Toward Efficient Indoor Positioning for Cloud Services in SIoT

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Abstract—**The Social Internet of Things(SIoT) introduces the concept of social relations to objects, so as to realize the discovery of objects and services, the interaction between objects, and the connection of goods network. The cloud-services in SIoT which are capable of perceiving real environments, can combine with indoor positioning technologies based on Wireless Networking Technologies to provide convenient services to users. However, indoor positioning algorithms using the received signal strength indicator (RSSI) are vulnerable to environmental interference, and the positioning results are unstable. This paper proposes an indoor positioning technology based on multidimensional spatial similarity. In particular, the fingerprint node database is optimizing by the Machine Learning(ML) mechanism in the cloud. The fingerprint nodes are screened by multidimensional spatial similarity. Moreover, the distance among the nodes is used as a weight factor to improve the traditional triangle localization algorithm. Furthermore, the weighted median Gaussian filter which can reduce the adverse effects of noise on the positioning accuracy is used to improve the efficiency of target positioning. Finally, tests are conducted in a laboratory environment. The results show that the accuracy of our method is higher than that of traditional indoor positioning methods, while the average positioning error is reduced significantly. In summary, our method has stronger anti-interference ability and meets the requirements of indoor positioning.**

Keywords-**Social Internet of Things; Cloud Services; Indoor Positioning; Machine Learning; Multidimensional Spatial Similarity; Weight Median Gaussian Filter**

I. Introduction

In general, the Social Internet of Things(SIoT) is created by the fusion of social networks and the Internet of Things(IoT). It has matured with the popularity of smart and portable items. SIoT applied the form of association existing in social networks to people with people, things with things and people with things. That makes smart items socially capable. Therefore, the SIoT has the advantages of discovering and providing services, good scalability, and the ability to apply the concept of social networking to the Internet of Everything [1].

Indoor positioning system is one of the most important application in SIoT. In recent years, more and more researchers have developed a strong interest in indoor environment positioning technology, with developing of edge computing and improving of computing power of portable devices [2], [3]. Currently, cloud services based on indoor positioning are also significantly improved in different areas, such as advertising recommendation, employee positioning and so on [4], [5]. Moreover, indoor location in cloud services can be combined with other application technologies to make full use of social Internet of things resources [6]. Therefore, there is an urgent need to develop indoor positioning technology in cloud service of SIoT.

In indoor positioning area, researchers have proposed indoor positioning methods based on measurement sensors, ultrasonic wave, infrared ray, and visual models etc. [7], [8]. Although the above-mentioned positioning methods are feasible, the implementation of traditional indoor positioning methods is based on complex infrastructure support, including complicated operation, unsatisfactory positioning effect, high hardware requirements, and poor anti-interference ability [9]. It is often difficult to set up the infrastructure required for their implementation. Hence, it is difficult to apply these methods to real environments [10].

To avoid the specific and complex infrastructure support, an indoor positioning method based on the received signal strength indicator (RSSI) [11], [12] has attracted considerable research attention in recent years. These methods mainly base on widespread, distributed, low-power WiFi signal transmitters [13], [14] in infrastructure. The principle of WiFi-based indoor positioning is that a WiFi fingerprint signal database is established on the basis of the strength of the wireless signal transmitted from a limited number of wireless access points (APs) according to the reference position, followed by matching of the current WiFi signal data for position estimation. However, there are also still many problems in RSSI-based indoor positioning methods, such as establishing data sets with a large number of reference nodes and multipath effect etc. [15]. Also, their application is limited.

To address the above-mentioned challenges, it is imperative to develop an indoor positioning method with low computational complexity and small positioning errors. To this end, the WiFi-based multidimensional spatial similarity (MDSS) indoor positioning method is proposed, which aims to acquire and make full use of the mutual information between signals. Thus, such a system can take full advantage of the mutual information among reference positions, which can significantly improve locating accuracy.

The MDSS indoor positioning system demonstrates that too many reference positions of the fingerprint data sets are not necessary and it involves three steps. First, reliable fingerprint data sets are established. Second, the multidimensional spatial similarity (MDSS) is used to determine the AP subsets for improving the accuracy of indoor positioning. Third, weights are used to modify the positioning error. The experiments are conducted in a real environment, where existing methods are compared with the MDSS method. The results demonstrate that our system can improve the performance of indoor environments when compare to others methods.

The main contributions of this paper are as follows:

1) Optimization for fingerprint data sets: To overcome the incidence of random errors, we divide the RSSI fingerprint data set collection phase into the signal collection phase and the cloud preprocessing phase. In the signal collection phase, the centrifugal direction (CD) method is used to receive the signal from eight directions at reference positions. In the cloud preprocessing phase, the weighted median Gaussian filter is used to process the signal data to reduce the influence of signal interference.

2) Multidimensional spatial similarity: To improve the positioning accuracy, it is necessary to find the closest AP subset from the RSSI fingerprint data sets. Multidimensional spatial similarity (MDSS) is used to facilitate indoor positioning on the basis of the high correlation between signal and distance. By calculating the correlation, the proposed method can achieve dimension reduction.

3) Modifying the positioning error: Weights are used to implement indoor positioning. The incidence of random errors will be higher, if the position of the measured point is directly predicted by the closest AP subset. To overcome this problem, we select weights based on the signal to improve the accuracy. Specifically, the weight parameters are set to give larger weights according to stronger AP signals to improve the accuracy. The weights can decrease not only the workload but also the data preprocessing time.

4) Experimental results: The experimental results show that our proposed system outperforms several other RSSI-based models. Moreover, we also conduct experiments to demonstrate the effectiveness of our proposed multidimensional spatial similarity mechanism in modifying the positioning error.

The remainder sections of this paper are organized as follows. Section II discusses the related work. Section III we present the detailed design of our proposed MDSS system. In Section IV, we conduct some experiments in micro-environment to show the performance of MDSS system and discuss the contrast experiments. In Section V, we conclude this paper and present prospect for future work.

