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Proposal of Separate Channel Fingerprinting using Bluetooth Low Energy

Shigemi Ishida*, Yoko Takashima*, Shigeaki Tagashira†, Akira Fukuda*
*Graduate School/Faculty of Information Science and Electrical Engineering, Kyushu University, Japan
Email: {ishida, takashima, fukuda}@f.ait.kyushu-u.ac.jp
†Faculty of Informatics, Kansai University, Japan
Email: shige@res.kutc.kansai-u.ac.jp

***Abstract*—BLE (Bluetooth Low Energy) based localization is a next candidate for indoor localization. In this paper, we propose a new BLE-based fingerprinting localization scheme that improves localization accuracy. BLE is a narrow band communication that is highly affected by frequency selective fading and channel gains. We employ channel-specific features to location fingerprint to improve localization accuracy. Current BLE standards provide no API to retrieve an advertising channel number. We therefore developed a separate channel advertising scheme to measure RSS (Received Signal Strength) on each advertising channel. To demonstrate the feasibility of the separate channel fingerprinting, we conducted initial evaluations. Experimental evaluations showed that the separate channel fingerprinting improves accuracy by approximately 12 %.**

***Index Terms*—Bluetooth Low Energy, localization, fingerprinting, separate channel advertising.**

I. Introduction

Indoor localization is more required to effectively manage human mobility and to extend location-based services in indoor environments. Much effort has been paid to develop indoor localization schemes using technologies such as ultrasound, infrared light, and wireless signals. In particular, the localization scheme using BLE (Bluetooth Low Energy) is a next candidate for indoor localization. BLE is a low-power wireless technology suitable for battery-powered mobile devices. BLE is prevalent nowadays and smartphones equipped with Bluetooth modules can receive BLE signals.

BLE-based localization systems, however, are suffered from low accuracy due to their low-power operation. Apple iBeacon is one of the famous localization systems using BLE, which is suffered from low accuracy. The iBeacon therefore 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 also an *unknown* status for failures.

Several studies have reported on BLE localization in terms of range-based localization schemes [1–3] and a fingerprinting scheme [4]. These works install BLE beacons in an environment to broadcast advertising packets. A user device measures RSS (Received Signal Strength) of the advertising packets and estimates own location. These works are suffered from high localization error up to approximately five meters because of unstable RSS of BLE signals. Frequency separation of three advertising channels makes channel response completely different, resulting in the RSS instability.

In view of this, this paper proposes a new BLE-based localization scheme that improves localization accuracy. Our key idea is quite simple: we employ channel-specific features to fingerprints. BLE is a narrow band communication and is highly affected by multipaths and a channel-specific gain due to an antenna frequency response. We separately calculate a fingerprint for each advertising channel to describe channel-specific features.

We install BLE beacons that transmit signals including transmission channel information. We then build a fingerprint database that includes signal strength in the three advertising channels. The BLE standards provide no API to retrieve advertising channel information on reception of advertising packets. We therefore developed a separate channel BLE advertising that periodically switches the transmission channel and embeds transmission channel number in advertising packets. Note that some OSs such as iOS above 7 optionally provide advertising channel information. We avoid to use such non-standard APIs to realize localization on all standards-compliant devices.

By conducting initial experimental evaluations, we demonstrate the feasibility of the separate channel fingerprinting. Specifically, our key contributions are threefold:

- We propose a BLE-based fingerprinting scheme that separately uses three advertising channels. To the best of our knowledge, this is a first attempt to employ channel-specific information in fingerprinting scheme for accuracy improvement.
- We present a separate channel advertising scheme that transmits different advertising packets in each advertising channel.
- We demonstrate the feasibility of the separate channel fingerprinting scheme with initial experimental evaluations using actual BLE beacons.

The rest of this paper is structured as follows. Section II reviews related works to clearly show our novelty. Section III presents the design of our BLE fingerprinting scheme employing separate channel fingerprints. Initial evaluations were conducted in Section IV. Finally, Section V concludes the paper.

II. Related Works

To the best of our knowledge, BLE fingerprinting employing separate fingerprints in three advertising channels is novel in

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the field of BLE localization. Indoor localization is a popular research field. We limit our review of indoor localization studies in this section to localization schemes using wireless signals.

