Smartphone-Based Collaborative and Autonomous Radio Fingerprinting

Yungeun Kim, Yohan Chon, and Hojung Cha, *Member, IEEE*

***Abstract*—Although active research has recently been conducted on received signal strength (RSS) fingerprint-based indoor localization, most of the current systems hardly overcome the costly and time-consuming offline training phase. In this paper, we propose an autonomous and collaborative RSS fingerprint collection and localization system. Mobile users track their position with inertial sensors and measure RSS from the surrounding access points. In this scenario, anonymous mobile users automatically collect data in daily life without purposefully surveying an entire building. The server progressively builds up a precise radio map as more users interact with their fingerprint data. The time drift error of inertial sensors is also compromised at run-time with the fingerprint-based localization, which runs with the collective fingerprints being currently built by the server. The proposed system has been implemented on a recent Android smartphone. The experiment results show that reasonable location accuracy is obtained with automatic fingerprinting in indoor environments.**

***Index Terms*—Inertial sensors, location fingerprinting, node localization, smartphone, WiFi-based fingerprinting.**

I. Introduction

LOCATING mobile objects is an essential function needed by location-aware applications in pervasive computing environments [1], [2]. The Global positioning system (GPS) [3] has commonly been used in outdoor environments and been widely adopted in modern mobile devices such as smartphones. In indoor environments, however, no outstanding solution has been found due to practical issues which are related to complicated infrastructure requirements. Conventional mechanisms for indoor node localization are based on various types of infrastructure support, which include received signal strength (RSS) fingerprints [4], ultrawideband (UWB) [5], ultrasound [6], radio-frequency identification (RFID) [7], inertial measurement units (IMUs) [8], etc.

Among the diverse approaches for indoor node localization, the RSS-based fingerprinting system is considered practical since the system can easily be deployed using the current wireless local area network (i.e., IEEE802.11 WiFi infrastructure) [4], [9]. The RSS fingerprinting mechanism generally requires two phases of operation. In the offline learning phase, a set of received signal strength from access points (APs) in the vicinity is collected by site survey and stored with corresponding location information in a fingerprint map. The mobile user will then measure RSS at his/her current position in real time, which is compared with the fingerprint map, to find the best-matching RSS upon which the prestored location is reported back to the user.

Several issues should be considered for the practical use of the RSS fingerprint-based localization. In particular, constructing a high-quality RSS fingerprint map is an essential part of the system since localization accuracy highly depends on fingerprint quality. The RSS map-building process typically requires an extensive and thorough site surveying, usually done manually with specific hardware and software tools. Much effort has recently been given to reducing the cost and complexity of fingerprint map building. Some have focused on the effective method of constructing the map database itself [10], and others have focused on improving the location accuracy of the RSS fingerprint mechanism [11], [12]. Specifically, the core problem of offline map building has been dealt with using various approaches with a hope to reduce or even eliminate the process [13]–[15]. However, the techniques are employed in restricted environments [13], [14] or mandate a user's active participation based on *a priori* map information on the site [15].

In this paper, we propose an autonomous RSS fingerprinting mechanism, based on the use of microelectromagnetic systems (MEMS)-based inertial sensors (i.e., IMU) for indoor mobile node localization. While the previous system required a time-consuming and laborious site survey to construct the fingerprint map, the proposed system enables mobile users to collect the RSS fingerprints automatically in daily life by conducting inertial sensor-based self-localization. The RSS value as well as the estimated location is stored together with the localization error imposed by inertial sensors. The position error incurred by the inertial sensors is estimated by analyzing the moving patterns of the mobile user. The run-time fingerprints of individual mobile users collectively construct a global RSS map for the region. The fingerprint map is then used to enhance the localization accuracy of smartphone users whenever inertial sensor-based tracking behaves poorly due to time drift error.

Our technique is feasible because the number of smartphones in use is increasing, and the devices are commonly equipped with WiFi as well as inertial sensors, such as an accelerometer and a magnetometer. The proposed system can easily be deployed at any site because the mechanism does not require any anchor nor any physical map information. Many indoor localization systems assume the availability of a site map with which

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The authors are with the Department of Computer Science, Yonsei University, Seoul 120, Korea (e-mail: ygkim@mobed.yonsei.ac.kr; john@mobed.yonsei.ac.kr; hjcha@cs.yonsei.ac.kr).

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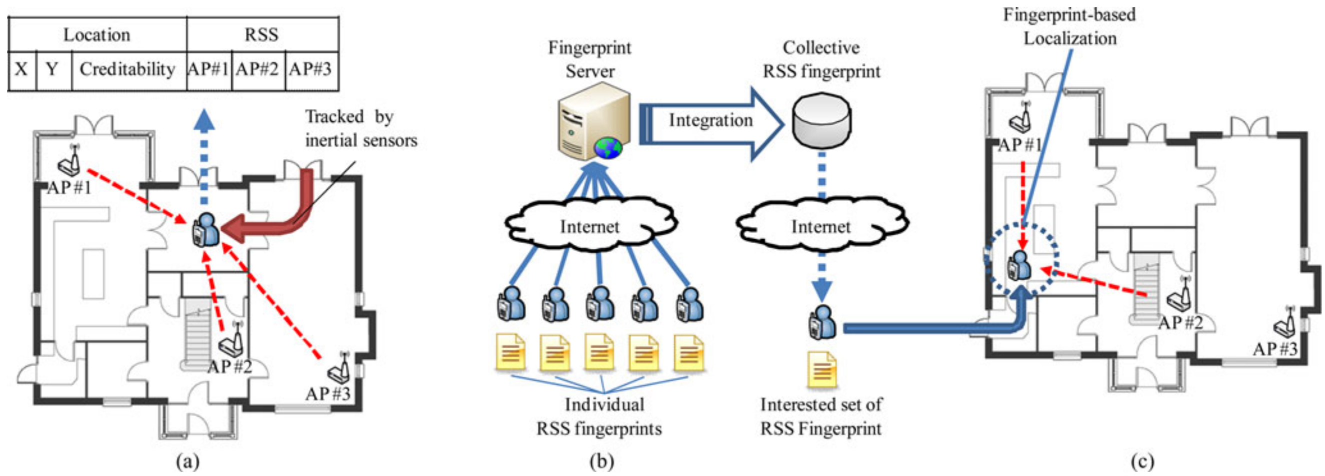

Fig. 1. System overview. (a) RSS fingerprint collection. (b) Collective RSS fingerprint construction. (c) Fingerprinting-based localization.

the localization accuracy is improved by making use of *a priori* knowledge on paths and walls in the building. Obtaining a map for an anonymous building is, however, not always possible; we believe any realistic and generalized indoor localization system should be freed from this fundamental restriction.

The remainder of this paper is structured as follows: Section II presents the overview of the proposed system, followed by descriptions of how mobile users are tracked, and error is estimated in Section III. Sections IV and V describe the method used to construct collective fingerprints and the fingerprint-based localization, respectively. Section VI discusses the experiment results. Section VII summarizes the related work on indoor localization systems. We conclude the paper in Section VIII.

