Simultaneous Indoor Localization Based on Wi-Fi RSS Fingerprints

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Abstract. Indoor localization has been extensively investigated over the last few decades, especially in the industrial area of wireless sensor networks. For indoor positioning, many techniques have been proposed over the Wi-Fi signal's deployment. Wi-Fi Received Signal Strength (RSS) fingerprinting approach especially the deterministic algorithms have received much attention. However, as the deterministic algorithms use RSS of the test point (TP) by ignoring the other TPs, two or more TPs will take the same location while physically far apart, and the reverse can also be true. Thus, to improve positioning accuracy, this study proposes Wi-Fi RSS fingerprint based simultaneous indoor localization (SIL). The proposed approach was tested on the data collected from Huazhong University of Science and Technology teaching buildings. Experimental results show error reduction upto 9.8%, and 13.2% in MDE (Mean Distance Error) and standard deviation, respectively.

Keywords: Indoor localization · Simultaneous localization · Wi-Fi Fingerprinting · RSS · Multidimensional scaling

1 Introduction

Location recognition has become a necessity for today's Internet of Things (IoT) applications. Location estimation and prediction are investigated in two separate indoor and outdoor categories. Comparatively, there has been considerable development in positioning through satellite deployment and use for global positioning systems (GPS). This GPS improvement is unlikely to provide accurate indoor positioning due to weak signal propagation in a complex indoor environment. The short-range signal, such as Bluetooth, Wi-Fi, and RFID, are used to estimate the locations in an indoor environment [10]. From the signals above, Wi-Fi RSS has received significant attention for its massive penetration of wireless local area networks (WLAN) and has become a victorious procession of signal accumulation and aggregation with the indoor environment without the requirement for additional infrastructure.

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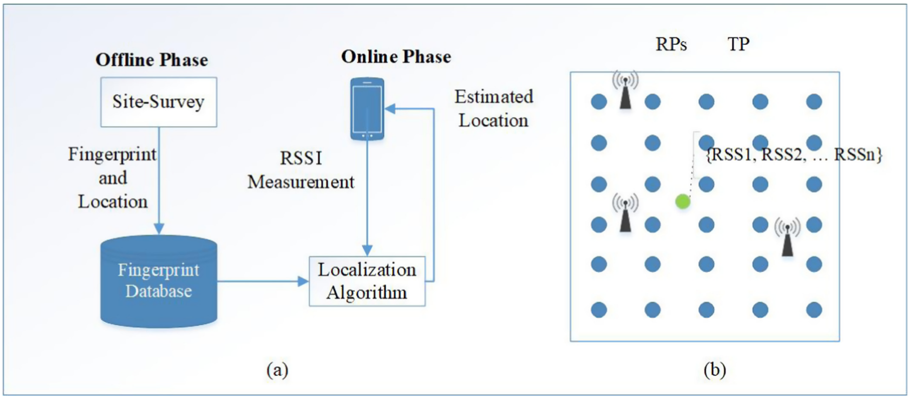

Fig. 1. (a) Fingerprinting workflow (b) TP allocation.

Many research and investigation endeavors have been concerned with the construction of indoor positioning systems (IPS) based on the RSS from the access points (AP) in wireless local area networks [14]. Furthermore, in the past decade, the fingerprint technique has been extensively investigated for most RSS-based indoor positioning schemes. The fingerprinting is implemented in two separate phases: offline phase (site-survey), which is done through the site-survey, or recently, the most used crowdsourcing approach. In this phase, the RSS vectors are collected from all detected Wi-Fi signals from different APs at many RPs in known locations as the fingerprint or signature. Therefore, each fingerprint represents each RP in an indoor environment. All collected RSS vectors that make up the site-survey fingerprints will be stored in the database or radio map for consultation in the online phase. In the online phase (signature-match): the server measures the RSS vector of TP with a location from the pre-built database or radio map. It uses a specific similarity metric in the signal space to compare the TP with the fingerprints, such as the Euclidean distance [2]. Figure 1 illustrates the fingerprint approach workflow.

Furthermore, two types of algorithms, deterministic and probabilistic, are used for fingerprinting localization[16]. The traditional deterministic indoor localization algorithms use a similarity metric to compare the online signal measurement with a fingerprint in the fingerprint database. For instance, it measures the TP location to the nearest RP's fingerprint location in the signal space. Euclidean distance, Manhattan distance, cosine similarity, and Tanimato similarity have been implemented to compare and analyze signal space. Deterministic algorithms are simple for implementation, can be easily applied based on K nearest neighbors (kNN), and often low in terms of computational complexity. Other advanced, accurate, and low computational cost deterministic algorithms are support vector machines and linear discriminant. Probabilistic algorithms use statistical inference between the measurement of the TP signal and the stored fingerprints in the online phase [24]. These algorithms find the location of the

TP with the highest probability of the training data. Moreover, each estimated location can be indicated by a confidence interval in probabilistic algorithms. Probabilistic algorithms with high precision are the Bayesian network, the maximization of expectations, the Kullback-Leibler divergence, the Gaussian process, and the conditional random field [3].

Most of the current research on Wi-Fi fingerprint-based indoor localization is based on an independent location estimation, and each TP's location is located independently. Indoor localization occurs regardless of the location of the relative RPs, or the location of other TPs. Subsequently, the TP localization is usually considered independently in the approach mentioned above. This measurement noise or uncertainty may lead to a spatially dispersed set of neighboring points, which significantly reduces the localization accuracy [9]. As a result, this inaccurate location estimation can lead to an error-prone indoor localization. It can delegate one location to two physically distanced TPs or assign different locations to two physically close TPs. For all of these reasons, it should acquire and use the information of RPs or neighboring relative TPs as a solution. The result of the location estimation can be improved and become reliable by using this approach. Additionally, this will also drive the localization process to high precision concerning the precision of the indoor localization based on Wi-Fi RSS fingerprints.

