IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received June 22, 2017, accepted July 12, 2017, date of publication July 19, 2017, date of current version August 8, 2017.

Digital Object Identifier 10.1109/ACCESS.2017.2728789

Path-Loss-Based Fingerprint Localization Approach for Location-Based Services in Indoor Environments

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This work was supported in part by the National Natural Science Foundation of China under Grant 61601169, Grant 61572172, and Grant 61401107, in part by the Open fund of State Key Laboratory of Acoustics under Grant SKLA201706, in part by the Natural Science Foundation of Jiangsu Province of China under Grant BK20140248, in part by the Maoming Engineering Research Center on Industrial Internet of Things under Grant 517018, and in part by the International and HongKong, Macao & Taiwan collaborative innovation platform and major international cooperation projects of colleges in Guangdong Province under Grant 2015KGJHZ026.

ABSTRACT Wireless local area network fingerprint-based indoor localization schemes have been widely studied because of the increasing requirements of location-based services (LBSs). The features of fingerprint-based localization are known to have higher precision in indoor environments than traditional methods, such as triangulation. However, the precision depends on the amount of pre-created received signal strength (RSS) fingerprints, which is associated with the number of reference points (RPs) of the RSS measurements and the available signal sources in the environment. In this paper, we consider the resource limitations of todays' wireless environment and propose an improved fingerprint-based localization approach that adapts a path loss model for fingerprint creation and localization. Based on the proposed approach, we present two related localization schemes. The first is a path-loss-based fingerprint localization (PFL) scheme and the second is a dual-scanned fingerprint localization (DFL) scheme. The PFL attempts to improve positioning precision, and the DFL attempts to guarantee positioning reliability. Several simulations are performed, and they show that the proposed schemes improve the positioning precision and reliability in resource-limited environments, which would improve the practicability of fingerprint-based localizations in indoor LBSs.

INDEX TERMS Location based services, wireless local area networks, fingerprint localization, path loss.

I. INTRODUCTION

In the Internet of Things (IoT) era, indoor location-based services (LBSs) have rapidly increased to improve the convenience of human life in areas such as healthcare monitoring and personal tracking. However, the widely-used Global Positioning System (GPS) does not work well in indoor environments [1]. Hence, with the increased public deployment of Wireless Local Area Networks (WLANs), WLAN-based indoor localization techniques have been widely studied to achieve the localization requirements of various LBSs [2]–[4]. Compared with GPS localization, which measures the absolute coordinates of wireless devices, WLAN-based localization is a scheme that measures relative coordinates from particular reference points (RPs), such as WLAN Access Points (APs), or from pre-measured location information.

WLAN-based localization has flexible adaptability because WLANs have become a universal civilian network. However, such localization also faces technical difficulties because of irregular indoor signal propagation factors. For example, to use well-known distance-based localization techniques, such as Time of Arrival (TOA) [5], Time Difference of Arrival (TDOA) [6], Angle of Arrival (AOA) [7] and Received Signal Strength (RSS) [8], signal propagation distances among unknown targets and neighboring RPs must be determined. However, complex indoor environments cause

None-Line of Sight (NLOS) and multi-path signal propagations, which generate various losses of signal and leads to inaccurate distance evaluations [9], [10]. Additionally, fingerprint localization [11]–[13], which is another typical indoor localization scheme, requires the creation of an RSS fingerprint database (RSS-map) with a site survey. Normally this process is time consuming and complex, and it usually requires sufficient signal sources to guarantee the fingerprint resolution.

Our research targets WLAN fingerprint-based localization schemes, which have been a research focus in recent years because of their high precision and adaptability. Generally, fingerprint-based localization includes two phases. The first phase is an off-line phase, which creates a fingerprint database by measuring RSS in a batch of known locations (RPs), and the second phase is an on-line phase, which analyzes the similarity of RSS patterns (fingerprint scan) of unknown targets against the information in a fingerprint database.

Currently, the major challenge associated with fingerprint localization is how to decrease the positioning cost [14]–[17]. Normally, the cost of fingerprint-based localization can be categorized into one of two types. The first is the database creation cost, which includes the site survey and human resources for collecting RSS data at RPs, and the second is the cost of installing signal sources that provide the RSS information to the RPs (e.g. APs). The resolution of the fingerprint in each RP depends on the number of available signal sources; thus, the number of signal sources installed in a building becomes a critical factor in fingerprint-based localizations. However, according to studies on wireless interference [18]–[21], the performance of the wireless network decreases if too many signal sources share the same area because of the increasing co-channel interference among transmissions. Therefore, an increased number of signal sources in a building may improve the positioning precision while decreasing the performance of wireless networks. Recent research to improve the performance of WLAN-applied mechanisms has examined the implementation of a sleep function for idle APs [22] or a decrease in the transmission range of APs [23], which implies that the practicability of WLAN fingerprinting may encounter issues with signal source limitations.

In most LBSs, reliable positioning is another important localization demand in personal tracking and room-level monitoring. Hence, in this article, positioning evaluation factors are classified as positioning precision and positioning reliability. The positioning reliability refers to the probability of positioning precision under a particular positioning requirement. The relationships among positioning precision, positioning reliability and positioning resources in fingerprint-based localizations are described as follows:

- Positioning precision usually depends on the number of RPs; however, when the number of RPs reaches a certain value, the effects of other factors will be reduced, such as the number of signal sources and the fingerprint method used.
- Positioning reliability increases with the number of signal sources because the number of signal sources indicates the resolution of each RPs fingerprint.
- Less investment in deploying RPs decreases the positioning precision but has a weaker effect on the positioning reliability with a sufficient number of signal sources.
- Limited signal sources cause unreliable positioning precision, even if the number of RPs is sufficient.

This article proposes a localization approach that improves the positioning precision under limited signal sources. In fingerprint-based localizations, additional dimensions of analyzable factors would theoretically increase the fingerprint resolution and improve the positioning precision under the same resources, which would decrease the cost of signal sources required to guarantee a certain positioning precision. In the article, we utilize the path-loss exponent (PLe) of the path loss model in fingerprint-based localizations. The PLe is a sensitive factor related to the signal propagation distance and signal fading factors, which means that the PLe can represent an environmental identification factor in indoor positioning. According to such a feature, an extended WLAN fingerprint-based localization approach that uses the PLe is presented in this article, and it is referred to as Path-loss based Fingerprint Localization (PFL). The PFL utilizes PLe to create a fingerprint database in the off-line phase, and it matches the patterns of calculated signal propagation distances in positioning unknown targets the on-line phase.

We analyzed the traditional fingerprint scheme and the PFL via simulations, and our results indicate that the PFL has higher precision. However, several unexpected outlier cases indicate high positioning errors and low positioning reliability. Hence, we proposed another scheme that combines the RSS and PLe in a fingerprint scan, which is referred to as Dual-scanned Fingerprint Localization (DFL). The DFL scheme works as follows: in an on-line phase, a set of potential locations of an unknown target is estimated by clustering algorithms (e.g., Nearest Neighbor) by scanning RSS values and analyzing the physical distances among referenced RPs. Using the same method employed in PFL, the PLe is then scanned among the potential locations set to locate unknown targets. The first scan of the DFL is performed to remove outlier estimates to guarantee positioning reliability, and the second scan is performed to precisely locate the unknown target. With several simulations, we proved that the the DFL provides improved positioning reliabilities in resource-limited wireless environments.

