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An effective random statistical method for Indoor Positioning System using WiFi fingerprinting☆

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ABSTRACT

In the paper, an effective random statistical method is proposed for Indoor Positioning System (IPS) using WiFi fingerprinting. The proposed method consists of two phases: the offline handling process and the online positioning process. The offline handling process is used to collect a large number of WiFi signals at each indoor reference point and then create an offline database. This process handles the noise of WiFi signals and normalizes the database about location fingerprints for IPS. To further improve the accuracy of indoor positioning, the Mahalanobis distance is utilized to determine the indoor location for the online positioning process. Compared to the Weighted K-Nearest Neighbor (WKNN) algorithm based on Euclidean distance, experimental results show that it can improve the positioning accuracy using the proposed random statistical method. For the proposed random statistical method, the maximum positioning error is less than 0.75 meters. However, the average positioning error is 1.5 meters using the WKNN algorithm. In addition, it can effectively handle the noise of WiFi signals using the proposed random statistical method in different indoor environments.

1. Introduction

With the development of WiFi technology and smartphone, Indoor Positioning System (IPS) has paid more attention. Many IPS applications have been studied and achieved [1–3]. Global Positioning System (GPS) [4] is used in outdoor environments and it has well position in practice. The GPS technology mainly relies on signal propagation in the air. As it encounters the buildings with complex architecture (such as supermarkets, commercial centers, hospitals, airports, etc.), it will interfere with signal propagation. For indoor positioning, wireless communication technology such as WiFi is paid more attention. It can built on mobile phones [5]. Meanwhile, WiFi access points can be seen everywhere in indoor environments and the smartphones can be used to receive WiFi signals.

For WiFi positioning technology, the popular indoor positioning algorithm is location fingerprinting algorithm. It is not interested in the location of WiFi access points. However, the fingerprint approach method is affected by two main problems in practical positioning applications. The first problem is that, for collecting data in the house, it takes too much time and manpower to create training database for IPS in the offline handling process. The second problem is the accuracy still far from the positioning location using the fingerprint approach method. It is due to WiFi signals are significantly affected by indoor environmental conditions. For the accuracy, the recent studies have pretty good strides about the accuracy within 2 m but positioning algorithms take much time [6,7] and a result reached 1.54 m [8].

To improve positioning accuracy, in the paper, the random statistical method for IPS is proposed. The proposed method is based on the traditional location fingerprinting algorithm [9]. It consists of two stages: the offline handling process and the online positioning process. For the offline handling process, at each reference point (RP) location, it will collect a large number of WiFi signals in different indoor environments and then handle the noise of WiFi signals to build a standardization database about location fingerprints for IPS. For the online positioning process, the positioning algorithm collects actual WiFi signals to determine indoor location, it uses the Mahalanobis distance to determine the accuracy of the positioning results. The Mahalanobis distance is calculated from the location where the smartphone collects actual WiFi signals to each RP location in the room. The indoor positioning result is RP location so that Mahalanobis distance from location gets actual WiFi signals to RP location has the minimum value. In addition, to prove the effectiveness of the proposed method, the experimental results between the proposed method and the WKNN algorithm based on Euclid distance are compared.

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The rest of the paper is organized as follows. In Section 2, this paper reviews related researches. Section 3 presented the random statistical method for IPS using WiFi fingerprinting. The experimental results and evaluation of the proposed method are described in Section 4. Section 5 is conclusions.

2. Related researches

Traditional fingerprinting approach can be divided into two phases: offline phase and online phase. During the offline phase, the process of data collection is performed in an environment. The location coordinates of RPs and respective signal strengths from WiFi access points are collected. During the online phase, the indoor positioning algorithm uses the currently observed signal strengths and previously collected information of RPs to find out an estimated location. The main challenge to the positioning algorithms based on location fingerprints is that the received signal strength can be affected by diffraction, reflection, scattering and absorption during the propagation in indoor environments.

For the offline phase, the previous researches are mainly focused on improving the quality of the database of fingerprints. In [10], it proposed that personal direction should be taken into consideration when collecting WiFi signal strengths. In [11], it presented an extension and improvement of current indoor localization model based on the feature extraction of 46 magnetic field signal features. By adding more auxiliary features to WiFi signal fingerprints in the offline phase, it will help the online positioning to be more accurate as in [10,11]. The management and utilization on the database of fingerprints were studied in [12–15]. In [12,13], it gave their way to update the database of fingerprints automatically. In [14,15], it proposed two methods about how to organize the database of fingerprints. Although they did not improve the positioning accuracy, they managed to improve the efficiency of algorithms. In addition, in [16], it studied how to optimize the placement of collecting points, which could improve location performance.

For the online phase, the previous researches are focused on how to improve the accuracy of positioning. In [7,17], it mentioned the sensor fusion, but extra sensors are necessary, which would increase the cost of positioning. In [18], it proposed a weighted fingerprinting approach based on the relationship between the average value and the standard deviation of WiFi signal strength. The data fusion method was applied to the WiFi positioning [19]. In [20,21], it proposed new algorithms integrating traditional algorithms. At the same time, researches adopted machine learning to propose new algorithms [22]. The researches on online phase are abundant, but some of them may take too much time and calculation. Whereas specific to positioning applications, in [23,24], it presented IPS developed for Android smartphones. However, the accuracy is not adequate. It indicates that choosing between the precision and the practical application is worth considering.

Some researchers have been interested in Wi-Fi fingerprint localization methods based on important access points (IAP) to build location fingerprints database and estimate location indoor positioning [25–29]. IAP is WiFi access point with the highest received signal strength (RSS). The positioning algorithms were proposed to determine location for improving positioning accuracy. However, the experimental results of positioning algorithms were achieved the average positioning error greater than 2 m.

In [30], it proposed F-score-weighted indoor positioning algorithm integrating WiFi-RSS and Magnetic field (MF) fingerprints. The proposed approach was to create a training database for IPS based on WiFi-RSS value and MF fingerprints value at each RP location in the offline phase. And in the online phase, the F-score-weighted indoor positioning algorithm was used to estimate the indoor positioning result. However, the experimental results of the authors could achieve 91% of the average positioning error less than 3 m.

For the above research works, there are still some issues as follows: firstly, it cannot handle WiFi signals error as collecting in the offline phase. Secondly, it takes too much time to calculate for positioning in the online phase.

In this paper, we propose the method to overcome the two major issues. The details of the proposed method are given in Section 3.

3. The proposed random statistical method

The Fig. 1 shows the indoor positioning application based on WiFi fingerprinting technology. The random statistical method is proposed to handle WiFi signals error in indoor environments. It also improves positioning accuracy for IPS.

