Design of BLE 2-Step Separate Channel Fingerprinting

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

***Abstract*—Bluetooth Low Energy (BLE)-based localization is a promising candidate of indoor localization for low power mobile and Internet of Things (IoT) systems. Localization accuracy of BLE-based localization systems is lower than other localization technologies relying on wideband wireless communication such as WiFi due to limited channel bandwidth. In our previous paper, we proposed an accuracy improvement method named separate channel fingerprinting (SCF), which, however, suffers from a high maximum localization error more than 6 meters. This paper therefore presents 2-step separate channel fingerprinting (2S-SCF). 2S-SCF first coarsely estimates location by conventional BLE fingerprinting and utilizes SCF to estimate the fine-grained location. We experimentally demonstrate that 2S-SCF successfully reduced localization errors 95 % of time with a small maximum localization error.**

***Index Terms*—Indoor localization, Bluetooth Low Energy (BLE), separate channel fingerprinting (SCF), channel diversity.**

I. Introduction

Indoor localization is one of the fundamental components in many Internet of Things (IoT) systems. For low-power IoT devices, Bluetooth Low Energy (BLE) based localization systems have been focused because of their both low power operation and wide availability. BLE-based localization systems measure received signal strength (RSS) of BLE signals on three advertising channels and estimate location.

Frequency separation of advertising channels deteriorate localization accuracy [1]. BLE uses 2-MHz narrow-band channels and tends to be affected by frequency selective fading where channel gain is highly dependent on location. In addition, big frequency difference up to 78 MHz between advertising channels implies different channel responses on three advertising channels, resulting in unstable RSS.

The literature has studied on accuracy improvement in BLE localization systems [1–5]. In these approaches, RSS outliers are excluded using filters to improve localization accuracy. We also proposed BLE separate channel fingerprinting (SCF), which is a fingerprinting localization method employing channel diversity to improve localization accuracy [6–8]. We experimentally proved that SCF successfully improved localization accuracy by approximately 28.5 % compared to localization without channel diversity.

Although SCF exhibits a small mean localization error, SCF suffers from a big maximum localization error. Localization errors are distributed in a wide range, which implies the low reliability of SCF. Particle and Kalman filters might be helpful to reduce localization errors [4, 9]. Stability of localization results should be improved to reduce the influence of outliers.

In this paper, we present BLE 2-step SCF (2S-SCF), which takes advantages of fingerprinting localization with and without channel diversity. 2S-SCF is based on an observation that probability of small localization errors is higher in fingerprinting without channel diversity compared to fingerprinting with channel diversity. We first coarsely estimate location without channel diversity and then employ channel diversity to estimate a fine-grained location. We conducted experimental evaluations in our university building to demonstrate effectiveness of 2S-SCF.

Our main contributions are threefold:

- We show that both conventional BLE fingerprinting and SCF suffer from a big maximum localization error more than 6 meters. We also reveal that localization errors are distributed in a wide range.
- We present the design of 2S-SCF, a 2-step fingerprinting localization method that takes advantages of fingerprinting with and without channel diversity. To the best of knowledge, this is the first study focusing on stability of localization accuracy in the field of BLE fingerprinting localization.
- We experimentally evaluate 2S-SCF using actual BLE devices in a corridor environment. The experimental evaluations reveal that 2S-SCF effectively reduces maximum localization error.

The remaining of this paper is organized as follows. Section II summarizes related work. Section III briefly presents the design of SCF as well as its issues, followed by the design of 2S-SCF in Section IV. In Section V, we evaluate localization performance of 2S-SCF. Finally, Section VI concludes the paper.

II. Related Work

Wireless indoor localization technologies are well investigated and there are many published papers. We limit our review in this section to BLE-based localization technologies.

To improve localization accuracy, many BLE-based localization technologies borrow ideas from well studied WiFi localization technologies. Using filters to reduce the influence of RSS outliers is a simple but effective approach to improve localization accuracy. Zhu et al. proposed a localization

doi: 10.1109/VTC2020-Spring48590.2020.9128872

method combining Gauss filter and piecewise function in model training of radio signal strength decay [2]. Zhu et al. also filters out the distances based on geometric constraints to remove RSS outliers in a location estimation phase. Particle and Kalman filters also help to remove incoherent RSS samples and incorrect localization results caused by RSS outliers [3, 9]. Paterna et al. combines Kalman filter with weighted trilateration to more improve localization accuracy [4]. Reducing the number of outliers is still important in these methods to get stable localization results.