II. Related Work

According to the various optimized methods, most existing indoor positioning data sets can be roughly divided into non-RSSI data sets and RSSI data sets.

Non-RSSI data sets fall under indoor positioning methods based on complex infrastructure support. Thus far, such methods have been studied intensively in the literature. For example, [7] proposed a method for indoor positioning based on radio frequency identification (RFID) technology, [14] proposed a three-edge positioning method on basis of the intensity line of the wireless signal, [16] proposed the location of the user by means of infrared beacons. However, RFID does not provide the strength of the tag signal, and the data processing is slow and suffers from a long delay in [14] and [16].

By the means of WiFi infrastructure, [11] designed a three-edge positioning method based on the WiFi fingerprint database. [17] and [12] designed an indoor positioning method on the basis of a WiFi fingerprint data set. Albeit at the low investment cost, however, these methods can only provide a general range, i.e., the positioning accuracy is relatively low and the production of the fingerprint data set in the offline phase involves a complicated workload.

In addition, some other problems persist. Hence, it is difficult to establish effective RSSI fingerprint data sets. Nevertheless, the data sets are crucial for indoor positioning. The MDSS method proposed in this paper fully exploits the multidimensional space between the WiFi access points and the measured points to improve the utilization of the data sets.

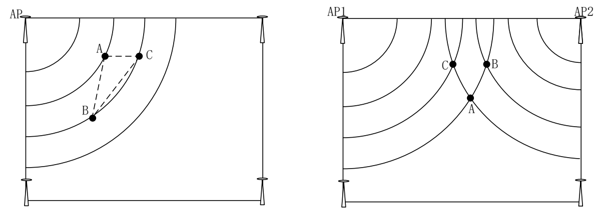
III. System Model

To achieve positioning results with high accuracy, this paper proposed the MDSS method, which involves optimization of the fingerprint data sets, processing by multidimensional spatial similarity, and modification of the positioning error, in cloud server. The AP selection strategy and the weight parameters can enable the MDSS method to decrease the computational cost and increase the localization accuracy.

A. AP Selection Strategy

When the AP signal is received, the distance between the measured point and the AP is positively correlated with the received signal strength. When only one AP signal is received, the difference between the signals received at different positions cannot represent the actual distance between the two positions. As shown in Figure 1(a), the actual distance between C and A is less than the distance between C and B. However, owing to the propagation characteristics of the signal, the difference between the signal strengths received at C and A is greater than the difference between the signal strengths received at C and B. Therefore, it is impossible to achieve indoor positioning with a single wireless signal transmission node. As shown in Figure 1(b), after adding an AP, when the signal transmitted by $AP1$ is received, according to the signal propagation theory, A and B are on the same signal intensity line. The signal strength received at C is greater than that received at A or B. When the signal transmitted by $AP2$ is received, A and C are on the same signal intensity line, and the signal strength received at B is greater than that received at A or C. Therefore, as the number of APs increases, the difference between the signal strength vectors at different positions also increases. As an AP is added, the positioning error range is effectively reduced.

Therefore, when a sufficient number of AP signal transmitters are evenly distributed in the positioning area, the physical distance between the signal strength vectors collected at any two positions will be conspicuous, and the positioning error will decrease [12]. When the number of APs is greater than 5, the positioning error will gradually stabilize. We find that the number and distribution of APs are closely related to the positioning results [12].



(a) (b)

Figure 1. Signal transmitter propagation model placed at different scene.

B. Design for RSSI Fingerprint Data Sets

First, in the signal collection phase, we use the centrifugal direction (CD) method to measure the signal data in each of the eight directions (i.e., up, down, left, right, top left, bottom left, top right, and bottom right) at the reference positions. The measurement is repeated n times for each direction, and the signal data from the n measurements are respectively stored in the matrix $P_j = [RSSI_1, RSSI_2, \cdots, RSSI_n], j \in (1, 8)$.

In the signal preprocessing stage, the data in the matrix W are preprocessed by a Gaussian filter before the weighted median filter is applied. After the weighted median filter is applied, the signal data $P_{i(k,8)} = [P_1, P_2, \cdots, P_8]$ in the eight directions are added as the RSSI fingerprint map of the position. Subsequently, the RSSI fingerprint maps are collected at each reference position and processed by the mean filter, and the signal-to-distance equation. Equation (1) is defined as the RSSI fingerprint data sets with the coordinates of the reference positions.

$$D_{(k,m)} = [D_1, D_2, \cdots, D_m] = \begin{bmatrix} D_{11} & D_{21} & \cdots & D_{m1} \\ D_{12} & D_{22} & \cdots & D_{m2} \\ \vdots & \vdots & \ddots & \vdots \\ D_{1k} & D_{2k} & \cdots & D_{mk} \end{bmatrix} \tag{1}$$

In the experimental environment, the signal data measured at each reference position follow a Gaussian distribution. Hence, in this study, the Gaussian filter is first used to process the noise. Gaussian probability curve can fit the RSSI data and remove part of the noise. Statistical methods based on intermediate values are more useful for reducing the effects of random errors. The median filter first sorts all the collected RSS data in ascending order and then takes the intermediate value as a valid value.

Actually, the signal strength value is still close to the intermediate value. To reduce the influence of the error, a threshold T is established.