The first contribution of this article is the proposed PFL. Traditional research for improving WLAN-fingerprint-based localization have primarily investigated effective RSS analysis schemes, such as by improving scanning algorithms [10], [24], specifying devices [12], or detecting activity [13]. The PFL adapts a novel environmental path-loss factor in the fingerprint estimation in addition to RSS, which improves the positioning precision by increasing the specificity of the fingerprint analysis and reducing the resources required to guarantee a certain positioning precision. The second contribution is the proposal of the DFL. The DFL attempts to improve positioning reliability to meet the universal requirements of todays LBSs. Simulations with the proposed approaches showed that the PFL has high positioning precision, whereas others produced outlier estimates. The DFL has lower precision than the PFL but shows higher positioning reliability, although the precision of the DFL is still higher than that of traditional fingerprint-based localizations.

The remainder of this paper is structured as follows. Section II provides a brief survey of traditional WLAN-based indoor localizations and presents a performance analysis of triangulation and fingerprint-based localizations. Section III introduces the path-loss-based fingerprint approaches and two related localization schemes, PFL and DFL. Section IV presents a performance analysis of the PFL and DFL via simulations. Section V presents the conclusions.

II. BACKGROUND ON WLAN-BASED INDOOR LOCALIZATION

Table 1 lists the traditional WLAN-based localization approaches for universal LBSs studied in recent years. The approaches can be categorized into two types by the studied methods, which are distance-based geometric calculations and pattern-based data analyses. Localizations based on TOA, TDOA, AOA and RSS include distance-based calculations, and they estimate unknown locations through geometric calculations, such as triangulation with propagation model [25]. Fingerprint-based localization is a pattern-based analysis that estimates unknown locations by analyzing the signal environment via data mining methods, such as similarity analysis, clustering, etc.

In this section, we discuss the practicability and limitations of conventional WLAN-based localization schemes in indoor environments. We focus on propagation model based RSS triangulation and fingerprint-based localization, which are typical and widely studied localization schemes for todays LBSs.

RSS-based triangulation normally involves two phases. The first phase is the collection of RP location information (signal sources, usually APs) in a target region. For example, a GPS and WLAN-equipped vehicle travels through all the streets in a city, records the coordinates in a certain period, and collects RSS data from all nearby APs. When the trip is over, the LBS server integrates the information and calculates the signal propagation distances from each of the recorded coordinates to nearby APs via the RSS data collected for the coordinates, and it then triangulates the locations of all detected APs with the distance and coordinate information. The second phase is the localization of unknown targets. An unknown target sends RSS information from three or more nearby RPs to a localization server, and then

TABLE 1. WLAN based localization schemes.

Approach	Scheme	Description	Reference
TOA/TDOA	Distance based	Uses geometric calculations to locate an unknown target. Requires estimating signal distances by measuring the time and time difference of signals transmitted from RPs.	[5], [6], [37], [39]
AOA	Distance based	Calculates locations of unknown targets by estimating the angle of incidence at which signals arrive at the receiving RPs.	[7], [39], [41]
RSS	Distance based	Uses geometric calculations with propagation model, usually triangulations. Estimates distances according to the receiving signals power from RPs and by signal variation factors with propagation model, such as path-loss.	[8], [9], [27], [41]
	Fingerprint based	Analyze the similarity of RSS patterns between an unknown target and a pre-created signal map, which contains the RSS information from every RP in each divided area.	[10], [11], [12], [13], [14], [15], [16], [17], [28], [29], [30], [31], [32], [33], [34], [35], [36], [41]

the server triangulates the location of the target by calculating the signal propagation distances according to the received RSS information. Based on the phases, the major challenge associated with the scheme is determining how to precisely calculate the signal propagation distance.

Fingerprint-based localization utilizes RSSs from different signal sources to identify each location, pre-create a RSS-based fingerprint database and then localize unknown targets by matching RSS patterns from the database. This process also involves two phases, known as the off-line and on-line phase. Both phases use RPs to create a RSS map and localizing unknown targets. However, the RPs in fingerprint-based localization are fundamentally different from the RPs in triangulation because they represent a number of known locations but not signal sources. The locations of RPs are relative coordinates in a building, and the patterns of RSS information for each RP generate a RSS map in the off-line phase. Then, the unknown targets can be localized by analyzing the similarities between the sensed RSS information and RSS patterns in the RSS-map in the on-line phase.

In fingerprint-based localizations, the density of RPs and the number of signal sources are the key factors that improve the practicability of localization.

A. PERFORMANCE ANALYSIS OF RSS-BASED INDOOR TRIANGULATION

We present positioning simulations to compare the practicability of RSS-based triangulation and WLAN fingerprint-based localization in indoor environments. The simulations are based on a RSS-map dataset created by the KIOS research center [12]. The training data of the dataset include Wi-Fi RSS data collected at 105 locations among 9 APs in a 560 m^2 typical office environment, and the test data include RSS data collected at 96 locations. The locations of unknown targets are calculated by following path loss model [26]:

$$RSS = TX_{PWR} + GAIN_{TX} - PL + GAIL_{RX} \quad (1)$$

$$PL = PL_{REF} + 10log(d^n) + s \quad (2)$$

where TX_{PWR} is the transmission power of APs; $GAIN_{TX}$ and $GAIN_{RX}$ are the antenna gains in the sender and receiver sides, respectively; PL_{REF} is the path loss at a determined distance, which is usually 1 meter; d is the signal propagation distance; n is the PLe (path-loss exponent); and s is the standard deviation associated with the degree of shadow fading. We set TX_{PWR}, $GAIN_{TX}$ and $GAIN_{RX}$ to 12 dBm, 2 dBi and 2 dBi, respectively, which refers to the currently-populated AP and smartphone specifications. We also set n to 4 and s to 5 dB (averaged values introduced in [26]). PL_{REF} is obtained experimentally, and the value is 20 dB in 1 meter. The locations of unknown targets are triangulated by the calculated distance among 3 random APs by solving equation (3), where X and Y are the target's coordinates, X_{RPi} and Y_{RPi} are the ith RPs coordinates and d is the distance between the target and RP.

$$\begin{bmatrix} (X_{RP1} - X)^2 + (Y_{RP1} - Y)^2 \\ (X_{RP2} - X)^2 + (Y_{RP2} - Y)^2 \\ (X_{RP3} - X)^2 + (Y_{RP3} - Y)^2 \end{bmatrix} = \begin{bmatrix} {d_{RP1}}^2 \\ {d_{RP2}}^2 \\ {d_{RP3}}^2 \end{bmatrix} \quad (3)$$

Fig. 1 shows the results of the simulations. Only 39% of the 96 training samples showed positioning errors under 5 meters, which indicates a lack of reliability in the positioning. The reason for the lack of reliability is that the distance information is sensitive to the triangulation factors and an average PLe value must be used in the distance calculations because the PLe cannot be predicted if the location is unknown. Therefore, the deviations in PLe lead to unreliable distance information in the triangulations which also lead to difficulties in AP selections for most precise triangulations. The precision can be improved by increasing the dimensions of multilateration [equation (3)] or performing multiple triangulations. As shown in Fig. 2, in this case we localize the targets by calculating the midpoint of multiple triangulations, using 6 and 9 APs for dual and triple triangulations respectively. However, the unpredictable environmental factors still limit the practicability of distance-based geometrical positioning schemes in indoor environments.