To determine the location of Smartphone/User in indoor based on WiFi fingerprinting technology, we have installed q WiFi devices as access points (APs) at q different locations in indoor, such as $AP_1, AP_2, \ldots, AP_q$. The indoor location is divided into a grid of equal distance reference points. Then, indoor is marked with N reference points (with $N > 0$) according to a uniform distribution and paste label as $RP_1, RP_2, RP_3, \ldots, RP_N$. The Mobile application of the Client is used to collect WiFi signals such as the received signal strength indication (RSSI) value ($rssi_1, rssi_2, \ldots, rssi_q$) from q APs and send to the Server. The Server is responsible for data process and store full of RPs into fingerprinting database during the offline handling process. In addition, the function of Server is to determine indoor location and send the positioning result for the User to know where User is standing in location of indoor during the online positioning process.

3.1. The proposed random statistical method for IPS using WiFi fingerprinting

The random statistical method is proposed for IPS using WiFi fingerprinting because RSSI values collected from q APs are continuously changed. It is due to the influence of indoor environment conditions. Therefore, the random statistical method is proposed to estimate its real RSSI value as the exact value or standard RSSI value at an indoor location. The proposed method is based on traditional location fingerprinting method, and it uses statistical method to standardize WiFi signals. It is shown in Fig. 2. It also determines indoor location with high accuracy.

The offline handling process consists of two phases. Firstly, smartphones are used to collect indoor WiFi signals based on the map of the marked RPs. The map of RPs are formed by dividing the indoor locations into a grid of equal distance RPs. Then WiFi signals with RSSI value are collected from q APs based on the smartphone at RP location, and continue to collect RSSI value from other RPs until all RSSI values of all indoor RPs are collected. Secondly, standardization database about location fingerprints is built. For standardization database about location fingerprints, it contains RP_t location information, the expected value and matrix covariance of RSSI values collected at RP_t location (for $t = 1, 2, \ldots, N$).

The online positioning process consists of three phases. Firstly, as user is in indoor, the smartphone is used get actual WiFi signals from indoor q APs and send it to the Server. The Server will determine indoor location for the user/smartphone. Secondly, for indoor positioning based on Mahalanobis distance, positioning algorithm calculates the distance from actual RSSI value in the online positioning process (called x) to each indoor RP_t location (for $t = \overline{1, N}$). This algorithm use Mahalanobis distance to determine the indoor positioning result. The Mahalanobis distance

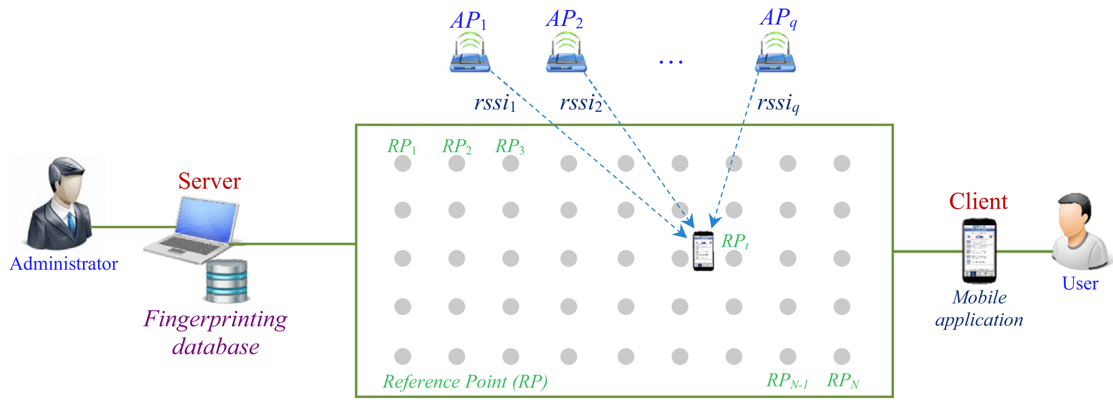


Fig. 1. The indoor positioning application based on WiFi fingerprinting technology.

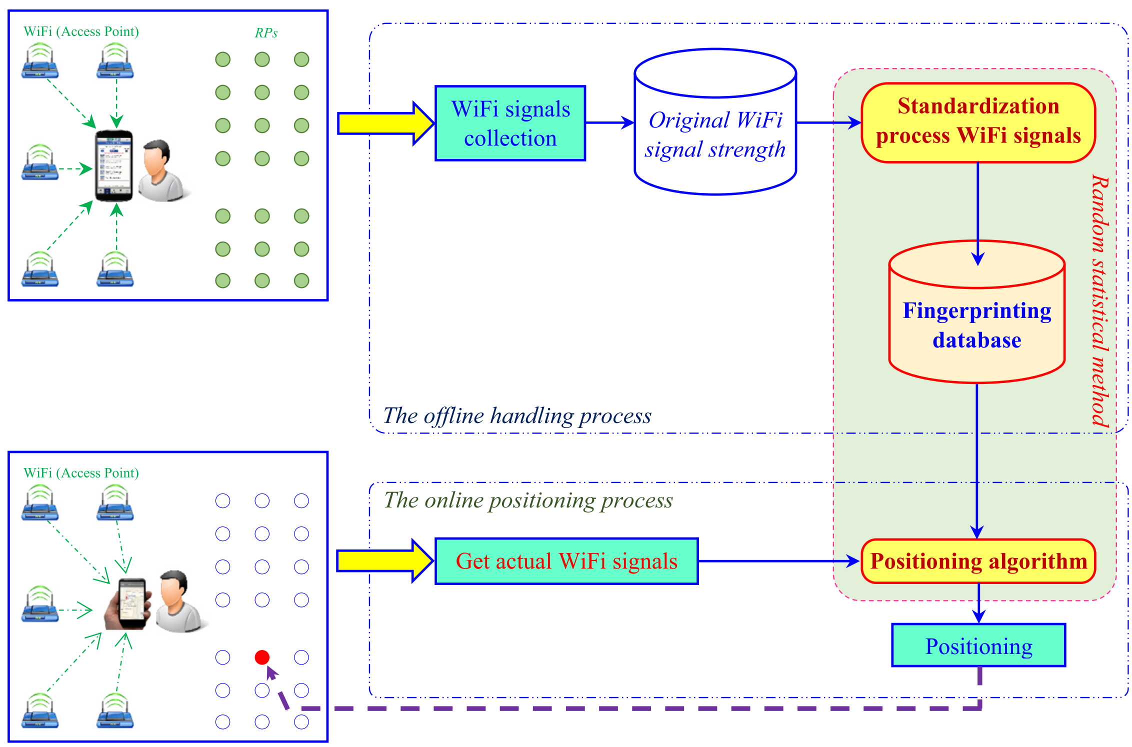


Fig. 2. The operation model of IPS and the applied random statistical method.

is calculated based on the important value pair as the expected value and matrix covariance of RP_t location in the Fingerprinting database and x. The positioning result is RP_t location such that Mahalanobis distance from x to RP_t location has the minimum value. Thirdly, to show the positioning result on Smartphone, Mobile application on Smartphone received positioning result from Server is RP_t location information of the positioning algorithm. Then, the Mobile application displays a red dot positioning on the 2D physical map at coordinates of indoor RP_t location.