II. System Overview

The proposed system consists of mobile users and the fingerprint server. The mobile users automatically collect the RSS fingerprints for WiFi APs in the vicinity while localizing their position based on their smartphones. The fingerprint server constructs a collective RSS map by integrating individual fingerprints received from the mobile users; then it supplies the map to newly entered users for localization or even back to the mobile users to further enhance the localization accuracy. Fig. 1 illustrates the overall structure of the proposed system. The localization of the mobile object is achieved in three steps: local collection of the RSS fingerprints, construction of the global RSS fingerprint map, and the localization process.

Anonymous mobile users track their position with inertial sensors in the smartphone and measure RSS from the surrounding APs. The tracked position is usually not accurate due to the drift error of inertial sensors. Consequently, a credibility estimation model should be devised based on the moving distance as well as the moving pattern of the mobile object. The mobile users contribute to the composition of the RSS fingerprint map by providing local position, credibility, and actual RSS values.

The fingerprint server constructs a global RSS fingerprint map based on the individual fingerprints uploaded by the mobile users. Since mobile users tend to move around different paths in real life, the credibility of the RSS fingerprint map would increase as the number of mobile users in a region of interest increases. To maintain high accuracy of fingerprints, the server also filters out unreliable data based upon the estimated location credibility and the RSS similarity.

The location accuracy of the inertial sensors generally decreases due to the drift error as time elapses. With our system, a mobile user makes use of the global RSS map to enhance the localization accuracy while collecting the local RSS fingerprints with inertial sensors in smartphone. This way, a severely drifted error from inertial sensors can be revised with the global fingerprint map. Additionally, a mobile phone which has only a WiFi device without inertial sensors can also be localized.

III. Collecting Received Signal Strength Fingerprints

The position of a smartphone on the human body significantly affects tracking performance. The ideal position would be in the hand while being used, because the orientation of smartphone is stationary and the same as the direction of the user. In handheld devices, however, accurate tracking of movement is hard to achieve since the device orientation, as well as its relative position on the body, frequently changes as the mobile user moves around. Hence, the proposed system performs pedestrian tracking and RSS fingerprint collection while the device is stationary in a certain position, such as in a pocket or hand. The system stops collecting RSS fingerprints when the user changes the position of the smartphone. This is feasible because most recent smartphones provide a solution to acquiring its current orientation. The initial location and direction of mobile user is also essential to track the user's trajectory with inertial sensors. In the proposed system, the starting location is one of the entrances of a building, which can be obtained by GPS or a preinstalled anchor node. The direction can also be obtained by keeping the trajectory of the user while GPS-based localization is available. In this paper, we assume that the initial location and direction is known *a priori*.

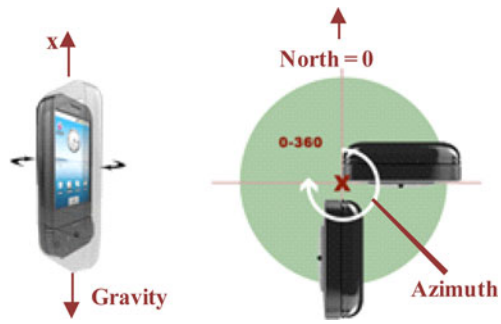

Fig. 2. Overall process to determine the direction of movement axis. We first find the relative horizontal plane to the ground and determine the movement axis by the initial direction of movement.

A. Mobile User Tracking With Android Smartphone

IMU-based tracking can be divided into integration method and step counting method. The integration scheme first finds the orientation by integrating angular velocity from gyroscope. Based on the orientation, the gravity acceleration is subtracted and the position is then estimated by integrating remaining acceleration. This scheme is, however, difficult to implement on smartphone because the performance of inertial sensors in smartphone is limited. In our work, we count steps with three-axis accelerometer and determine heading with three-axis magnetometer. This approach is practical since recent smartphones are usually equipped with accelerometer and magnetometer. A peak-detection algorithm is used to find the stepping points of time. We eliminated insignificant peaks and generated rightful points that are significantly away from the average, by utilizing the means and standard deviation of acceleration.

Unlike the foot-mounted IMU, the carrying position of smartphone is unconstrained and this results in practical difficulty in finding the heading of user's movement. As illustrated in Fig. 2, the orientation of the smartphone is represented by azimuth, roll and pitch. Especially, azimuth represents the degree of the phone being rotated on the axis of gravity. Hence, we can obtain user's heading with the initial direction and the changed azimuth value. In our scheme, the heading of user's step is determined as follows:

$$\mathrm{Hd}_{\mathrm{cur}} = \mathrm{Hd}_{\mathrm{init}} + (\mathrm{Az}_{\mathrm{cur}} - \mathrm{Az}_{\mathrm{init}}) \quad (1)$$

where $\mathrm{Hd}_{\mathrm{cur}}$ and $\mathrm{Az}_{\mathrm{cur}}$ represent, respectively, the direction and the azimuth value of user's current state. $\mathrm{Hd}_{\mathrm{init}}$ and $\mathrm{Az}_{\mathrm{init}}$ represent the initial values. Since $\mathrm{Hd}_{\mathrm{init}}$ is known *a priori*, $\mathrm{Hd}_{\mathrm{cur}}$ is determined with $\mathrm{Az}_{\mathrm{init}}$ and $\mathrm{Az}_{\mathrm{cur}}$.

$\mathrm{Az}_{\mathrm{cur}}$ and $\mathrm{Az}_{\mathrm{init}}$ are obtained from the orientation buffer O, which stores W recent roll, pitch, and azimuth values, as follows:

$$O = \{(a_i, r_i, p_i) | i = 1, 2, \ldots, W\} \quad (2)$$

Here, a_i, r_i, and p_i stand for the ith azimuth, roll, and pitch value, respectively. These values are noisy due to user's movement. Hence, deciding appropriate $\mathrm{Az}_{\mathrm{cur}}$ from the noisy values is crucial to enhance the heading accuracy. We propose two methods of deciding $\mathrm{Az}_{\mathrm{cur}}$, i.e., finding the median value and finding the most stable value. The first scheme simply selects the median of the azimuth values in the orientation buffer as $\mathrm{Az}_{\mathrm{cur}}$, i.e.,

$$\mathrm{Az}_{\mathrm{cur}} = \mathrm{median}\{a_0, a_1, \ldots, a_W\}. \quad (3)$$

The second scheme searches for the most stable azimuth value by finding the most stable roll and pitch value as follows:

$$\mathrm{Az}_{\mathrm{cur}} = \mathrm{median}\left\{ a_i | \forall j : \begin{array}{l} |r_i - r_{\mathrm{stb}}| + |p_i - p_{\mathrm{stb}}| \\ \leq |r_j - r_{\mathrm{stb}}| + |p_j - p_{\mathrm{stb}}| \end{array} \right\} \quad (4)$$

where r_{stb} and p_{stb} represent the roll and pitch value, respectively, when the user stands still. During user's stepping motion, a stable time exists where the acceleration caused by user is the smallest. This moment is detected by finding the most similar roll and pitch values with those values in standing still. The azimuth value at that time is then selected as $\mathrm{Az}_{\mathrm{cur}}$. The calibration step to obtain r_{stb} and p_{stb} should be conducted in advance for this method. The performance is further dealt in Section VI.