We introduce the variable T to improve the signal accuracy. Assume that there are k APs in the experimental environment. Hence, k values can be measured at reference position A. When the square root of the deviation between the measured data and the intermediate value is greater than the threshold, the weight is determined by the square root of the deviation. Otherwise, the weight is determined by the threshold. The calculation of T is shown in Equation (2), where RSS_{ki}, $i \in (i = 1, 2...., n)$, is the signal value array from one AP and RSS_{km} is the intermediate value of $RSSI_{ki}$.

$$T = \frac{\sqrt{\sum_{i=1}^{n} \left(RSS_{ki} - RSS_{km}\right)^2}}{n} \tag{2}$$

Therefore, if the difference between the measured data and the intermediate value is large, the corresponding weight ratio is small vice versa. After n repetitions, n arrays of measurements are obtained from each AP. The n measurements from each AP are sorted by size, and the intermediate value is taken as RSS_{km}. The weight ω_{ki} of the i measured values from each of the k APs is calculated as shown in Equation (3).

$$w_{ki} = \frac{\frac{1}{1+max\left\{T, \sqrt{(RSS_{ki}-RSS_{km})^2}\right\}}}{\sum_{i=1}^{n} \frac{1}{1+max\left\{T, \sqrt{(RSS_{ki}-RSS_{km})^2}\right\}}} \tag{3}$$

We follow the general regularity of signal propagation and reasonably use weighted values to process the signal data. The threshold T plays the role of filtering the signal error in the calculation of the weighted value, which effectively reduces the impact of the errors.

Then, the RSS_{ki} array and its corresponding weight ω_{ki} array are used to perform an inner product operation according to Equation (4). Finally, the measured value of one AP at A is obtained. By performing the above-mentioned operations on the k APs, we can obtain the fingerprint map at A.

$$RSS_{ki} = \sum_{i=1}^{n} w_{ki} * RSS_{ki} \tag{4}$$

In this study, the original RSS data collected at a certain measured point are tested using different filtering methods to compare their filtering effects. The raw data and processed data are summarized in the following table:

Table I
THE DIFFERENT FILTERS HAVE INFLUENCE ON ERROR OF RSS DATA.

	Variance	Standard deviation	Mean	Maximum value	Minimum value	Fluctuation range
	/m		/dBm			
Raw data	1.87	3.16	-59.27	-53.39	-66.59	13.20
Weighted median filter	1.63	2.05	-58.45	-54.18	-65.67	11.49
Gaussian filter	1.39	1.89	-57.13	-55.63	-63.26	7.53
Weighted median Gaussian filter	1.07	1.03	-58.55	-55.98	-60.27	4.29

From the data in this table, we can see that the last filtering method is obviously superior to the others, and the processed data are more stable, as shown in Figure 2.

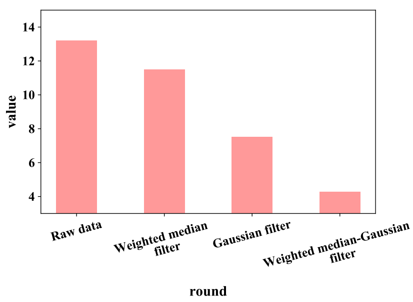


Figure 2. Fluctuation range of different filters.

The signal data are collected at m reference positions by the CD method, and the data are measured n times in each direction. Assume that there are k AP transmitters. The matrix formed by the data from one direction of one reference position is $P_{1(k,n)}$, the matrix formed by the data from every direction of one reference position is $P_{2(k,8)}$, and the matrix formed by the data measured at each reference position is $P_{3(k,m)}$.

For each direction of each reference position, the n measured values corresponding to each AP are processed by a weighted median Gaussian filter to form the matrix $P_{2(k,8)}$. The k-dimensional vectors of the 8 directions of the m reference positions are reduced by the mean filter to obtain the matrix $P_{3(k,m)}$. Using the signal-to-distance equation, we can convert the signal strength data in the matrix $P_{3(k,m)}$ into a corresponding matrix with respect to the distance. Assume that the matrix is $D_{(k,m)}$, where n_m is the registered number of measurements, n_d is the registered number of directions, and n_p is the registered number of reference positions. The algorithm is presented in Algorithm 1.

C. Design for Multidimensional Spatial Similarity

The objective of the MDSS method is to find the n closest samples based on the multidimensional spatial similarity in the fingerprint data sets using Algorithm 1. In this process, by assuming that there are m reference positions and k APs,

Algorithm 1: Process of creating RSSI fingerprint data sets.

Input: RSSI data collected by APs at each reference position
Output: RSSI fingerprint data sets
Initialization: Set n_p = 0, n_m = 0, n_d = 0; Initialize $P_{1(k,n)}$, $P_{2(k,8)}$, $P_{3(k,m)}$, $D_{(k,m)}$.
for *each of m reference positions* **do**
  for *measuring 8 directions at each reference position* **do**
    for *n measurements in each direction* **do**
      if $n_m \leq n$ **then**
        measure the values of the direction at the reference position ;
        add data to $P_{1(k,n)}$;
        n_m + = 1 ;
      else
        measure the next direction ;
    if $n_d \leq 8$ **then**
      process $P_{1(k,n)}$ by the weighted median Gaussian filter ;
      add data to $P_{2(k,8)}$;
      n_d + = 1 ;
    else
      measure the next reference position ;
  if $n_p \leq m$ **then**
    process $P_{2(k,8)}$ by the mean filter ;
    add data to $P_{3(k,m)}$;
    n_d + = 1 ;
  else
    return $P_{3(k,m)}$;
Numerical Conversion: Process $P_{3(k,m)}$ by the signal-to-distance equation ;
Numerical Storage: Obtain the data for $D_{(k,m)}$ with the coordinates of the reference positions ;
final ;
return $D_{(k,m)}$;

we calculate the multidimensional spatial similarity between the measured points and the RSSI fingerprint data sets using the Euclidean distance formula. The inputs are RSSI vectors $R_{1(k,1)}$ at the measured points and RSSI fingerprint data sets $D_{(k,m)}$. The output $S_{(m,1)}$ is a sorted array based on the multidimensional spatial similarity between the measured points and the reference positions. $R_{2(k,1)}$ is the matrix for storing the distance corresponding to $R_{1(k,1)}$. $M_{(m,1)}$ is the result of the multidimensional spatial similarity between $R_{2(k,1)}$ and $D_{(k,m)}$. Then, by sorting $M_{(m,1)}$ by size, the result $S_{(m,1)}$ is obtained. The multidimensional spatial similarity between the measured points and the fingerprint reference positions is shown in Algorithm 2.