3.2. The proposed random statistical method to building fingerprinting database for IPS

Assuming that standard RSSI value at the RP_t location is $\mu_t = \left(\mu_1^t, \mu_2^t, \mu_3^t, \mu_4^t, \mu_5^t\right)$ corresponding to 5 WiFi devices. μ_t has unknown standard value.

At each RP_t location (for $t = 1, 2, \ldots, N$) to collect n RSSI values from 5 APs in the room, as n = 100 and different environmental conditions are considered in the room, the random statistical method receives n RSSI values by random vector X^t with the expected value of μ_t, and the covariance matrix is defined as:

$$\Sigma^t = \left(cov\left(X_i^t, X_j^t\right)\right)_{i,j=\overline{1,5}} = \begin{pmatrix} \sigma_{t,1}^2 & \lambda_{1,2}^t & \lambda_{1,3}^t & \lambda_{1,4}^t & \lambda_{1,5}^t \\ \lambda_{2,1}^t & \sigma_{t,2}^2 & \lambda_{2,3}^t & \lambda_{2,4}^t & \lambda_{2,5}^t \\ \lambda_{3,1}^t & \lambda_{3,2}^t & \sigma_{t,3}^2 & \lambda_{3,4}^t & \lambda_{3,5}^t \\ \lambda_{4,1}^t & \lambda_{4,2}^t & \lambda_{4,3}^t & \sigma_{t,4}^2 & \lambda_{4,5}^t \\ \lambda_{5,1}^t & \lambda_{5,2}^t & \lambda_{5,3}^t & \lambda_{5,4}^t & \sigma_{t,5}^2 \end{pmatrix} \tag{1}$$

where $\lambda_{i,j}^t \equiv cov\left(X_i^t, X_j^t\right) = E\left(X_i^t, X_j^t\right) - E\left(X_i^t\right)E\left(X_j^t\right)$ for $i, j = \overline{1,5}$ (with $i \neq j$); $\lambda_{i,i}^t \equiv \sigma_{t,i}^2 = Var\left(X_i^t\right) = E\left(\left(X_i^t\right)^2\right) - \left[E\left(X_i^t\right)\right]^2$ for $i = \overline{1,5}$; $X^t = \left(X_1^t, X_2^t, X_3^t, X_4^t, X_5^t\right)$, mean $i = \overline{1,5}$: $E\left(X_i^t\right) = \mu_i^t$ (i.e, $E\left(X^t\right) \equiv \mu_t$).

$\left\{X_k^t\right\}_{k=1}^n$ is n the sample RSSI value received by the random vector X^t at RP_t location. $X_k^t = \left(X_{1,k}^t, X_{2,k}^t, X_{3,k}^t, X_{4,k}^t, X_{5,k}^t\right)$ is point

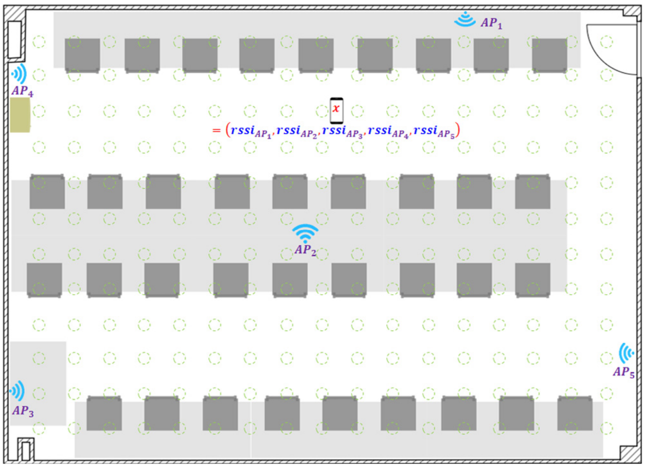


Fig. 3. Get actual RSSI value to determine the indoor positioning result.

5-dimensional coordinates recorded by X^t at RP_t location at the kth time (for $k = \overline{1, n}$).

Then, the estimate for the experimental expected value μ_t at RP_t location is calculated as:

$$m^{(t)} = \frac{1}{n}\sum_{k=1}^{n} X_k^t = \left(\frac{1}{n}\sum_{k=1}^{n} X_{1,k}^t, \frac{1}{n}\sum_{k=1}^{n} X_{2,k}^t, \ldots, \frac{1}{n}\sum_{k=1}^{n} X_{5,k}^t\right) \quad (2)$$

The estimate for the experimental covariance matrix Σ^t at RP_t location is $\lambda_{i,j}^t = cov\left(X_i^t, X_j^t\right)$, for $i, j = \overline{1, 5}$. The estimate value for $\lambda_{i,j}^t$ is α_{ij}^t as follows: $\alpha_{ij}^t = \frac{1}{n}\sum_{k=1}^{n}\left(X_{i,k}^t \cdot X_{j,k}^t\right) - \left(\frac{1}{n}\sum_{k=1}^{n} X_{i,k}^t\right) \cdot \left(\frac{1}{n}\sum_{k=1}^{n} X_{j,k}^t\right)$, for $i, j = \overline{1, 5}$.

Then, the experimental covariance matrix Σ^t is estimated by:

$$\Sigma^t = \left(\alpha_{ij}^t\right)_{i,j=\overline{1,5}} \quad (3)$$

The covariance matrix Σ^t is the symmetric matrix $\left(\alpha_{ij}^t = \alpha_{ji}^t\right)_{i,j=\overline{1,5}}$, thus, it only need to compute by triangular matrix.

After collecting n RSSI values as ($rssi_{AP_1}$, $rssi_{AP_2}$, $rssi_{AP_3}$, $rssi_{AP_4}$, $rssi_{AP_5}$) and coordinate information of each RP_t location based on different environmental conditions in the room, a number of RSSI values and coordinates information of RP_t location is uploaded to the Server (for $t = \overline{1, N}$). In the Server, it calculates the estimate for the expected value $m^{(t)}$ by Eq. (2) and covariance matrix Σ^t by Eq. (3) of each RP_t location corresponding, we get each record as (ID_t, (x_t, y_t), $m^{(t)}$, Σ^t) of each RP_t location and save it into Fingerprinting database (for $t = \overline{1, N}$). In the Fingerprinting database there are all N records. Thus, we have completed the construction of a standardization database about location fingerprints as Fingerprinting database.

