Improved Wi-Fi RSSI Measurement for Indoor Localization

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Improved Wi-Fi RSSI Measurement for Indoor Localization

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***Abstract*—Indoor localization based on Wi-Fi received signal strength indication (RSSI) has the advantage of low cost and easy implementation compared with a range of other localization approaches. However, Wi-Fi RSSI suffers from multipath interference in indoor dynamic environments, resulting in significant errors in RSSI observations. To handle this issue, a number of different methods have been proposed in the literature, including the mean method, Kalman filter algorithm, and the particle filter algorithm. It is observed that these existing methods may not perform sufficiently well in ever-changing dynamic indoor environments. This paper presents an algorithm to improve RSSI observations by using the average of a number of selected maximum RSSI observations. Smoothness index is employed to evaluate the quality of RSSI so as to select an appropriate number of RSSI observations. Experiments were conducted in four rooms and a corridor within an office building and the results demonstrate that the proposed method considerably outperforms the existing algorithms in terms of positioning accuracy which is defined as the cumulative distribution function of position error.**

***Index Terms*—Indoor localization, Wi-Fi signal strength, average of maximum RSSI observations, smoothness index, dynamic environment**

I. Introduction

Wireless Fidelity (Wi-Fi) positioning system has become more and more popular in indoor environments due to the wide deployment of Wi-Fi in recent years. The positioning method based on received signal strength indication (RSSI) [1] has become the mainstream of indoor positioning, with advantages of low cost, wide coverage and without the need of any hardware addition or modification [2]. This method is generally divided into two categories: the trilateration algorithm and the location fingerprint positioning method [3-4]. The trilateration algorithm is based on the principle of Distance Intersection [5], and the fingerprint positioning method is based on the use of a database and specific geometric or probabilistic algorithm to calculate the location of the unknown point [6]. The extraction of RSSI is vital to both the trilateration algorithm and the fingerprint positioning method. The mean value of RSSI is usually taken as its true value in Wi-Fi indoor positioning. However, the mean value of RSSI does not always accurately reflect the dynamic behavior of RSSI, caused by a variety of factors such as multipath and non-line-of-sight (NLOS) propagation in indoor environment [7]. Kalman filter and particle filter can be utilized for RSSI based ranging and positioning, so that positioning accuracy can be improved to some extent [8]. However, these algorithms are typically intended to mitigate either the linear or nonlinear noise, which may not be effective to deal with the ever-changing dynamics of the indoor environment. This paper proposes an algorithm using the average of a number of maximum RSSI observations, motivated by analysis of the spatial resolution of the signal strength of Wi-Fi [9] and RSSI signal characteristics [10] in different scenarios. The performance of the proposed Wi-Fi indoor positioning method is compared with that of the mean, Kalman filter and particle filter methods under both steady-state environment and dynamic environment. The experimental results demonstrate that it has a better positioning accuracy than other three methods.

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II. Algorithm of RSSI Integration Based on the Maximum

A. *Analysis of the Spatial Resolution of the Signal Strength of Wi-Fi*

The spatial resolution of the signal strength of Wi-Fi is the scale of the RSSI "measuring ruler". According to the wireless signal attenuation model [11], Wi-Fi signal intensity attenuation model is described by

$$P_{r,\mathrm{dB}}(d)=P_{r,\mathrm{dB}}(d_0)-\eta 10\log_{10}(\frac{d}{d_0}) \tag{1}$$

where $P_{r,\mathrm{dB}}(d_0)$ and $P_{r,\mathrm{dB}}(d)$ are the received signal power at points which have a distance d_0 and d to the transmitter, respectively, and η is the pathloss exponent. Since d_0, $P_{r,\mathrm{dB}}(d_0)$, and η are known in advance through modeling and $P_{r,\mathrm{dB}}(d)$ is the measured received signal power, the

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unknown distance d can be calculated by

$$d_i = d_0 10^{\frac{P_{r,\mathrm{dB}}(d_0) - P_{r,\mathrm{dB}}(d_i)}{10\eta}} \tag{2}$$