The remainder of this paper is organized as follows. Section 2 describes related work on Indoor Localization based on Wi-Fi RSS Fingerprints. The detailed structure of SIL architecture is discussed in Sect. 3. In Sect. 4, there is an explanation of performance evaluation and results. Finally, we draw conclusion in Sect. 5.

2 Related Work

Technically, the utilized indoor localization methods are divided into range-based and range-free [22]. The range-based method is the most used between these methods. The range-based technique is appropriate for applications that need high accuracy. The current prevalent types of range-based localization techniques are Received Strength Signal (RSS), Angle of Arrival (AOA), Time of Arrival (TOA), and Time Difference of Arrival (TDOA). Compared to these methods, the TOA is more accurate than the other methods. Unlike other time-synchronized methods, the TOA and TDOA are less strict time synchronization, which makes it easy to implement [4,13,23].

As discussed in the [8], the collaborative indoor localization is classified into two categories: Distance-based and proximity-based schemes.

Distance-based Scheme: Advanced sensors of smartphones or IoT devices are used for indoor localization in this scheme, and these sensors include Bluetooth, Wi-Fi direct, ultrasound. Although this scheme has been impressive in using the distance for localization, it often lacks an accurate distance measurement compared to the proximity-based scheme. The [9] has proposed a Wi-Dist, a generic framework applicable to a wide range of sensors such as peer-assisted and

INS, and the wireless fingerprint Wi-Fi, CSI, RFID. Wi-Dist indoor localization approach fuses on the noisy fingerprint of wireless technology with uncertain mutual distances achieved from their bounds. It collaboratively considers the distance limits and noisy fingerprints to reduce the indoor localization error. The system requires the mean and variance of fingerprint's RSS and optimize its location using Semi-Definite Programming (SDP). Figure 2 depicts peer-assisted localization.

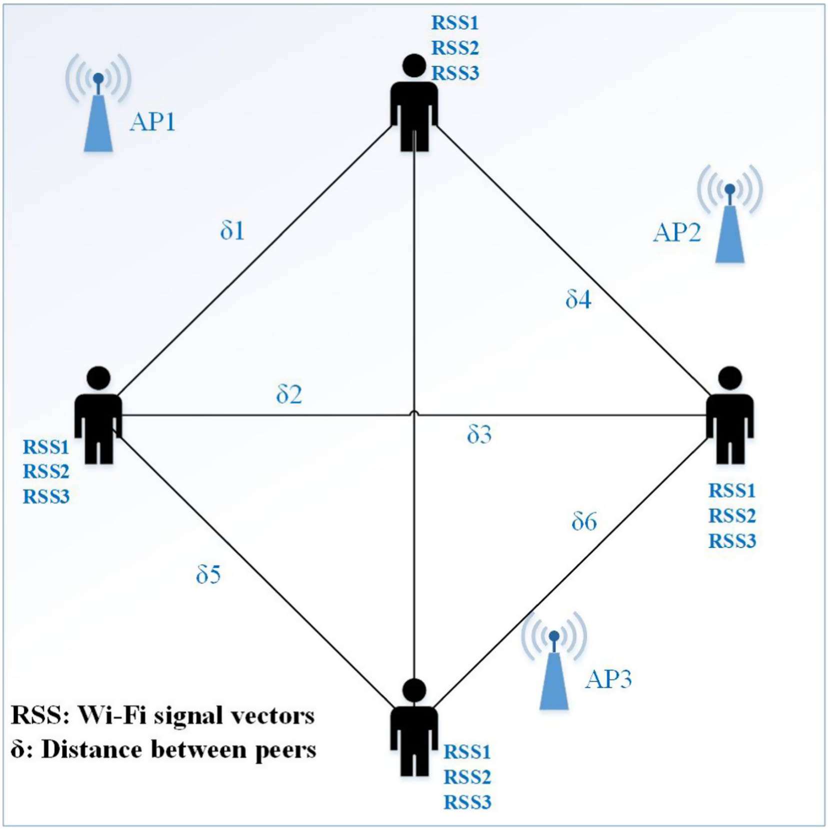

Fig. 2. Peer-assisted localization scheme that uses the distance to refine the localization error.

In [19], the privacy-preserving multi-model has been proposed based on the Wi-Fi RSS, Cellular RSS, light, and sound. This work has also developed its system based on an infrastructure-free model of indoor localization. The system uses the existing Wi-Fi RSS of the access point with the data from the smartphone's light and sound sensors to increase indoor localization's granularity. The system helps the areas with low Wi-Fi signal coverage to distinguish themselves in a region or room level. Besides, this system has used weighted fusion for further improvement of the localization accuracy. Moreover, to degrade the energy consumption for footprint, it has automatically used a Wi-Fi scan to generate it when the device Wi-Fi is on. Another collaborative Bluetooth-based approach is proposed in [17], which aggregates multiple Bluetooth devices' location information. The system takes advantage of the enhanced kNN algorithm to localize devices based on Bluetooth distance measurements. The work in [23] details another system that has proposed Multi-Anchor Nodes Collaborative Localization (MANCL). MANCL system has divided the localization procedure into four-part: ordinary node localization, iterative localization, improved 3D Euclidean distance estimation, and 3D DV-Hope distance estimation.