B. Location Credibility Estimation

The proposed system constructs global RSS fingerprints by integrating local RSS fingerprints. To achieve high credibility of the global fingerprints, the quality of each local RSS fingerprint should be estimated. The location error would increase with the step count due to the error in step length or step detection mechanism. Moreover, as the smartphone is not strapped to a certain position of human body, the sensors typically generate noise when the user generates intense movement. The credibility of each location is estimated by accumulating the standard deviation of acceleration. In the proposed system, we first initialize the credibility at the starting location and then reduce it with the standard deviation of acceleration at each step as follows:

$$c_{\mathrm{cur}} = c_{\mathrm{prev}} - \alpha \cdot \sigma_{\mathrm{acc}} \quad (5)$$

where c_{cur} is the credibility of current step, c_{prev} is the credibility of previous step, σ_{acc} is the standard deviation of synthetic vector of three-axis accelerations, and α is the scale factor of σ_{acc}. Additionally, we check if the smartphone's position is changed. When the axis of gravity acceleration is changed, the system acknowledges it, then stops locating and collecting RSS. The evaluation of credibility estimation will be discussed in Section VI.

C. Collecting RSS

Mobile users track their position with inertial sensors and measure RSS from the surrounding APs immediately. The position error as well as of the RSS values are stored at the corresponding position in the fingerprint map, which is managed by equally spaced grids. The grid spacing significantly affects the performance of the entire system. A large grid spacing leads to low localization accuracy, whereas a small spacing results in a shortage of time to collect a sufficient amount of RSS samples. In our work, we empirically selected the best grid spacing based on the typical walking speed of mobile users. The tuple T stored at each grid has the following form:

$$T = (x, y, c, S) \quad (6)$$

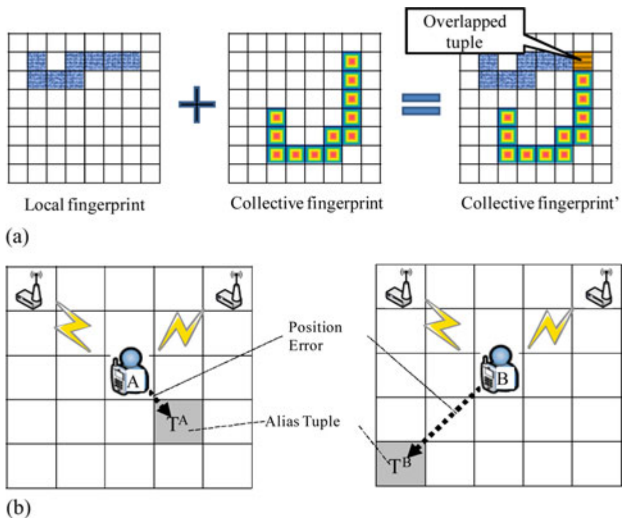

Fig. 3. RSS fingerprint filtering. (a) Overlapped tuples. (b) Alias tuples.

ALGORITHM I. PSEUDO CODE FOR COLLECTIVE FINGERPRINT UPDATE

```
Procedure Update( LF ) //Update CF with newly uploaded LF

for all tuple T_LF (x_LF,y_LF,c_LF,S_LF) in LF
  Overlapped = false
  for all tuple T_CF (x_CF,y_CF,c_CF,S_CF) in CF
    //check overlapped grid
    if (x_LF,y_LF) = (x_CF,y_CF)
      Overlapped = true
      if c_LF > c_CF
        T_CF = T_LF
    //check for alias tuple
    else if Diff (S_LF , S_CF ) < ε_same
      if c_LF > c_CF
        T_CF = null
      else
        T_LF = null
  //copy T_LF to T_CF when no overlapping
    if Overlapped = false
      T_CF = T_LF
```

where x and y represent the coordinates of the grid, c is the estimated credibility of the position tracked by inertial sensors, and S is the RSS set received from the APs in the vicinity. S is stored as

$$S = \{(\mathrm{ID}_1, \mathrm{SS}_1), (\mathrm{ID}_2, \mathrm{SS}_2), \ldots, (\mathrm{ID}_n, \mathrm{SS}_n)\}. \tag{7}$$

Here, n represents the number of APs and ID is the MAC address of the AP. SS is the mean value of the RSS samples while the mobile user is staying at the current grid. The mobile users need to upload the local fingerprints whenever possible. This is why the proposed system requires less active participation of users while existing systems require users to directly input one's own current location.

IV. Fingerprint Map Construction

The server constructs a collective RSS fingerprint (CF) by integrating the local RSS fingerprints (LF) generated by the mobile users. CF is managed by equally spaced grids. When a new LF is received, the server copies all tuples in LF to the corresponding position in CF. To maintain a high accuracy of CF, the server should filter out unreliable tuples based on location credibility and the degree of RSS similarity.

A. Filtering With Location Credibility

Fig. 3(a) explains a simple method of filtering. The position of a tuple in LF may overlap with the one in CF. In this case, the system decides if the tuple in CF should be changed with the tuple in LF by comparing the credibility of the tuples. When the overlapped tuples occur at (x, y), the tuple in CF is updated as

$$T_{\mathrm{CF}} = \begin{cases} (x, y, c_{\mathrm{CF}}, S_{\mathrm{CF}}), & c_{\mathrm{LF}} \le c_{\mathrm{CF}} \\ (x, y, c_{\mathrm{LF}}, S_{\mathrm{LF}}), & c_{\mathrm{LF}} > c_{\mathrm{CF}} \end{cases} \tag{8}$$

where T_{CF} and T_{LF} represent the tuple in CF and LF, respectively. T_{CF} should be replaced by T_{LF} when c_{LF} is larger than c_{CF}. This filtering method keeps the system in high accuracy as more LFs are collected at the server.

B. Alias Filtering with RSS Difference

Fig. 3(b) shows a case such that both A and B stay at the position (x, y) and measure RSS, but their tuples T^A and T^B are stored at different positions because of the location error of inertial sensors-based localization. We call T^A and T^B the alias tuples which are defined as having similar RSS measurement but are stored at a different grid. Since the alias tuples complicate the localization algorithm in the training phase, the server should detect and filter them out. The proposed system finds alias tuples in CF for each tuple in LF using

$$\mathrm{Diff}(S_{\mathrm{LF}}, S_{\mathrm{CF}}) < \varepsilon_{\mathrm{same}}. \tag{9}$$

Diff(S_{LF}, S_{CF}) is calculated by averaging the RSS difference between T_{LF} and T_{CF} for each AP. $\varepsilon_{\mathrm{same}}$ represents the threshold to determine if two RSS sets are collected at the same location. In other words, T_{LF} and T_{CF} are collected at the same location if Diff($\mathrm{S_{LF}}$, $\mathrm{S_{CF}}$) is smaller than $\varepsilon_{\mathrm{same}}$.

Finally, for all tuples in LF, alias tuples in CF are detected by checking (9). When alias tuples T_{LF} and T_{CF} are found, the server filters out the one that has low location credibility. Algorithm I explains the entire process of updating CF when a new LF is introduced in the server.

