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A New Weighted Algorithm Based on the Uneven Spatial Resolution of RSSI for Indoor Localization

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ABSTRACT The weighted K-nearest neighbor (WKNN) algorithm is one of the most frequently used algorithms for indoor positioning. However, the traditional WKNN algorithm weights the reference points' coordinates by the inverse of the received signal strength indication (RSSI) difference, which is not accurate enough because of the exponential relationship between RSSI and physical distance. Furthermore, methods based on probabilistic model or data fusion do not consider the uneven spatial resolution of the Wi-Fi RSSI. Therefore, in order to improve the positioning accuracy of traditional location algorithms, this paper proposes a new weighted algorithm based on the physical distance of the RSSI. Experiments were conducted in an office building and the results demonstrate that the proposed method considerably outperforms the KNN, Euclidian-W-KNN, Manhattan-W-KNN, EWKNN, LiFS, and GPR in terms of positioning accuracy, which is defined as the cumulative distribution function of position error.

INDEX TERMS Weighted K-nearest neighbor, spatial resolution, Euclidean distance, physical distance of RSSI.

I. INTRODUCTION

Indoor positioning methods based on Wi-Fi received signal strength indication (RSSI) [1], [2] are generally divided into two categories: the trilateration algorithm and the location fingerprint positioning method. The trilateration algorithm [3] utilizes RSSI to measure the distance between two nodes based on the channel propagation model. On the contrary, fingerprint positioning method [4], [5] utilizes a RSSI database and specific geometric or probabilistic algorithm to calculate the location of the unknown point without channel propagation model. So the fingerprinting positioning algorithm has gained increasing attention as it requires neither the location of Wi-Fi access points (APs, also termed hotspots) nor the channel propagation model.

The most frequently used method in fingerprint positioning is the weighted k-nearest neighbors (WKNN) algorithm, which weights the reference points' coordinates by the inverse of the RSSI distance. Niu *et al.* [6], [7] utilize the KNN (K-Nearest Neighbor) classification method with three different weighted distances (Euclidian-W-KNN, Manhattan-W-KNN and KL-W-KNN) and find that the KNN algorithm with the Manhattan distance performs best. However, it will suffer from the exponential relationship between RSSI and physical distance. Moreover, both fusion methods and probabilistic methods [8]–[13] have not addressed the problem of the uneven spatial resolution of Wi-Fi RSSI. Ranging error is roughly proportional to the real physical distance, while RSSI Euclidean distance is a logarithm function of real physical distance. Motivated by this consideration, this paper proposes a new weighted algorithm based on the real physical distance between test point and reference point (RP) and real physical distance of Wi-Fi RSSI. Experimental results demonstrated that the positioning accuracy of the proposed algorithm is significantly better than that of other methods, such as KNN, Euclidian-W-KNN, Manhattan-W-KNN [6], [7], EWKNN [8], LiFS [9] and GPR [10]. Meanwhile, the proposed algorithm is insensitive to the variation of the parameters in the channel propagation model.

II. RELATED WORKS

A. K-NEAREST NEIGHBOR (KNN)

The NN algorithm [14] is the basic matching method in fingerprint positioning. First, one calculates the Euclidean distance between the online observed RSSI vector at the test point and the fingerprint observed offline at the *i-th* RP, recorded in the fingerprint database as

$$L_i = \sqrt{\sum_{j=1}^{M} (P_{r,\mathrm{dB}}(d^j) - P_{r,\mathrm{dB}}(d_i^j))^2}, \quad i = 1, 2, \ldots, N \quad (1)$$

where $P_{r,\mathrm{dB}}(d^j)$ is the online observed RSSI of the *j-th*AP at the test point which have a distance d^j to the transmitter, and $P_{r,\mathrm{dB}}(d_i^j)$ is the offline observed RSSI of the *j-th* AP at the *i-th* RP which have a distance d_i^j to the transmitter. It is assumed that there are M APs and N RPs. Once all the N RSSI Euclidean distances are calculated, one finds out the smallest Euclidean distance. The corresponding RP is selected and its position is taken as the estimate of the test point position.