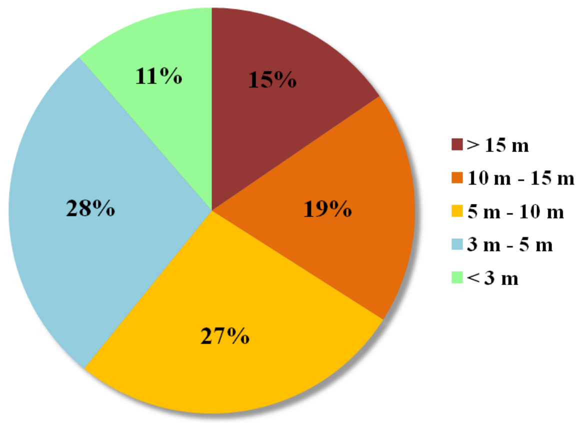

FIGURE 1. Distribution of positioning errors by RSS-based triangulations.

Because traditional RSS-based triangulations are not practicable in indoor environments in reason of the irregular signal propagation factors, research has focused on advanced methods of improving adaptability in indoor environments, such as mitigating the signal fading impact [9] and increasing the triangulation dimension [27].

Here, we analyze the WLAN-fingerprint-based localization and create the RSS fingerprint database for the off-line phase according to the training data of the KIOS dataset. In the on-line phase, we evaluate the similarity of RSS patterns between unknown samples and RPs according to the following steps. First, we create a database that contains the minimum and maximum RSS values of every RP among all APs. It is noted that the RSS values vary with the time duration at each RP because of the irregular variation of indoor signal fading factors. Hence, measuring RSS values over different time periods or collecting user feedback would help enhance the serviceability of the fingerprint database. Second, we calculate the sum of the Manhattan distance from the training samples minimum and maximum RSS values to each RPs minimum and maximum RSS values from all APs as similarity values. Finally, we set the coordinate of the RP that has the smallest similarity value as the location of the sample.

Laoudias *et al.* [12] used the Euclidean distance of multidimensional RSS values to evaluate the RSS similarity, which is a simple, practical and easily adaptable similarity analysis. In this article, we used the cumulative Manhattan distance according to the minimum and maximum RSS values in each RP, which is a simpler similarity analysis. The following equation explains the method, where k represents the index of RPs and n is the number of signal sources:

$$sim(k) = (\sum_{i=1}^{n}(|RSS_{RP(i)min} - RSS_{min}| + |RSS_{RP(i)max} - RSS_{max}|))/n \quad (4)$$

And the following pseudo-code 1 explains the localization process.

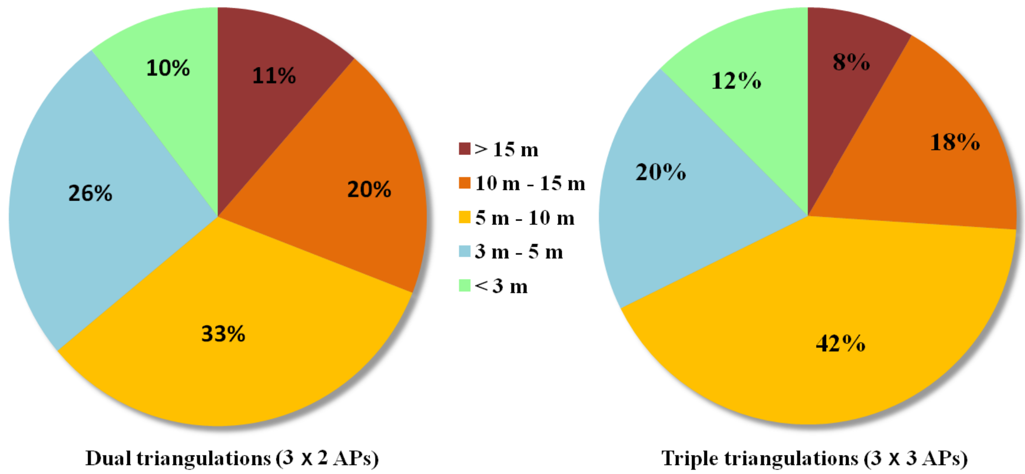

FIGURE 2. Distribution of positioning errors by RSS-based multiple triangulations.

Pseudo-code 1 RSS Based Fingerprint Localizations

```
Input: Location target; FingerprintSet RPs;
APSet APs;
double temp, sim = POSITIVE_INFINITY;
Output: Coordinates c;
forall the p ∈ RPs do
    temp = 0;
    forall the r ∈ APs do
        temp +=
        Abs(p.RSSMin(r) − target.RSSMin(r)) +
        Abs(p.RSSMax(r) − target.RSSMax(r));
    end
    temp = temp/APs.getSize();
    if temp < sim then
        sim = temp;
        target = p;
    end
end
c = target.getCoordinates();
```

Fig. 3 shows the result of the simulations. Our results indicate that 80% of 96 test samples show positioning error under 5 meters, which represents a considerable improvement in positioning reliability. These results are similar to that of the original experiments in [12], which demonstrates that our similarity calculation method is simple but reliable.

Compared with the RSS-based triangulation method, the fingerprint-based localization approach showed a much higher practicability in our simulations. However, based on the resources used, the fingerprint simulations used 9 APs while the triangulation simulations only used 3 APs to reach the same positioning reliability. Hence, we ran the following simulations to determine the reliability of the fingerprint-based localization under limited resources. In this simulation, we used 6 and 3 APs in our analysis of the fingerprint-based

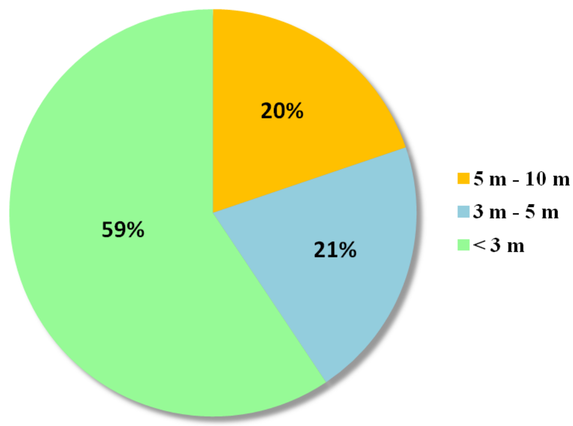

FIGURE 3. Distribution of positioning errors by fingerprint-based localization.

localization scheme. The APs are selected by considering whether they are sufficiently spaced apart to measure dissimilar RSS patterns.

Fig. 4 shows that 68% and 59% of the test samples reach positioning error under 5 meters, which implies that the practicability of fingerprint-based localization depends on the number of available signal sources. However, an unknown target can sense multiple signal sources because it is placed in a signal-overlapped area. As mentioned in Section I, a signal-overlapped area causes mutual interference among signal sources and decreases the performance of wireless networks. Currently, studies to improve wireless performance are focused on reducing the signal-overlapped area, which means fingerprint-based localizations may encounter additional problems associated with resource limitations and implies that studies on fingerprint-based localization should focus on improving localization schemes under limited resources.