V. Localization

The mobile user performs self-localization by inertial sensors. Due to the drift error of inertial sensors, the error in the estimated position increases as time advances, and eventually the estimated position will not be reliable anymore. In our system, however, the position of the mobile user is revised with the recursive usage of the RSS fingerprints downloaded from the server. The location of the mobile user is adjusted to the location of the closest matching fingerprint in CF with the currently observed RSS set S_{Ob}, and the credibility is also updated as that of the fingerprint.

The closest matching fingerprint is the tuple which has the smallest Diff(S_{Ob}, S_{CF}), as described in Section IV. However,

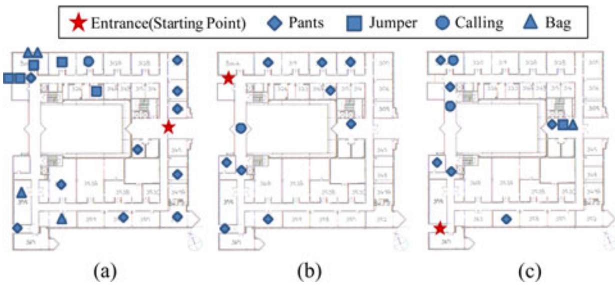

Fig. 4. Survey on the 40 participant's paths to work and their phone position from three different entrances. (a) Entrance 1. (b) Entrance 2. (c) Entrance 3.

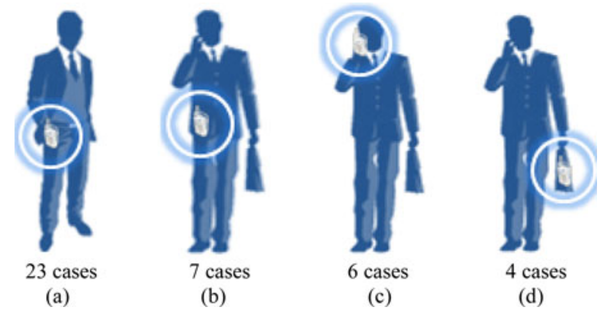

Fig. 5. Smartphone's positions. (a) Pocket. (b) Jumper. (c) Hand. (d) Bag.

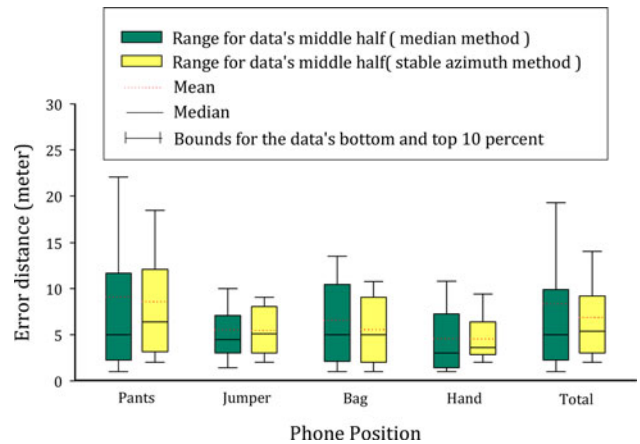

Fig. 6. Accuracy of inertial sensor-based localization according to the phone position.

the system does not guarantee that CF has the fingerprints of all locations in the building. Hence, it is possible that the smallest RSS difference is very large if the fingerprint of the current position does not exist in CF at all. Consequently, the revised position would become worse than the previous one. To prevent this problem, we perform the revision process only when the smallest RSS difference is smaller than the predefined value $\varepsilon_{\mathrm{same}}$. This method improves the quality of revision but decreases the chance of revision. However, the revision process is not frequently required because inertial sensors maintain a high accuracy for a relatively long period of time after each revision.

Meanwhile, the position of mobile user is updated when the location credibility of the fingerprint is smaller than the current location credibility. This scheme prevents the system from revising the current location with the worse one.

VI. Experimental Results

This section discusses the experiment results that were conducted to evaluate the proposed system. We will first describe the platform design and experimental environments. Preliminary experiments are then explained to obtain various parameters used in a real scenario. The performance of the proposed system is compared with the ground-truth RSS fingerprint, which is constructed by a conventional site-survey method.

A. Experimental Setup

To evaluate the proposed system in real environments, we implemented the system on the HTC Hero [16], which is an Android smartphone equipped with both an accelerometer and a magnetometer. The experiments were conducted in an engineering building at Yonsei University. The site is 60×66 m and has three entrances. The number of APs detected inside the building is between 5 and 25, depending on the location of the user. To construct diverse types of LF in the experiments, we surveyed 40 participants' paths to work, as well as their phone position at each entrance, as shown in Fig. 4. We then collected 40 LFs based on the result of the survey. Fig. 5 shows the distribution of phone positions for the participants.

B. Localization Performance with Inertial Sensors

The current location of a mobile user is estimated by inertial sensor-based localization. The localization performance is significantly influenced by the quality of local RSS fingerprints and consequently on the quality of global RSS fingerprints. To estimate the accuracy of inertial sensor-based localization, we analyzed the average location error of all the paths. We compared the performance of two methods, described in Section III-A, for finding heading. Fig. 6 shows the location error depending on smartphone's placement. As we expected, the method based on the stable azimuth showed better result than the median method. The average error was 8.4 and 6.9 m with each scheme, and the bounds on bottom and top 10% was 1.0–19.1 and 2.0–14.1 m, respectively. Additionally, we analyzed the localization performance depending on the phone placement with the stable azimuth method. The average error was 8.57, 5.45, 5.55, and 4.55 m in case of pants, jumper, bag, and hand position, respectively. The hand and jumper case showed the best results because of the stable placement condition while walking. With the phone placed in the bag, the performance is suboptimal because the device is not tightly fixed inside the bag. The performance with the pants case is the worst since the phone was usually shaking while user is walking.

Fig. 7(a) and (b) shows the average error and credibility according to the moving distance. The average error increases as the moving distance increases due to the cumulative error on step counting and heading determination. The error was slightly decreased when the moving distance was over 50 m. This is because long paths have few turning points and have the shape of a closed loop in our experiment setup. The location error of jumper, bag, and hand case showed similar slope, whereas the

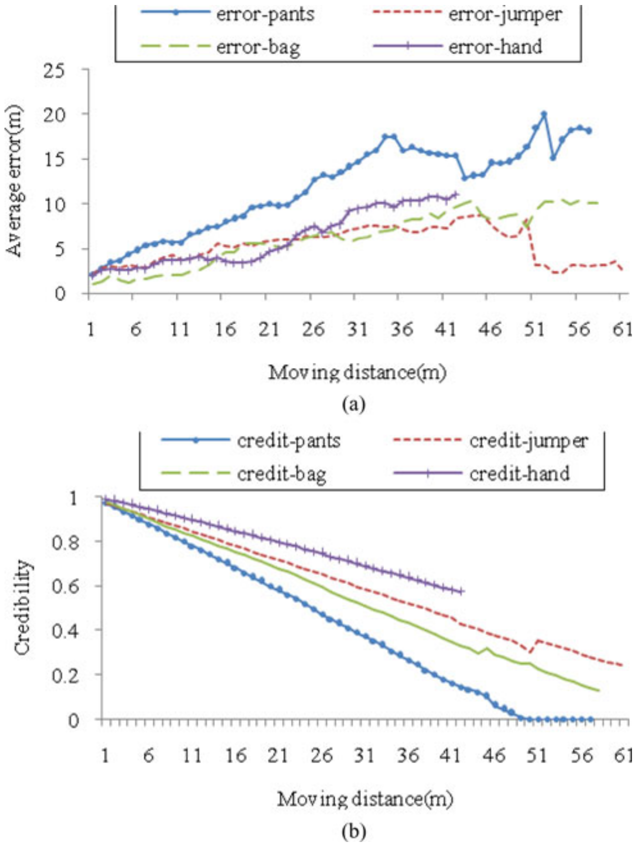

Fig. 7. Location error and credibility according to the moving distance. (a) Location error increases as moving distance increases. The pants case increases more rapidly than others due to the instability. (b) Credibility decreases as moving distance increases. The pants case rapidly decreases due to the instability. (a) Location error according to the moving distance. (b) Credibility according to the moving distance.