Algorithm 2: Comparison of multidimensional spatial similarity

Input: $R_{1(k,1)}$: RSS values collected at the measured point;
$D_{(k,m)}$: RSSI fingerprint data sets;
Output: $S_{(m,1)}$: RSSI multidimensional spatial similarity distance;
Initialize $R_{2(k,1)}$, $M_{(m,1)}$, and $S_{(m,1)}$;
Convert $R_{1(k,1)}$ by the signal-to-distance equation into $R_{2(k,1)}$;
Main Loop:
if *any vector in* $D_{(k,m)}$ *is not compared* **then**
  compute the multidimensional spatial similarity between $R_{2(k,1)}$ and $D_{(k,m)}$;
  store the results in $M_{(m,1)}$;
sort the values in $M_{(m,1)}$ to be stored in $S_{(m,1)}$;
final ;
return $S_{(m,1)}$;

D. Modify the positioning error

After the RSS values from each AP are processed by Algorithm 1, the RSSI fingerprint data sets and the measured signal data are taken as the input of Algorithm 2. We assume that we can get the coordinates of three reference positions with the closest multidimensional spatial similarity. This paper adopts the weighted triangle localization method to estimate the coordinates of the measured points.

The formula for calculating the weight parameter is as follows:

$$w_1 = \frac{d_2 + d_3}{2 * \sum_{i=1}^{3} d_i}, \quad w_2 = \frac{d_1 + d_3}{2 * \sum_{i=1}^{3} d_i}, \quad w_3 = \frac{d_1 + d_2}{2 * \sum_{i=1}^{3} d_i} \tag{5}$$

where d_1, d_2, and d_3 are the distances between the measured point and the three AP nodes. The mathematical model of the indoor positioning algorithm proposed in this paper is as follows:

$$(x_{est}, y_{est}) = w_1 * (x_1, y_1) + w_2 * (x_2, y_2) + w_3 * (x_3, y_3) \tag{6}$$

where (x_1, y_1), (x_2, y_2), and (x_3, y_3) are the intersection coordinates. Through the above-mentioned methods, more accurate positioning coordinates can be obtained.

The error calculation formula is as follows:

$$d_{error} = \sqrt{(y_{est} - y_{real})^2 + (x_{est} - x_{real})^2} \tag{7}$$

where (x_{est}, y_{est}) is the coordinate of the predicted position and (x_{real}, y_{real}) is the real coordinate.

The proposed method predicts the measured point on the basis of the multidimensional spatial similarity. In this process, the output $S_{(m,1)}$ of Algorithm 2, the RSSI fingerprint data sets $D_{(k,m)}$, and the real position P_{real} are the input variables. To predict a more accurate result, this method takes the first 3 values from the output $S_{(m,1)}$ of Algorithm 2. Then, the 3 values, after transformed into distance with their coordinates, are input to the triangle localization formula to obtain the coordinates $P_{(3,2)}$ of the intersection points. The weight vector $W_{(3,1)}$ is crucial for improving the position result P_{est}. The error V_{error} is the basis for measuring the quality of positioning methods. A few variables still need to be explained. $ls_{(3,1)}$ are the first three values from $S_{(m,1)}$, and the first 3 coordinates corresponding to $ls_{(3,1)}$ from $D_{(k,m)}$ are $D_{1(3,2)}$. The procedure of indoor positioning based on multidimensional spatial similarity is shown in Algorithm 3.

Algorithm 3: Indoor positioning algorithm based on multidimensional spatial similarity

Input: $S_{(m,1)}$: output of Algorithm 2;
$D_{(k,m)}$: RSSI fingerprint data sets;
P_{real}: real position;
Output: C_{est}: predicted position of the measured point;
V_{error}: error of positioning;
initial: $ls_{(3,1)}$, $D_{1(3,2)}$, $W_{(3,1)}$, $P_{(3,2)}$, P_{est}, and V_{error};
Take the first 3 values from $S_{(m,1)}$ as $ls_{(3,1)}$;
Take the first 3 coordinates corresponding to $ls_{(3,1)}$ from $D_{(k,m)}$ as $D_{1(3,2)}$;
Take $ls_{(3,1)}$ into Equation (5) to calculate the weights as $W_{(3,1)}$;
Take $D_{1(3,2)}$ into the triangle localization formula to calculate the coordinates of the intersection points as $P_{(3,2)}$;
Take $W_{(3,1)}$ and $P_{(3,2)}$ into Equation (6) to predict the measured position as P_{est};
Calculate the error V_{error} by Equation (7);
final ;
return C_{est} and V_{error} ;

It is important to fix the signal acquisition device at each reference position to prevent human error. We collected 10 samples in each of the 8 directions, and we collected the signal at intervals of 2 s. The laboratory environment was deployed as shown in Figure 3.

At the measured points, the signal strength values of all the WiFi APs were collected using the same signal receiver. In the fingerprint data sets, the three reference position coordinates with the closest multidimensional spatial similarity to the measured points were selected. The evaluation involved three indoor positioning methods, namely the weighted KNN

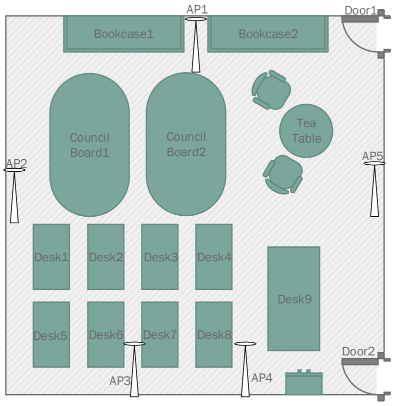


Figure 3. Laboratory layout.

positioning algorithm, the triangle localization method, and the MDSS method proposed in this paper. Each set of experiments was conducted in the same laboratory environment, and the data collected at the same measured points were used. The weighted KNN positioning algorithm used the fingerprint data sets processed by the Gaussian filter, while the triangle localization method and the proposed MDSS method used the fingerprint data sets processed by the weighted median Gaussian filter. Thus, the weighted KNN algorithm and the triangle localization method were used for comparison with the proposed MDSS method.

