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Dynamic threshold location algorithm based on fingerprinting method

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The weighted K-nearest neighbor (WKNN) algorithm is used to reduce positioning accuracy, as it uses a fixed number of neighbors to estimate the position. In this paper, we propose a dynamic threshold location algorithm (DH-KNN) to improve positioning accuracy. The proposed algorithm is designed based on a dynamic threshold to determine the number of neighbors and filter out singular reference points (RPs). We compare its performance with the WKNN and Enhanced K-Nearest Neighbor (EKNN) algorithms in test spaces of networks with dimensions of 20 m × 20 m, 30 m × 30 m, 40 m × 40 m and 50 m × 50 m. Simulation results show that the maximum position accuracy of DH-KNN improves by 31.1%, and its maximum position error decreases by 23.5%. The results demonstrate that our proposed method achieves better performance than other well-known algorithms.

KEYWORDS
dynamic threshold, EKNN, fixed K value, KNN, position fingerprint, WKNN

1 | INTRODUCTION

In recent years, fingerprinting methods have been extremely attractive to researchers because they do not require sophisticated hardware, and they provide better accuracy [1–3]. Location fingerprint algorithms involve two stages, namely the offline stage and the online stage [4,5]. The offline stage is used to generate a database, which is used to estimate the position in the online stage. One of the well-known algorithms of estimation location is the K-nearest neighbor (KNN) method. However, the disadvantage of KNN is that it can decrease the positioning accuracy because it selects a fixed number of nearest K neighbors around a measured point to calculate the measured point's position. For example, if the K value is set to 5 in the KNN algorithm, the measured point calculates its own position based on the positions of five neighbors exactly. However, there are only three or four points that have small distances regularly. If five neighbors are used to determine the position in this scenario, it will reduce the positioning accuracy. If the same value is used in scenarios such as a hall and a corridor, it will decrease the positioning accuracy in the hall. Therefore, it is better to select the appropriate value of K dynamically during the positioning process of fingerprinting, and the positioning accuracy will be improved.

Several modified strategies have been proposed to correct the problem above. In [6], a large number of simulations are used to show that it is improved when the K value is set to 3 or 4 in KNN. A new method to select the optimal K value is proposed in [7]. However, the method is complex because it requires that the database be divided based on the relationship between the signal feature and spatial positioning. A hybrid fingerprinting/angle of arrival (AOA) location scheme is proposed in [8]. In this method, the AOA algorithm mainly determines the number of neighbors, and the fingerprint is used for location estimation. This improves the positioning accuracy, but the cost is increased. In [9], an enhanced

K-nearest neighbor (EKNN) method is described. While this algorithm has a higher positioning accuracy, it is difficult to select the threshold. The positioning accuracy may be decreased when the threshold value is either too large or too small. Other modified algorithms have been presented in [10,11]. Reference [12] uses different KNN and WKNN methods to compare the performance of a probabilistic fingerprint-based indoor positioning system compared with different smartphones. In this paper, we propose a novel dynamic threshold location algorithm that is based on KNN (DH-KNN). The proposed method uses a dynamic threshold to find the best nearest neighbors, and to filter out the unnecessary ones in order to improve the positioning accuracy.

The remainder of this paper is organized as follows: In Section 2, we briefly describe the principle of the EKNN algorithm. Section 3 describes the proposed algorithm. Then, in Section 4, we analyzed and compared the performance of our proposed algorithm. Finally, we present our conclusions in Section 5.

2 | ENHANCED *K*-NEAREST NEIGHBOR ALGORITHM

The EKNN algorithm is a kind of dynamic K value positioning algorithm [9] that has three steps. The first step is to set a threshold THs, which is used to select the reference points (RPs) whose Euclidean distance is less than THs. The second step is to give a new threshold $\mathrm{TH_T}$, which is given by the average Euclidean distance of the selected RPs, $\mathrm{TH_T}$ is also used to select the new RPs whose Euclidean distance is less than $\mathrm{TH_T}$. The last step is to estimate the location by using the latest selecting RPs. If the original value of THs is suitably set, it will achieve a better positioning accuracy. This method is discussed in detail in [9]. However, in general, it is difficult to determine the optimal value of THs.