Fingerprinting is a popular method in localization using wireless signals due to its high accuracy [5]. 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 [6–11]. These studies primarily uses WiFi but are applicable to other wireless technologies including ZigBee, UWB (Ultra Wide Band), and Bluetooth.

Fingerprinting using Bluetooth Classic utilizes inquiry process to measure RSS [12, 13]. Bluetooth inquiry takes 5.12 seconds to discover 99 percent of scanning devices [14], 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 [15]. 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

A. System Overview

A BLE separate channel fingerprinting system consists of two components: separate channel advertising and fingerprinting utilizing separate channel information. Figure 1 shows an overview of the BLE separate channel fingerprinting system. BLE beacons are installed in an environment. Each BLE beacon transmits advertising packets including transmission channel information in three advertising channels.

In a learning phase, user devices receive the advertising packets and handle advertising packets from a BLE beacon in different channels as if there are BLE beacon operating in three different channels, resulting in separate channel location fingerprint.

In an estimating phase, a user device receives advertising packets and measures signal strength of the each advertising packet. The user device then estimates its location by comparing the signal strength with location fingerprints.

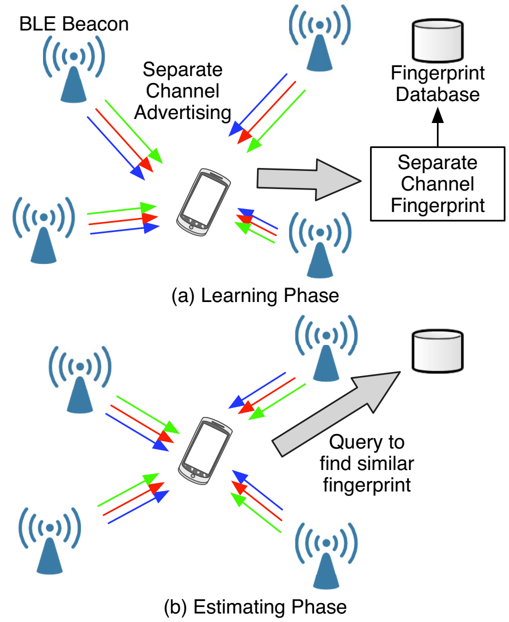

Fig. 1. System overview. (a) In a learning phase, a user device measures RSS of advertising packets in three channels and construct a separate channel location fingerprint. The separate channel location fingerprint is stored into a fingerprint database. (b) In an estimating phase, a user device measures RSS of advertising packets in three channels and compares the RSS with fingerprints in the fingerprint database to estimate own location.

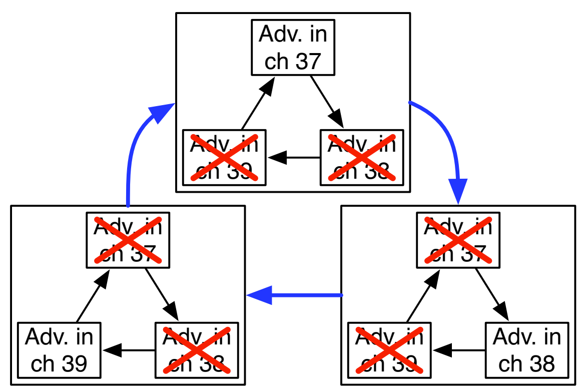

Fig. 2. Overview of separate channel advertising

Following subsections describe details of the each component.

B. Separate Channel Advertising

Figure 2 depicts an overview of separate channel advertising. In a separate channel advertising scheme, BLE beacons apply a mask to limit their advertising channels. BLE beacons embed its advertising channel information into advertising packets. User devices that receive an advertising packet decode the embedded data to retrieve transmission channel information. The channel mask is periodically updated to change an advertising channel, as shown in Fig. 2.

We implemented BLE beacons that send advertising packets compatible with Apple iBeacon. BLE beacons embed advertising channel information as 2-bit data into a `Minor` field in an iBeacon advertising packet.