However, in complex and dynamic indoor propagation environments, fading usually occurs, which may result in the near-far problem. That is, the RP far from the test point may have a smaller Euclidean distance L_i than the nearest neighbor RP. Therefore, the NN algorithm may produce a significant position estimation error. The KNN algorithm [15] is intended to deal with the issue associated with the NN algorithm. Instead of selecting only one RP with the smallest Euclidean distance, the KNN algorithm selects k ($k > 1$) smallest Euclidean distances. The average of the positions of these k corresponding RPs is then taken as the position estimate of the test point:

$$(x, y) = \frac{1}{k} \sum_{i=1}^{k} (x_i, y_i) \quad (2)$$

B. WEIGHTED K-NEAREST NEIGHBOR (WKNN)

The WKNN algorithm [16] also selects k RPs to calculate the position of the test point. But it assigns a weighting coefficient to the position coordinates of each RP instead of taking the simple average. In general, the weighting coefficient depends on the RSSI Euclidean distance between the RP and the test point, which is determined by:

$$\omega_i = \frac{\dfrac{1}{\left(\sum\limits_{j=1}^{M} \left|P_{r,\mathrm{dB}}(d^j) - P_{r,\mathrm{dB}}(d_i^j)\right|^p\right)^{1/p}}}{\sum\limits_{i=1}^{k} \dfrac{1}{\left(\sum\limits_{j=1}^{M} \left|P_{r,\mathrm{dB}}(d^j) - P_{r,\mathrm{dB}}(d_i^j)\right|^p\right)^{1/p}}} \quad (3)$$

where ω_i is the weighting coefficient for the *i-th* RP, p is selected as one for the Manhattan distance and two for Euclidean distance [17]. The estimated position of the test point is then the weighted average of the positions of RPs:

$$(x, y) = \sum_{i=1}^{k} \omega_i (x_i, y_i) \quad (4)$$

Clearly, a small RSSI Euclidean distance is assigned with a larger weighting coefficient to emphasize the contribution of the RPs closer to the test point.

III. THE PROPOSED WEIGHTED ALGORITHM BASED ON THE UNEVEN SPATIAL RESOLUTION OF WIFI RSSI

A. THE UNEVEN SPATIAL RESOLUTION OF WIFI RSSI

As indicated in [18], Wi-Fi signal intensity attenuation model can be described by

$$P_{r,\mathrm{dB}}(d_i) = P_{r,\mathrm{dB}}(d_0) - \eta 10 \log_{10}(\frac{d_i}{d_0}) \quad (5)$$

where η is the path loss exponent. Since d_0, $P_{r,dB}(d_0)$, and η are known in advance through modeling and $P_{r,dB}(d_i)$ is the measured RSSI, the unknown distance d_i can be calculated by

$$d_i = d_0 10^{\left(\frac{P_{r,\mathrm{dB}}(d_0) - P_{r,\mathrm{dB}}(d_i)}{10\eta}\right)} \quad (6)$$

From (7) the differential distance can be readily obtained as

$$\begin{aligned} \Delta d_{ij} &= d_i - d_j \\ &= d_0 10^{\left(\frac{P_{r,\mathrm{dB}}(d_0) - P_{r,\mathrm{dB}}(d_i)}{10\eta}\right)} - d_0 10^{\left(\frac{P_{r,\mathrm{dB}}(d_0) - P_{r,\mathrm{dB}}(d_j)}{10\eta}\right)} \end{aligned} \quad (7)$$

In the case where the transmitter and receiver are on the same floor, the path loss exponent is 2.76, d_0 is chosen to be 1 m, and $P_{r,\mathrm{dB}}(d_0)$ is −31.7dBm [19]. Table 1 displays a range of RSSI values and the corresponding propagation distances. The differential distances between each pair of neighboring RSSI values are also shown.

TABLE 1. Relationship between WIFI RSSI and physical distance.

RSSI(dBm)	d(m)	Δd(m)
-100	298.289	
-99	274.414	23.876
-98	252.449	21.965
-97	232.243	20.206
…	…	…
-75	37.054	3.224
-74	34.089	2.966
-73	31.360	2.729
…	…	…
-50	4.603	0.400
-49	4.235	0.368
-48	3.896	0.339
…	…	…
-25	0.572	0.050
-24	0.526	0.046
-23	0.484	0.042

As shown in Table 1, given the same differential RSSI value, a larger pair of RSSI values produces a smaller differential distance. The differential RSSI and the differential distance has a nonlinear relationship, showing uneven spatial resolution, so it is inaccurate to assign weights only based on RSSI Euclidean distance for position estimation.

B. THE POSITIONING ERROR OF WKNN

Now let us analyze the positioning error of WKNN based on simulation results. Consider five test points (TP1, TP2, TP3, TP4, and TP5) and only two RPs (RP1 and RP2). For better understanding, one dimensional positioning is considered and the five test points are located between the two RPs. Table 2 shows the positioning errors of the WKNN method at these five test points.