Fig. 5 compares the positioning precision by cumulative distribution function (CDF) of positioning errors between

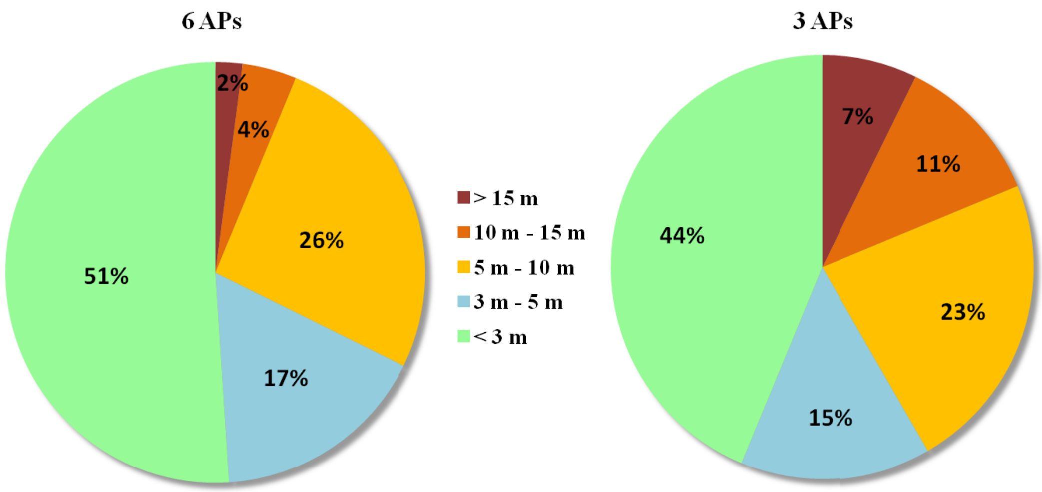

FIGURE 4. Distribution of positioning errors by fingerprint-based localization (6 and 3 APs).

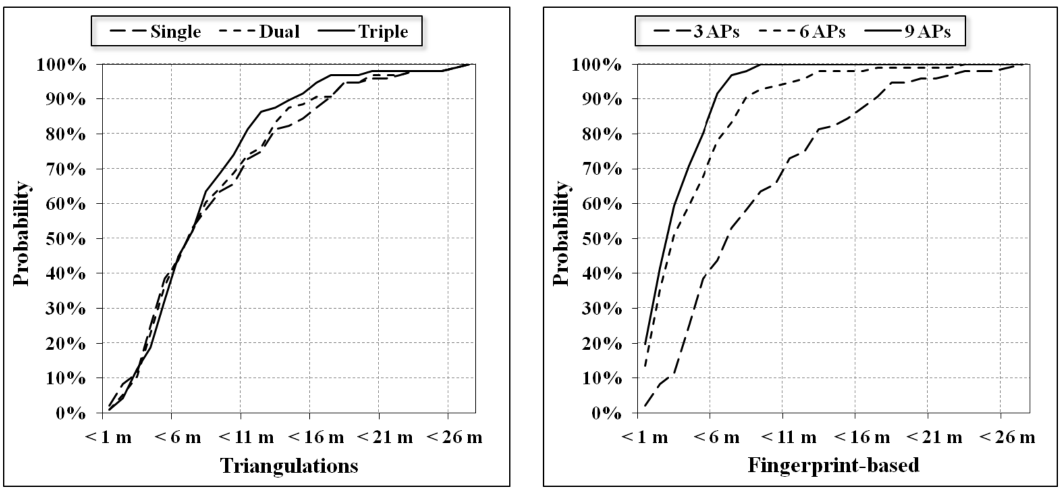

FIGURE 5. Comparisons of the CDF of positioning errors between triangulations and fingerprint-based localizations.

triangulations and fingerprint-based localizations. We see the positioning precision of triangulations is slightly improved by multiple triangulation method with an increased number of APs; and in case of fingerprint-based localizations the positioning precision is improved significantly. Thus, the results suggest that fingerprint-based localizations may have better practicability than triangulations in indoor environments.

B. RELATED WORKS

The above simulations show that fingerprint-based localization has a higher precision and reliability in indoor environments than traditional WLAN triangulations; thus, it has been applied in many studies of state-of-the-art technologies for todays indoor LBSs. Torres *et al.* [28] demonstrated the practicability of fingerprint-based localizations in room-level positioning via exhaustive experiments and claimed that the scheme is a robust and affordable solution for in-home monitoring problems. Zhou *et al.* [29] pointed to the effects of irregular environmental factors on fingerprint-based localizations and characterized the theoretical relationship between the positioning error and RSS distribution by using a Fisher Information Matrix. Hernandez *et al.* [30] developed a continuous space estimator via support vector regression to cover positions not stored in the fingerprint database, and it decreased the cost of site surveying in the off-line phase. Wang *et al.* [31] presented a deep-learning-based fingerprinting scheme that analyzed the features of channel state information and obtained the optimal weights as fingerprints. D'Souza *et al.* [32] extended the fingerprint localizations by using context-aware information on mobile users, and they built a floor plan with the information and reduced the required number of signal sources and the effect of wireless interference. Chen *et al.* [33] presented a cooperative fingerprint localization method that utilized the RSS fingerprint database and pair-wise distances measured by mobile users. The method targeted multi-user indoor environments and effectively improved the positioning precision, which presents tolerance to large-ranging errors and out-of-date fingerprint databases. Kanaris *et al.* [34] fused Bluetooth technologies in WLAN fingerprint localizations, and they presented a localization algorithm that filters the WLAN fingerprint database by Bluetooth beacon data and locates targets in fragments of the initial fingerprint dataset, which improved the computational performance in the on-line phase. Li *et al.* [35] proposed a fingerprint collaboration and assistant-node-based localization method, which utilizes distance information among assistant nodes and unknown targets in similarity analyses and mitigates the ranging errors with an adaptive Kalman filter using colored noise. Niu *et al.* [36] attempted to avoid the site survey cost and developed a crowdsourcing-based fingerprint localization system, and they also designed an algorithm that combines calibrations and multi-dimensional scaling to position unknown targets.

The localization schemes with millimeter wave (MMW) communications and the approaches of simultaneous localization and mapping (SLAM) with WLANs deserve special mention as the state-of-the-art techniques for indoor localizations. MMW communications are introduced as shorter propagation distances but less path-loss impacts, which implies a beneficial distance-based localization approaches for indoor environments. According to the MMW properties, Guidi *et al.* [37] proposed an idea that embedding massive antenna arrays at MMW to next generation Smatphones and presented a state-space model with Baysian mapping approach. With numerical simulations, they proved that the indoor positioning precision can reach centimeter levels. Olivier *et al.* [38] noted that the path loss of MMW can easily exhibit 30 to 40 dB more attenuation (30 to 100+ dB in case of 802.11 WLANs), and they proposed improved triangulation, AOA and fingerprinting schemes which achieved sub-meter positioning precisions by experiments with 60GHZ MMW. SLAM is a localization approach that recognizes an unknown environment while simultaneously keeping track of locations of automatically/randomly moving targets, which provides a solution to the challenges of reducing cost for WLAN fingerprint-based localizations [39]. Mirowski *et al.* [40] proposed a method named SignalSLAM which simultaneously generates the WLAN signal map with referenced RSS from different types of signal sources (Bluetooth, NFC and etc.) from participated users. Zhou *et al.* [41] proposed an SLAM method named EDGES. It includes three steps, firstly measures RSS and creates clustered RSS graphs, then assembles them into a logical graph and finally maps the logical graph into ground-truth graph which realizes the indoor WLAN SLAM.