error with the pants case increases rapidly. The credibility of pants case is decreased rapidly compared with other cases. The results show that the credibility estimation is successful in reflecting the stability depending on the smartphone's placement. However, credibility estimations failure, meaning credibility is higher although location accuracy is lower, may exist. For example, the hand case showed higher credibility than that of the jumper case at several sections although the hand case has larger location error. Credibility estimation failures impair the quality of collective fingerprint. Hence, we evaluated the degree of the credibility estimation failure by comparing the location error and the credibility of all possible pair of tuples with each other. Fig. 8 shows that the ratio of credibility estimation failure in case of pants, jumper, bag, and hand was 21.8%, 16.4%, 10.8%, and 14.3%, respectively. The pants case failed most often because of its unstable placement. The overall ratio of credibility estimation failure was 14.8%, which is high enough to impair the quality of collective fingerprint. Fig. 9 shows the CDF on the degree of credibility estimation failure, which is obtained by calculating the difference of location errors. Sixty seven percent of the failed case showed a lower degree than a 5-m difference, which has little impact on the quality of collective fingerprint. Moreover, the remaining 33% of failed cases can be filtered out in the

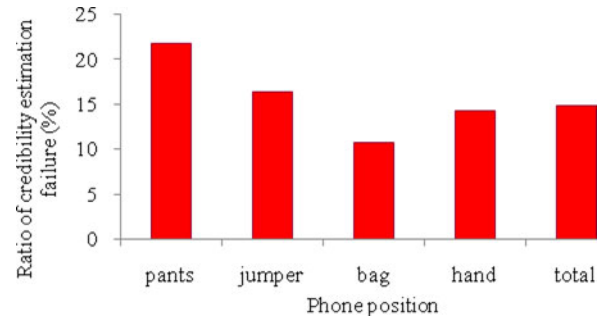

Fig. 8. Ratio of credibility estimation failure.

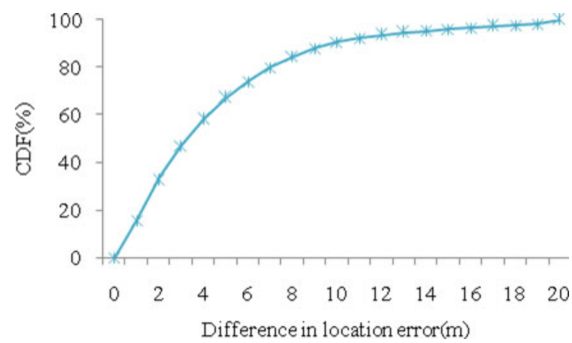

Fig. 9. CDF of the degree of credibility estimation failure.

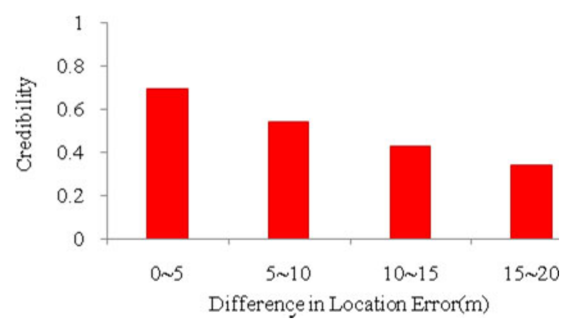

Fig. 10. Credibility according to the degree of credibility estimation failure.

filtering phase while constructing the collective fingerprint. As shown in Fig. 10, the failed cases of higher degree than 5 m have the relatively lower credibility which exhibits high chance to be filtered out while constructing collective fingerprint. The quality and the coverage of the collective fingerprints are evaluated in Section VI-D.

C. Preliminary Experiments

The various system parameters in the proposed system have a significant influence on the quality of fingerprints and consequently on the accuracy of localization. To obtain a reasonable degree of localization accuracy, many parameters should be appropriately adjusted. These include grid spacing, the threshold for finding the fingerprints of same location.

1) Grid Spacing: First, we measured the average number of scans per each grid according to the grid spacing. As shown in Table I, grid spacing of 1, 2, 3, 4, and 5 m showed the average number of scans per each grid to be 0.7, 1.4, 2.0, 2.6, and 3.4,

TABLE I
EFFECT OF GRID SPACING

	# of AP scans per a grid	Location error	Grid hit rate
1 m	0.7	3.1 m	20.1%
2 m	1.4	2.6 m	34.3%
3 m	2.0	3.0 m	50.3%
4 m	2.6	3.5 m	58.1%
5 m	3.4	4.4 m	62.8%

respectively. Note that the 1-m grid spacing cannot guarantee one scan per one grid. Further experiments were conducted to find the optimal grid spacing. A set of localizations was performed by changing the grid spacing from 1 to 5 m while walking around the building at a speed of 1.3 m/s, which is the typical human walking speed. Table I also shows the location error, and the correct estimation, which is the probability that the target is present in the estimated grid. The grid hit rate becomes higher with increased grid spacing. However, a large grid spacing caused a large localization error since the system cannot find out where the target is placed in an estimated grid. The grid spacing of 3 m showed the best result in all aspects: the average of 2.0 scans per grid, the grid hit rate of 50.3%, and the average error of 3.0 m. We selected 3 m as the grid spacing throughout the experiments.

2) Threshold for the Same Fingerprints ($\varepsilon_{\mathrm{same}}$): As mentioned before, $\varepsilon_{\mathrm{same}}$ is useful for the alias filtering when updating CF and for preventing low quality of location updates in the localization process. We empirically determined the value by averaging the difference of fingerprints which are collected at the same location. We collected 500 fingerprints at 50 different locations and averaged the RSS variation of fingerprints collected at the same location. As shown in Fig. 11(a), the maximum RSS variation is about 9 dBm, and 84.3% of data are within 5 dBm. The high setting of $\varepsilon_{\mathrm{same}}$ may produce a false-positive error when detecting alias tuples, hence we conducted a further experiment to find the rate of false-positive error according to the value of $\varepsilon_{\mathrm{same}}$. We collected 100 fingerprints at 50 different locations and counted the false-positive errors when detecting fingerprints at the same location. As shown in Fig. 11(b), the higher value of $\varepsilon_{\mathrm{same}}$ produced more false-positive errors when detecting alias tuples, and the error rate reached 59.5% at 9 dBm, and an error rate of 18.2% was showed by the $\varepsilon_{\mathrm{same}}$ of 5 dBm. Therefore, 5 dBm is chosen for $\varepsilon_{\mathrm{same}}$ throughout the experiments.

