations. By analyzing the localization results, we confirmed that localization errors tend to concentrate on a single value at each target location. For more detailed evaluation, we need more number of samples at many target locations.

Table I shows localization accuracy at each target location. Separate channel fingerprinting exhibited better localization accuracy than unified channel fingerprinting at four target locations among seven locations. At three target locations showing lower localization accuracy suffered from NLOS (non line-of-sight) environment from a BLE beacon 24 that is in front of elevators. RSS of BLE beacon 24 highly varies in many places, which degrades localization performance. We need to reduce the influence of unstable RSS to more improve localization accuracy.

V. CONCLUSION

This paper presents an actual BLE-based indoor localization system utilizing separate channel fingerprinting. Separate channel fingerprinting handles three BLE advertising channels as separate channels in a fingerprint space to increase location-specific features. The basic ideas of separate channel fingerprinting was presented in our previous work, which lacks evaluation of localization error in a practical environment. We therefore developed an actual localization system using separate channel fingerprinting and conducted experimental evaluation. The experimental evaluation revealed that separate channel fingerprinting by approximately 28.5 %.

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