IV. Performance Evaluation

WiFi signal data sets were collected and uploaded to the cloud server by the mobile device, and the positioning model ran on the cloud server. The MDSS method was implemented in a laboratory with dimensions of 10m*10m. To facilitate the setting of the reference positions and subsequent modeling, we divided the laboratory into units of 2 square meters. Then, we placed 5 WiFi signal transmitter nodes and set 12 reference positions evenly in the laboratory to collect location data, as shown in Figure 4.

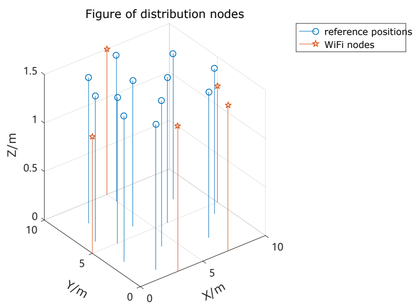


Figure 4. Distribution diagram of WiFi nodes and reference positions.

A. Experiments

In the experiments, RSSI fingerprint data set for the triangle localization method and the MDSS method, was processed by the weighted median Gaussian filter. Then, the weighted KNN method, the triangle localization method, and the MDSS method were used to achieve positioning. The errors of the three methods are the basis for comparing their performance. The experimental steps are outlined in Algorithm 4. $D_{(k,m)}$ represents the fingerprint data sets, $S_{(m,1)}$ is the output of Algorithm 2, and P_{real} represents the real coordinate of the measured points.

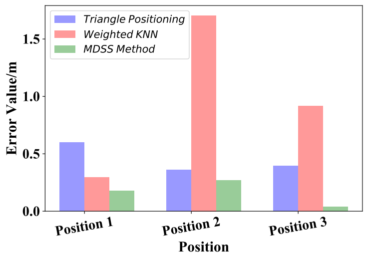
Algorithm 4: Experimental steps

Input: M_p: measured points matrix composed of $RSSI$ vectors and coordinates
Output: $C_{estimate}$: predicted coordinates matrix of M_p;
V_{est}: error matrix of $C_{estimate}$

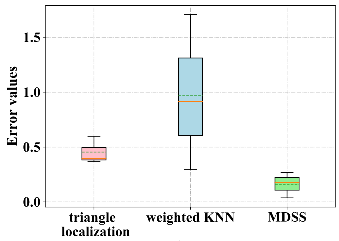
Initialize: V_i, P_{KNN};
for *each vector* V_i *from the measured points matrix* M_p **do**
  if *the MDSS method* **then**
    Create $D_{(k,m)}$ using Algorithm 1;
    Process vector V_i from M_p using Algorithm 2;
    Process $D_{(k,m)}$, $S_{(m,1)}$, and real coordinate P_{real} using Algorithm 3;
    goto return;
  if *the Weighted KNN method* **then**
    Create $D_{(k,m)}$ and M_p using the Gaussian filter;
    Filter the closest K reference positions P_{KNN} from the $D_{(k,m)}$;
    Calculate the weights: $\omega = \frac{\frac{1}{RSSI_i}}{\sum_{i=1}^{m}\frac{1}{RSSI_i}}$;
    Predict the positions: $(x_{KNN}, y_{KNN}) = \omega_{KNN} \cdot P_{KNN}$;
    Calculate the error using Equation (7);
    goto return;
  if *the Triangle localization method* **then**
    Create $D_{(k,m)}$ using Algorithm 1;
    Use $D_{1(}3,2)$ as the basis for positioning;
    Calculate the intersection points using triangle localization formula;
    Predict the measured points using mean forumla;
    Calculate the error using Equation (7);
    goto return;
Compare the experimental results of all the positioning algorithms.
final ;
return $C_{estimate}$ and V_{est};

B. Comparison of positioning results

In this paper, the positioning coordinates and actual coordinates of the three positioning methods are summarized in Table II, and the errors of the three methods are shown in Figure 5.



(a)



(b)

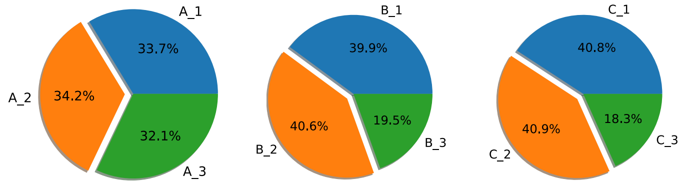
Figure 5. Comparison of positioning error.

Table II
THE POSITIONING COORDINATES OF THE THREE POSITIONING METHODS AND ACTUAL COORDINATES.

Real coordinates		Triangle positioning	Weighted KNN algorithm	MDSS method
x	5	5.166	4.953	4.985
y	6	6.575	6.29	6.177
Error/m		0.598	0.294	0.1778
x	3	3.072	4.39	2.752
y	5	5.363	5.99	5.105
Error/m		0.3698	1.706	0.269
x	5	5.209	5.001	5.022
y	8	8.336	7.084	8.03
Error/m		0.395	0.916	0.037

From the experimental results, it can be concluded that as the weighted KNN method uses only the Gaussian filter to process the received data set, the results of the proposed method are significantly better. Thus, the weighted median Gaussian filter is more suitable than the Gaussian filter for the indoor positioning problem under the experimental conditions.