A stigmergic approach is another solution tackling the RSS instability. The stigmergic approach shares localization results among BLE devices that strengthen confident localization results [10]. In the stigmergic approach, min-max localization results [11] derived from multiple BLE devices are integrated. Environmental changes on radio propagation are taken into considerations by *evaporation*, which decreases the contribution of old localization results. Li et al. proposed an RSS compensation method based on RSS fluctuations observed on multiple BLE gateway devices [12]. 2S-SCF can be combined with these methods to more improve localization accuracy.

For better localization accuracy, fingerprinting localization using BLE is investigated because fingerprinting exhibits good performance in WiFi localization systems [13]. Faragher et al. investigated the feasibility of BLE-based fingerprinting [1], which demonstrates that the BLE-based fingerprinting achieved errors less than 2.6 meters 95 % of time with BLE beacons installed at every 30 m^2. Fingerprinting using neural network has also been proposed [5], which, though, requires huge amount of training data. BluePrint is another approach of fingerprint-like localization [14]. BluePrint uses NUFO, i.e. near, uncertain, far, and out, instead of RSS and perform fingerprint-like localization with NUFO states of reference BLE beacons. A NUFO state is determined by applying threshold to RSS. The discretization into NUFO states reduces the influence of RSS fluctuations and achieved errors less than 2.20 meters 75 % of time.

We also have reported BLE SCF employing channel diversity to improve fingerprinting localization accuracy [6, 7], which is applicable in addition to other fingerprinting methods to more improve localization accuracy. We experimentally demonstrated that SCF improved localization accuracy by 28.5 % and achieved errors less than 2.01 meters 90 % of time. SCF, however, suffers from a big maximum error problem; the maximum localization error is bigger than the localization without channel diversity.

III. Separate Channel Fingerprinting (SCF)

Separate channel fingerprinting (SCF) is a fingerprinting localization method employing channel diversity to improve localization accuracy [6, 7]. Figure 1 shows the overview of SCF. SCF consists of training and estimation phases, as the same as other fingerprinting methods do. BLE beacons are installed in a localization target area and periodically sending advertisement packets on three advertising channels. Training phase constructs a fingerprint database that stores separate channel fingerprints consisting of BLE beacon RSS measured on three advertising channels. Estimation phase also calculates a fingerprint from RSS measured at a user location, which is compared to the database fingerprints finding the nearest database fingerprint to estimate location of the user.

We employ separate channel advertising because BLE standard provides no application programming interface (API) to recognize the channel where an RSS is measured. BLE beacons apply a mask to restrict their advertising channel and embed transmission channel information in advertisement packets. We use Apple iBeacon-compatible advertisement packets and embed channel number in a `minor` field. A channel mask is periodically updated to send advertisement packets on all the three advertising channels. Although BLE standards defines no API for channel masking, many BLE beacons in the market come with a channel masking API.

However, SCF suffers from a big maximum localization error problem. A maximum localization error in SCF is greater than that of unified channel fingerprinting (UCF), which is the conventional BLE fingerprinting method that equally deals with RSS on three advertising channels without channel information.

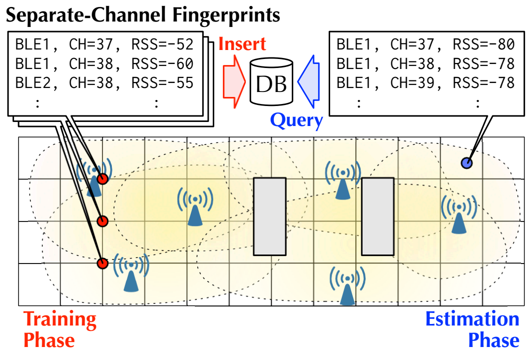


Fig. 1. Overview of separate channel fingerprinting (SCF) [7]. SCF consists of training and estimation phases. BLE beacons in a localization target area are sending advertisement packets on three advertising channels. Training and estimation phase measure RSS of the BLE beacons to calculate fingerprints, which are used for location estimation. SCF separately handles RSS on three advertising channels to employ channel diversity, while normal fingerprinting uses no channel-information.