Paper [18] has proposed a system based on infrastructure-free collaborative indoor localization. This system has determined a case in which the infrastructure-based indoor localization is not applicable. The system has designed a novel algorithm called Collaborative Indoor Positioning Scheme (CLIPS), which uses the RSS map as a reference. It uses the dead reckoning to disqualify the invalid candidates. Compared to peer-assisted, this system's unique advantage is that this algorithm does not require any additional infrastructure for localization. Peer-assisted (PA) localization method in [18], and [15] use sound for distance measurement between devices. As shown in Fig. 2, it transmits an audio signal to its close peers. First, the server initializes the peer's location with the Wi-Fi fingerprint, then measures the distance between them through the acoustic ranging, and finally calculates the new location. The high localization precision in the PA indoor localization depends on the high precision of distance measurement. Hence, the graph's shape is rigid, and if there are distance measurement errors, the location estimation will be significantly influenced. Moreover, pairwise measurements are needed to build a complete graph. Accordingly, the synchronization in the PA approach becomes complicated and can be exposed to measurement error. Range-based collaborative localization is considered as non-linear minimum optimization. Thus, many methods are introduced to solve this problem, such as maximum likelihood in [21] and multidimensional scaling in [7].

Proximity-based Scheme: The user temporary stops to measure the inter-node distance between each other based on this scheme [11]. The proximity scheme can be used for dynamic measurement as [5]. It proposes a collaborative localization system to enhance position estimation by taking advantage of more accurate information from neighboring nodes within the same cluster. The system uses ZigBee radio to detect its neighboring nodes in the cluster. Accordingly, the system computes and attaches a confidence score to the system's calculated position (e.g., Ekahau). The mentioned confidence measures the probability of estimated location. Finally, a collaborative error correction adjusts the TP's estimated location using the estimated locations of neighboring nodes. Figure 3 depicts the design of the ZigBee Collaborative localization system.

Furthermore, in range-free paper [24] introduces a Probabilistic Neural Network-based localization approach that eliminates the RSS distance relationship noise and inconsistency. The approach features two processes: Global

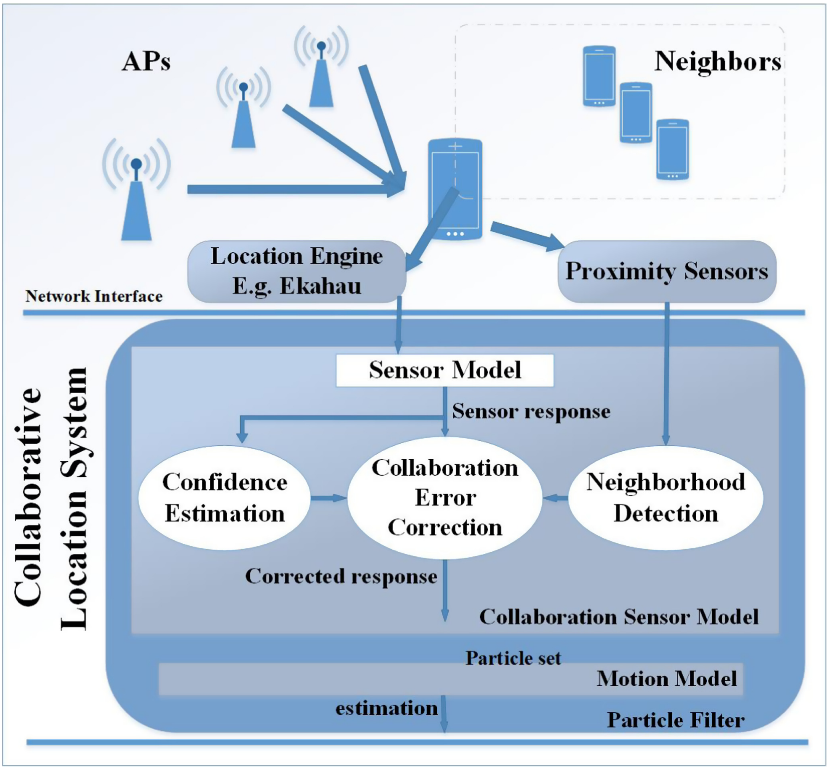

Fig. 3. ZigBee based localization.

Optimization and Regional Compensation. In this method, the APs are exchanging information about the TP to localize it collaboratively.

To summarize, the collaborative localization emerging in the above works has shown a significant improvement in localization precision even though several issues need to be considered in actual deployment. Computational complexity is one of those issues that must be considered in collaborative localization. Due to the pairwise communication and synchronization, the computational complexity is high for collaborative localization [9]. User mobility also makes the node collaboration challenging, as the relative positions of peer users change frequently. During the social interaction, smartphone's sensor collaboration may also unleash the information of the device owners [6]. Therefore, to address the privacy issues, smartphone collaborative localization in future work requires a specific security protocol for the information sharing [19].

3 MDS-based Model: SIL

This part examines the proposed model and its related parts that are coming up with a solution for the simultaneous indoor localization based on Wi-Fi RSS fingerprints.