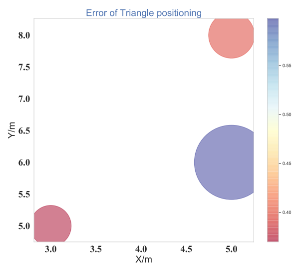
The pie charts, Figure 6(a)-6(c), are used to display the weight parameters for each reference location of the MDSS method. The greater the proportion, the closer the distance. We use the bubble charts to visually show the accuracy of these three methods in Figure 7(a)-Figure 7(c). From these



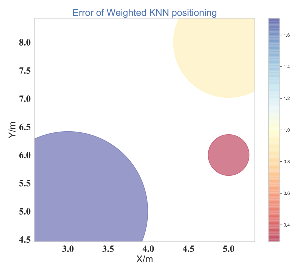
(a) (b) (c)

Figure 6. Weight ratio.

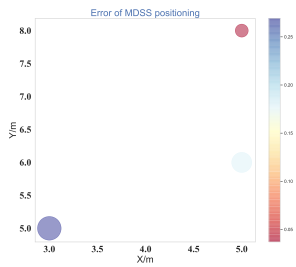
figures, we can see the magnitude of the error is proportional to the size of the bubble charts. In contrast, the errors of triangle localization method and weighted KNN method are larger than MDSS method. In Figure 5(b), the horizontal axis represents the localization methods, and the vertical axis denotes the ranges and positions of errors values. The errors of MDSS method are from 0.037 to 0.269, while the errors of triangle localization method are from 0.395 to 0.598 and weighted KNN method are from 0.294 to 1.706 respectively.



(a)



(b)



(c)

Figure 7. Error comparison

From Figure 5(b), we can see that the proposed method has less positioning error range and more accurate. Compared with the triangle localization method, the accuracy error is also particularly obvious that the positioning error of the MDSS method is lower than that of the triangle localization method. Thus, the positioning results of the proposed method are more stable and robust. The MDSS method shows greater localization performance.

V. Conclusion

This paper proposed the MDSS method to achieve indoor positioning. The proposed method was experimentally compared with two other positioning methods in the same laboratory environment. The results showed that, compared with the traditional RSSI indoor positioning algorithm, the MDSS method only collected a small amount of reference position signal data in the RSSI fingerprint data set acquisition phase. Further, in the positioning phase, the weighted median Gaussian filter with strong anti-interference ability was used to process the data, and the obtained positioning results were satisfactory. However, certain problems persisted. For example, factors such as WiFi position changes and signal strength attenuation should be considered, and large fluctuations would occur if there was a pedestrian or any other obstruction between the transmitter and the receiver. In addition, the edge devices were not fully utilized to optimize cloud location model. Therefore, how to dynamically generate and store WiFi fingerprint data by cloud technology is a topic for future research.

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Response to Reviewer 1's Comments

Your comment: *1. Contributions: This paper focuses on the issues of vulnerability, instability and environmental interference in indoor positioning algorithms that uses received signal strength indicator (RSSI). These issues can prevent cloud-services in Social Internet of Things (SIoT) from providing convenient services to users. In particular, the authors propose an indoor positioning technology based on multidimensional spatial similarity. The proposed approach supports* (1) *optimization for ?ngerprint data sets to overcome the incidence of random errors,* (2) *multidimensional spatial similarity to improve the positioning accuracy, and* (3) *modifying the positioning error by assigning weights to implement indoor positioning. Furthermore, the proposed approach is noticeably evaluated using a laboratory environment.*
.

Our response: Thank you for your summary of our work.

Your comment: *2. Strength: Overall, the paper is very well presented and organized. The research problem is stated, the contributions are clearly justified, and the proposed approach is noticeably evaluated. .*

Our response: Thank you for your appreciation for our work.

Your comment: *3. Weaknesses: (1) However, I was expecting more details about hardware specification in the laboratory environment. I mean what kind of APs, WiFi signal transmitters, cloud server (which cloud service was used).*

Our response: Thank you for your comments. We used the TP-Link WIFI routers as a transmitter for the AP. We used the system developed by our laboratory to collect signal data. The system established a data transmission link with the laboratory server. We regard this server as a cloud server.

Your comment: *(2) In addition, in which language the proposed system is developed?*

Our response: For our indoor positioning system, we used Python language combined with numpy,pandas, dataframe and other packages for programming.

Response to Reviewer 2's Comments

Your comment: *Contributions: The paper presents an approach to indoor localization based on signal strength. It uses statistical classification techniques. An evaluation is provided to show the accuracy of the proposed system.*

Our response: Thank you for your summary for our work.

Your comment: *Comments: (1) The paper has very little to do with Cloud research and is in fact more in the area of pervasive computing. The four contributions of the paper listed on page two of the paper are all about pervasive computing. "cloud services based on indoor positioning" are mentioned early in the introduction but are not really defined and do not really appear as the case study of the paper throughout the narrative.*

Our response: Thank you for your suggestion. Your opinion does point out the problem of this paper. In fact, when doing experiments, we collect signal data through the system developed by our laboratory. The system established a data transmission link with the laboratory server. It was through this software that we realized the cloud positioning. The following is the schematic diagram of our indoor positioning system, as shown in Figure A.