TABLE 2. Positioning errors of the WKNN.

	Real Coordinate (m)	RSSI	Estimated coordinate (m)	Coordinate error (m)
RP1	5	-48.32		
RP2	11	-59.30		
TP1	6	-50.99	6.461	0.461
TP2	7	-53.18	7.655	0.655
TP3	8	-55.02	8.664	0.664
TP4	9	-56.63	9.539	0.539
TP5	10	-58.04	10.310	0.310

As shown in Table 2, given the same two RPs, the positioning error based on WKNN increases as the location of the test point goes towards the middle of the two RPs. The positioning error is the largest when the location of the test point is in the middle of the two RPs. Therefore, the uneven spatial resolution of RSSI affects the positioning accuracy of WKNN considerably. One way to deal with the problem is to use physical distance to assign weights.

C. PROPOSED ALGORITHM BASED ON THE PHYSICAL DISTANCE OF WIFI RSSI

The above analysis indicates that the uneven spatial resolution of RSSI should be taken into account to enhance positioning accuracy. Here, we propose to use physical distance instead of RSSI distance to generate weights for position calculation. Two different physical distances are defined. The first physical distance (D_i) is defined as the square root of the sum of the differences between the distance from test point to an AP and that from RP to the AP as

$$D_i = \sqrt{\sum_{j=1}^{M}\left(d_0 10^{\left(\frac{P_{r,\mathrm{dB}}(d_0)-P_{r,\mathrm{dB}}(d^j)}{10\eta}\right)} - d_0 10^{\left(\frac{P_{r,\mathrm{dB}}(d_0)-P_{r,\mathrm{dB}}(d_i^j)}{10\eta}\right)}\right)^2}$$
$$= d_0 10^{\frac{P_{r,\mathrm{dB}}(d_0)}{10\eta}} \sqrt{\sum_{j=1}^{M}\left(10^{\frac{-P_{r,\mathrm{dB}}(d^j)}{10\eta}} - 10^{\frac{-P_{r,\mathrm{dB}}(d_i^j)}{10\eta}}\right)^2} \tag{8}$$

which means

$$D_i \propto \sqrt{\sum_{j=1}^{M}\left(10^{\frac{-P_{r,\mathrm{dB}}(d^j)}{10\eta}} - 10^{\frac{-P_{r,\mathrm{dB}}(d_i^j)}{10\eta}}\right)^2} \tag{9}$$

From formula (5), the partial derivative of $P_{r,dB}(d_i)$ with respect to d is obtained as

$$\frac{\partial(P_{r,dB}(d_i))}{\partial(d)} = -\frac{10\eta}{\ln 10} \bullet \frac{1}{d} \tag{10}$$

That is,

$$\frac{\partial(|P_{r,dB}(d_i)|)}{\partial(d)} \propto \frac{1}{d} \tag{11}$$

Therefore, for the *i-th* RP, the first physical distance based weight, denoted as DDW (differential distance based weight), is defined as

$$DDW_i = \frac{\frac{1}{D_i}}{\sum_{i=1}^{k}\frac{1}{D_i}} = \frac{\frac{1}{\sqrt{\sum_{j=1}^{M}(10^{\frac{-P_{r,\mathrm{dB}}(d^j)}{10\eta}} - 10^{\frac{-P_{r,\mathrm{dB}}(d_i^j)}{10\eta}})^2}}}{\sum_{i=1}^{k}\frac{1}{\sqrt{\sum_{j=1}^{M}(10^{\frac{-P_{r,\mathrm{dB}}(d^j)}{10\eta}} - 10^{\frac{-P_{r,\mathrm{dB}}(d_i^j)}{10\eta}})^2}}} \tag{12}$$

Using the propagation model based distance formula (6), the second physical distance for the *i-th* RP is defined as the square root of the sum of the distances from the RP to all the APs:

$$R_i = \sqrt{\sum_{j=1}^{M}\left(d_0 10^{\left(\frac{P_{r,\mathrm{dB}}(d_0)-P_{r,\mathrm{dB}}(d_i^j)}{10\eta}\right)}\right)^2} \tag{13}$$