Although many BLE modules provide vendor specific HCI (Host Control Interface) to limit transmission channels, advertising channel mask is not defined in a BLE standards specification. We need to use specific BLE beacon hardware, which is a limitation of our scheme.

C. Fingerprinting utilizing Separate Channel Information

Fingerprinting utilizing separate channel information consists of a learning phase and estimating phase, which is same as conventional fingerprinting.

In a learning phase, we construct location fingerprints based on RSS (Received Signal Strength) of BLE beacons observed at that location. We divide localization area into small areas and measure RSS of BLE beacons in the each small area. At each area, we collect RSS samples for a specific duration. Let i denote a small area and n denote the number of BLE beacons. Location fingerprint R_i in an area i is an n-th vector:

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

where $\overline{r_{ij}}$ $(j = 1, 2, \ldots, n)$ is an average RSS of a BLE beacon j in an area i. We used $-\infty$ as an RSS of undetected BLE beacons. We also calculate the standard deviation vector σ_i for all the BLE beacons j $(j = 1, 2, \ldots, n)$ in each area i:

$$\sigma_i = \{\sigma_{i1}, \sigma_{i2}, \ldots, \sigma_{in}\}, \tag{2}$$

where σ_{ij} $(j = 1, 2, \ldots, n)$ is a standard deviation of RSS of a BLE beacon j.

In an estimating phase, we estimate location of a user device based on distance between fingerprints. A user device measures RSS of BLE beacons and calculate a fingerprint $x = \{\overline{x_1}, \overline{x_2}, \ldots, \overline{x_n}\}$ in a same manner as Eq. (1). The user device next calculates distance between the calculated fingerprint x and the fingerprints R_i derived in a learning phase. We used ℓ^1 norm for distance calculation. The device location i is finally estimated as

$$i = \arg\min_i distance(R_i, x), \tag{3}$$

$$\text{where } distance(R_i, x) = \frac{1}{n} \sum_{j=1}^{n} |\overline{r_{ij}} - \overline{x_j}|.$$

Undetected BLE beacons described in $-\infty$ are ignored in distance calculation.

To avoid huge localization errors, we apply a simple filter based on the standard deviation vector σ_i. Location is estimated as *unknown* when there is one or more $\overline{x_j}$ that satisfies $|\overline{r_{ij}} - \overline{x_j}| > \sigma_{ij}$.

IV. Initial Evaluation

To demonstrate the feasibility of BLE separate channel fingerprinting described in Section III, we evaluated accuracy of location estimation. As an initial evaluation, we installed a small number of BLE beacons and estimated a small number of locations.

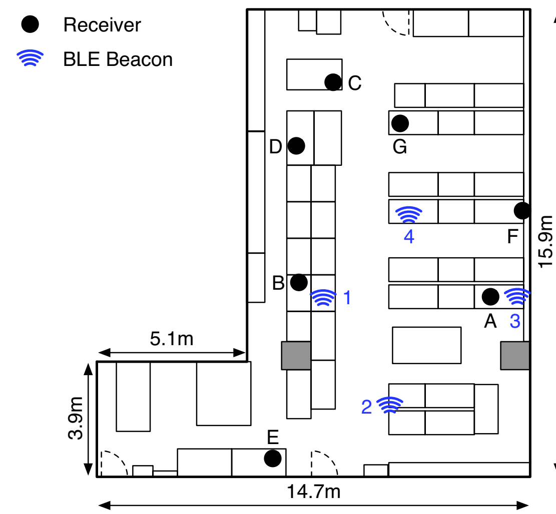

Fig. 3. Experiment setup. Numerical labels 1–4 indicate BLE beacon locations and alphabetical labels A–G indicate receiver locations to be estimated.