From (2) the differential distance can be readily obtained as

$$\Delta d_{ij} = d_i - d_j = d_0 10^{\frac{P_{r,\mathrm{dB}}(d_0) - P_{r,\mathrm{dB}}(d_i)}{10\eta}} - d_0 10^{\frac{P_{r,\mathrm{dB}}(d_0) - P_{r,\mathrm{dB}}(d_j)}{10\eta}} \tag{3}$$

Similar to the results reported in [12], the pathloss exponent in an office building with rooms separated by concrete walls and corridors is selected to be 3, d_0 is chosen to be 1 m, and $P_{r,\mathrm{dB}}(d_0)$ is -20dB. Table I displays a range of RSSI values and the corresponding propagation distances. The differential distance between each pair neighboring RSSI values are also shown. The left panel is for the integer RSSI and the interval is 1dB, while the right panel is for RSSI interval of 0.1dB. All the distances and the differential distances are calculated using (2) and (3) and the given RSSI values. Note that the RSSI provided by the system is an integer number, while the average of a number of RSSI observations can be a fraction.

TABLE I
RELATIONSHIP BETWEEN WI-FI

RSSI(dB)	d(m)	Δd(m)	RSSI(dB)	d(m)	Δd(m)
-100	464.159		-100	464.159	
-99	429.866	34.293	-99.9	460.610	3.549
-98	398.107	31.759	-99.8	457.088	3.522
…	…	…	…	…	…
-70	46.416	3.703	-71	50.119	0.386
-69	42.987	3.429	-70.9	49.736	0.383
…	…	…	…	…	…
-40	4.642	0.370	-44.5	6.556	0.051
-39	4.299	0.343	-44.4	6.506	0.050
…	…	…	…	…	…
-22	1.166	0.093	-20.2	1.015	0.008
-21	1.080	0.086	-20.1	1.008	0.008

As shown in Table I, given the same RSSI difference, larger RSSI produces smaller differential distance, providing better spatial resolution. That is, to achieve better positioning accuracy, higher RSSI should be employed. Another observation is that differential RSSI of 0.1dB produces much smaller differential distance (and hence much better spatial resolution) than differential RSSI of 1dB. Therefore, it is an advantage to use average of a number of RSSI observations instead of individual RSSI observations for position determination. Based on the above consideration, we propose a new RSSI extraction method as described in the following subsection.

B. Proposed RSSI Extraction Algorithm

Usually, the determination of RSSI signal characteristics is mainly based on the mean or probability of RSSI signal. However, due to multipath and non-line-of-sight propagation in complex and dynamic indoor environment, characteristics of RSSI can be rather different temporally and spatially. There are basically four general situations as follows. 1) The observed signal shows normal distribution under a steady-state environment, assuming no multipath interference. 2) The signal probability distribution will forms two centers when the multipath interference is as strong as the line of sight signal and both are stable, namely bimodal distribution. 3) The signal probability distribution is left-skewed in the presence of weak multipath interference. 4) The signal probability distribution is right-skewed if multipath interference is stronger than the signal. Therefore, the mean of RSSI signal does not accurately reflect the dynamic behavior of RSSI. Meanwhile, the Kalman filter algorithm [13] and the particle filter algorithm [14] may not be able to effectively handle complex RSSI measurement noise in ever-changing dynamic indoor environment.

In an indoor environment which is the application scenario for the proposed localization method, due to walls and other structures, multipath propagation usually prevail, causing significant fluctuation in the RSSI observed by a mobile device, which is also called fading. That is why typically the average of the RSSI over a certain period is used as RSSI. Meanwhile, shadowing such as due to the presence of a pedestrian between transmitter and receiver especially close to either of them will considerably reduce the RSSI. In addition, the Wi-Fi radio channel is generally shared by different systems or devices such as various Bluetooth devices and microwave oven, which use the same frequency band, so there may exit co-channel interference if such devices are nearby and in operation. The interference may also decrease RSSI considerably. That is, RSSI is significantly affected by fading, shadowing, and interference. The strong RSSI would be mainly affected by fading, while the weak RSSI may be affected by one or more of the three factors. To avoid the effect of shadowing and interference, the weakest RSSI values should be excluded. Therefore, it is proposed to make use of the maximum RSSI values for localization purpose, which also improves differential distance as indicated by the theoretical results shown in Table I. Since the maximum RSSI values are also typically affected by fading, averaging can be used to reduce the effect of fading to achieve better localization performance. Averaging also produces fractional RSSI values instead of integer values provided by device, enabling smaller differential distance as mentioned earlier. The flowchart of the proposed RSSI measurement scheme is shown in Figure 1.