Then, the second physical distance based weight, denoted by RPDW (RP distance based weight), for the *i-th*RP is determined by:

$$RPDW_i = \frac{\frac{1}{R_i}}{\sum_{i=1}^{k}\frac{1}{R_i}} = \frac{\frac{1}{\sqrt{\sum_{j=1}^{M}\left(d_0 10^{\left(\frac{P_{r,\mathrm{dB}}(d_0)-P_{r,\mathrm{dB}}(d_i^j)}{10\eta}\right)}\right)^2}}}{\sum_{i=1}^{k}\frac{1}{\sqrt{\sum_{j=1}^{M}\left(d_0 10^{\left(\frac{P_{r,\mathrm{dB}}(d_0)-P_{r,\mathrm{dB}}(d_i^j)}{10\eta}\right)}\right)^2}}}$$
$$= \frac{\frac{1}{\sqrt{\sum_{j=1}^{M}\left(10^{\left(\frac{-P_{r,\mathrm{dB}}(d_i^j)}{10\eta}\right)}\right)}}}{\sum_{i=1}^{k}\frac{1}{\sqrt{\sum_{j=1}^{M}\left(10^{\left(\frac{-P_{r,\mathrm{dB}}(d_i^j)}{10\eta}\right)}\right)}}} \tag{14}$$

It can be seen from (12) and (14) that both weights are independent of parameters d_0 and $P_{r,dB}(d_0)$ in the channel propagation model, so that only the knowledge of one parameter (i.e. the path loss exponent) is required.

We propose to combine the two weights to form the final weight ω_i for the $i\text{-}th$ RP as

$$\omega_i = \frac{DDW_i \cdot RPDW_i}{\sum_{i=1}^{k} (DDW_i \cdot RPDW_i)} \tag{15}$$

The final position estimate is obtained by substituting (15) into (4). The flowchart of the proposed weighted algorithm is shown in Figure 1.

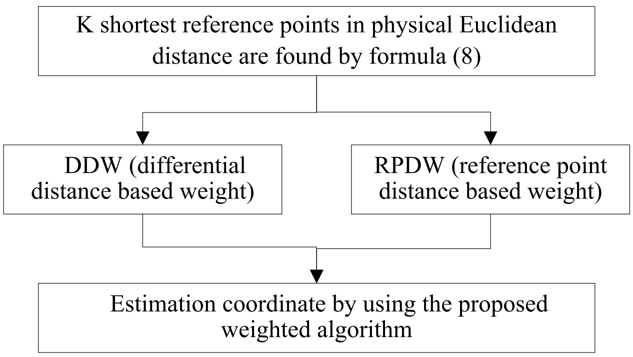

FIGURE 1. The flow chart of indoor positioning based on the proposed weighted algorithm.

IV. EXPERIMENT AND ANALYSIS OF ITS RESULT

In order to evaluate the performance of the proposed algorithm, experiments were conducted in Science and Technology Building of Shenzhen University. The left panel in Figure 2 shows the floor plan of the twelfth floor of dimensions of 52.5m×52.5m, where Wi-Fi RSSIs from more than 50 Wi-Fi hotspots were received. It should be note that a large part of these Wi-Fi hotspots are not in the twelfth floor, but in the neighboring floors. The right panel in Figure 2 shows the floor plan of the fourteenth floor of dimensions of 52.5m×52.5m, the mobile can receive Wi-Fi RSSIs from more than 50 hotspots. At each test point, only six APs (i.e. $M = 6$) with the largest RSSI values were selected for both good accuracy and low computational complexity. The sampling rate of 1 s was used to collect the RSSI for about 40 seconds at each RP, and the sampling rate of 0.2 s was used to collect the RSSI for 5 seconds at each test point. The 67 points denoted by triangles of the location area are selected as RPs, while other 153 points denoted by solid dot are the test points whose positions are to be determined. The distance between the adjacent points is about 2 meters. For convenience, an independent coordinate system is established in each floor for position determination purpose.

On each floor the same ordinary Android mobile phone was used to collect data during both offline training phase and online location phase (MI 3 for the twelfth floor and MEIZU-M57A for the fourteenth floor). In reality, the type of smartphone used for collecting training fingerprints may be rather different from that carried by a pedestrian, which collects data during online location phase. For instance, one is MI and the other is MEIZU. To handle such device heterogeneity, the relationship between RSSI (relative RSS) of one type of device and that of a different type of device should be established in advance for this proposed method. Also, it is useful to determine if there is an RSS offset between two different types of device. If the RSS offset is rather minor and the devices use the same relative RSS to calculate RSSI, the proposed method can be used in presence of device heterogeneity. Otherwise, to use the proposed method, one needs to find out the offset and the difference in RSSI calculation so that the RSSI observed by a device can be converted to that observed by a different device. This will be useful future research. Due to significant variation in RSSI observations caused by fading, the observed RSSI values over a short period of time are usually pre-processed such as by the mean algorithm. In this paper, the improved Wi-Fi RSSI measurement method in [20] has been used to preprocess the RSSI data.