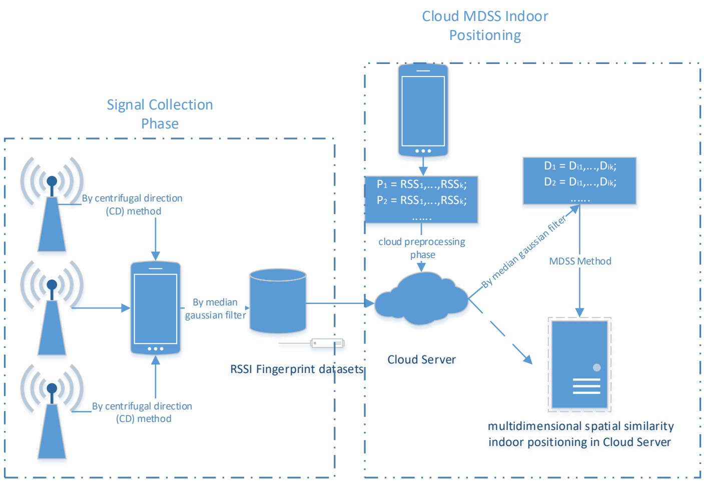
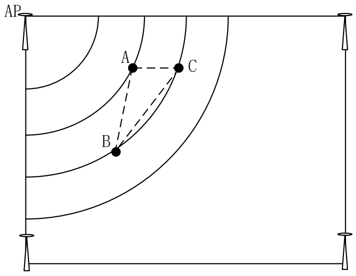


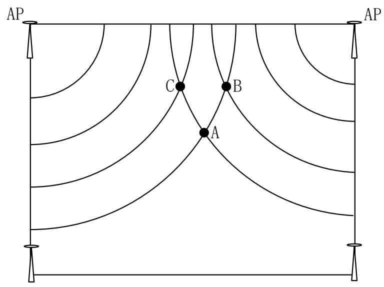
Figure A: The framework of MDSS indoor positioning.

Your comment: *(2) Figure 1 provides a model of perfect signal diffusion with nice equidistance line. In practice WiFi signal (or similar communication signals like bluetooth) are rarely so nicely shaped. So localizing based on such a model can be done only theoretically.*

Our response: Thank you very much for your comments. Your opinion is undoubtedly correct, and we did collect data to confirm this conclusion in the initial stage of the laboratory. In fact, we use the contour method only to show that multiple WIFI transmitters are essential for achieving more accurate indoor positioning. Because, theoretically, as shown in Figure 2(a), assuming that the signal strength at point B and point C is the same, we just know the signal strength at AP from one point is not enough to figure out which point B and C are closer to point A. When we set up another AP emitter, we can screen out the points closer to point A with more evidence, as shown in Figure 2(b). Figure B has nothing to do with the signal strength collected in the real environment. In order to meet the submission requirements, we deleted some secondary images. There is a diagram showing the effect of the number of AP signal transmitters on the error of indoor positioning results, as shown in Figure C. We found that when the number of AP reached 5, the positioning error would not change significantly, so we set the number of AP to 5.



(a)



(b)

Figure B: Signal transmitter propagation model placed at different scene.

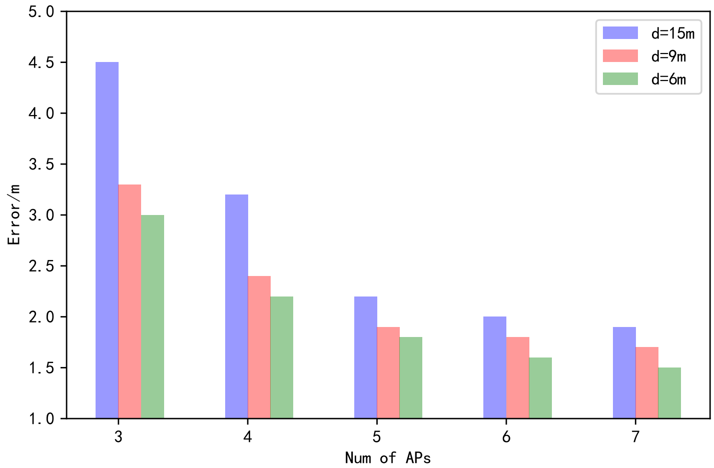


Figure C: The effect of the number of AP on the positioning error.

<u>**Your comment:**</u> *(3) The presentation should be more formal. E.g., Theorem 1 does not contain a mathematical statement to be proved, but rather a qualitative proposition.*

<u>**Our response:**</u> Thank you for your review. As for the following Equation (1), it is indeed one of our means to deal with the error of signal transmission. We have removed the content of theory 1 and changed it to the following content:

To improve the signal accuracy, we introduce the variable T, Assume that there are k APs in the experimental environment. Hence, k values can be measured at reference position A. When the square root of the deviation between the measured data and the intermediate value is greater than the threshold T, the weight is determined by the square root of the deviation. Otherwise, the weight is determined by the threshold T. The calculation of T is shown in Equation (1), where RSS_{ki}, $i \in (i = 1, 2...., n)$, is the signal value array from one AP and RSS_{km} is the intermediate value of $RSSI_{ki}$.

$$T = \frac{\sqrt{\sum_{i=1}^{n} (RSS_{ki} - RSS_{km})^2}}{n} \tag{1}$$

Therefore, if the difference between the measured data and the intermediate value is large, the corresponding weight ratio is small vice versa. After n repetitions, n arrays of measurements are obtained from each AP. The n measurements from each AP are sorted by size, and the intermediate value is taken as $RSSI_{km}$. The weight ω_{ki} of the i measured values from each of the k APs is calculated as shown in Equation (2).

$$w_{ki} = \frac{\frac{1}{1+max\left\{T, \sqrt{(RSS_{ki}-RSS_{km})^2}\right\}}}{\sum_{i=1}^{n} \frac{1}{1+max\left\{T, \sqrt{(RSS_{ki}-RSS_{km})^2}\right\}}} \tag{2}$$

We follow the general regularity of signal propagation and reasonably use weighted values to process the signal data. The threshold T plays the role of filtering the signal error in the calculation of the weighted value, which effectively reduces the impact of the errors.