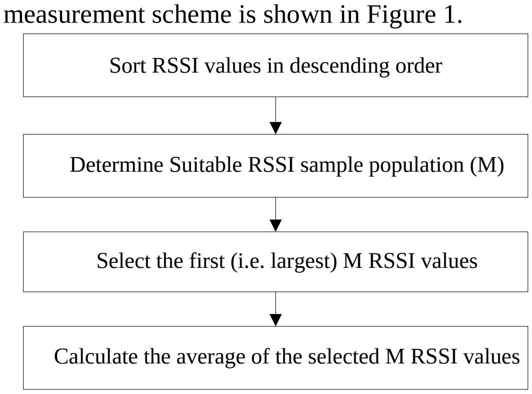

Fig. 1. The flow chart of improved RSSI measurement algorithm.

We also have conducted a comparative analysis of the impact

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of different RSSI characteristics (the median, mode, and the maximum) on Wi-Fi indoor positioning accuracy in another paper of ours [15]. The conclusion is that the maximum RSSI produces better positioning accuracy than other RSSI characteristics in general. However, in some cases the maximum RSSI produces poor positioning performance. That is why we propose to use the average of those M selected maximum RSSI to reduce or eliminate the impact of possible instability of the single maximum RSSI. The suitable value of M will be determined empirically from the experimental data as described in the next section.

III. EXPERIMENT AND ANALYSIS OF ITS RESULT

In order to evaluate the performance of the proposed RSSI extraction algorithm, experiments were conducted in four rooms (404, 408, 412, and 414) and one corridor on the fourth floor of the Office Building of School of Geodesy and Geomatics within Wuhan University. Figure 2 shows the floor plan of the fourth floor, where there are six APs denoted by △ and located in five different rooms. The space of interest in each room is divided into grids whose dimensions are 1.3m× 1.3m. The four vertices (circle) of the location area in each room are selected as reference points, while other grid points (solid dot) are the test points whose positions are to be determined. The sampling rate of 1 s was used to collect the data for 6 minutes at each grid point. To ensure consistency, all the data are collected using the same mobile phone. For convenience, an independent coordinate system is established in each room for position determination purpose.

A. Determination of the Number (M) of RSSI Values

In order to quantify the impact of different signal extraction algorithms on positioning performance, we use the curve smoothness index denoted by S as a measure. According to [16], the curve smoothness index is defined as

$$S=\sum_{i=2}^{N-1}\sqrt{(RSSI_i-\frac{RSSI_{i-1}+RSSI_i+RSSI_{i+1}}{3})^2} \quad (4)$$

where N is the number of sample points on a curve (i.e. the number of position points) and here $RSSI_i$ is the mean of the M selected maximum RSSI values at the ith position point. The smaller the value of S is, the smoother the signal curve is, and the better quality of RSSI is.

The RSSI curve smoothness and positioning accuracy will depend on M. Thus, it is important to choose an appropriate value for M to achieve good positioning performance. RSSI data collected in the corridor are used to evaluate the effect of M on the smoothness. The mobile moves along the straight line from the right end point next to the door and 16 position points (i.e. N=16) are selected. Figure 3 shows the smoothness index of the original RSSI observations with respect to M which ranges from 5 to 20 and six APs.

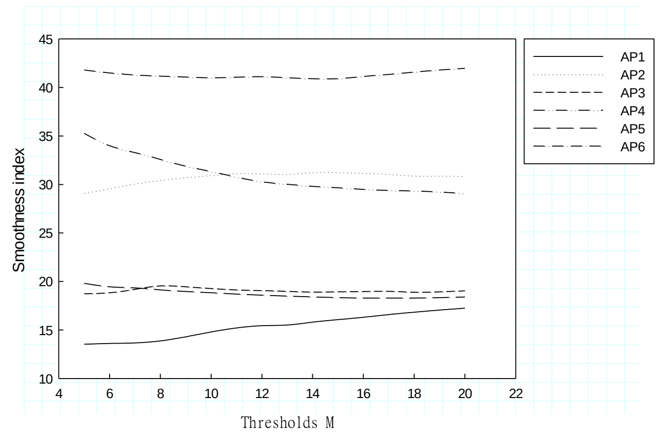

Fig. 3. The effect of M on smoothness index.