A. INFLUENCE ON LOCATION ACCURARY OF DIFFERENT PATH LOSS EXPONENT VALUES

As indicated by (12) and (14), the weight ω_i is dependent on the path loss exponent. Thus, it is useful to know how the path loss exponent affects the weight. The accuracy measure is the cumulative distribution function (CDF) of the position error which is the distance between the true and estimated positions. The path loss exponent in free space is 2 [21], [22] and in an office building with rooms separated by concrete walls and corridors, it is about 3 [23]. Thus, a number of path loss exponents ranging between 2 and 3 are tested.

Table 3 shows the CDF of the position error in the fourteenth floor with respect to path loss exponent range from 2.0 to 3.0. A total of 153 test points are tested and twelve different position error thresholds are selected, which are 0.3, 0.5, 1, 2, 3, 4, 5, 6, 7, 8, 9 and 10 m, respectively. We can see that the impact of path loss exponent on the CDF is insignificant, with the CDF standard deviation for each error threshold being between 0.51% and 2.03%. Therefore, the proposed weighted algorithm is insensitive to the selection and variation of parameter η in the channel propagation model.

B. LOCATION ACCURARY COMPARISON

Now let us compare the positioning accuracy among the six different algorithms (KNN, Euclidian-W-KNN, Manhattan-W-KNN [6], [7], EWKNN [8], LiFS [9] and the proposed). Preprocess of RSSI data is the same for different algorithms, and the method in [20] has been adopted in the pre-processing of RSSI data for all these six algorithms. The accuracy measure is still the CDF of the position error. Since the impact of the path loss exponent on the CDF is rather minor, path loss exponent is simply set at 2.

From the results displayed in Figure 3, we can see that the proposed algorithm significantly outperforms the other two algorithms. For instance, when error threshold is 2 m and 4 m, the CDF of the proposed algorithm is

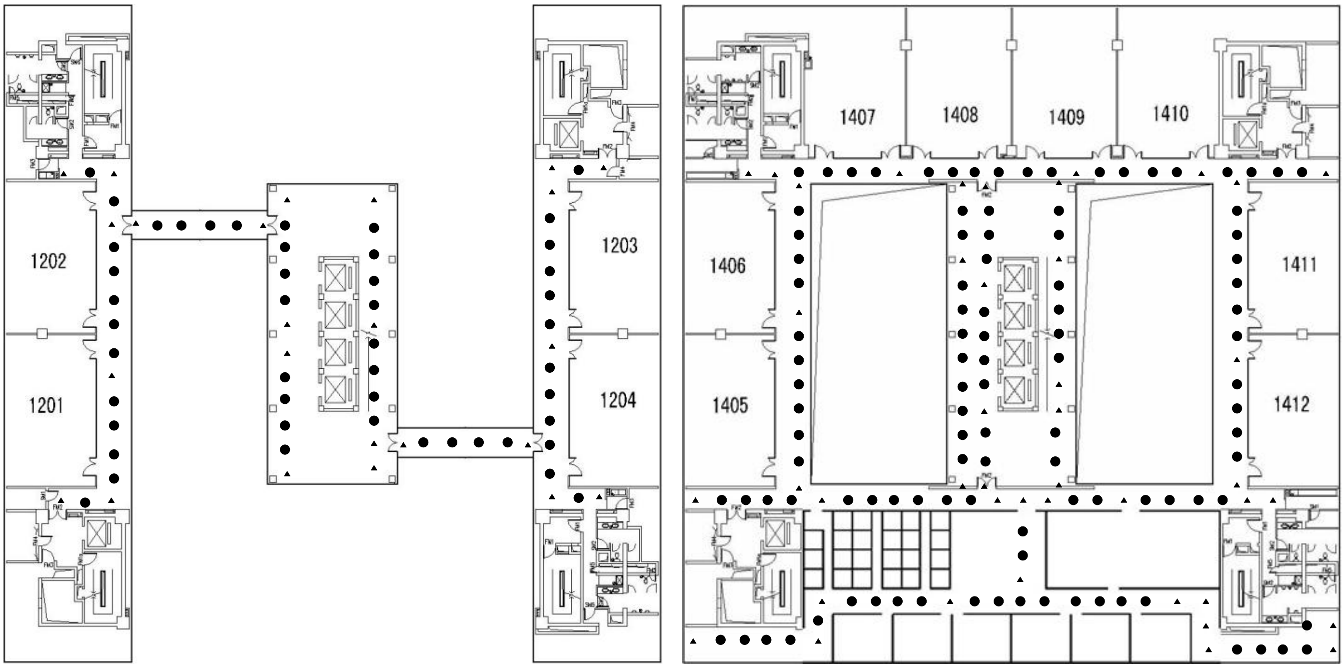

FIGURE 2. The schematic diagrams of experimental point distribution.