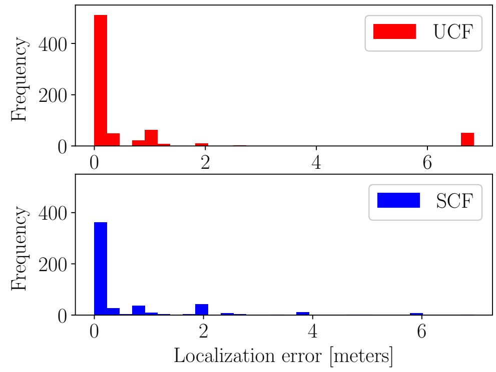


Fig. 2. Localization error distribution for unified channel fingerprinting (UCF) and separate channel fingerprinting (SCF). UCF is a fingerprinting method without channel information.

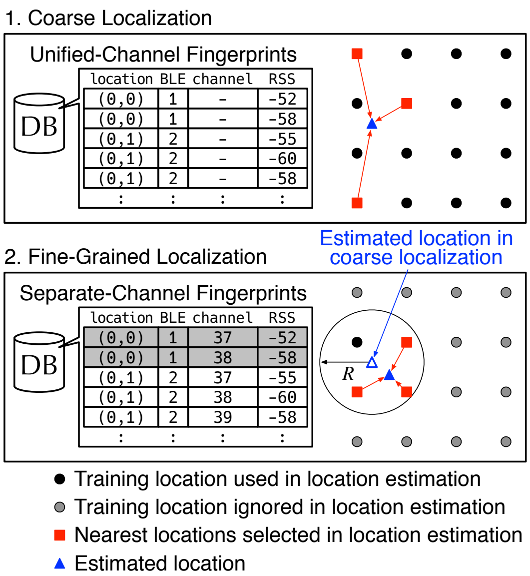


Fig. 3. Overview of 2-step separate channel fingerprinting (2S-SCF). In step 1, 2S-SCF performs coarse localization, which coarsely estimates a target location with all the database fingerprints without channel information. In step 2, a target location is estimated using database fingerprints in a area limited by the result of coarse localization with channel information.

Figure 2 shows distribution of localization errors of both UCF (above) and SCF (below). We draw Fig. 2 using RSS data collected in Section V. Although UCF and SCF show small mean localization errors of 0.707 and 0.589 meters, respectively, maximum errors of both SCF and UCF are more than 6 meters.

IV. 2-Step SCF (2S-SCF)

A. Key Idea

The key idea of 2S-SCF is that we take advantages of both SCF and UCF. Based on Fig. 2, probability of small localization errors is higher in UCF, while SCF shows a smaller maximum localization error. 2S-SCF first coarsely estimates the target location using UCF, then performs fine-grained localization.

B. Overview

Figure 3 shows the overview of 2S-SCF. Here we assume that a fingerprint database is constructed prior to localization. 2S-SCF estimates the target location in two steps. The first step is UCF. We find database fingerprints nearest to a target fingerprint without channel information and estimate the target location. In the second step, we perform fingerprinting with database fingerprints in a restricted area based on the result of the first step. Database fingerprints outside of the restricted area are ignored in this step.

2S-SCF again consists of training and estimation phases, as the same as other fingerprinting methods do. Following subsections describe details of the each phase.

C. Training Phase

In a training phase, we construct both separate- and unified-channel fingerprint databases. We measure RSS of multiple BLE beacons at many locations in a localization target area. Let $\mathbf{L}$ be a set of training locations where RSS is measured. We collect BLE advertisement packets from BLE beacons for a specific time period at every location in $\mathbf{L}$ and measure RSS of the packets, creating an RSS-sample set $\mathbf{A}_i$ for each location i. To calculate separate-/unified-channel fingerprints, we also define a subset $\mathbf{A}_{i,j}(c) \subset \mathbf{A}_i$ consisting of RSS samples of the BLE beacon j measured on the advertising channel $c \in \{37, 38, 39\}$.