From Figure 3, we can see that the RSSI smoothness index of different APs varies with M in different ways. As M increases, the smoothness index of some APs increases, while that of some other APs decreases or increases first and then decreases.

Clearly, the smoothness index does not have any consistent variation trend over the range of values of number M for all the APs. To choose a best possible value of M, we can sum up the smoothness indexes of all the APs as shown in Table II and examine how number M affects the summed smoothness index (S-sum). Although the variation in the summed smoothness index is not very significant, S-sum is the minimum when M is equal to 13. Therefore, 13 is considered as the most suitable value for M.

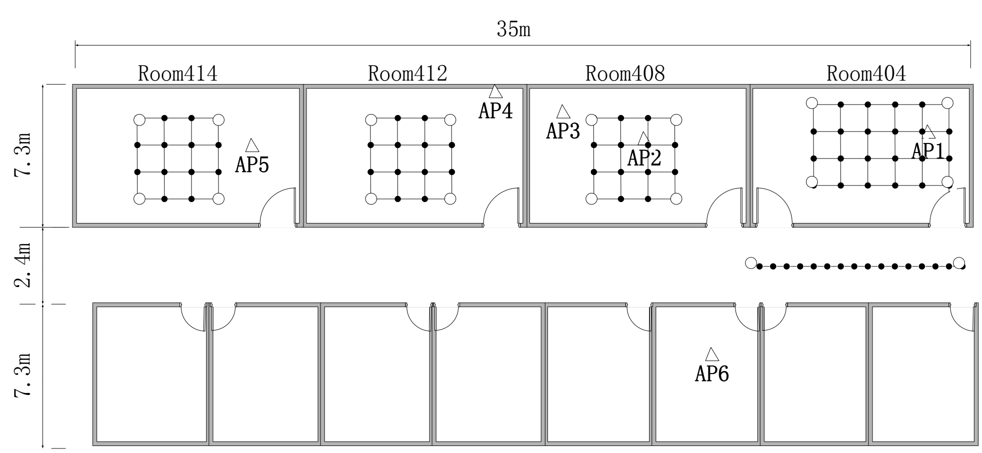

Fig.2. The schematic diagram of experimental site and point distribution

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TABLE II
SUMMED SMOOTHNESS INDEX (S-SUM) VERSUS M

M	5	6	7	8	9	10	11	12
S_{sum}	158.27	157.00	156.86	156.75	156.41	156.20	156.00	155.61
M	13	14	15	16	17	18	19	20
S_{sum}	155.08	155.10	155.18	155.40	155.69	155.85	156.25	156.60