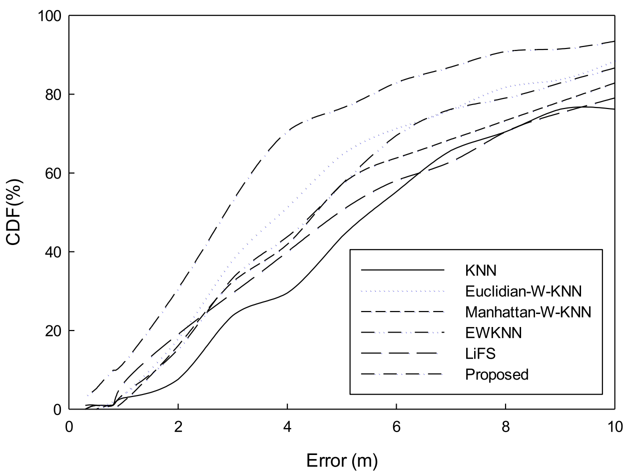

FIGURE 3. Comparison of location accuracy of six algorithms in terms of CDF.

respectively 30.72% and 70.59%, which is significantly higher than the 7.84% and 30.07% of the KNN, the 18.30% and 51.63% of the Euclidian-W-KNN, the 16.34% and 42.48% of the Manhattan-W-KNN, the 15.69% and 44.44% of the EWKNN, and the 19.61% and 40.52% of the LiFS. For error threshold of 3 m, the CDF of the proposed algorithm is 52.94%. It is a good positioning accuracy when considering that the distance between the adjacent two RPs is about 10 meters.

Next, let us examine the positioning accuracy of the six different algorithms in terms of error vector at each test point, which is represented by an arrow pointing from the real position to the estimated position. From the results of the fourteenth floor displayed in Figure 4, we can see that the proposed weighted algorithm produces smaller error vector than the other algorithms. Table 4 shows the corresponding statistical results.

From the results of the fourteenth floor displayed in Table 4, we can see that the proposed weighted algorithm produces an 80^{th} percentile error of 5.32m, which is significantly better than the 10.67m, 7.22m 9.55, 8.50, and 10.03m of KNN, Euclidian-W-KNN, Manhattan-W-KNN [6], [7], EWKNN [8] and LiFS [9], respectively. And, from the results of the twelfth floor displayed in Table 4, we can see that the proposed weighted algorithm produces an 80^{th} percentile error of 8.72m, which is significantly better than the 10.36m, 9.40m, 10.47m, 9.81m and 15.44m of KNN, Euclidian-W-KNN, Manhattan-W-KNN, EWKNN, and LiFS, respectively. Note that a large part of Wi-Fi hotspots used for localization in the twelfth floor are in the neighboring floors, which has degraded in localization accuracy with weaker RSSI.

In addition, the proposed physical distance based weighted algorithm not only can apply to the deterministic algorithm, but also can apply to the probabilistic algorithm. Next, the positioning accuracy of physical distance based one probabilistic algorithm is examined. Figure 5 shows the positioning accuracy comparison between the two different algorithms (GPR [9], and the proposed -GPR).

From the results displayed in Figure 5, we can see that the proposed solution based GPR algorithm significantly outperforms the normal GPR algorithm. For instance, when error threshold is 2 m and 4 m, the CDF of the proposed -GPR and is respectively 38.10% and 65.71%, which are significantly higher than the 22.86% and 55.24% of the GPR.

TABLE 3. The effect of path loss exponent on the positioning accuracy in terms of CDF (%).