Let n denote the number of BLE beacons. A separate-channel database fingerprint S_i at the training location i is a $3n$-th vector including channel information:

$$S_i = [s_{i,1}(37), s_{i,1}(38), s_{i,1}(39), s_{i,2}(37), \cdots, s_{i,n}(39)], \tag{1a}$$

$$s_{i,j}(c) = \text{med}\left[\mathbf{A}_{i,j}(c)\right], \tag{1b}$$

where med[ ] represents the median of the set. We note that an element $s_{i,j}(c)$ is marked as missing when $\mathbf{A}_{i,j}(c)$ is an empty set , i.e., no advertisement packet from the beacon j is received on the channel c at the location i.

For a unified-channel database fingerprint, we merge RSS samples measured on three advertising channels. The unified-channel database fingerprint $\hat{S}_i$ is an n-th vector:

$$\hat{S}_i = [s_{i,1}, s_{i,2}, s_{i,3}, \cdots, s_{i,n}], \tag{2a}$$

$$s_{i,j} = \text{med}\left[\bigcup_{c\in\{37,38,39\}} \mathbf{A}_{i,j}(c)\right]. \tag{2b}$$

D. Estimation Phase

An estimation phase performs localization in two steps.

1) Coarse Localization: We first measure RSS of BLE beacons at the target location and calculate the unified-channel target fingerprint $\hat{T}$ in the same manner as in a training phase. Let $\mathbf{B}$ be a set of RSS samples measured at the target location and $\mathbf{B}_j(c) \subset \mathbf{B}$ be a subset of RSS samples of the BLE beacon j measured on the advertising channel c. The unified-channel target fingerprint $\hat{T}$ is calculated as:

$$\hat{T} = [r_1, r_2, r_3, \cdots, r_n], \tag{3a}$$

$$r_j = \text{med}\left[\bigcup_{c\in\{37,38,39\}} \mathbf{B}_j(c)\right]. \tag{3b}$$

We then perform coarse localization using the k-nearest-neighbor (kNN) method. Coarse localization finds k of $\hat{S}_i$ that are nearest to $\hat{T}$. Distance between fingerprints is defined by root-mean-square. Let $Y = [y_1, y_2, \cdots, y_k]$ and $Z = [z_1, z_2, \cdots, z_k]$ be any fingerprints. Distance $D(Y, Z)$ between the fingerprints Y and Z is defined as:

$$D(Y, Z) = \begin{cases} \sqrt{\frac{1}{m}\sum_{l=1}^{k}(y_l - z_l)^2} & (m \geq \frac{k}{2}), \\ \infty & (m < \frac{k}{2}), \end{cases} \tag{4}$$

where m is the number of elements available, i.e., not missing, in both Y and Z. Elements missing in either Y or Z are ignored in a root-mean-square calculation. We apply the simple filtering method to reduce the influence of RSS outliers as we define $D(Y, Z) = \infty$ when $m < k/2$; when the number m of elements available both in Y and Z is less than half of the number of elements $k/2$, we regard Y and Z are significantly different.

The target location is finally estimated by calculating the weighted center of coordinates corresponding to the k of the nearest fingerprints. Let $\hat{\mathbf{N}}_k$ be a set of locations corresponding to the nearest database fingerprints. Coordinates $\hat{P}$ of the target location is finally estimated as:

$$\hat{P} = \frac{\sum_{i \in \hat{\mathbf{N}}_k} \frac{1}{D(\hat{S}_i, \hat{T})} X(i)}{\sum_{i \in \hat{\mathbf{N}}_k} \frac{1}{D(\hat{S}_i, \hat{T})}}, \tag{5}$$

where $X(i)$ is the coordinates of the location i. Note that location estimation fails when the number of database fingerprints having finite distance to the target fingerprint is less than k.