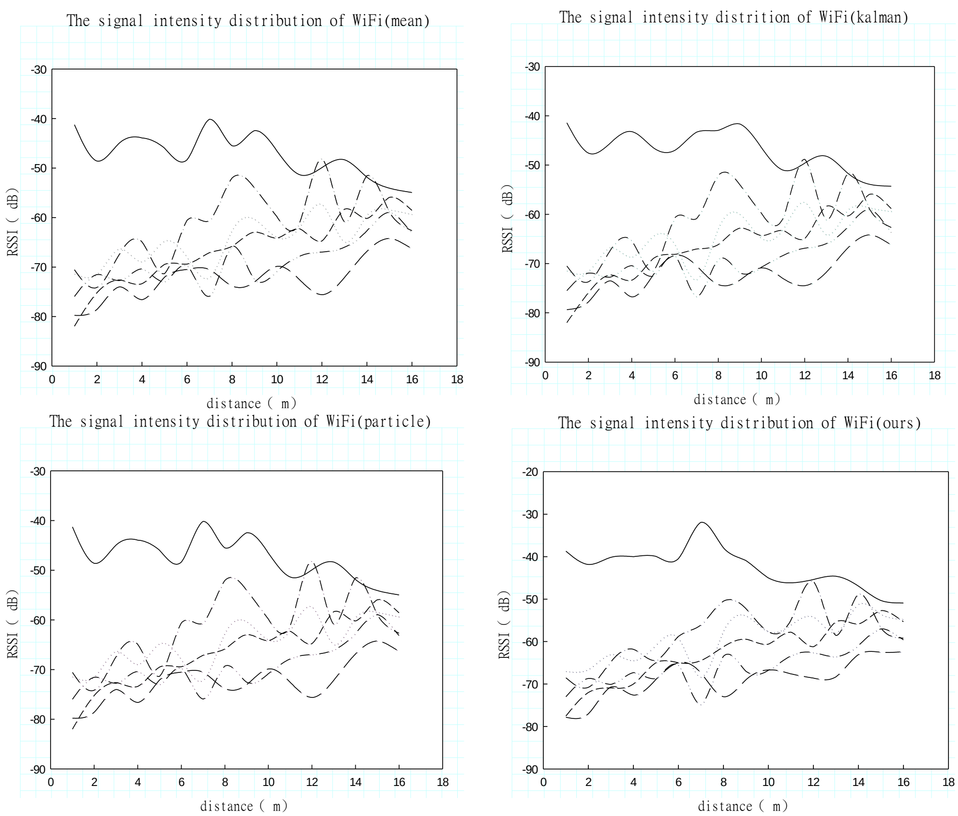

Fig. 4. The signal intensity distribution of four different algorithms (different line types represent different APs)

TABLE III
COMPARISON OF THE CURVE SMOOTHNESS INDEX OF FOUR ALGORITHMS

	AP1	AP2	AP3	AP4	AP5	AP6	All APs
Mean	23.81	31.71	21.03	28.49	17.97	53.83	176.84
Kalman filter	15.16	33.99	20.03	24.84	17.13	52.51	163.66
Particle filter	23.81	31.75	21.07	23.90	17.13	53.85	171.51
Proposed	15.51	31.08	18.98	30.03	18.49	41.00	155.08

B. Analysis of One Dimensional RSSI Spatial Distribution

According to the signal intensity attenuation principle, the longer the distance from the sampling point to the AP (signal source) is, the weaker the signal intensity is. Therefore, in order to facilitate the analysis, data collected on a straight line of 16 m in the corridor close to room 404 was employed. Four different algorithms (i.e. the average value [17], Kalman filter [18], particle filter [19], and the proposed method) were used to process the original RSSI observations. Figure 4 shows the one dimensional distribution of the processed RSSI observations over distance.

From Figure 4, we can see that on average the smoothness of the RSSI curve of the proposed algorithm is better than those of other three algorithms. Generally speaking, the variation in signal intensity or RSSI along the line in the corridor should be smooth and without any abrupt and abnormal change. The curve on the top is associated with AP1. As the mobile moves on the line, it is closer to AP1 until the distance between them is the shortest and then the distance increases. The RSSI distribution is basically consistent with the distance variation. As for the other 5 APs, the distance decreases as the mobile moves. Thus, the observed RSSI distribution is also in accordance with the distance change.

Table Ⅲ gives the curve smoothness index of the RSSI observations processed by the four different algorithms. Although it is a bit difficult to determine which algorithm has the best smoothness index from the individual values associated with individual APs, it can be seen that the proposed algorithm achieves the minimum summed smoothness index, which means possible best positioning accuracy.

C. Analysis of Two Dimensional RSSI Spatial Distribution

Contour map is employed to show the two dimensional RSSI distribution. Taking the AP1 in room 404 as an example, the contour maps of the radio signal strength produced by the four algorithms are shown in Figure 5. A saltation points in the contour map refers to a point where the RSSI is very different from those of the surrounding points. The number of saltation points is an important index to describe the RSSI distribution pattern. Smaller number of saltation points in a contour map indicates better quality of RSSI distribution. Table Ⅳ presents the number of saltation points in the contour maps of four different rooms associated with individual APs and each of the four algorithms. We can see that the number of saltation points of the proposed algorithm is considerably smaller than those of the other three algorithms.