	0.3(m)	0.5(m)	0.8(m)	1(m)	2(m)	3(m)	4(m)	5(m)	6(m)	7(m)	8(m)	9(m)	10(m)
η =2.0	3.27	5.23	9.80	11.76	30.72	52.94	70.59	76.47	83.01	86.93	90.85	91.50	93.46
η =2.1	3.27	3.92	9.80	12.42	33.33	52.94	70.59	76.47	83.01	86.93	90.85	91.50	93.46
η =2.2	1.96	3.92	7.84	13.73	34.64	54.90	69.93	76.47	82.35	86.93	90.85	92.81	93.46
η =2.3	1.96	3.27	7.84	12.42	35.29	53.59	68.63	76.47	81.05	86.93	89.54	92.81	93.46
η =2.4	1.96	3.92	7.84	11.76	36.60	53.59	69.93	77.78	81.05	83.01	88.89	92.81	93.46
η =2.5	1.96	3.92	7.19	12.42	37.25	53.59	69.93	76.47	81.05	83.01	88.89	92.81	93.46
η =2.6	1.31	3.92	9.15	11.11	36.60	53.59	68.63	76.47	81.05	83.01	88.89	92.81	93.46
η =2.7	1.96	3.92	9.15	11.11	36.60	51.63	67.97	75.82	80.39	83.01	88.24	92.81	93.46
η =2.8	1.96	3.92	9.15	11.11	35.29	51.63	68.63	76.47	80.39	83.01	88.24	92.81	94.77
η =2.9	1.31	3.92	7.84	11.11	35.29	51.63	69.93	77.78	79.08	83.01	88.24	92.81	94.77
η =3.0	1.31	3.27	7.84	11.11	34.64	50.98	69.93	77.78	79.08	82.35	86.93	91.50	93.46
Mean	2.02	3.92	8.50	11.82	35.12	52.82	69.52	76.77	81.05	84.37	89.13	92.45	93.70
STD	0.68	0.51	0.92	0.85	1.85	1.20	0.89	0.68	1.34	2.03	1.28	0.61	0.53