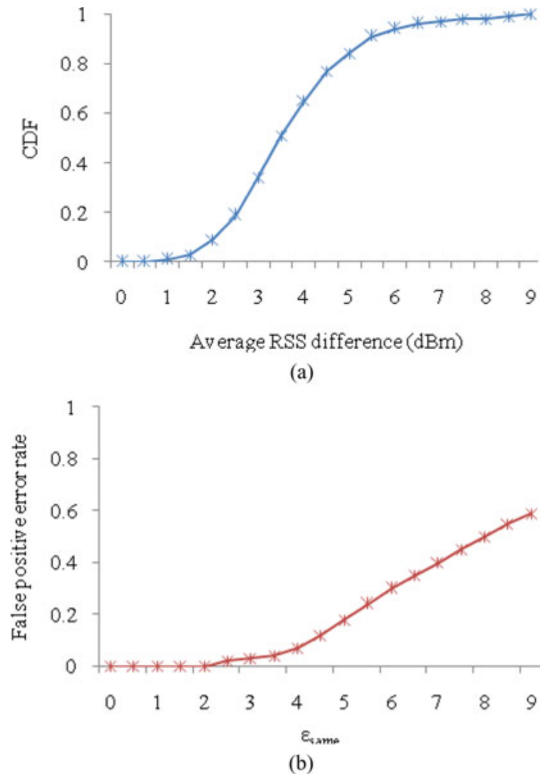

Fig. 11. Experimental result for finding optimal $\varepsilon_{\mathrm{same}}$ value. (a) Maximum RSS variation was 9 dBm, and 84.3% of data are within 5 dBm. (b) Higher $\varepsilon_{\mathrm{same}}$ produced more false-positive errors on detecting alias tuples. $\varepsilon_{\mathrm{same}}$ of 5 dBm showed error rate of 18.2%. (a) CDF of average RSS difference at the same location. (b) False-positive error rate according to the value of $\varepsilon_{\mathrm{same}}$.

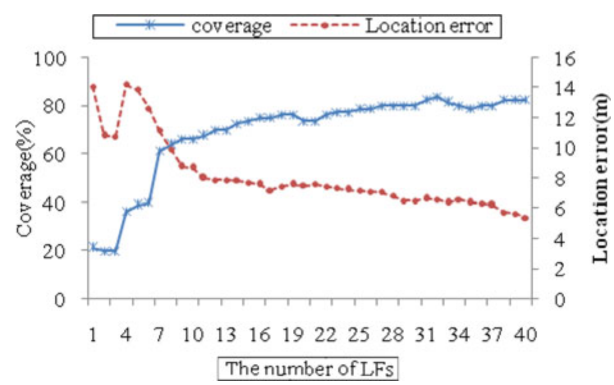

Fig. 12. Coverage and the accuracy of global radio map according to the number of LFs.

D. Accuracy of Collective Fingerprints

We evaluated the quality of collective fingerprint, which is constructed with multiple instances of LFs. First, we analyzed the coverage and the accuracy of the collective fingerprint according to the number of LFs. The coverage is the ratio of the fingerprinted grids to total grids (i.e., 80 grids) of the target area. The accuracy is the mean location error in all fingerprinted grids. As shown in Fig. 12, the coverage and the accuracy increase in proportion to the number of collected LFs. As collected LFs reach 40, the proposed system attains coverage of 82.5% and a location error of 5.42 m. With this experiment, we validate that the proposed system can indeed construct more accurate and larger radio map as more LFs are collected.

We also evaluated the quality of collective fingerprint according to the number of APs. In our experiment environment, maximum 25 APs were detected in certain grid points. We constructed three different collective fingerprints by manually limiting the selected number of APs: sparse case (2–5 APs), normal case (6–10 APs), and dense case (11–25 APs). Fig. 13 shows the fingerprinted grids of the collective fingerprint for each case.

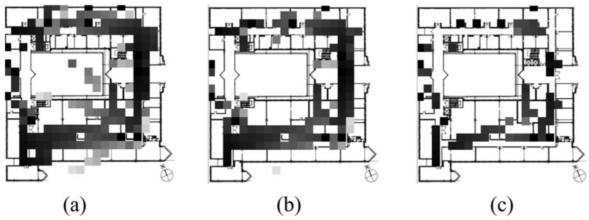

Fig. 13. Fingerprinted grids of collective fingerprint depending on the number of APs. (a) Dense case (11∼25 APs). (b) Normal case (6∼10 APs). (c) Sparse case (2∼5 APs).

TABLE II
QUALITY OF GLOBAL RADIO MAP ACCORDING TO THE NUMBER OF APS

	Coverage	Location error
Sparse	60.0 %	5.4 m
Normal	82.5 %	5.4 m
Dense	85.0 %	6.3 m

The gray level of the grid represents the degree of credibility (the darker grid has a higher credibility). In the sparse case, the number of fingerprinted grids is too few because many alias tuples are produced and filtered out with fewer APs. In contrast, the dense case showed abundant fingerprinted grids since less alias tuples are filtered out with many APs. This resulted in unnecessary grids in the center of building. The normal case showed better result in fingerprinting accuracy than the dense case; the grids are formed along corridors, and bad grids are eliminated. As shown in Table II, the sparse, normal, and dense cases showed location error of 5.4, 5.4, and 6.3 m and coverage of 60%, 82.5%, and 85% respectively. The collective fingerprint can be accurately constructed with six–11 APs by effectively filtering out alias tuples. The analysis shows that having many APs is not necessarily helpful to obtain accurate collective fingerprint. When many APs are detected in a grid, a scheme to select appropriate set of APs should be considered. In the subsequent evaluations we use the collective fingerprint of normal case.

E. Localization Error with Global Radio Map

We conducted the fingerprint-based localization with the collective fingerprint constructed in the previous section. In this system, the localization is performed both to locate a mobile user without inertial sensors (i.e. WiFi interface only) as well as to adjust the position of the inertial sensor-based localization. We evaluated the system for both cases.

1) Tracking a WiFi Only Mobile User: We compared the performance of the proposed approach with two traditional approaches; probabilistic approach with 20 RSS samples per grid and the RADAR approach with 1–2 samples per grid. The probabilistic approach [17] estimates the current location using the mean and variation of observed RSS value. RADAR is a modified version of RADAR [4], in which radio map is constructed by walking along a predefined path. A mobile user was walking along the corridor of the building for 200 m. We estimated the location of user and compared the results with ground truth to compute the location error for each approach. Fig. 14 shows that the probabilistic approach, i.e., the RADAR approach, and the proposed approach showed, respectively, the average location error of 4.1, 4.7, and 6.9 m. The proposed system showed higher error than other approaches, due to the location error of IMU-based tracking as well as a small number of RSS samples. As shown in Table III, however, the proposed system has no intended training time while the probabilistic and RADAR approaches spent 27 min and 4 min, respectively, on offline training. The training time of other approaches would rapidly increase as the target area becomes larger, whereas the proposed system spends no cost for offline training. The experiment indeed validated that the proposed system showed reasonable accuracy without intended offline training cost.