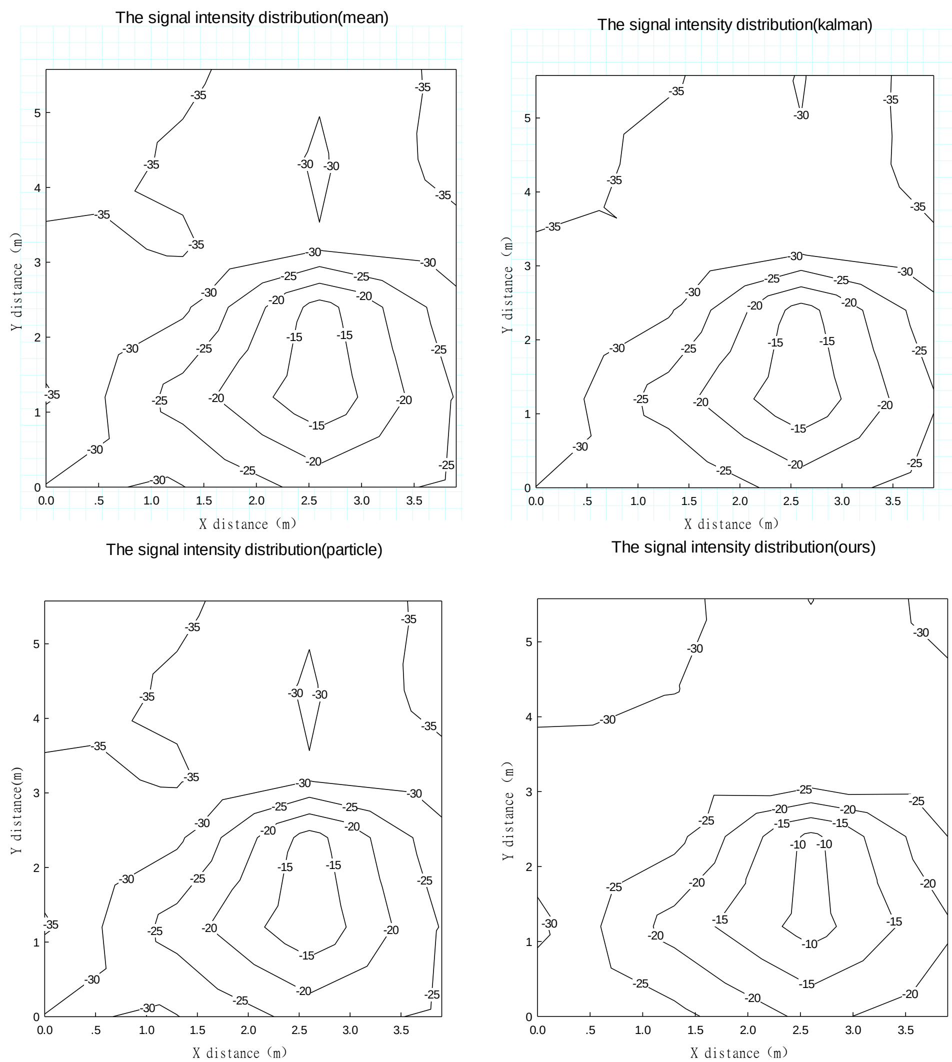

Fig.5. Signal intensity distribution (contour map) of AP1 in room 404

TABLE Ⅳ
COMPARISON OF NUMBER OF SALTATION POINTS OF FOUR ALGORITHMS IN FOUR ROOMS

	AP1	AP2	AP3	AP4	AP5	AP6
Mean	{3, 2, 0, 2}	{2, 0, 2, 2}	{1, 1, 3, 3}	{2, 3, 2, 2}	{3, 2, 2, 3}	{4, 1, 2, 3}
Kalman filter	{2, 1, 1, 2}	{2, 0, 1, 2}	{1, 2, 2, 3}	{2, 3, 2, 2}	{3, 2, 2, 2}	{4, 1, 1, 3}
Particle filter	{3, 2, 0, 2}	{2, 0, 2, 2}	{1, 1, 3, 3}	{2, 2, 2, 1}	{3, 2, 2, 2}	{3, 1, 2, 3}
Proposed	{0, 2, 0, 1}	{2, 0, 1, 0}	{1, 0, 2, 2}	{1, 1, 1, 1}	{3, 2, 2, 1}	{2, 1, 0, 3}