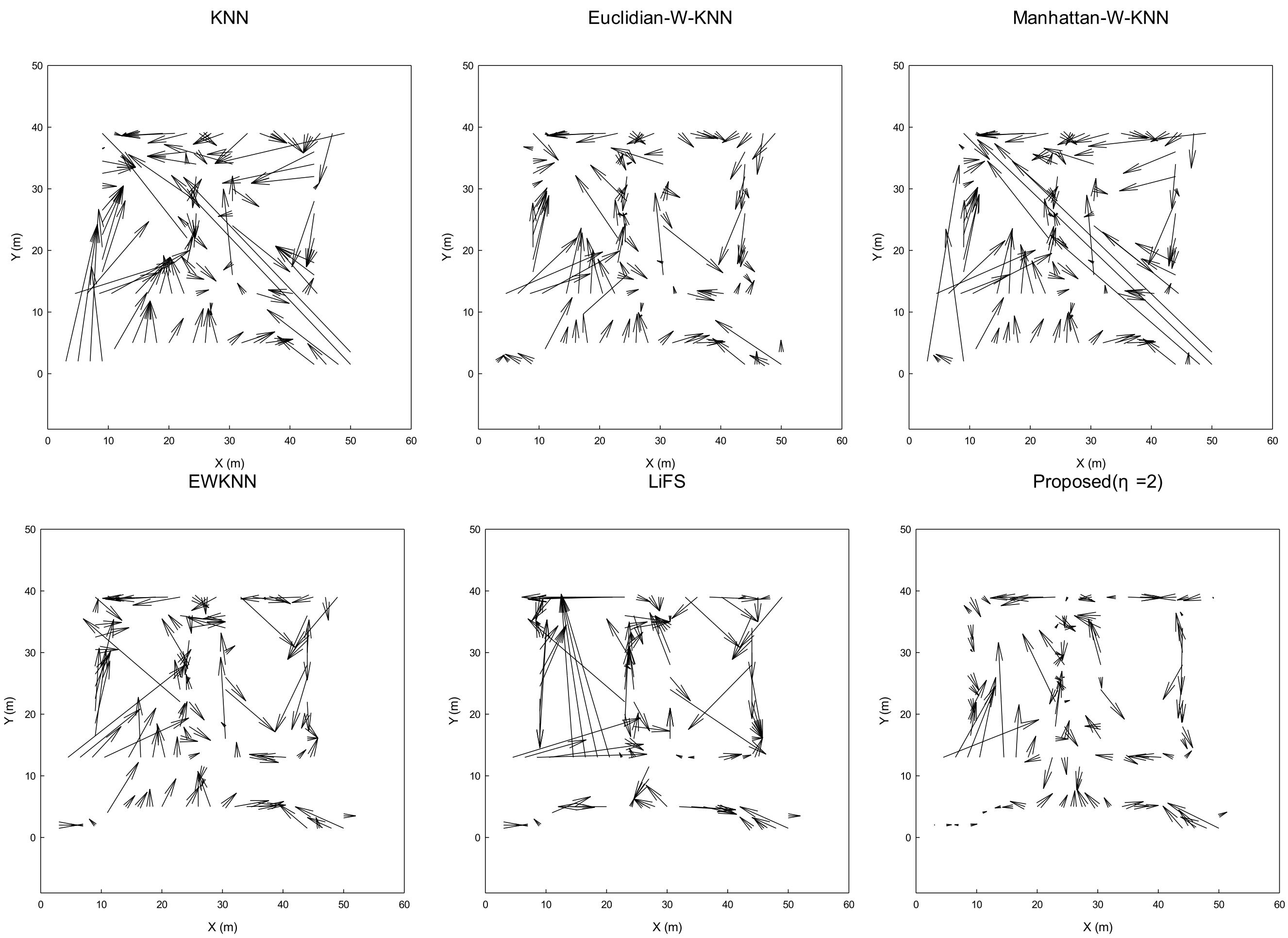

FIGURE 4. Comparison of location accuracy of six algorithms in terms of error vector.

Therefore, the proposed physical distance based weighted algorithm can achieve a performance gain when applied to both the deterministic algorithm and the probabilistic algorithm.

C. COMPARISON OF COMPLEXITY AND ROBUSTNESS

In addition to positioning accuracy, algorithm complexity and robustness are also important positioning performance indexes. Table 5 shows the complexity and robustness

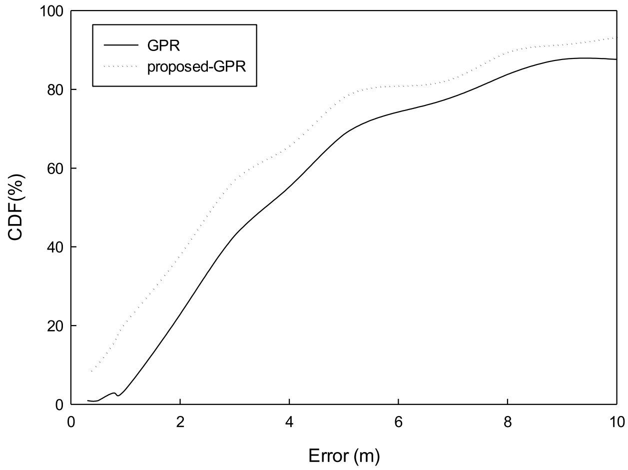

FIGURE 5. Comparison of location accuracy of two probabilistic algorithms in terms of CDF.

TABLE 4. Positioning error statistics.

floor	Algorithm	Mean (m)	Var (m^2)	RMSE(m)	80^{th} (m)
12	KNN	7.62	11.51	8.34	10.36
	Euclidian-W-KNN	6.93	11.10	7.69	9.40
	Manhattan-W-KNN	7.26	12.04	8.04	10.47
	EWKNN	7.39	15.37	8.36	9.81
	LiFS	8.85	48.96	11.28	15.44
	Proposed	6.17	12.85	7.13	8.72
14	KNN	7.55	47.12	10.21	10.67
	Euclidian-W-KNN	4.94	12.92	6.11	7.22
	Manhattan-W-KNN	7.04	70.05	10.93	9.55
	EWKNN	5.50	17.17	9.42	8.50
	LiFS	7.00	39.70	6.89	10.03
	Proposed	3.89	11.76	5.18	5.32

TABLE 5. Complexity and robustness comparison of the seven different algorithms.

Algorithm	Complexity	Robustness
KNN	Low	Weak
Euclidian-W-KNN	Low	Weak
Manhattan-W-KNN	Low	Weak
EWKNN	Low	Weak
LiFS	High	Weak
GPR	High	Strong
Proposed	Low	Strong

comparison of the seven different algorithms. The complexity of KNN, Euclidian-W-KNN, Manhattan-W-KNN, EWKNN and proposed algorithm is much lower than the LiFS and GPR algorithm. Considering the exponential relationship between RSSI and physical distance, the proposed algorithm based on the physical distance of RSSI would have stronger ability of interference tolerance with handling the Uneven Spatial Resolution of Wi-Fi RSSI.

V. CONCLUSION

This paper presented a new weighted algorithm for indoor localization. The algorithm is intended to cope with the issue of uneven spatial resolution of RSSI. The two different physical distances are exploited for determining the weighting coefficients. The algorithm only requires the knowledge of one parameter, i.e. the path loss exponent in the propagation model, but it is insensitive to the uncertainty in this model parameter. 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 KNN, Euclidian-W-KNN, Manhattan-W-KNN, EWKNN, LiFS and GPR.

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