Our work is highly motivated by above contributions. The practicability of fingerprint-based localizations depends on the resolution allocated in each fingerprint, which is related to number of available signal sources. However, few of the related researches target the resource limited indoor environment such as building floors with only 3-5 available APs. Therefore, our works utilized the path-loss exponent as fingerprint factor via RSS in order to improve the quality of the fingerprints in resource-limited environments for the practicability of fingerprint-based localizations in modern LBSs.

III. PATH-LOSS-BASED WLAN FINGERPRINT APPROACHES: PFL AND DFL

We describe the proposed path-loss-based WLAN fingerprint approach in this section. The approach aims to improve the practicability of fingerprint-based localizations under limited signal sources. Traditional WLAN-fingerprint-based localization utilizes RSSs from multiple signal sources to create a fingerprint database and to position unknown targets. However, RSSs are sensitive to signal propagation factors; therefore, fingerprint-based localization methods are usually associated with high costs because of the need to guarantee a certain level of positioning precision, such as through a high density of RPs and a sufficient number of signal sources. Our approach can exploit additional environmental factors when scanning fingerprints to improve the analyzability of each fingerprint, which are PLe and signal propagation distance. The path-loss model [equation (1), (2)] shows that the path loss among signal transmissions is the major influencing factor for RSSs and may also represent the signal propagation pattern in irregular indoor environment.

A. THEORETICAL ANALYSIS

The practicability of the fingerprint-based localizations depends on the analyzability of the fingerprint database which is related to the deviations of the fingerprint values in every RP. Therefore, theoretically the fingerprint database with clearer fingerprint variations should represent the environmental differences more specifically and leads improved indoor localizations.

In order to prove the advantage of the proposed approaches, we compared the RSS, PLe and signal distance values from a fingerprint dataset, the dataset includes RSS data and physical locations of RPs, values of PLe and signal distance are calculated by path-loss model. Fig. 6(a) shows a comparison of the variations of RSS and PLe values in several RPs with an assigned AP; and Fig. 6(b) is about RSS values and physical distances. The Fig. 6 only shows the differences of variations, values in X axis are not related to each other, same points in X axis may represent different RP samples.

From Fig. 6(a), we see the variations of RSS and PLe values showed similar patterns. It is because both the RSS and PLe values follow the path-loss model [equation (2)], and the result suggests that the analyzability would not be significantly improved if only the PLe is used as fingerprint. The variation patterns of RSS and signal distance in Fig. 6(b) clearly showed a different result. The signal distances showed clearer variations than measured RSSs. The reason is, the location of RPs were artificially determined that the physical distances from RPs to a signal source follow uniform distribution compare to the measured RSS and PLe values which depend on signal propagation factors.

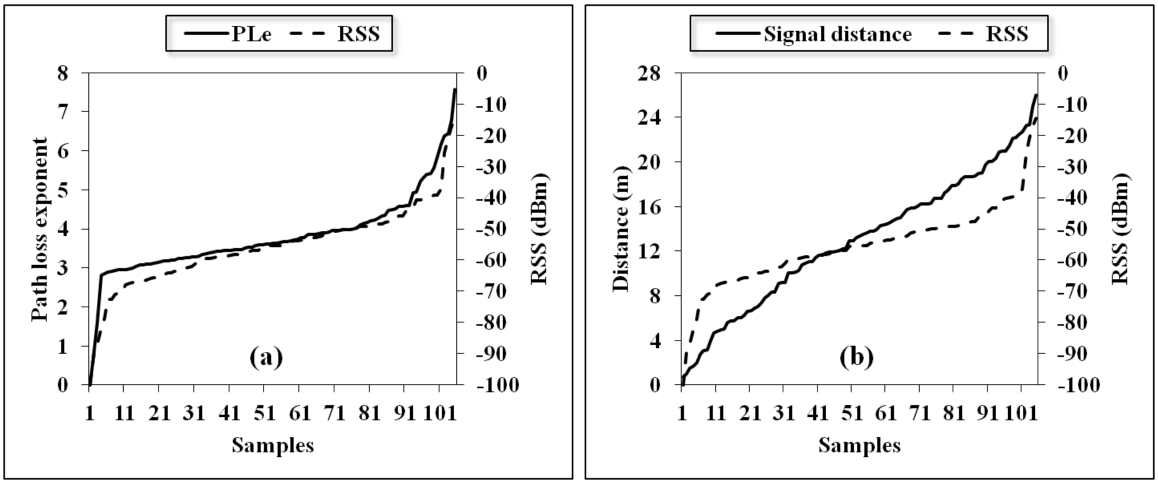

FIGURE 6. Comparisons of the variations of the RSS, PLe and signal distance values in a fingerprint dataset.

The comparison in Fig. 6 implies that the signal distances calculated by RSS and PLe should result a higher analyzability, and the fingerprint localization approaches with the path-loss-based signal distance calculation would provide higher localization practicability for indoor LBSs.

B. PROPOSAL OF A PATH-LOSS-BASED FINGERPRINT LOCALIZATION

The first scheme of the proposed approach is the PFL scheme. In this scheme, we categorize RPs into two levels because the scheme requires two types of location information. The first level (RP_{L1}) is defined as the coordinates of sensible signal sources (APs), and the second level (RP_{L2}) is defined as the coordinates of known locations during RSS collections. The optimized number of installed RP_{L1}s should be one per room in the building because the walls between rooms are the major influencing factor producing RSS differences. For RP_{L2}s, the number should be *area / required positioning precision*^{2}. The PFL works as follows.

1) In the off-line phase, a fingerprint database is creased by sets of PLe values in every RP_{L2}. The PLe set in each RP_{L2} is calculated according to the measured RSSs and the distance from the current location to every RP_{L1}.
2) In the on-line phase, sets of estimated signal propagation distances are utilized in fingerprint scans to localize unknown targets. The set of signal propagation distances between an unknown point and every RP_{L1} is estimated according to the measured RSSs and the set of PLe values in the fingerprint database.

The distance (d) and PLe (n) can be calculated by equations (5) and (6), which are reversed from the path loss model [equations (1) and (2)]. The shadow fading deviation (s) can use an averaged constant because it has a limited influence on the calculations (approximately ±2 dB deviations in the path loss calculations). And equation (7) is about the similarity calculations.

$$d = 10^{\frac{TX_{PWR} - RSS + GAIN_{TX} - PL_{REF} + GAIN_{RX} + s}{10n}} \quad (5)$$

$$n = \frac{TX_{PWR} - RSS + GAIN_{TX} - PL_{REF} + GAIN_{RX} + s}{10 log d} \quad (6)$$

$$sim\_d(k) = \sqrt{\sum_{i=1}^{n} (d_{RP(i)} - d)^2} \quad (7)$$

The following pseudo-code 2 explains the positioning processes of the PFL.