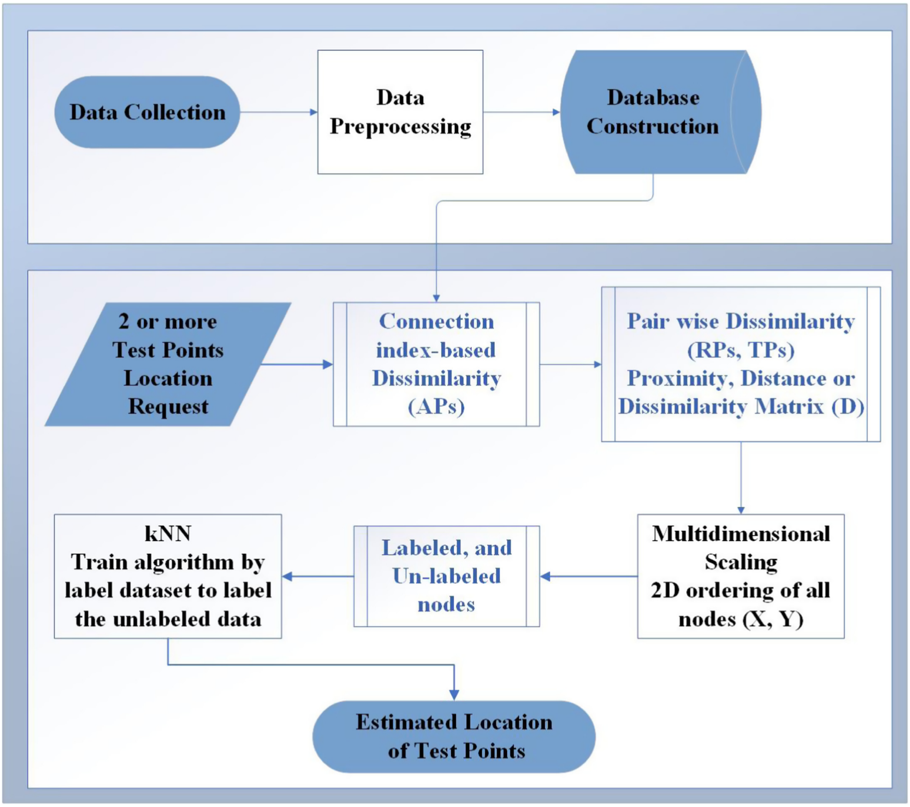

Fig. 4. System architecture.

3.1 SIL Architecture

The general architecture of the indoor fingerprinting localization based on Wi-Fi RSS involves two phases. The first phase is the offline phase, consisting of two sub-phases: data collection and database construction. The second phase is the online phase, which localizes the TP's RSS based on matching the database data. Therefore, this proposed simultaneous indoor localization model also consists of the same two general phases. The offline phase of the model implements the data collection and data pre-processing. The RSS data for this simulation has been retrieved from the smartphone's Wi-Fi sensors. Smartphones and IoT devices are commonly used in indoor localization to adapt to different applications, and indoor environment data collection is one of its applications. Following this, the users' smartphones are used to measure the required data as a signature at each point in the indoor area and build the indoor localization radio map or fingerprinting database. The RSS of the Wi-Fi signal as a signature to build the radio map from those IoT devices is available through the previously developed android or iOS application using application programming interfaces (APIs). These applications will scan the Wi-Fi signal available in the indoor environment from the APs, and this information consists of the Wi-Fi signal BSSID, SSID, and RSS [19]. The RSS is utilized as the signature for each measured point from the data retrieved through the smartphone. RSS vector with their related location is being used to construct the radio map. Since the measured data consists of extensive records of the RSS vector and its location, it must be pre-processed to construct a precise radio map for the online phase use. During the pre-processing process, the noisy data have been evacuated from the dataset. Moreover, each point's signature in the database becomes shrunk in the number of RSS received from the APs. In the online phase, the TPs would be localized with the aid of the proposed model.

In the online phase, an adaptive MDS-based model like [7], and [12] has been proposed, which builds the process of matching for the fingerprints. The new point or the collaboration of two points is localized based on the adapted dissimilarities among the points and the database RPs. The proposed adaptive MDS-based model is localizing points based on the previous mappings of the sampled data in terms of the adaptive dissimilarities (D), and by the Euclidean distance between the interpolated points.

In addition to the original MDS algorithm in which other points influence the mapping of a point, it uses kNN to label the unlabeled point with the position of its neighboring RPs that have been interpolated by the MDS dissimilarity function. Figure 4 details the flowchart of the proposed model for simultaneous indoor positioning based on Wi-Fi RSS the fingerprints.

3.2 Preprocessing of Data

The simulation data should be analyzed and processed in order to build the fingerprint database. The dataset collected by the site-survey is pre-processed to deduct the sensitivity of data's initial values for the simulation to validate the feasibility and effectiveness of the proposed model [20]. In data collection, testbed 1 was collected ten times for the offline phase and twenty times for the online phase at each point, and the zero was delegated to the non-received RSS. Moreover, the data for testbed 2 was collected ten times for offline and online phases at each point, respectively. Since the RSS varies due to indoor environmental reflections, here for the fingerprint database construction, the number of RSS measurements from each AP at each point is averaged using Eq. 1. Moreover, the zero value is also replaced with the value of –100 (dBm), which indicates the extremely poor signal. Identically, Fig. 5 illustrates the RSS instability during different time stamps (Table 1).

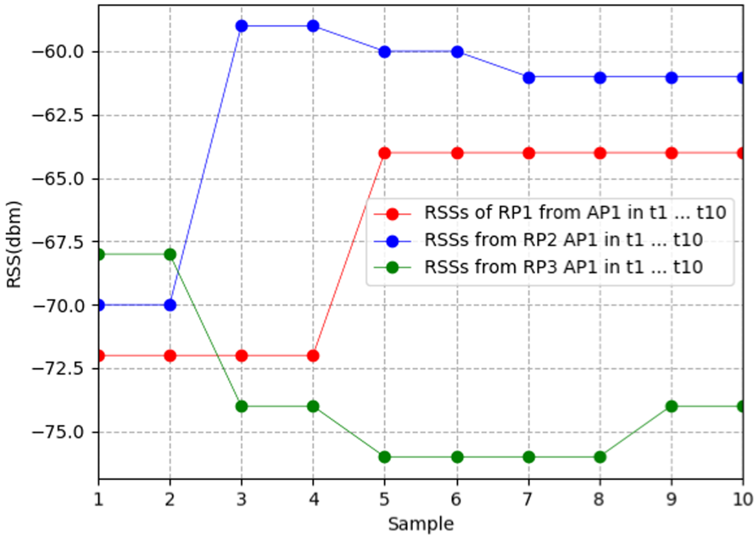

Fig. 5. Behavior and variance of the RSS measurements.

$$RSS_l = \frac{1}{t}\sum_{n=1}^{t} RSS_n \tag{1}$$

3.3 SIL Algorithm

For the MDS-based localization, the dataset consists of *N1* RPs, and *N2* TPs from the L APs. The RPs are with their known location coordinates as a label, and the TPs are with unknown location coordinates. Therefore, here the dataset is consisting of $N = N1 + N2$ points from $L = L1 \cap L2$ APs.