To determine the indoor location in the online positioning process, the positioning algorithm relies on the actual RSSI value received in the room and important pairs of values as $m^{(t)}$ and Σ^t of each RP_t location in the Fingerprinting database to determine indoor positioning result (see Fig. 3).

3.3. The online positioning process

(1) Get actual WiFi signals to determine indoor location: To determine indoor location of User/Smartphone, the Mobile application on Smartphone is used to get actual RSSI value with WiFi signals from 5 APs in the room as $x = (rssi_{AP_1}, rssi_{AP_2}, rssi_{AP_3}, rssi_{AP_4}, rssi_{AP_5})$ and send x to Server. Then, the server runs the positioning algorithm to determine the indoor location of the User/Smartphone.

(2) Indoor positioning based on Mahalanobis distance: Due to the influence of indoor environmental for WiFi technology, RSSI values collected at RP_t location is always changing. Therefore, the random statistical method has collected n RSSI values at each RP_t location in different indoor environmental conditions. Then standardization database about location fingerprints is built. To determine the indoor location for the location that gets actual RSSI value and compare n RSSI values at each RP_t location in the Fingerprinting database, Mahalanobis distance is proposed to calculate the distance between actual RSSI value $x = (rssi_{AP_1}, rssi_{AP_2}, rssi_{AP_3}, rssi_{AP_4}, rssi_{AP_5})$. It is calculated along with the value pair as $m^{(t)}$ and Σ^t of RP_t location in the Fingerprinting database. The Mahalanobis distance is calculated as follows:

$$d\left(x, m^{(t)}\right) = \sqrt{\left(x - m^{(t)}\right) . \left(\Sigma^t\right)^{-1} . \left(x - m^{(t)}\right)^T}, \text{ for } t = \overline{1, N}. \quad (4)$$

where x is the actual RSSI value received in the online positioning process, $m^{(t)} = \left(m_1^{(t)}, m_2^{(t)}, m_3^{(t)}, m_4^{(t)}, m_5^{(t)}\right)$ is the expected value and Σ^t is the covariance matrix of RP_t location.

By the positioning algorithm, the smallest Mahalanobis distance is obtained by Eq. (4), it is shown as $d_{min} = min_{1 \le t \le N}\left(d\left(x, m^{(t)}\right)\right)$. The indoor positioning result of User/Smartphone is RP_t location so that Mahalanobis distance from x to RP_t location is d_{min}.

4. Experiment results and discussions

Fig. 4 shows the experimental IPS model in a room. The size of the room is 9.0 m × 6.5 m. To implement the positioning application in the room, there are fixed 5 APs as AP_1 (*Franky*, Mercury), AP_2 (*Gold*, TP-Link), AP_3 (*Mamasita*, Mercury), AP_4 (*Gogosala*, TP-Link), AP_5 (*Hussein*, Mercury) at 5 different locations with height from 1.1 m to 1.6 m.

The prototype system of Wireless LAN for IPS in the room is shown in Fig. 5. It contains two parts such as the Server and the Smartphone Client. The Server is responsible for processing, storing information of all RPs to create a Fingerprinting database. In addition, the indoor positioning result for User/Smartphone is obtained in the Server. The Smartphone Client is responsible for collecting RSSI values in the room and sends all these values to the Server. Moreover, the Smartphone Client receives indoor positioning result from the Server and displays this result on the 2D map (physical map) of the room.

For the Server, the configuration of the devices includes Dell Latitude E6420, Intel(R) Core(TM) i7-2620M 2.70 GHz Dual-core processor with Hyper-Threading technology and 8 GB DRR3 SDRAM. For the Smartphone Client, it consists of Samsung Galaxy Note 3 SM-N900T, 32 GB and Black (T-Mobile) Smartphone.

4.1. Collect WiFi signals to build an experimental database

To build a Fingerprinting database, WiFi signals in the room is collected. The indoor locations are divided into a mesh network of RPs with even spacing, includes all 205 RPs. Fig. 6 shows the even distribution of 205 RPs in the room. 5 locations APs are fixed.

In this paper, the distance between RPs in the room is 0.5 m. For the previous works, the distance between RPs is greater than 1 m, such as 2 m [6], 1.5 m [8], 2.4 m [30]. Table 1 shows the parameters for collecting RSSI values from 5 APs for 205 RPs in the room. It includes two parameters related to RPs as the distance between two RPs and the number of RPs in the room,

Fig. 4. The experimental IPS model in the room.

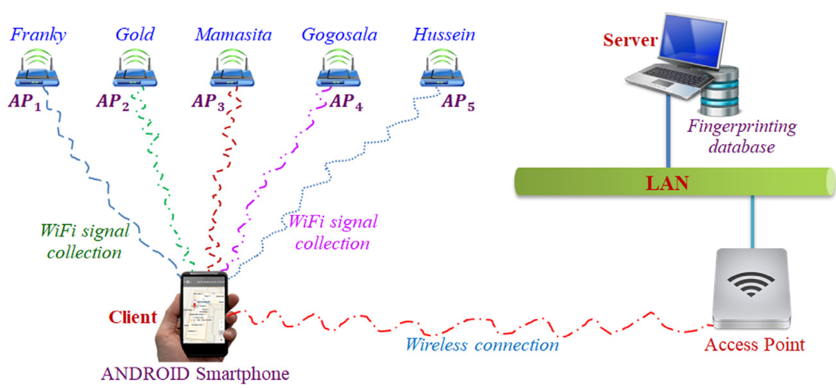


Fig. 5. Prototype system of Wireless LAN for IPS in the room.

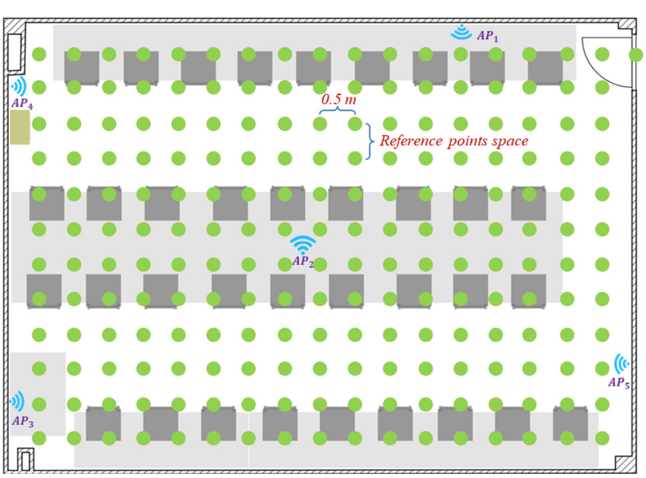


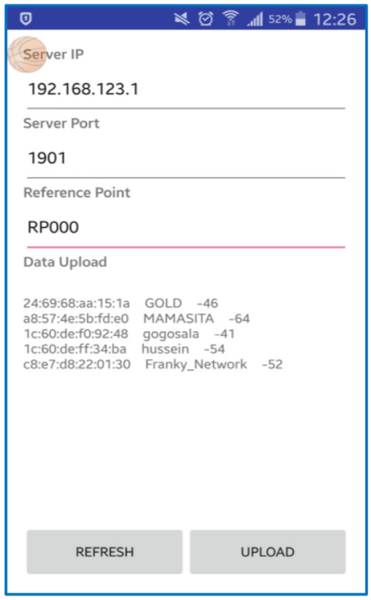
Fig. 6. Distribution of 205 RPs and 5 locations APs in the room.