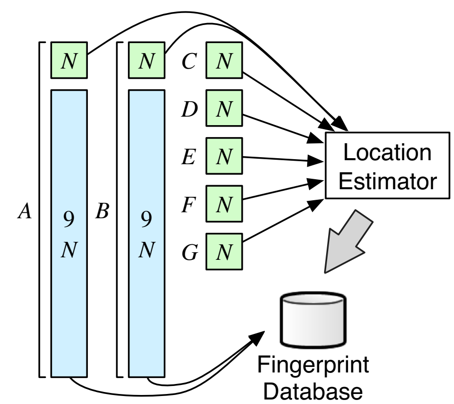

Fig. 4. Data usage in ten-fold cross-validation

A. Experiment Setup

Figure 3 depicts an experiment setup. Four BLE beacons were installed in our laboratory at locations having numerical labels in Fig. 3. Each BLE beacon transmitted advertisement packets every 100 milliseconds and switched an advertising channel every 300 milliseconds, as described in Section III-B. We note that there were 20 WiFi APs operating in a 2.4-GHz band in and around our laboratory.

We collected RSS (Received Signal Strength) of each BLE beacon at locations labeled `A` and `B` for approximately 60 minutes using two receivers. At the same time, we also collected RSS at locations labeled `C` to `G` for approximately 10 minutes at each location using another receiver. The BLE beacon was a BLED112 dongle from Bluegiga and receiver was MacBook Pro.

Using the collected RSS data, we estimated locations as `A`, `B`, or `unknown`. Location estimations were evaluated using

TABLE I
EXPERIMENT RESULTS

(a) The number of TPs, FNs, FPs, and TNs

	TPs	FNs	FPs	TNs
Conventional	1,117	59	1,977	836
Proposed	1,319	30	1,775	864

(b) Accuracy, precision, recall, and F-measure

	Accuracy	Precision	Recall	F-measure
Conventional	0.49	0.36	0.95	0.52
Proposed	0.55	0.43	0.98	0.59

a ten-fold cross-validation. As shown in Fig. 4, we divided the RSS data at locations `A` and `B` into ten chunks. Let N be the number of $1/10$ RSS data. The $9N$ data was used to construct location fingerprints and the N data was used as an input of a location estimator. N data at locations `C` to `G` were also used as an input of the location estimator, which should be estimated as `unknown`.

Comparing estimated locations with actual locations, we evaluated the number of true positives (TPs), false negatives (FNs), false positives (FPs), and true negatives (TNs). TP, FN, FP, and TN are defined as the case that locations were correctly estimated, locations were mistakenly estimated as `unknown`, locations were mistakenly estimated as `A` or `B`, and locations were correctly estimated as `unknown`, respectively. Using the number of TPs, FNs, FPs, and TNs, we also evaluated an accuracy, precision, recall, and F-measure defined as:

$$\mathrm{Accuracy} = \frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{FP}+\mathrm{FN}+\mathrm{TN}}, \tag{4}$$

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}}, \tag{5}$$

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}}, \tag{6}$$

$$\mathrm{F}_{\mathrm{measure}} = \frac{2\cdot\mathrm{Precision}\cdot\mathrm{Recall}}{\mathrm{Precision}+\mathrm{Recall}}. \tag{7}$$

B. Results

Table I shows experiment results. The total number of estimations was 3,988 times. Table I-a shows that the separate channel fingerprinting reduced the number of FPs and increased the number of TPs. We can also confirm that the number of FNs were reduced and the number of TPs were increased.

Table I-b shows that an accuracy, precision, recall, and F-measure were increased by separate channel fingerprinting. Accuracy was improved by $(0.55-0.49)/0.49\times 100 \simeq 12\,\%$. We can conclude that the separate channel fingerprinting has the capability that increases accuracy of location estimation.

Accuracies of both conventional and proposed methods, however, were approximately 0.5, which was too low for practical applications. The main reason of the low accuracies was a big number of FPs. In our experiment, locations where an RSS fingerprint was distant from any fingerprints in a database with a specific distance threshold were estimated as `unknown`. Fingerprinting schemes provide no considerations on location estimation outside of target areas, which results in a high number of FPs.

V. CONCLUSION

In this paper, we proposed a BLE separate channel fingerprinting that employs channel-specific features in fingerprinting. BLE standards provide no API to distinguish advertising channels. We therefore developed a separate channel advertising scheme, which enables standards-compliant BLE devices to recognize advertising channels. Using the separate channel advertising scheme, we conducted initial evaluations and demonstrated that the separate channel fingerprinting improves localization accuracy by approximately 12 %. We are now working on development of localization system utilizing the separate channel fingerprinting.

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