In this implementation, the MDS-based model goal is to estimate the TP location based on the RP fingerprints and pairwise RSS distance measurement from all localization points. In contrast, non-MDS based localization estimates TP's location based on the distance measurement between the TPs and RPs.

The simultaneous indoor localization problem can be formulated in the MDS problem. It has been assumed that the Eq. 2 is the RSS vector of N points in L dimensional space:

$$X = \left[rss_1\ rss_2\ \ldots\ rss_L\right]^T \tag{2}$$

Each point continuously estimates its inter-point distances with the Euclidean-distance using Eq. 3, and exchanges this information with other points on the fingerprint map. Therefore, all points involved in collaboration share their pair-distances, and it will be stored in a matrix (D) called the dissimilarity matrix which is shown in Eq. 4.

Table 1. List of notations.

Notations	Descriptions
N	Number of points
L	Number of access points
$L1$	Access points, numbers of access points in RP fingerprint
$L2$	Access points, number of access points in TP fingerprint
$N1$	Reference Points, number of RPs
$N2$	Test Points, number of TPs
X	$N \times M$ Configuration matrix
D	Dissimilarity Matrix
rss_N	Measured RSS vector of N points
$S_{rss(X)}$	MDS configuration matrix
θ_i	Location of i node
$d_{ij(X)}$	Euclidean distance between two RSS vector of points
rss_l	Measured RSS of l AP
$\theta_i^{n2}, \widehat{\theta}_i^{n2}$	Real and estimated locations of i TP

$$d\left(rss_i, rss_j\right) = \sqrt{\sum_{i=1}^{n} \left(rss_{il} - rss_{jl}\right)^2} \tag{3}$$

where $i, j = 1, 2, ..., n \ and \ i \ \neq j$

$$D = \begin{bmatrix} 0 & \dots & d_{ij} & \dots & d_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ d_{i1} & \dots & 0 & \dots & d_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ d_{n1} & \dots & d_{nj} & \dots & 0 \end{bmatrix} \tag{4}$$

Moreover, the $\theta_i = \left[\theta_{i1}\ \theta_{i2}\right]^T$ is the location coordinates of i^{th} point. As it mentioned before, here the dataset is consisting of N points, which are the summation of N_1 points as a RP and N_2 as a test point. So then, here the signatures are $rss_i, 1 \leq i \leq N1$ with the known location as its label, and $rss_i, N1+1 \leq i \leq N$ with the unknown location. The MDS solution of the configuration matrix X can be obtained by minimization of the following STRESS function:

$$S_{rss(X)} = \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \left(d_{ij(X)} - \delta_{ij}\right)^2 \tag{5}$$

Where $d_{ij(X)} = \left\| rss_i - rss_j \right\|$ is the distance between rss_i, and rss_j, and δ_{ij} is the distance measurement between i, and j. Finally, the simple kNN algorithm needs to be applied to the MDS solution of dissimilarity function of $S_{rss(X)}$ to estimate each test point's location coordinates from known coordinates of the reference points. Algorithm 1 details the MDS solution for simultaneous indoor localization based on the fingerprints.

Algorithm 1. MDS-based fingerprint localization.

Input: LocationSet N1, Fingerprint (), double (temp, sim = POSITIVE-INFINITY)
Output: DissimilaritySet (), Coordinate c

```
procedure D DISSIMILARITY CONSTRUCTION
    N ← length(X)
    d<1
    for i ← 1, N − 1 do
        for j ← i + 1, N do
            V_d ← X_i − Y_j
            d ← d + 1
        end for
    end for
end procedure
procedure c DISSIMILARITY BASED LOCALIZATION
    for i ← 1, N_1 do
        for 1 ← 1, 2 do
            temp+ = square(V_N2(r) − V_N1(r))
        end for
        temp = sqrt(temp)
        if temp<sim then
            sim = temp
            N2 = N1
        end if
    end for
    c = N1.getCoordinates()
end procedure
```

4 Experiments and Results

In this section, the necessary RSS data collection, evaluation parameters, and positioning results are discussed for the proposed SIL method of indoor localization. The performance evaluation of the proposed SIL is compared to the traditional RSS-based indoor localization scheme. Moreover, two scenarios have been considered for the proposed method's performance evaluation, one is based on testbed 1, and another is testbed 2.