Table 1
WiFi signals collecting parameters for RPs in the room.

Parameters	Value	Comments
Distance between RPs	0.5 m	The average distance of each normal adult footsteps
Time to collect 1 RSSI value	5 s	Determined by actual demands
Frequency to collect RSSI values	10 Hz	Determined by the mobile device
Number of RPs collected	205	Determined by room size

a parameter about the frequency of communication between Smartphone and 5 APs to collects RSSI values, and one parameter about the time interval to Smartphone collects 1 new RSSI value from 5 APs in the room.

Based on the proposed random statistical method, we collect 100 RSSI values of each RP_t location in the room (for $t = 0, 1, 2, \ldots, 204$) with different indoor noise conditions. At each RP_t location, we have collected 35 RSSI values in the morning (8:0 am to 11:45 am), 20 RSSI values at noon (12:30 pm to 3:50 pm), 35 RSSI values in the afternoon (4:00 pm to 6:45 pm) and 10 RSSI



ID_RP	AP1: Franky	AP2: Gold	AP3: Mamasita	AP4: Gogosala	AP5: Hussein
RP000	-54	-48	-60	-47	-51
RP000	-53	-45	-63	-46	-54
RP000	-53	-47	-63	-44	-51
RP000	-55	-48	-60	-48	-52
RP000	-54	-46	-63	-47	-53
RP000	-52	-48	-65	-45	-52
RP000	-55	-44	-60	-48	-52
RP000	-57	-46	-62	-47	-54
RP000	-54	-43	-63	-43	-55
RP000	-56	-46	-65	-45	-53
RP000	-56	-45	-62	-42	-54
RP000	-54	-47	-61	-46	-53
RP000	-52	-46	-64	-41	-54
RP000	-52	-47	-63	-42	-52
RP000	-54	-41	-63	-44	-52
RP000	-57	-42	-62	-41	-53
RP000	-58	-44	-62	-44	-54
RP000	-55	-41	-63	-46	-52
...	...	...	...	...	...
RP000	-56	-41	-63	-47	-53
RP000	-57	-43	-60	-48	-54
RP000	-58	-42	-63	-46	-52
RP000	-56	-41	-61	-47	-54
RP000	-54	-45	-62	-48	-51
RP000	-55	-42	-64	-45	-54

Fig. 7. The Smartphone Client and 100 RSSI values collected at the RP_0 location.

Table 2
Different indoor noise conditions for wiFi signal collecting.

Main noise conditions	Cases collecting of RSSI value
(a) Number of people working and moving in the room	1÷5 people, 6÷10 people, 11÷15 people, 16÷20 people.
(b) The number of Computers and Laptops (C&L) operating in the room	1÷5 C&L, 6÷12 C&L, 11÷18 C&L, 16÷24 C&L.
(c) How to hold a Smartphone to collect WiFi signals	Low (1 m): horizontal, inclined (45°), vertical. High (1.3 m): horizontal, inclined (45°), vertical.
(d) The direction of the smartphone holder (compared to APs in the room) when collect WiFi signals	Rotate by 4 direction (90°) at one RP in the room.

Table 3
Parameters affecting the experimental environment in the room in case 1.

Main noise conditions	Case collecting of RSSI value
Number of people working and moving in the room	1÷5 people
The number of computers and laptops operating in the room	4 computers and 2 laptops
How to hold a Smartphone to collect WiFi signals	High (1.3 m): inclined (45°)
The direction of the smartphone holder when collect WiFi signals	Always keep the smartphone in front of User and stand on the RP location

Table 4
Parameters affecting the experimental environment in the room in case 2.

Main noise conditions	Case collecting of RSSI value
Number of people working and moving in the room	6÷10 people
The number of computers and laptops operating in the room	8 computers and 5 laptops
How to hold a Smartphone to collect WiFi signals	High (1.3 m): inclined (45°)
The direction of the smartphone holder when collect WiFi signals	Always keep the smartphone in front of User and stand on the RP location

values in the evening (7:00 pm to 8:30 pm) with the parameters as shown in Table 1.

For each indoor noise condition, RSSI values sequence is collected from RP_0 location to RP_{204} location and uploaded to Server. During collection of RSSI values from RP_0 location to RP_{204} location, the indoor noise condition can be changed because noise conditions (a), (b), (c) and (d) in Table 2 are changed.

Fig. 7 shows the Smartphone Client and 100 RSSI values with 100 fingerprints of RP_0 location collected from 5 APs as AP_1 (*Franky*), AP_2 (*Gold*), AP_3 (*Mamasita*), AP_4 (*Gogosala*) and AP_5 (*Hussein*). Similarly, at the RP_0 location, we have collected 100 RSSI values at the RP_1 location, finally, we have collected 100 RSSI values at the RP_{204} location with different indoor noise conditions as in Table 2.

Fig. 8 shows the variation of 100 RSSI values collected from 5 APs at RP_0 location in the room with the influence of different indoor environments as in Table 2.

4.2. Standardization process WiFi signals

Fig. 9 shows each expected value corresponding to 205 RPs as the result of the standardization process WiFi signals by the proposed method via Eq. (2) and all these values together with their corresponding covariance matrix are stored in the Fingerprinting database. The expected value of RP_t is considered as the standard RSSI value at RP_t location (for $t = 0, 1, 2, \ldots, 204$). Fig. 10 shows the result of handle the noise of WiFi signals from 5 APs for 205 RPs in the room by the proposed method.