2) Fine-Grained Localization: Using the set of RSS samples collected in a coarse localization, we calculate a separate-channel target fingerprint T:

$$T = [r_1(37), r_1(38), r_1(39), r_2(37), \cdots, r_n(39)], \tag{6a}$$

$$r_j(c) = \mathrm{med}\,[\mathbf{B}_j(c)]. \tag{6b}$$

Instead of using all the database fingerprints, we calculate distance between a database fingerprint S_i and a target fingerprint T for the limited number of database fingerprints. As shown in Fig. 3, we only use database fingerprints collected in a circular area of radius R centered on the estimated location in coarse localization. We again choose k of database fingerprints closest to a target fingerprint and estimate coordinates P of the target location:

$$P = \frac{\sum_{i \in \mathbf{N}_k} \frac{1}{D(S_i, T)} X(i)}{\sum_{i \in \mathbf{N}_k} \frac{1}{D(S_i, T)}}, \tag{7}$$

where $\mathbf{N}_k$ is a set of locations corresponding to the closest database fingerprints.

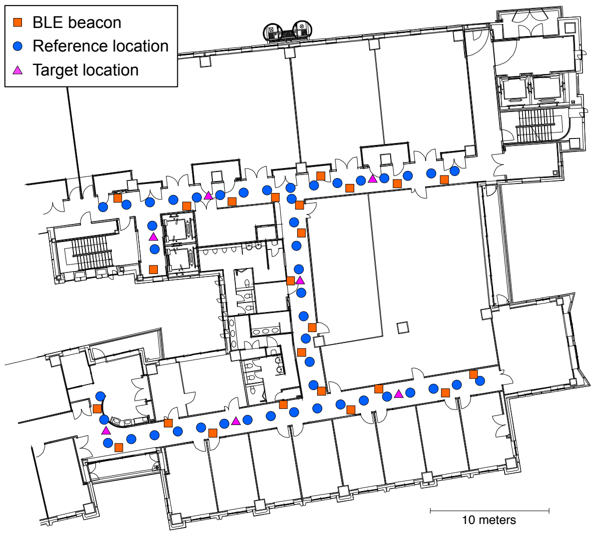
We perform fine-grained localization only when coarse localization successfully estimated a target location. Fine-grained localization again has a chance to fail when the number of database fingerprints, having finite distance to a target fingerprint, in the limited area is less than k. An actual value of the area-limit radius R is determined in Section V.

V. Evaluation

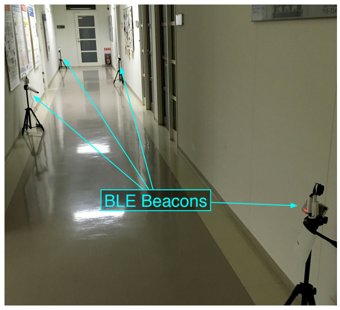
To demonstrate the effectiveness of 2S-SCF, we conducted experimental evaluations in a corridor in our university building.

A. Experiment Setup

Figure 4 shows an experiment setup. We choose an H-shaped corridor in our university building as the localization target area. We installed 24 Silicon Labs BLED112 beacons



(a)



(b)

Fig. 4. Experiment setup. (a) 24 BLE beacons were installed in an H-shaped corridor in a 19×32-m^2 area. (b) Each BLE beacon is installed at a height of approximately 1 meter on a tripod.

at a height of approximately 1 meter using tripods because the attachment of objects to walls and ceilings in our building is restricted. BLE beacons were sending advertisement packets every 30 milliseconds with a random delay up to 20 milliseconds and switched transmission channel at every 100 milliseconds with a random delay up to 200 milliseconds. Note that channel switching in separate channel advertising seems to require few hundreds of milliseconds, though the BLED112 datasheet has no description about the latency required for channel-mask update. We observed that 20 WiFi APs were used in the same 2.4-GHz band in the target area, which might have interfered with BLE advertisement packets.

We measured RSS of BLE beacons using an Apple MacBook Pro receiver at 46 reference locations with approximately 2-meter grid, as shown in Fig. 4. At each reference location, RSS samples were collected for 120 seconds. We calculated unified-/separate-channel database fingerprints $\hat{S}_i, S_i$ at each reference location i.