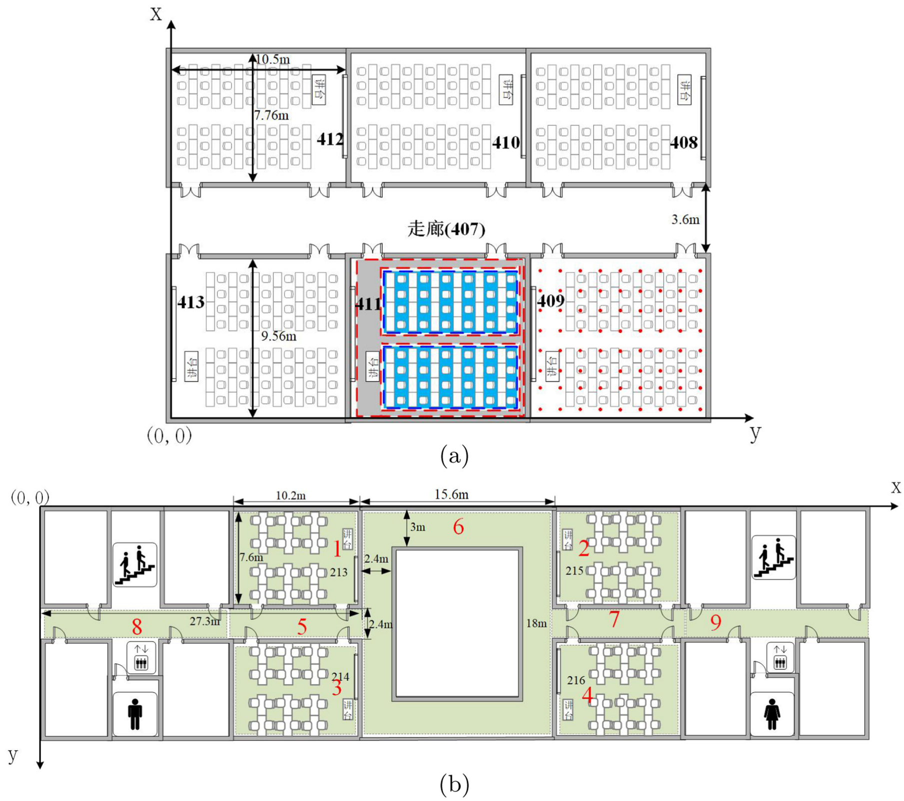

Fig. 6. Experimented environment layouts (a) Building D, fourth floor and (b) Building N, second floor.

4.1 Experimental Setup

The data collection and processing, and simulation measurements have been conducted to validate the proposed SIL system based on the fingerprinting method. Here, the proposed system's experimental setup divides into two parts: the data collection and processing and its simulation. The data collection step has been previously done through the site-survey method for indoor localization by our school's lab. The retrieved data is then processed to prepare the desired data for experimentation and performance measurement. The system simulation step and then evaluation of the obtained results are carried out to reach the desired outcome. This research's experimental setups are built on two testbeds, the fourth floor of Building D (east teaching building) and the second floor of Building N (south first teaching building) of Huazhong University of Science and Technology. Therefore, the data has the required diversity to evaluate the proposed model and measures its performance.

The required data from sampling includes a list of Wi-Fi APs along with SSID, BSSID (MAC address), RSS, and the sample's location coordinates. Later, the two crucial datasets (RSS vector and its location) are used as a fingerprint or signature to validate the system. The RSS vector heard from a list of APs have the values started from 0 (dBm) as an excellent signal to the –100 (dBm) as an extremely weak signal. Many factors affect the RSS signal as the distance between APs and sample points, but the fingerprint-based localization degrades these side effects. The Wi-Fi network has different RSS measurements in different frequency channels, but here, for this experiment, the RSS measurement is taken at a data frequency of 1 (Hz) for both testbeds.

Testbed 1: As Fig. 6a shows, the area includes six classrooms and one corridor, and the total area is 717 (m^2). The width of concrete walls between the areas is 0.3 (m). The smartphone has been held flat right on the agent's chest, and all samples are collected in the same orientation. The offline phase's sampling process is conducted between 0.6 (m), and for the online phase in between 1 (m). Huawei Hol T00 is used to collect sampling data in testbed 1 for this research. Moreover, the device has collected two types of data, site-survey data for the offline phase to build the fingerprint database and test data for the online phase to evaluate the system performance.

Testbed 2: The second testbed area is the second floor of the south 1st building of Huazhong University of Science and Technology, as it is shown in Fig. 6b. It includes four classrooms and one corridor, and the total area is 592 (m^2). The classroom size is 10.2 7.6 (m^2). The other labels are shown in the same figure. The origin of the coordinates is (0,0). The x and y axes are shown in the picture. Oppo R9sk (Op9) is used to collect sampling data in testbed 2 for model evaluation in this paper. Moreover, the distance between two adjacent sampling points is 0.6 (m) and 1 (m) for offline and online sampling, respectively.

4.2 Evaluation Metrics

In order to evaluate the SIL method localization accuracy, the Mean Distance Error (MDE) and Standard Division (STD) are used as evaluation metrics in this paper. If the (N), are considered as number of TPs, real location of TP and estimated location of TP, the MDE and STD have been calculated as follows:

$$MDE = \frac{1}{n2} \sum_{n2=1}^{N2} \| \theta_n^{n2} - \widehat{\theta}_n^{n2} \|^2 \tag{6}$$

$$\sigma = \sqrt{\frac{\sum_{n2=1}^{N} \left(\widehat{\theta}_n^{n2} - MDE \right)^2}{N2}} \tag{7}$$

4.3 Performance Evaluation

In this section, to evaluate the proposed method's performance, the cumulative distribution functions (CDF) of the proposed method and the kNN method have been plotted. Testbed 1 consists of 288 RPs and 110 TPs from 30 APs, and testbed 2 contains 221 RPs and 50 TPs from 27 APs as a fingerprint in the fingerprint database. Moreover, for all algorithms in the simulation of testbed 1, the kNN metric has been considered in two cases k = 2 and k = 8. In contrast, in the simulation of testbed 2, the k value is equal to 1, and for both testbeds, the metric of kNN for labeling the new fingerprint with the position is Euclidean distance.