4.3. Comparison with other positioning algorithm

To prove the effectiveness of the proposed method, the positioning performance of the random statistical method and the traditional WKNN algorithm are compared. In this experiment, the random statistical method and WKNN algorithm use the same Fingerprinting database in the online positioning process. 205

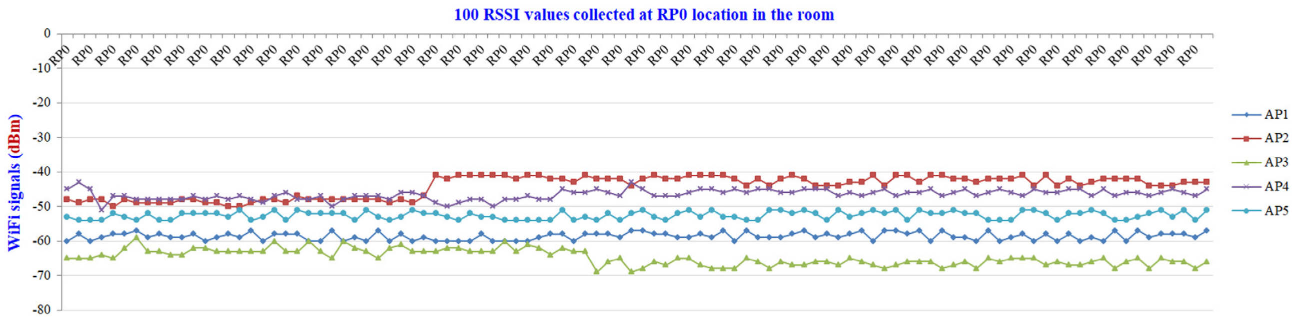


Fig. 8. Variation of WiFi signals collected from 5 APs at the RP_0 location in the room.

positioning results corresponding to 205 RPs are measured in the room. The experiment process determined the positioning result of User/Smartphone at locations as RP_0, RP_1, RP_2, …, and RP_{204} in the room. The experiment was conducted twice with two different indoor noise conditions.

Table 3 shows the environmental parameters that affect the actual RSSI value received in the room for the online positioning process in case 1.

Fig. 11 shows the positioning error of the random statistical method and the WKNN algorithm. It can be seen that the maximum positioning error of the random statistical method is 0.71 m at the RP_{26} location. Meanwhile, the maximum positioning error of the WKNN algorithm is 5.0 m at the RP_{196} location.

By calculating the average of the locations of RPs with positioning errors, average positioning error for the WKNN algorithm is 1.627 m, and the positioning error is at 74/205 locations with 36.1% location error. However, average positioning error for the random statistical method is 0.512 m, and the positioning error is at 18/205 locations with 8.8% location error. It is shown that using the random statistical method, it can handle the noise of WiFi signals. Meanwhile, a standardization database about location fingerprints is also well enough. For the positioning algorithms in the indoor system, the random statistical method is effective and can be used to improve the positioning accuracy.

From Fig. 12, it is shown that the smallest distance to determine the indoor positioning result of the random statistical method with Mahalanobis distance is much smaller than that of the WKNN algorithm with Euclidean distance on all RPs in the room. Thus, the proposed method has good reliability and efficiency. Fig. 13 shows the runtime of two positioning algorithms. It can be seen that the runtime of the indoor location is less than 0.016 s for the random statistical method and the WKNN algorithm.

Table 4 shows the environmental parameters that affect the actual RSSI value received in the room for the online positioning process in case 2.

Fig. 14 shows that positioning performance of the random statistical method in case 2. It has a higher accuracy than that of the WKNN algorithm. The maximum positioning error of the proposed method is 0.71 m at locations as RP_{16}, RP_{107}, RP_{123}, RP_{131} and RP_{169}. However, the maximum positioning error of the WKNN algorithm is 6.71 m at the RP_{190} location. By calculating the average of the locations of reference points with positioning errors, average positioning error results for the WKNN algorithm is 1.508 m, and positioning error at 78/205 locations with 38.1% location error. Moreover, average positioning error results for the proposed method is 0.550 m, and positioning error at 21/205 locations with 10.2% location error.

From Fig. 15, it shows that to determine the indoor positioning, the smallest distance using the proposed method with Mahalanobis distance is much smaller than that of the WKNN algorithm with Euclidean distance on all RPs in the room. Fig. 16

RP_t \ $m^{(t)}$	m_1	m_2	m_3	m_4	m_5
0	-58.64	-44.2	-64.76	-46.59	-52.56
1	-56.79	-44.16	-64.39	-45.71	-52.75
2	-55.79	-44.96	-67.29	-47.88	-51.06
3	-49.96	-49.23	-65.25	-52.07	-57.67
4	-41.76	-47.31	-60.02	-53.68	-50.46
5	-38.54	-51.59	-64.14	-46.52	-51.17
6	-45.53	-46.41	-65.01	-52.85	-52.22
7	-53.32	-53.59	-65.96	-49.69	-45.5
8	-58.4	-48.57	-65.93	-47.39	-50.53
9	-61.74	-50.93	-60.03	-47.6	-50.75
10	-64.96	-52.24	-65.05	-49.57	-44.44
…	…	…	…	…	…
100	-60.71	-47.77	-48.31	-44.96	-40.08
101	-60.38	-50.61	-46.44	-49.14	-49.01
102	-62.27	-51.19	-50.5	-47.81	-43.19
103	-55.53	-45.25	-58.23	-49.8	-45.97
104	-51.32	-48.16	-55.26	-50.15	-39.26
105	-53.75	-47.14	-57.98	-48.33	-37.16
106	-54.22	-42.37	-55.85	-53.37	-39.04
…	…	…	…	…	…
200	-68.21	-45.49	-52.25	-58.77	-49.65
201	-66.88	-45.41	-44.89	-49.1	-47.55
202	-67.9	-49.58	-46.31	-51.01	-48.23
203	-73.35	-52.11	-42.42	-56.05	-54.6
204	-70.9	-53.92	-34.75	-45.85	-52.22

Fig. 9. The expected value corresponding to 205 RPs.

shows the runtime of two positioning algorithms in case 2. It can be seen that to determine the indoor location, the runtime of the proposed method and the WKNN algorithm is also less than 0.016 s.

For the positioning algorithm of the proposed method and the WKNN algorithm, it has the same complexity with O(N). Although the distance calculation with the Mahalanobis distance is much complexity than that with the Euclidean distance, due to the data storage structure in the Fingerprinting database is efficient, the calculation time of the two positioning algorithms is nearly the same and less than 0.016 s via 205 positioning results in both cases in the experiment. It can be seen that the change in the indoor environment parameters does not affect the running time of the positioning algorithms.