RSS samples were then collected for 120 seconds at 7 target locations. We divided 120-second data into 10-second sliding windowed data and calculated unified-/separate-channel target fingerprints $\hat{T}, T$ for the each windowed data to estimate the

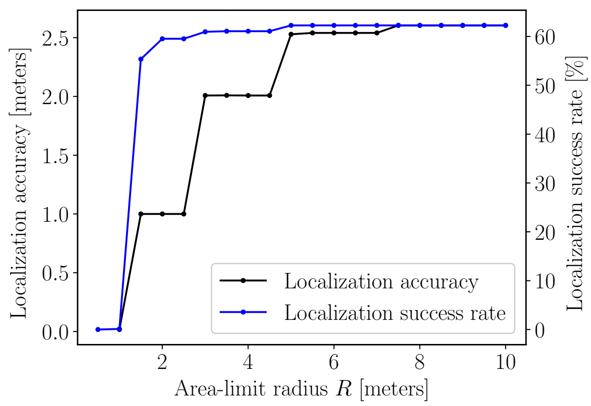


Fig. 5. Localization accuracy and success rate as a function of area-limit radius R. Increase in R resulted in increase in both localization accuracy and success rate.

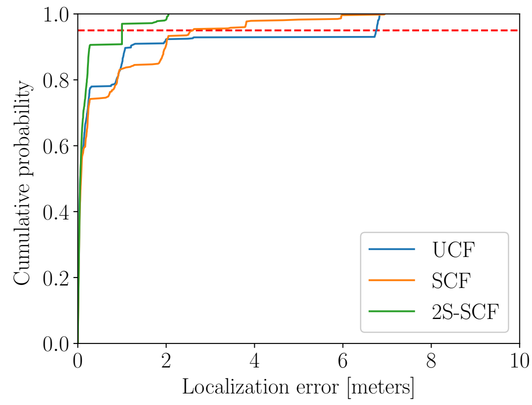


Fig. 6. Empirical cumulative distribution functions (ECDFs) of localization errors. 95 % probability is shown as a horizontal red dotted line, whose intersections of ECDF lines indicate localization accuracy. Localization accuracy of UCF, SCF, and 2S-SCF were 6.76, 2.60, and 1.00 meters, respectively.

target location. k of kNN was set to 2 because we conducted our experiments in a corridor consisting of straight lines.

We define two metrics to evaluate localization performance:

- *Localization accuracy* is the 95th percentile of localization errors for all localization trials. Localization errors are expected to be less than a localization accuracy 95 % of time.
- *Localization success rate* is the rate of successful localization to all localization trials. As we described in Section IV-D, we give up location estimation when the number of database fingerprints having finite distance from a target fingerprint is less than k in either coarse or fine-grained localization. High localization success rate indicates that sufficient number of database fingerprints are available for many localization trials. Note that localization success rate is affected by training fingerprint locations.

B. Area-Limit Radius

To determine area-limit radius R used in fine-grained localization, we first evaluated the localization performance while changing R from 0.5 to 10.0 meters.

Figure 5 shows localization accuracy and success rate of 2S-SCF as a function of area-limit radius R. Figure 5 indicates the following:

- Increase in R resulted in increase in both localization accuracy and success rate. There is a trade-off between localization accuracy and success rate because the lower accuracy indicates better performance, while the higher success rate indicates better.
- Localization success rate was almost saturated at approximately 60 % when $R \geq 2.0$ meters. Increase in R resulted in the increased rate of successful localization owing to sufficient number of database fingerprints in the limited area specified by R. On the other hand, many localization trials failed when the coarse localization result was far from an actual location, which resulted in the saturated success rate. Large R still suffered from the relatively low saturation of localization success rate because of unstable RSS. 2S-SCF gives up location estimation in these cases to improve localization accuracy.

We decided to use $R = 2.0$ meters, which exhibited a minimum localization accuracy with an almost saturated localization success rate. A localization success rate was 59.5 % at $R = 2.0$ meters. Note that localization success rates of UCF and SCF, which are independent of R, were 85.4 % and 62.3 %, respectively.