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TABLE Ⅴ
COMPLEXITY AND ROBUSTNESS COMPARISON OF DIFFERENT ALGORITHMS

	Mean	Kalman filter	Particle filter	Proposed
Complexity	Low	High	Very high	Low
Robustness	Weak	Medium	Medium	Strong

D. Location Accuracy Comparison

Now let us examine the effect of the four different RSSI extraction algorithms on positioning accuracy. For convenience, the simple and direct K nearest neighbor position determination algorithm is used to obtain position estimates using the RSSI observations processed by the four algorithms. The accuracy measure is the cumulative distribution function (CDF) of the position error which is the distance between the true and estimated positions. A total of 70 position points (56 points in the four rooms and 14 points in the corridor) are tested and six different position error thresholds are selected, which are 0.1, 0.2, 0.3, 0.5, 1.0, and 1.3 m, respectively. From the results displayed in Figure 6, we can see that the proposed RSSI extraction algorithm achieves significantly better positioning accuracy than the other algorithms. This also confirms that better RSSI quality produces better positioning accuracy.

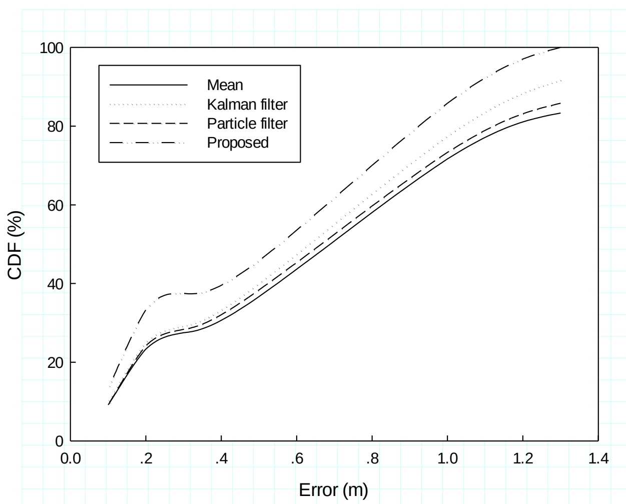

Fig.6. Comparison of location accuracy of four algorithms in terms of CDF

E. Comparison of Complexity and Robustness

In addition to positioning accuracy, algorithm complexity and robustness are also important positioning performance indexes. Table V shows the complexity and robustness comparison of the four different algorithms. Clearly, the complexity of both the mean algorithm and the proposed algorithm is much lower than the other two algorithms. The mean algorithm calculates the average of all RSSI observations, while the proposed algorithm computes the average of only the maximum RSSI observations. Usually, a signal with lower intensity would be more affected by interference than a signal with higher intensity. Therefore, the proposed maximum RSSI based algorithm would have stronger ability of interference tolerance.

Ⅳ. CONCLUSION

This paper presented the RSSI extraction algorithm for Wi-Fi indoor localization. The algorithm is based on the analysis of the characteristics of RSSI and the selection of a number of maximum RSSI values and their mean is employed for position determination. The performance of this algorithm was tested through conducting experiments in a typical office building. Experimental results demonstrated that the positioning accuracy of the proposed algorithm is considerably better than that of the mean algorithm, the Kalman filtering algorithm and the particle filter algorithm. In addition, the proposed algorithm has lower computational complexity and better robustness than the other three algorithms.

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Dr. Yu currently serves on the editorial boards of the *EURASIP Journal on Advances in Signal Processing*, IEEE TRANSACTIONS ON AEROSPACE AND ELECTRONIC SYSTEMS, and IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY. He was the lead Guest Editor for a special issue of *Physical Communication* on "indoor navigation and tracking" and for a special issue of the *EURASIP Journal on Advances in Signal Processing* on "GNSS remote sensing."