In the off-line phase, the PLe in each RP_{L2} is calculated by the averaged RSS value and then stored in a fingerprint database. In the on-line phase, the signal propagation distances from the unknown targets to all RP_{L1}s are calculated as the fingerprint of the target. Then, the distances from every RP_{L2} to RP_{L1}s are calculated by the PLe fingerprint in the database. Finally, the similarity of the two distance sets are analyzed by minimizing the Euclidean distances according to the Nearest Neighbour (NN) method. We used Euclidean distances in the similarity analysis instead of Manhattan distances because the latter require ranged values, and the distances among RP_{L2} to RP_{L1} are constant.

The PFL method improves the positioning precision compared with that of RSS fingerprint-based localizations because the PLe is influenced by both RSSs and the signal propagation distance, which is a more meaningful fingerprint factor for representing the environment than RSS.

C. PROPOSAL OF A DUAL-SCANNED FINGERPRINT LOCALIZATION

We focus on positioning reliability in this subsection. Normally, positioning reliability depends on positioning precision; however, it also is highly influenced by the analyzable fingerprint resolution, which is related to the number of available signal sources. A lack of signal sources leads the RPs to

Pseudo-code 2 Path-loss based fingerprint localizations

```
Input: Location target; LocationSet RP_L1, RP_L2;
Fingerprint f;
double d, n, temp, sim = POSITIVE_INFINITY;
Output: FingerprintSet fDATABASE;
Coordinates c;
// Off-line phase
forall the p ∈ RP_L2 do
    forall the r ∈ RP_L1 do
        d = getDis(p.getCoordinate(),
              r.getCoordinate());
        n = CalcPLe(p.getRSSAvg(r), d);
        p.add(r, n);
    end
    f = newFingerprint(p);
    fDATABASE.add(f);
end
// On-line phase
forall the p ∈ fDATABASE.getRP_L2() do
    forall the r ∈ RP_L1 do
        temp +=
        (getDis(p.getCoordinate(), r.getCoordinate())
        −CalcDis(p.getPLe(r), target.getRSSAvg(r)))^2;
    end
    temp = √temp;
    if temp < sim then
        sim = temp;
        target = p;
    end
end
c = target.getCoordinates();
```

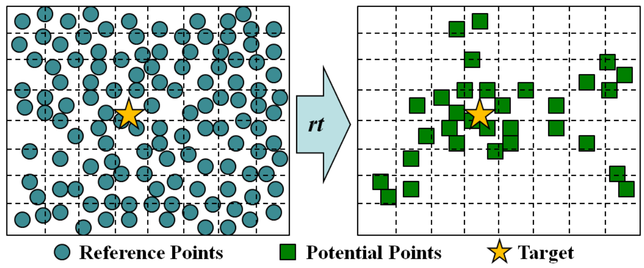

FIGURE 7. Estimating potential points using the DFL.

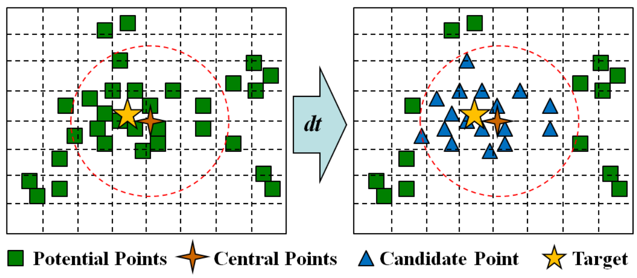

FIGURE 8. Clustering candidate points using the DFL.

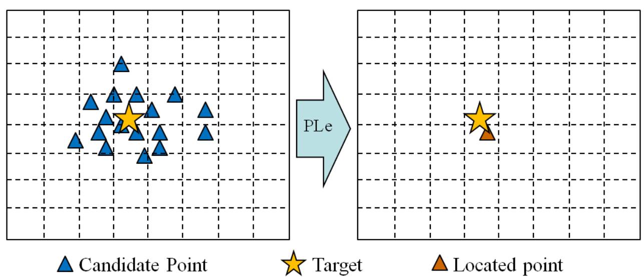

FIGURE 9. Locating a target using the DFL.

receive similar RSS data in different locations, which leads to decreased positioning reliability. However, freely increasing the signal sources in indoor environments is difficult because of several issues, such as personal privacy and interference problems.

Therefore, to improve positioning reliability under limited resources, we propose the DFL scheme. The off-line phase in the DFL is same as that in the PFL. In the on-line-phase, the fingerprint scanning processes are separated into two steps as follows.

1. Set a threshold of RSS differences (rt) according to the number of signal sources [equation (8)], and scan the RSS of an unknown target via RP_{L2}s, then estimate a set of potential points (PP) of the unknown target (Fig. 7).
2. Calculate the central point of the PPs and set a distance threshold (dt) according to the distribution of distances from the central point to PPs [equation (9)]. Remove the PPs that are further than dt. The remaining PPs consist of a set of candidate points (CPs) (Fig. 8).
3. Scan the PLe via CPs using the same method applied in the PFL. Locate the unknown target (Fig. 9).

$$rt = \frac{PL_{REF} - RS}{n \times c} \tag{8}$$

$$dt = \frac{\sum_{i=0}^{n} dis(PP_i, CentralPoint)}{N} \tag{9}$$

The values rt and dt are calculated using equations (8) and (9), where n is the number of signal sources, RS is the Receive Sensitivity of the wireless ends, c is a weighted coefficient related to the required positioning reliability (2 in normal) and N is the number of estimated PPs in the first scan. The following pseudo-code 3 explain the on-line phase of the DFL.

The DFL scheme focuses on positioning reliability to meet the universal requirements of todays LBSs. The underlying concept is to remove the most unreliable fingerprints instead of locating the most similar fingerprint, which is important because a resource-limited environment may create multiple reference locations that have similar fingerprints despite being located far apart. Therefore, considering location similarity and fingerprint similarity during positioning would help to improve the positioning reliability. The positioning

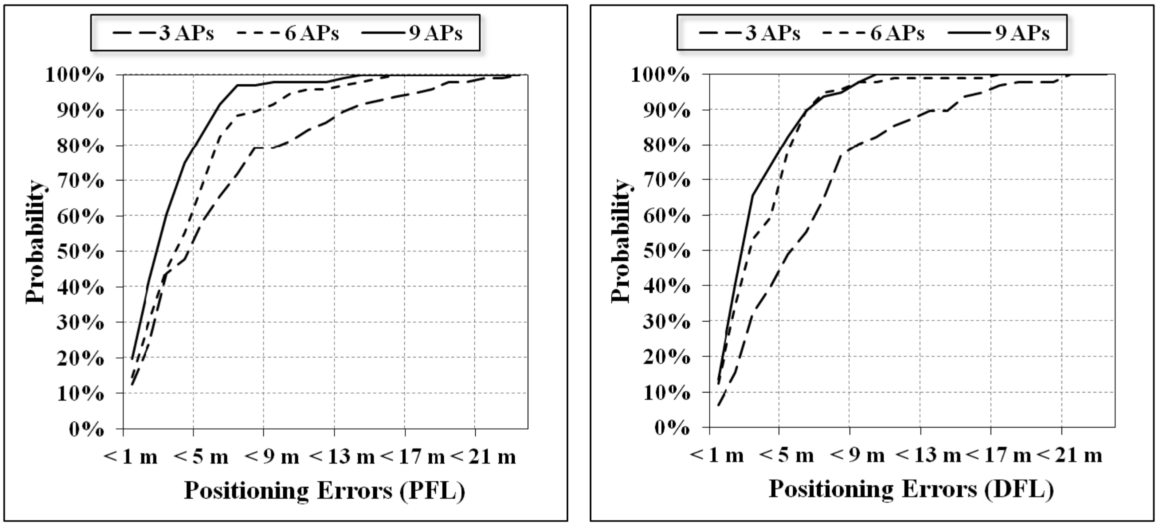

FIGURE 10. Comparisons of CDF of positioning errors between the PFL and DFL.