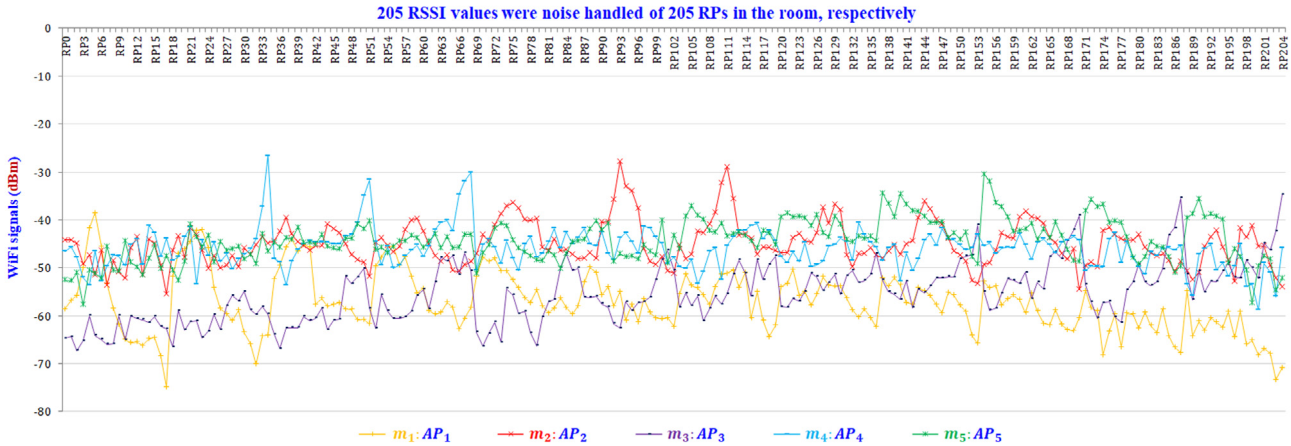


Fig. 10. The result of handling the noise of RSSI values over 205 RPs in the room by the proposed method.

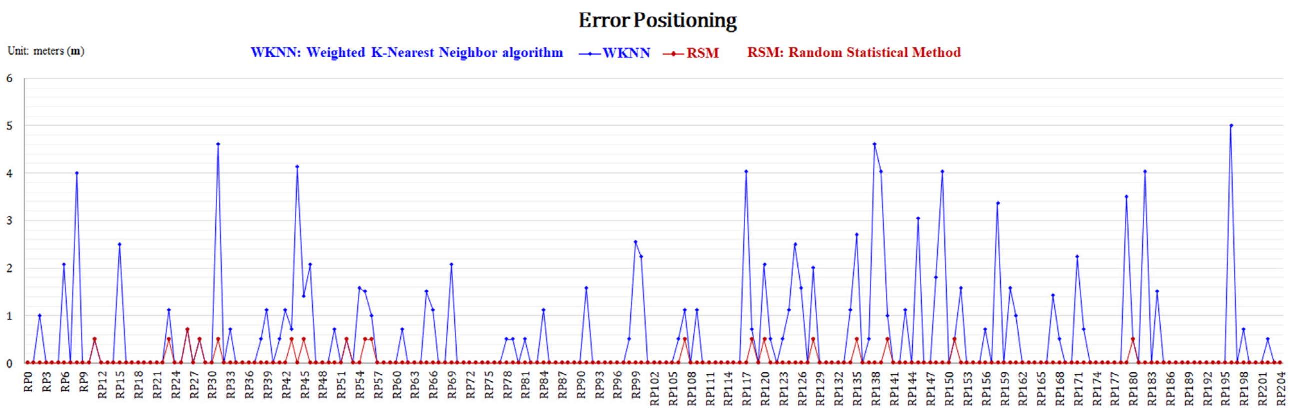


Fig. 11. The positioning error of two positioning algorithms via 205 RPs in the room in case 1.

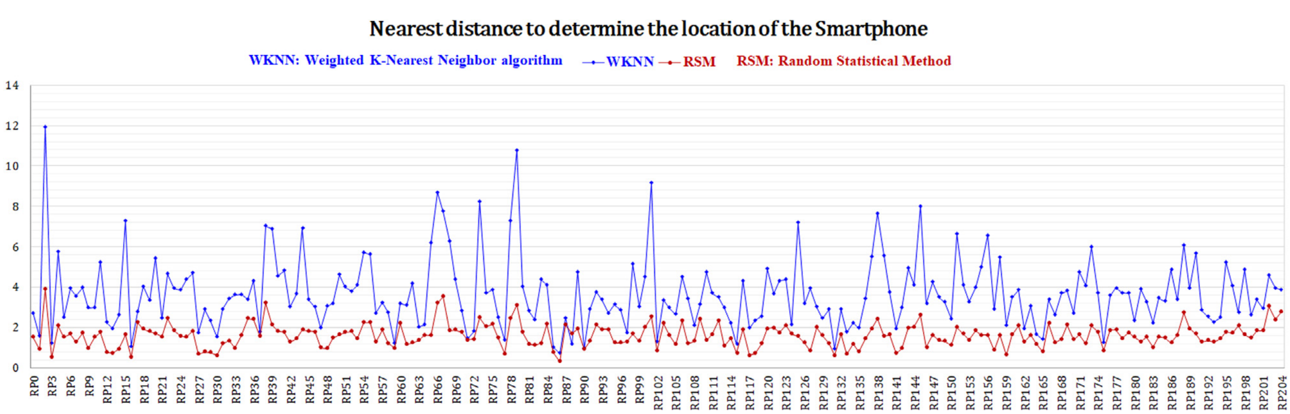


Fig. 12. The distance nearest between the actual RSSI value with the standard RSSI value via 205 RPs in case 1.

5. Conclusions

In the paper, to increase the reliability and improve the accuracy for IPS, a random statistical method is proposed and experimentally demonstrated in the indoor environment. An effective standardization database about location fingerprints is built in the offline handling process. Meanwhile, in the online positioning process, the indoor location is obtained based on the proposed method with the Mahalanobis distance. The experimental results show that the maximum positioning error is less than 0.75 m using the random statistical method with the Mahalanobis distance. In addition, the proposed method can effectively handle the noise of WiFi signals in different indoor environments.

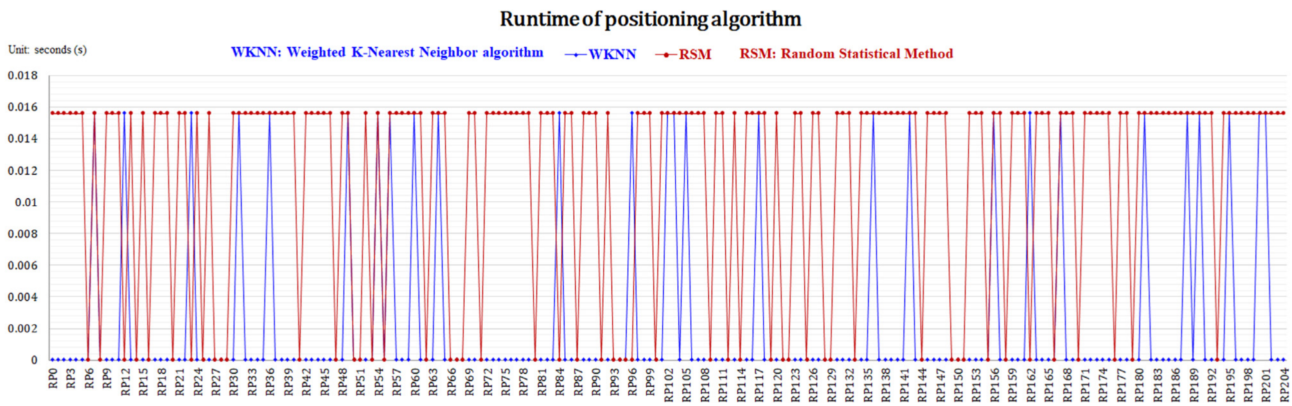


Fig. 13. The runtime of the WKNN algorithm and the positioning algorithm of the proposed method in case 1.