Your comment: *(4) Along with figures 4 and 5, it would be useful to see a map of signal strengths to understand how the space is (possibly) partitioned into localization areas.*

Our response: Thank you for your review. According to your reviews, we supplemented the signal strength diagram for the position, as shown in following Figure D:

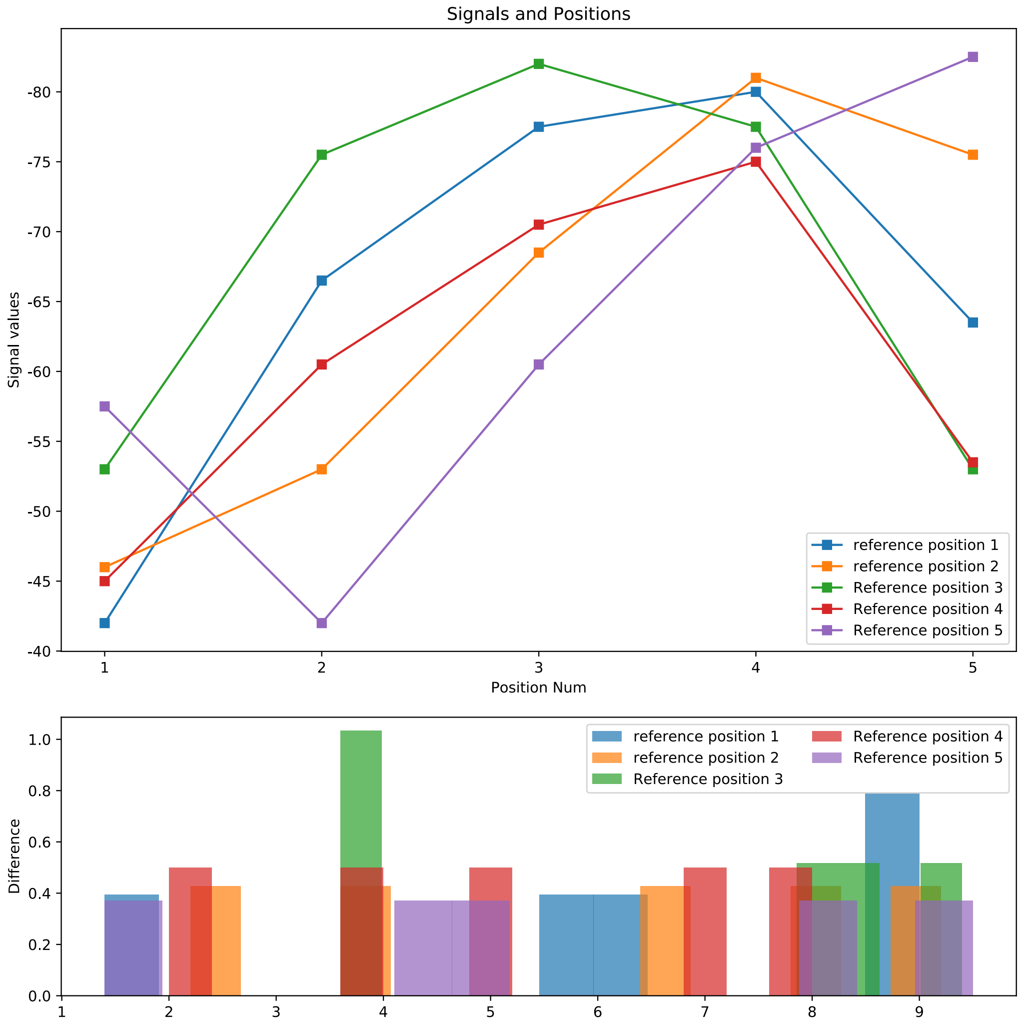


Figure D: The relationship between signal strength and position.

Response to Reviewer 3's Comments

Your comment: *Contributions:*

1. The RSSI fingerprint dataset collection phase has been divided into signal collection and cloud preprocessing, where the weighted Gaussian filter is used to reduce the influence of signal interference.

2. Multidimensional spatial similarity is used to facilitate indoor positioning. A weighting mechanism is adopted to further improve the accuracy.

3. Some experiments are conducted to demonstrate the effectiveness of the proposed approach.

Our response: Thank you so much for your summary and appreciation for our work.

Your comment: *Comments: It is not clear what machine learning mechanism is used to optimize the fingerprint node database.*

Our response: Thank you very much for your comments. In fact, we processed the fingerprint data set in two stages.

In signal collection phase, in order to obtain more accurate reference location data, we first divided each reference location into 8 directions through the centrifugal direction (CD) method, and then collected fingerprint data for each direction. We made n measurements for each set of AP transmitters. For a set of signal values for each AP, we first use gaussian filter denoising. Second, we use a median filter to sort all the RSS data collected in ascending order. Let's take the intermediate value as a reference value. Then, weight variables w_{ki} are adopted, as shown in Equation (3). If the difference between the measured data and the intermediate value is large, the corresponding value is given a small weight, and vice versa.

In the cloud preprocessing phase, in order to reduce the error, we still use median gaussian filter to process the signal data. We use Euclidean norm as the basis for obtaining similar reference positions in RSSI fingerprints database.

$$w_{ki} = \frac{\frac{1}{1+max\left\{T,\sqrt{(RSS_{ki}-RSS_{km})^2}\right\}}}{\sum_{i=1}^{n}\frac{1}{1+max\left\{T,\sqrt{(RSS_{ki}-RSS_{km})^2}\right\}}} \tag{3}$$

Actually, even if we use the above signal processing methods, there will inevitably be some error. Therefore, in order to further reduce the impact of error, we introduce the concept of threshold T, as shown in Equation (4). When the square root of the deviation between the measured data and the median value is greater than the threshold value T, the weight is determined by the square root of the deviation. Otherwise, the weight is determined by the threshold T.

$$T = \frac{\sqrt{\sum_{i=1}^{n}\left(RSS_{ki} - RSS_{km}\right)^2}}{n} \tag{4}$$

We can get the value of an AP at a reference location by taking the inner product of the signals array and the corresponding array of weights, as shown in Equation (5). By doing this with k APs, we can obtain a fingerprint at this reference location. The RSSI fingerprint database is collected at each reference location through the above methods.

$$RSS_{ki} = \sum_{i=1}^{n} w_{ki} * RSS_{ki} \tag{5}$$