C. Localization Accuracy

We then evaluated localization performance with $R = 2.0$ meters. In order to evaluate the relative performance, we compared performance of following three localization methods:

- *Unified Channel Fingerprinting (UCF)* is a conventional fingerprinting method. UCF estimates the target location with RSS of BLE beacons without channel information.
- *Separate Channel Fingerprinting (SCF)* is a localization method presented in [6, 7]. SCF estimates the target location with RSS of BLE beacons separately measured on three advertising channels.
- *2-Step Separate Channel Fingerprinting (2S-SCF)* is the localization method proposed in this paper.

Figure 6 shows empirical cumulative distribution functions (ECDFs) of localization errors for UCF, SCF, and 2S-SCF. A horizontal dotted red line indicates the probability of 95 %. Intersections of the horizontal line and ECDF lines indicate localization accuracies. Figure 6 indicates the following:

- 2S-SCF showed the lowest localization accuracy. Localization accuracies of UCF, SCF, and 2S-SCF were 6.76, 2.60, and 1.00 meters, respectively. Compared to SCF, 2S-SCF improved localization accuracy by $(2.60 - 1.00)/2.60 \times 100 = 61.5\,\%$. In 2S-SCF, fine-grained localization gives up localizations when there is big difference between database and target fingerprints to improve localization accuracy performance.
- 2S-SCF showed the lowest maximum error. Maximum localization errors of UCF, SCF, and 2S-SCF were 6.83,

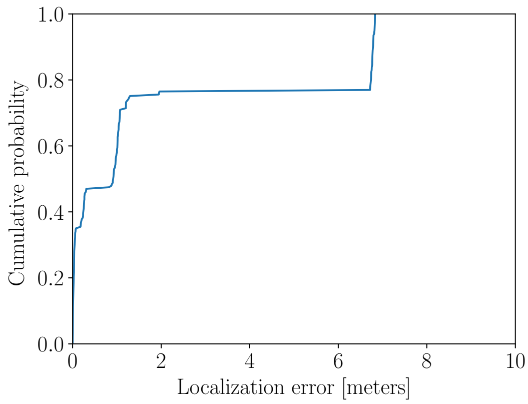


Fig. 7. Empirical cumulative distribution function (ECDF) of localization errors in 2S-SCF coarse localization when fine-grained localization failed.A localization error for more than 20 % of localization trials was greater than 6 meters, which was successfully excluded by 2S-SCF. However, small localization errors less than 2 meters were also excluded, which resulted in low localization success rate.

6.95, and and 2.05 meters. The decrease in maximum error by 2S-SCF is natural because 2S-SCF only relies on database fingerprints in the limited area determined by R. Localization error must be less than or equal to R. Small difference between the actual maximum error and R was caused by calculation rounding errors.

The above results confirm that 2S-SCF greatly improved localization accuracy with a small maximum localization error.

2S-SCF improves localization accuracy by giving up localization when the target fingerprint is significantly different from database fingerprints in the fine-grained localization step. To validate that the performance improvement was mainly made by a sacrifice of localization-success rate, we extracted unsuccessful localization trials and evaluated localization errors in a coarse localization step.

Figure 7 shows the ECDF of localization errors in 2S-SCF coarse localization, which is actually UCF, when fine-grained localization failed. Figure 7 reveals the following:

- Localization errors were greater than 6 meters for more than 20 % of unsuccessful localization trials. 2S-SCF successfully removed localization trials that degrade localization accuracy.
- Localization errors for approximately 80 % of unsuccessful trials were less than 2 meters. We confirmed that database fingerprints close to the actual target location were successfully selected in these trials. Distance between database and target fingerprints defined in Eq. (4), however, was infinity, which resulted in unsuccessful localization.

From the above results, we confirm that 2S-SCF gave up localization when target and database fingerprints were significantly different and improved localization performance. We still have a room to improve a localization success rate as we observed that coarse localization errors were less than 2 meters for approximately 80 % of unsuccessful localizations.

VI. Conclusion

In this paper, we presented BLE 2-step separate channel fingerprinting (2S-SCF), which is a BLE-based fingerprinting localization method improving localization accuracy with a small maximum localization error. The key idea of 2S-SCF is to combine fingerprinting with and without channel diversity using RSS measured on three advertising channels separated by up to 78 MHz. We first coarsely estimate the target location using a conventional fingerprinting method and then perform fine-grained localization using separate channel fingerprinting (SCF). Experimental evaluations demonstrated that 2S-SCF successfully reduced localization errors down to 1.00 meters 95 % of time with a maximum localization error of 2.05 meters. As for future work, we plan to extend 2S-SCF for large-scale environments.