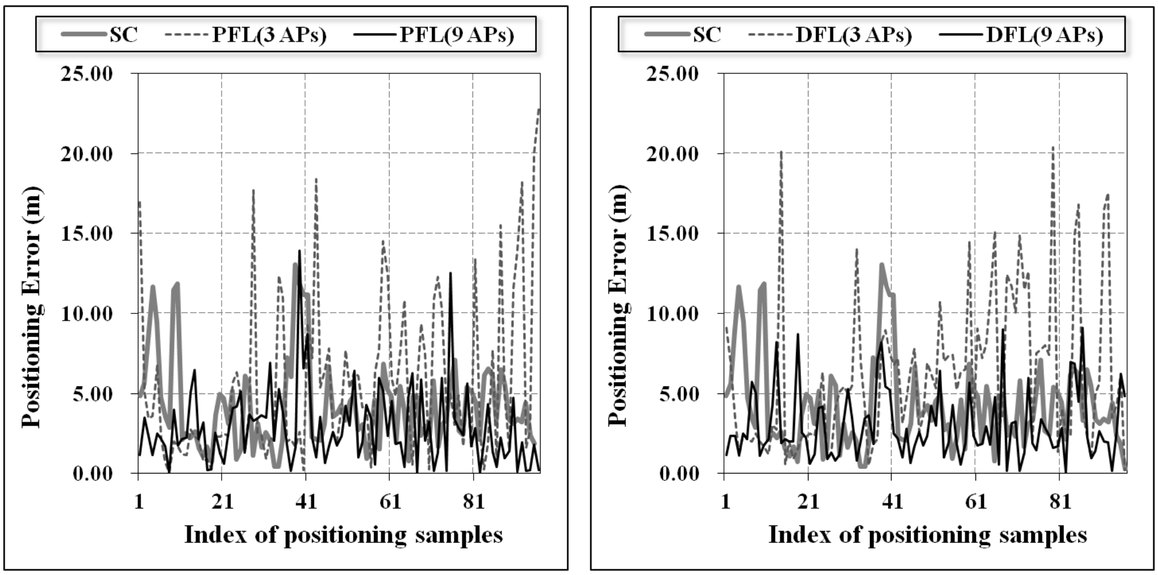

FIGURE 11. Comparisons of the positioning errors between the PFL and DFL.

precision of the DFL may be lower than that of the PFL because the first scan uses a traditional RSS analysis, which is because the RS is used to cluster the CPs, and RSSs are used in this analysis. An improved scheme for defining the threshold and clustering CPs represents a future focus of our research.

Table 2 summarizes the features of traditional RSS-based localization schemes and the proposed path-loss based localization schemes.

IV. PERFORMANCE ANALYSIS OF THE PATH-LOSS BASED LOCALIZATION APPROACH

In this section, we present positioning simulations to determine the performance of the proposed schemes. In the simulations, the fingerprint database for the off-line phase is created based on RSS data from the KIOS dataset. For the on-line phase, we simulate a randomly-moving target and generate RSS data according to the locations of signal sources and the PLe calculated for all RPs with a random deviation. The simulation environment is a 20 m $\times$ 30 m area where 9 available APs share the same wireless coverage. In the simulations, we target three factors for analysis: 1) influence of resources on the positioning, 2) positioning precision and 3) positioning reliability. The simulations are written with the Eclipse IDE by Java languages.

Fig. 10 shows the simulation results of CDF of positioning errors for cases with 3, 6 and 9 APs applied by the PFL and DFL, the CDFs in Fig. 10 give the probabilities of positioning

Pseudo-code 3 Double Scanned Fingerprint Localizations (Online-Phase)

```
Input: Location target; LocationSet RP_L1, RP_L2;
FingerprintSet fDATABASE; Coordinates cPoint;
double rt, dt, temp, sim = POSITIVE_INFINITY;
Output: Coordinates c;
rt = setThreshold(RP_L1.size());
// Start 1st scanning
forall the p ∈ fDATABASE.getRP_L2() do
    temp = 0; forall the r ∈ RP_L1 do
        temp +=
        Abs(p.RSSMin(r) − target.RSSMin(r)) +
        Abs(p.RSSMax(r) − target.RSSMax(r));
    end
    temp = temp/APs.getSize();
    if temp < rt then
        PP.add(p);
    end
end
cPoint = PP.calcCenter();
dt = setThreshold(PP); forall the p ∈ PP.getRP_L2() do
    if getDis(p.getCoordinate(), cPoint) < dt then
        CP.add(p);
    end
end
// Start 2nd scanning
forall the p ∈ CP.getRP_L2() do
    forall the r ∈ RP_L1 do
        temp +=
        (getDis(p.getCoordinate(), r.getCoordinate())
        −CalcDis(p.getPLe(r), target.getRSSAvg(r)))^2;
    end
    temp = √temp;
    if temp < sim then
        sim = temp;
        target = p;
    end
end
c = target.getCoordinates();
```

TABLE 2. Comparison of traditional and proposed fingerprint schemes.

Scheme	Positioning factors	Used algorithms
Traditional	RSS	Similarity analysis
PFL	RSS Path-loss exponent	Similarity analysis
DFL	RSS Path-loss exponent RSS/Distance Threshold	Similarity analysis Clustering

errors are under x values, while the y values correspond to the CDF percentiles.

Fig. 10 shows that the positioning precision is improved significantly by using an increased number of APs, which is related to the analyzable fingerprint resolution. Thus, the results suggest that the number of signal sources should be considered a major factor for indoor localization, Table 3 shows the mean and variation of positioning errors.

From Table 3, we see the PFL shows higher positioning precision than the DFL. The PFL positions are closer by approximately 0.5 m on average in the cases of 3 and 6 APs, which suggests that the PFL improves the positioning precision in resource-limited environments. However, we can also see that the DFL reaches higher positioning reliability faster than the PFL by comparing the CDFs of 6 and 9 APs in Fig. 10. Fig. 11 provides detailed results on the positioning errors for each positioning sample.

TABLE 3. Comparison of mean and variation of errors.