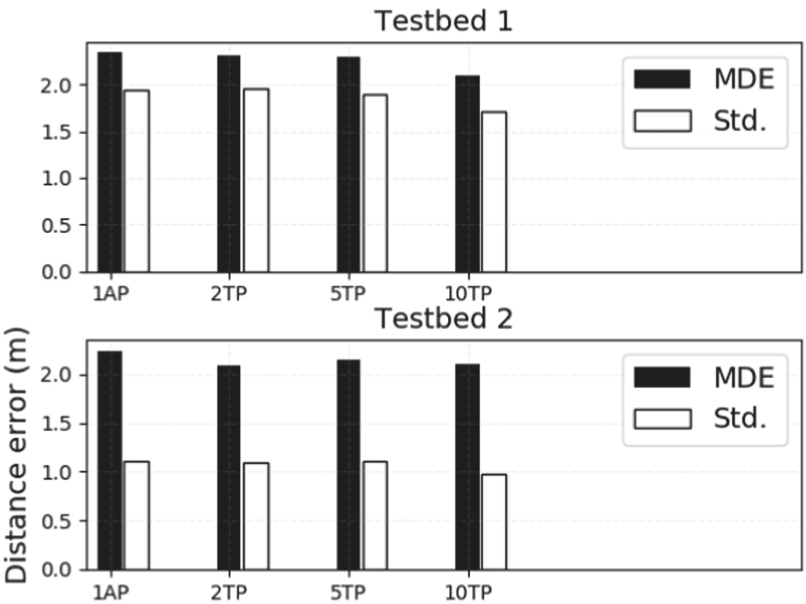

Fig. 7. MDE and Std. of different number of TP in MDS-based model, testbed 1 and 2.

Figure 7 demonstrates the localization error upon the collaboration of the different number of TPs in the MDS-based model. It shows the more TPs share the information for interpolation; the higher accuracy would gain the algorithm. The first line of CDF shows one TP per time localization, the second line 2 TPs per time, the third line 5 TPs per time, and 4th line 10 TPs per time. Form all clusters in a time localization, the 10 TPs per time localization shows the highest accuracy in MDE and standard deviation. Likewise, the MDEs and standard deviations related to the different number of TP information sharing in the MDS-based model are listed in Table 2. As the number of TPs for simultaneous localization increases, the error would decrease in the fingerprinting localization.

Table 2. Positioning error of TP collaboration in MDS-kNN, testbed 1 and 2.

	Testbed 1				Testbed 2			
	1TP	**2TP**	**5TP**	**10TP**	**1TP**	**2TP**	**5TP**	**10TP**
MDE (m)	2.34	2.31	2.29	2.10	2.24	2.09	2.14	2.09
STD (m)	1.95	1.95	1.89	1.71	1.10	1.09	1.11	0.97

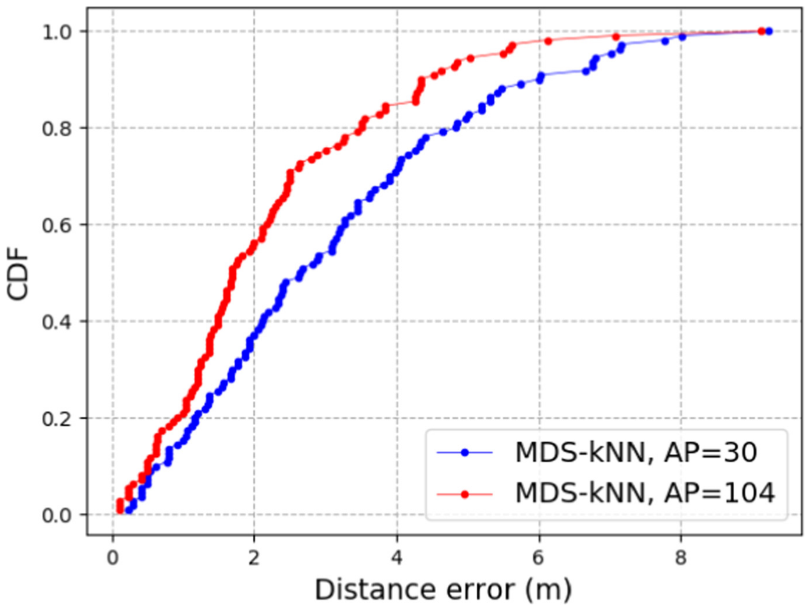

Fig. 8. The effect of AP removal on localization accuracy, testbed 1.

Figure 8 indicates the effect of number APs deployment on fingerprint positioning accuracy based on the k-nearest neighbor algorithm. As shown in Fig. 8, the smaller the number of AP, the better the accuracy for indoor positioning. The 104 APs CDF contains the APs, which has no signal transmission (0 dBm) or stopped sending the signal. Moreover, for building the database for simulation of models, it had been assigned to −100 dBm as the weakest RSS signal. In contrast, in the 30 AP approach, all those APs that had no signal, or stopped working in more than half of the database's RP, have been removed from the database. Therefore, the effect of noise and inconsistency over the fingerprint vectors of TP and RP has been degraded from the fingerprint database. For all of those reasons, the accuracy of fingerprinting has increased.