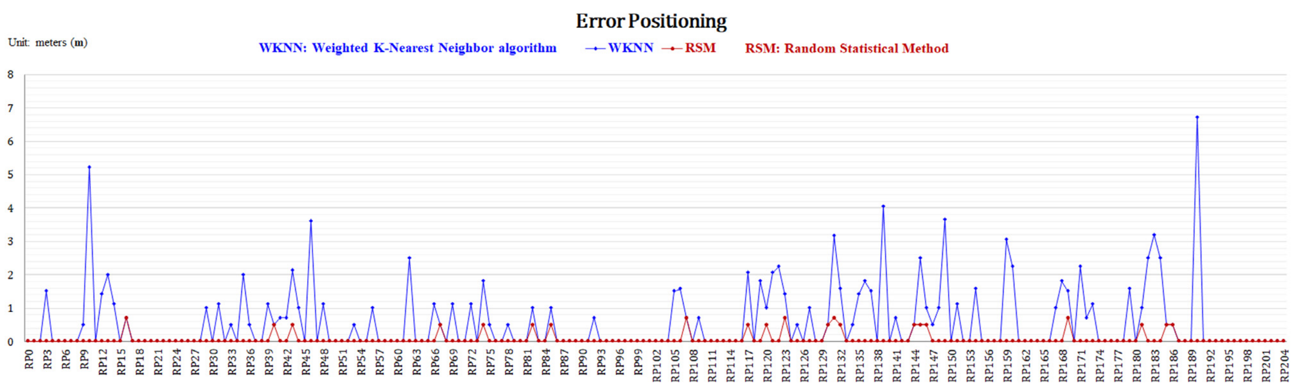


Fig. 14. The positioning error of two positioning algorithms via 205 RPs in the room in case 2.

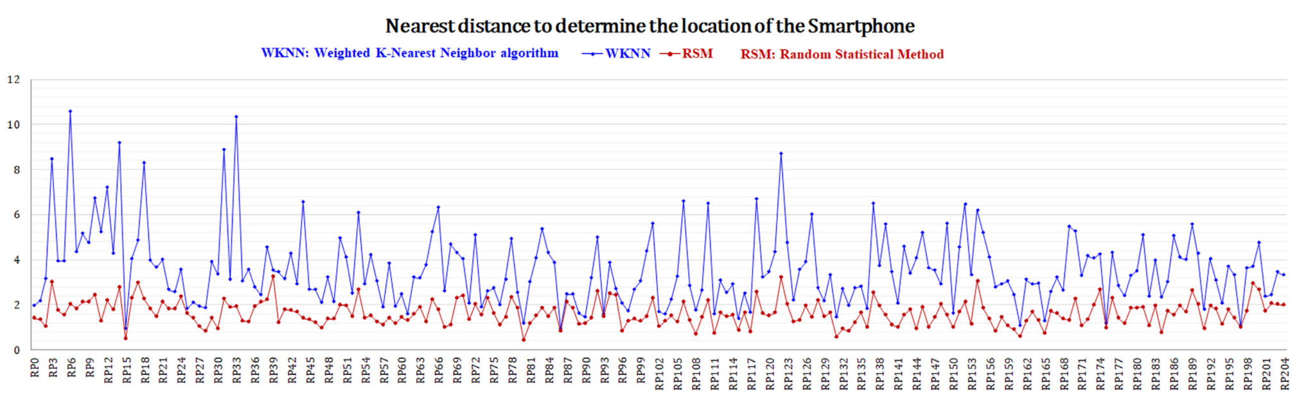


Fig. 15. The distance nearest between the actual RSSI value with the standard RSSI value via 205 RPs in case 2.

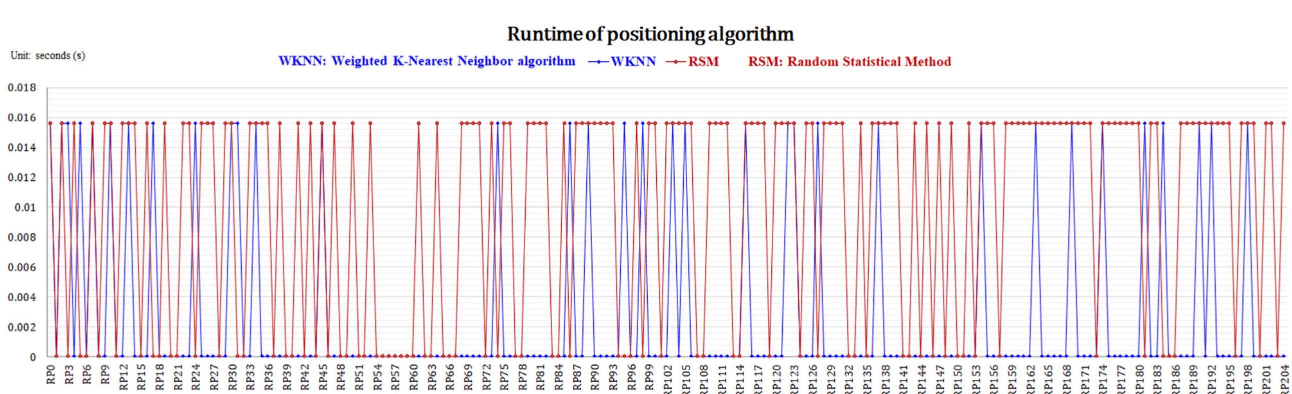


Fig. 16. The runtime of the WKNN algorithm and the positioning algorithm of the proposed method in case 2.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Duong Bao Ninh: Conceptualization, Methodology, Software, Investigation, Writing - original draft. **Jing He:** Supervision, Visualization, Resources, Project administration, Writing - review & editing. **Vu Thanh Trung:** Formal analysis, Software, Validation. **Dang Phuoc Huy:** Writing - review & editing.

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