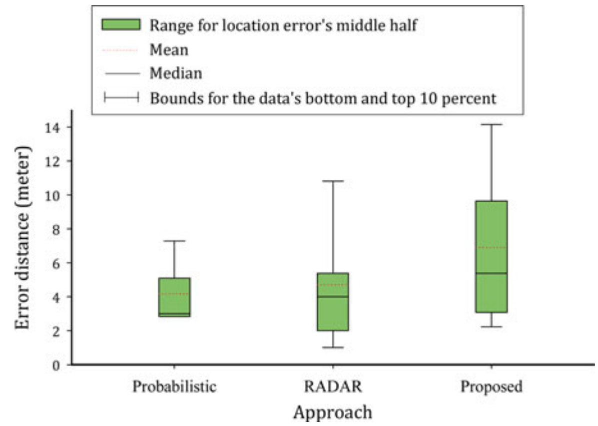

Fig. 14. Localization performance comparison with other approaches.

TABLE III
LOCALIZATION PERFORMANCE VERSUS OFFLINE TRAINING COST

	Location error	Intended training time
Probabilistic	4.1 m	27 minutes
RADAR*	4.7 m	4 minutes
Proposed	6.9 m	0 minutes

We also investigated how the accuracy of location estimation would be impacted by three factors: user orientation, time, and phone position. First, we evaluated the proposed system with a scenario, in which a mobile user was walking around the building clockwise carrying the phone in his hand during the day (we call this experiment as the "default" case). Then, we conducted additional experiments by changing each aspect from the default case, i.e., user walking counterclockwise, carrying the phone in pants pocket, and walking at night. Fig. 15 shows the location error of each case. In the default case, the mean location error was 6.9 m. The result in the evening, in the pants and walking counterclockwise showed location error of 7.9, 7.6, and 7.7 m, respectively. The result in the evening showed slightly worse than other cases because the LFs are collected in the morning, and the signal propagation environment differs at night than from during the day. However, all the case showed similar performance as the default case since the collective fingerprint was constructed

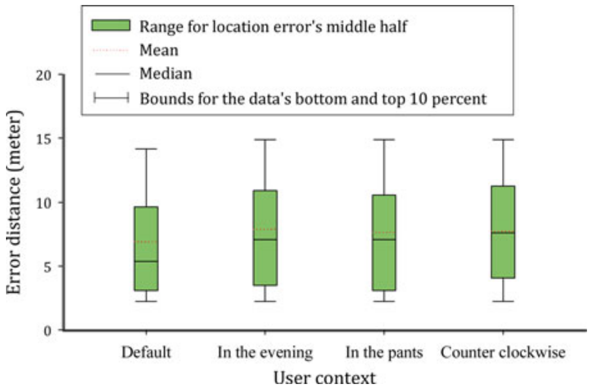

Fig. 15. Localization performance according to the user context.

with LFs, which are collected with diverse user context. With these experiments we validated that the proposed system is resilient to varying signal propagation environments as well as user contexts.

2) Fingerprinting-Based Location Update of an Inertial Sensor-Based Localization: We also conducted an experiment to evaluate if the proposed system can enhance the position accuracy when the smartphone poorly tracks a mobile user due to the time drift error of inertial sensors. In this experiment, a mobile user walked around the building for 3 min twice: first smartphone in the pocket and then in the hand. The CF that was constructed with 40 LFs was used for the fingerprinting-based revision. Fig. 16 shows the position error of the inertial sensor-based tracking and the fingerprinting-aided tracking. The real path of the user formed a closed loop; hence the error on the IMU-based tracking was not always increased even though the moving distance was increased. The dashed line represents the time when the fingerprinting-based location update occurs. As shown in Fig. 16(a), the revised method showed the average error of 9.4 m, while the inertial sensor-based tracking with pocket position showed 16.5 m. There were two significant revisions which reduced the location error from 17 to 2 m and from 31 to 6 m. The fingerprinting-based location update also showed a better result of 4.1 m in average location error, while the IMU-based tracking with messaging position showed 8.4 m [see Fig. 16(b)]. Note that the fingerprinting-based location update at 101 m has reduced the location error from 21.1 to 1 m. The experiment validates that the proposed system significantly reduced the time drift error of inertial sensor by using the collaboratively constructed RSS fingerprint map.

F. Discussions

With the proposed system, collecting enough number of RSS samples is difficult due to the mobility of the user. Consequently, the localization error ought to be greater than manual training approaches. Such limitations can be overcome by accumulating multiple users' data, which are currently filtered out due to the low credibility.

Constandache *et al.* [18] confirmed that one of the most power-consuming components of mobile phones is Wi-Fi, especially when frequent AP scanning is necessary. The proposed system also consumes power due to the continuous AP scanning during the training phase. However, the system operates only when the user enters indoor till the user reaches destination, minimizing power consumption.

The periodic update of radio map is a fundamental requirement for the localization schemes based on radio fingerprinting since RSS changes over time due to the environmental changes. The proposed system is advantageous thanks to the automatic radio map update scheme. The radio map is automatically reconstructed by new LFs day by day.

In our experiment analysis, we used one type of smartphone, HTC Hero. However, diverse types of smartphones would have different performance characteristics on Wi-Fi and inertial sensors that may influence the performance of the proposed system. Especially, different Wi-Fi chipsets can cause localization error due to the gap of RSS between the trained data and the observed data. To address this problem, Kjærgaard *et al.* [19] proposed a hyperbolic location fingerprinting, which records fingerprints as signal strength ratios between pairs of base stations instead of absolute signal strength values. We plan to apply this approach to our system in the future work.

VII. Related Work

For the past few years, active research has been conducted on localization methods based on the RSS fingerprints. RADAR [4] was the first WiFi-based localization system which utilized RSS from APs in the vicinity. Ekahau [9] commercialized the concept with enhanced localization accuracy. These systems, however, require an RSS map-building process via laborious offline training for a specific site of interest. Place Lab [13] and Skyhook [14] tried to reduce the cost for offline training by collecting the WiFi signals automatically while moving with a GPS-equipped vehicle. These systems are primarily targeted for outdoor environments and are certainly not applicable to indoor applications. Redpin [15] handled the offline training by incorporating a collaborative approach where users collect fingerprints while using the devices. The system mandates active participation of users to collect fingerprints because users must manually register new fingerprints frequently to enhance the location accuracy. Nattapong and Prashant [10] reduced the number of fingerprints by clustering the RSS signals with similar measurement values. Also, several studies were conducted to improve the positioning accuracy of the RSS fingerprint-based mechanism. Bayesian modeling [11] and statistical learning [12] belong to this category.