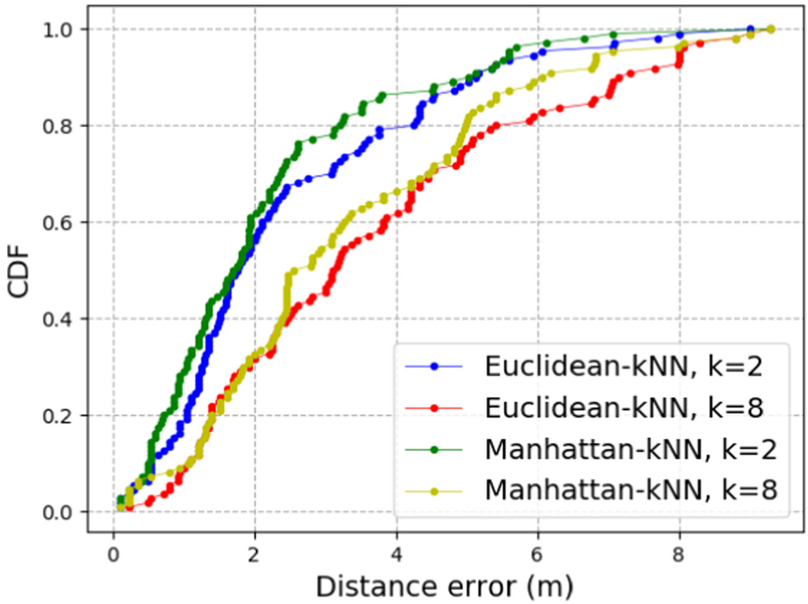

Fig. 9. The comparison of the Euclidean and Manhattan distance metrics in kNN, Testbed 1.

Figure 9 compares the used metric of kNN algorithm. The RSS signal similarity between the TP and selected votes of neighboring is calculated using Euclidean distance and cumulative Manhattan distance. The result shows that the Manhattan distance gains more accuracy than the Euclidean distance. Moreover, this result indicates that the cumulative Manhattan distance metric can provide the best similarity between the TP and RPs in the deterministic kNN algorithm. Besides, according to the paper [1], the cumulative Manhattan distance provides the best discrimination in high-dimensional data space than the Euclidean distance.

The CDF for the MDS-based and traditional kNN are shown comparatively in Fig. 10. The CDF indicates huge precision differences between both of the used methods of this paper. The CDF curve for the MDS-based model displays less inaccuracy than the kNN curve. The accuracy increase in both testbed 1 and testbed 2 demonstrates improved accuracy in mean distance error of 9.8% and 19.6%, respectively. The improvement of accuracy according to the standard deviation of 13.2% and 20.9% increase in testbed 1 and 2, accordingly. Both testbed's experimentation indicates that the proposed MDS-based model takes advantage of information-sharing and collaboration between TPs and RPs to increase the fingerprinting approach reliability and consistency in indoor localization. Finally, Table 3 records the mean distance error and standard deviation of the mentioned methods on testbed 1 and 2, respectively.

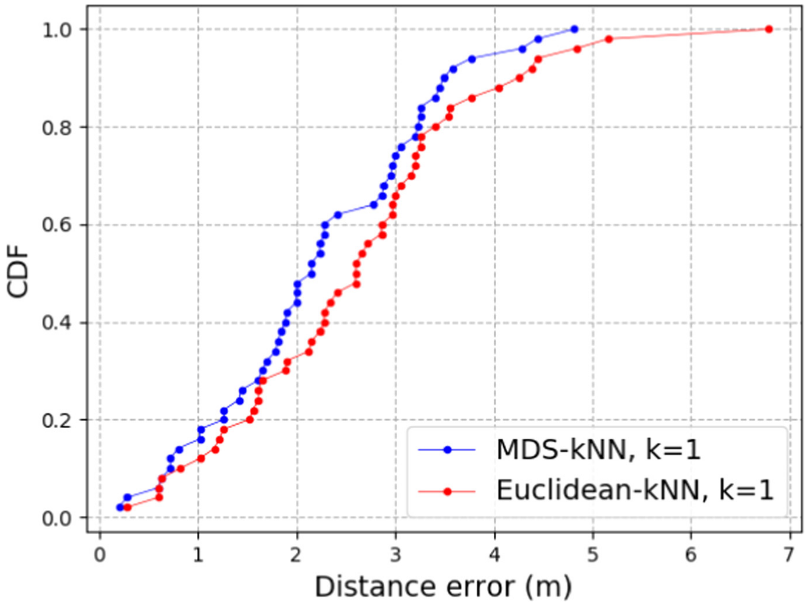

Fig. 10. The comparison of CDFs of the MDS-based and kNN models, testbed 2.

Table 3. MDE and Std. of experimented models, testbed 1 and testbed 2.

	Testbed 1 k = 2		Testbed 2 k = 2	
Method	**MDE (m)**	**STD (m)**	**MDE (m)**	**STD (m)**
MDS-kNN	2.21	1.64	2.09	1.02
kNN	2.45	1.89	2.60	1.29

5 Conclusion

In the fingerprinting approach, TP's localization has been done independently without consideration of other TPs and RPs. Thus, the collaboration concept helps the fingerprinting method leverage information-sharing among points to increase the localization precision. Therefore, in this paper, the effort has put into finding an approach to include the collaboration concept in fingerprinting and increase the localization precision.

This paper analyzes previous works and researches of indoor localization based on the Wi-Fi RSS fingerprints to find the solution for the mentioned fingerprinting problem. The literature review results come out with pre-summarized collaboration usage: Distance-scheme and Proximity-scheme. This paper's proposed method has been built on the proximity scheme of collaborative localization that is utilized the RSS distance in the MDS-based algorithm to build collaboration among RSS's fingerprints. This method integrates the TPs and the RPs information to localize the test points. This method's experimentation has been conducted on data collected from Huazhong University of Science and Technology teaching buildings as testbed 1 and testbed 2. The result demonstrates improvement in the MDS-based method compared to the deterministic kNN algorithm. The error results show up to 9.8%, and 13.2% error reduction in MDE, and standard deviation, respectively, for testbed 1. Moreover, the error results of testbed 2 show up to 19.6% and 20.9% error degradation in MDE, and standard deviation, respectively, for testbed 2. Several experiments have been conducted in both testbeds with different numbers of RPs, TPs, APs, and algorithmic metrics.

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