Scenario	Mean error	Error variation
PFL (3 APs)	5.61 m	0.05 - 22.83 m
PFL (6 APs)	3.42 m	0.08 - 20.19 m
PFL (9 APs)	2.87 m	0.05 - 13.93 m
DFL (3 APs)	6.11 m	0.19 - 20.36 m
DFL (6 APs)	3.83 m	0.05 - 15.47 m
DFL (9 APs)	2.98 m	0.05 - 9.08 m

Fig. 11 shows the positioning errors of the positioning samples. In order to prove the reliability of our simulations, we compared our simulation results with the positioning experiments presented in [12] which adapted a self-calibration (SC) method, and the results in the case of 9 APs showed similar patterns as expected. As shown in Fig. 11, certain positioning samples in the PFL show positioning errors of more than 10 meters, which indicates that increasing the positioning precision does not always guarantee the positioning reliability. As expected, the DFL presents improved positioning reliability where all samples show positioning errors lower than 10 meters; however, its positioning precision is lower than that of the PFL as shown in Fig. 10.

The positioning precision between traditional RSS-based models and the PFL and DFL is compared in Fig. 12. For the RSS-based fingerprint localization scheme, we used the cumulative Manhattan distance according to the minimum and maximum value of the RSS in the similarity analysis, which is presented in Section II-A. The positioning precision is compared according to the average positioning errors of all samples with an increasing number of APs. The simulation results show that the PFL has the highest positioning precision and the precision of DFL is lower than that of the PFL but higher than that of the RSS-based scheme. These findings demonstrate that the proposed a path-loss based localization approach would help to improve the positioning precision of indoor localizations and reduce the cost of installing signal sources. This conclusion is based on the similar precision between the 5 AP case of the PFL scheme and the 7 AP case of the traditional RSS-based scheme and the equivalent

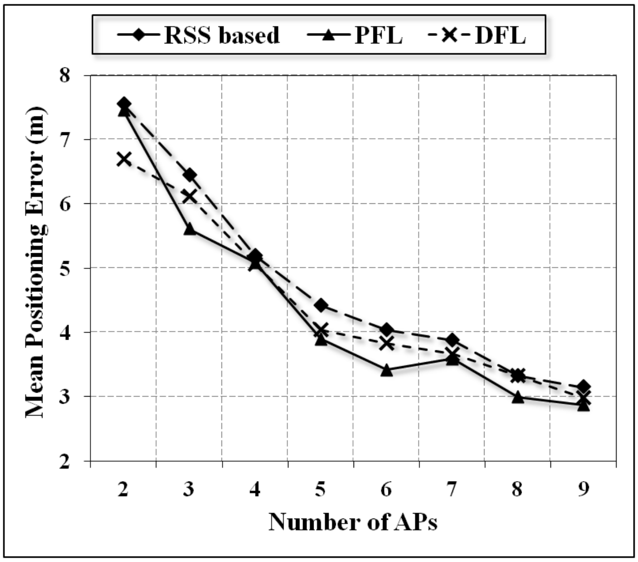

FIGURE 12. Comparison of the positioning precisions between RSS-based schemes and the proposed schemes.

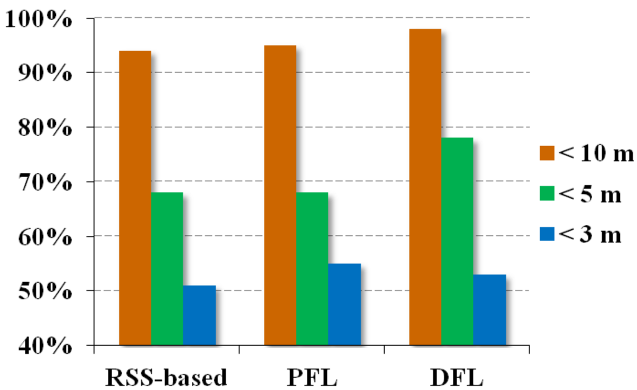

FIGURE 13. Comparisons of the positioning reliability between the RSS-based and proposed schemes.

precision between the 6 AP case of the PFL scheme and the 8 AP case of the RSS-based scheme. Fig. 13 shows a comparison of the reliability of the RSS-based scheme and the proposed approaches.

The positioning reliability is compared for the 6 AP case to analyze how the proposed schemes work in resource-limited environments. The RSS-based traditional scheme and PFL showed similar reliability, with 68% of the samples showing a positioning precision of less than 5 meters. The increased precision of the PFL over the traditional scheme is because it can locate unknown targets more precisely by analyzing more specified environmental fingerprints. However, the irregularity of indoor environments creates similar environmental fingerprints if the dimensions of the analyzable factors are limited; therefore, the positioning reliability is more dependent on the signal source resources than observed in the similarity analysis schemes. The DFL showed the highest reliability, with 78% of the samples showing a precision under 5 meters, which was expected because the DFL locates targets not only by scanning the similarity of fingerprints but also by analyzing the location differences of multiple similar points. Finally, the histogram of Fig. 14 summarizes the advancements of the proposed schemes, which compares the PFL, DFL, triple triangulations with propagation model and RSS based fingerprint presented in Section II. All of the fingerprint based localizations (RSS, PFL and DFL) result higher positioning precision and reliability than triangulations as expected. The PFL results in the highest positioning precision, with the highest number of samples showing positioning errors under 3 meters. The DFL resulted in the highest positioning reliability, with the lowest number of samples with positioning errors above 10 meters.

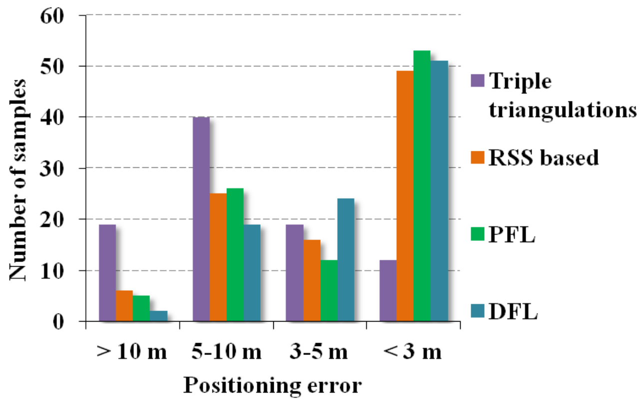

FIGURE 14. Comparisons of the positioning performance between the traditional and proposed schemes.

V. CONCLUSION

WLAN fingerprint-based localization schemes have been proposed for indoor LBSs because of their high precision and easy adaptability. However, the practicability of fingerprint localization depends on the cost invested in fingerprint creation and the available signal source resources. In this article, we propose a path-loss based fingerprint localization approach and present two related localization schemes, PFL and DFL. The PFL improves the positioning precision by analyzing environmental path-loss factors instead of RSSs, which reduces the costs associated with guaranteeing a certain level of precision. The DFL improves positioning reliability in resource-limited environments in two steps. The first step is clustering similar potential locations and removing unreliable ones. The second step is positioning targets from a CP set. The proposed schemes target positioning precision and reliability, respectively, which may be adopted in different situations. For instance, device tracking systems for industrial environments may adopt PFL to reach higher positioning precision, and employee tracking applications for office buildings may adopt DFL to guarantee less precise but more reliable room-level positioning. The simulation results suggest that the proposed approach would help to improve the practicability of fingerprint-based localizations for indoor LBSs.

ACKNOWLEDGMENT

The authors appreciate Christos Laoudias, Robert PichÂe and Christos G. Panayiotou of the KIOS research center for opening such variable RSS dataset.

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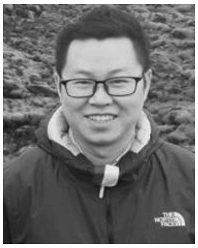

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