Meanwhile, many IMU-based localization systems have been developed, especially in the robotics area, to track the locations of mobile robots. Applying the technique to human tracking poses a new challenge since human behavior, compared to robots, is dynamic. Moreover, a subtle motion of human movement should be carefully considered to obtain reasonable tracking accuracy. Godha and Lachapelle [20] proposed a pedestrian navigation system that achieves accuracy of 2 m both indoors and outdoors by integrating GPS and IMU. Lasse and Tim [21] proposed a Monte-Carlo-based localization system which uses an accelerometer for step counting and a magnetometer to track

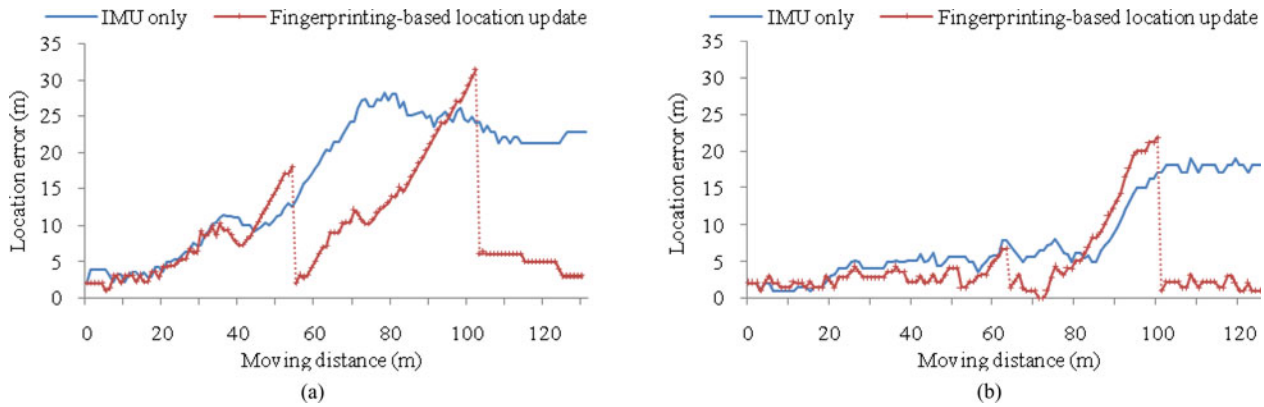

Fig. 16. Reduced location error by fingerprinting-based location update. Fingerprinting-based location update reduced average location error from 16.5 to 9.4 m in the pocket case (a) and from 8.4 to 4.1 m in the hand case (b). (a) Comparison in the pocket case. (b) Comparison in the hand case.

TABLE IV
SUMMARIZED FEATURES OF RELATED SYSTEMS FOR RADIO FINGERPRINTING

System	Off-line training: Trainer	Off-line training: Method	Platform	Accuracy
RADAR[4]	Administrator	Site-survey	Laptop	2~3 m
Place Lab[13]	Administrators	War-driving	Laptop, PDA, and cell phone	20~30 m
Redpin[15]	User collaboration(active)	User input	Smartphone	Room-level
Oliver[22]	Administrator	Automatic training with foot-mounted IMU	UMPC	1 m
Proposed system	User collaboration(passive)	Automatic training with smartphone-based IMU	Smartphone	6 m

orientation. The system showed a positioning error of 1–3 m by exploiting physical map information with anchors at known positions.

Several efforts have been made to integrate WiFi fingerprinting systems with inertial sensors. Oliver *et al.* [22] proposed a WiFi fingerprinting system in which the RSS fingerprints are automatically collected with IMU-based self-localization. The structure of the system is similar to ours, but the system assumed administrator-based offline training while our system collects fingerprints of anonymous mobile users. The system used foot-mounted IMU, which is impractical, and required detailed 2.5-dimensional description of a building for high accuracy IMU-based localization. Philipp *et al.* [23] proposed an improved version of Redpin [15] in which the quality of the RSS map was improved by detecting the position of device based on its accelerometer. Hui *et al.* [24] proposed a WiFi-based indoor localization system using particle filters with low-cost MEMS sensors. In the filtering process, the motion model was defined by low-cost MEMS sensors, whereas the observation model was provided by WiFi fingerprinting localization.

Other types of indoor localization systems have also been developed. The active badge location system [25] used infrared to find user location, but the limited range of infrared restricts node localization in a wide area. The Cricket system [6] and Active Bat system [7] were based on the use of costly ultrasonic devices for indoor localization in a limited space. Ubitag [5] achieved good localization accuracy by integrating the TDoA and AoA methods in a UWB network. The system requires a high-cost UWB tag. Furthermore, the signal interference problem must be solved to coexist with existing narrow band systems.

Table IV summarizes the key features of the proposed system compared with related systems for radio fingerprinting. While other systems require active user participation or an administrator to conduct site survey, our system automatically constructs a radio map by user collaboration. Also, in comparison with previous system that used laptops, PDAs, or cell phones, our system is implemented on latest smartphones which are equipped with inertial sensors; hence, we have specifically considered the unconstrained placement of smartphone device. Our system could localize the WiFi-only user with the location error of 6 m, which is reasonable accuracy for room-level location-based services.

VIII. CONCLUSION

This paper proposed an indoor localization system which has the following originality and contributions: First, the costly offline process of RSS map construction in conventional fingerprint-based localization is removed by the use of inertial sensors. To collect RSS fingerprints automatically, the proposed system conducts inertial sensor-based self-localization and estimates the credibility of the localization. Second, we successfully constructed the collective fingerprint map by a credibility-based user collaboration scheme. The proposed system is based on a passive user participation model, which collects and uploads fingerprints automatically in daily life. Also, the time drift location error of mobile user due to inertial sensors is reduced by filtering the fingerprints of low credibility. Third, to the best of our knowledge, the proposed system is the first Wi-Fi fingerprinting system that is actually implemented on a smartphone with the consideration of unconstrained device placement.

Our system can be used for various location-based applications such as finding lost children, indoor navigation system in a large shopping center, etc. For the future work, we plan to improve the proposed system in several aspects. The inertial sensor-based localization will be enhanced to improve the quality of local fingerprints. In addition, the distortion of the magnetometer should be detected for credibility estimation. A further set of large-scale experiments in diverse indoor environments is planned to understand the practical usage of the system. Finally, we plan to implement a seamless localization system by detecting the precise entrance position of the building, which was assumed to be known in the current work.

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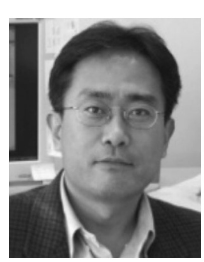
Yungeun Kim received the B.Sc. degree in 2008 from the Department of Computer Science, Yonsei University, Seoul, Korea, where he is currently working toward the Ph.D. degree.

His current research interests include mobile and ubiquitous computing and smartphone-based localization systems.

Yohan Chon received the B.Sc. degree in 2009 from the Department of Computer Science, Yonsei University, Seoul, Korea, where he is currently working toward the M.Sc. degree.

His current research interests include mobile and ubiquitous computing, context-aware computing, and power management on mobile platforms.



Hojung Cha (M'95) received the B.S. and M.S. degrees in computer engineering from Seoul National University, Seoul, Korea, in 1985 and 1987, respectively, and the Ph.D. degree in computer science from the University of Manchester, Manchester, U.K., in 1991.

He is currently a Professor of computer science with Yonsei University, Seoul, Korea. His current research interests include wireless and mobile systems, embedded operating systems, and sensor network systems.