Acknowledgment

This work was supported in part by JSPS KAKENHI Grant Numbers JP15H05708, JP17H01741, and JP18K18041.

References

[1] R. Faragher and R. Harle, “Location fingerpriting with Bluetooth low energy beacons,” *IEEE J. Sel. Areas Commun.*, vol. 33, no. 11, pp. 2418–2428, Nov. 2015.

[2] J. Zhu, Z. Chen, H. Luo *et al.*, “RSSI based Bluetooth Low Energy indoor positioning,” in *Proc. Int. Conf. Indoor Positioning Indoor Navig. (IPIN)*, Oct. 2014, pp. 526–533.

[3] G. Ionescu, C. M. de la Osa, and M. Deriaz, “Improving distance estimation in object localisation with Bluetooth Low Energy,” in *Proc. Int. Conf. Sens. Technol. Appl. (SENSORCOMM)*, Nov. 2014, pp. 1–5.

[4] V. C. Paterna, A. C. Augé, J. P. Aspas *et al.*, “A Bluetooth Low Energy indoor positioning system with channel diversity, weighted trilateration and kalman filtering,” *Sensors*, vol. 17, no. 12, pp. 1–32, dec 2017, article no.2927.

[5] C. Xiao, D. Yang, Z. Chen *et al.*, “3-D BLE indoor localization based on denoising autoencoder,” *IEEE Access*, vol. 5, pp. 12 751–12 760, Jun. 2017.

[6] S. Ishida, Y. Takashima, S. Tagashira *et al.*, “Proposal of separate channel fingerprinting using Bluetooth Low Energy,” in *Proc. IIAI Int. Congress Adv. Appl. Inf. (AAI), ESKM*, Jul. 2016, pp. 230–233.

[7] S. Ishida, S. Takaki, T. Yamamoto *et al.*, “Evaluation of BLE separate channel fingerprinting in practical environment,” in *Proc. IIAI Int. Congress Adv. Appl. Inf. (AAI), ESKM*, Jul. 2018, pp. 121–124.

[8] S. Ishida, Y. Takashima, S. Tagashira *et al.*, “Design and initial evaluation of bluetooth low energy separate channel fingerprinting,” in *New Trends in E-Service and Smart Computing, Studies in Computational Intelligence*, T. Matsuo, T. Mine, and S. Hirokawa, Eds. Springer, Jan. 2018, vol. 742, pp. 19–33.

[9] I. Radoi, G. Gutu, T. Rebedea *et al.*, “Indoor positioning inside an office building using BLE,” in *Proc. Int. Conf. Control Syst. Comput. Sci. (CSCS)*, May 2017, pp. 159–164.

[10] F. Palumbo, P. Barsocchi, S. Chessa *et al.*, “A stigmergic approach to indoor localization using Bluetooth Low Energy beacons,” in *Proc. IEEE Int. Conf. Adv. Video Signal Based Surveillance (AVSS)*, Aug. 2015, pp. 1–6.

[11] K. Langendoen and N. Reijers, “Distributed localization in wireless sensor networks: A quantitative comparison,” *Comput. Networks*, vol. 43, no. 4, pp. 499–518, Nov. 2003.

[12] G. Li, E. Geng, Z. Ye *et al.*, “Indoor positioning algorithm based on the improved RSSI distance model,” *Sensors*, vol. 18, no. 9, pp. 1–15, Sep. 2018, article no.2820.

[13] H. Liu, Y. Gan, J. Yang *et al.*, “Push the limit of WiFi based localization for smartphones,” in *Proc. ACM MobiCom*, Aug. 2012, pp. 305–316.

[14] Y. H. Ho and H. C. B. Chan, “BluePrint: BLE positioning algorithm based on NUFO detection,” in *Proc. IEEE GLOBECOM*, Dec. 2017, pp. 1–6.