3 | PROPOSED ALGORITHM

The location accuracy of the KNN algorithm is reduced because it uses a fixed K value. The EKNN algorithm adopts a dynamic K value and a fixed threshold, and its positioning accuracy is better than that of the ENN algorithm. In order to further improve the position accuracy, we propose a novel dynamic threshold position algorithm that is based on the location fingerprint algorithm, which is called DH-KNN. The proposed algorithm is divided into two stages: an offline stage and online stage. The offline stage serves to create a database using Euclidean distance values. The online stage serves to estimate the position using the database; it employs a dynamic threshold to select the number of neighbors dynamically.

Algorithm 1. DH-KNN algorithm

Offline stage: create database

Step 1. The RSS value of the measured point is received from anchor points (APs). The data vector with the RSS values stored in the database is compared to all of the RPs during the offline stage, and it is represented by

$$D_j = \sum_{i=0}^{N} (\mathrm{RSS}_i - \mathrm{RSS}_{ij})^2, \tag{1}$$

where N is the number of APs, RSS_i is the signal strength of the measured point received in the ith AP, RSS_{ij} is the signal strength of the jth RP received in the ith AP, and D_j is the Euclidean distance between the signal strength of the measured point and the signal of the jth RP.

Online stage: estimate location

Step 2. Scan all the values of D_j to find the smallest Euclidean distance, which is recorded min. Min multiplied by a coefficient value is TH.

$$\mathrm{TH} = a * \min. \tag{2}$$

Step 3. TH is the threshold used to filter out RPs. The RP for which the value of D_j is less than TH is placed in the set Q.

Step 4. The RPs in the set Q are used to estimate location of the measured point, which is calculated by

$$\omega_i = \frac{D_i}{\sum_{j=1}^{k} D_j} (i = 1, 2, \ldots, k); \tag{3}$$

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

where ω_i is the weight of the ith selected RP in Q, (x, y) is the measured point location, and (x_i, y_i) is the position of the ith selected RPs in Q. The pseudo code of DH-KNN is presented as follows.

1: **Meas[]** = RSSM_1, RSSM_2, RSSM_3, RSSM_4: Obtain the signal strength of the measured point.

2: For (int i = 1; $i < N$; i++);
{Calculate D_i;
If (D_i < min) **then** min = D_i; Find the optimal Euclidean distance value.
N is the total number of RPs. D_i is the Euclidean distance between the ith reference point and the measured point.

3: TH = $a * \min$; Calculate the threshold.

4: For (int i = 1; $i < N$; i++);
{**If** (D_i < TH) **then** ith → Q;
Substitute the reference points into Q}.

5: Calculate (x, y) using the KNN algorithm, where the value of K is the number of elements in Q.

6: **Output** the results.

4 | SIMULATION RESULTS AND ANALYSIS

In this study, we used the path-loss model [10,11] to simulate and verify our proposed algorithm (DH-KNN). It is defined as

$$P_l(d)(\mathrm{dB}) = P_l(d_0) + 10n\,\lg(d/d_0) \tag{5}$$

where $P_l(d)$ is the path loss, $P_l(d_0)$ represents the path loss at a distance of 1 m, n is the power decay index, and d is the distance between the transmitter and the receiver. The parameters are set as $P_l(d_0)$ = 62 dB and n = 2.

4.1 | Optimal coefficient in dynamic threshold location algorithm

The optimal coefficient, *a,* for localization estimation is given by the number of simulation results. There are two scenarios to be simulated.

Scenario 1. In this scenario, the sizes of the test space are networks with dimensions of 20 m × 20 m, 30 m × 30 m, and 40 m × 40 m. The distance between adjacent RPs is 1 m. Four APs are placed in the four corners, and the average position error of 200 samples is recorded. Figure 1 shows that the optimal coefficient, *a,* is 1.7 in the 30 m × 30 m network, and the optimal coefficient, *a,* is 1.8 in the 20 m × 20 m and 40 m × 40 m networks. The results could be used for indoor positioning with smartphones [13], and would result in energy savings of the devices.

Scenario 2. In this scenario, the size of the test space is a 50 m × 50 m network. The distances between two adjacent RPs are 1 m, 2.5 m, and 5 m, respectively. Four APs are placed in the four corners, and the average position error of 200 samples is recorded. Figure 2 shows that the optimal coefficient, *a*, is 1.7. The position error increases as the distance increases.

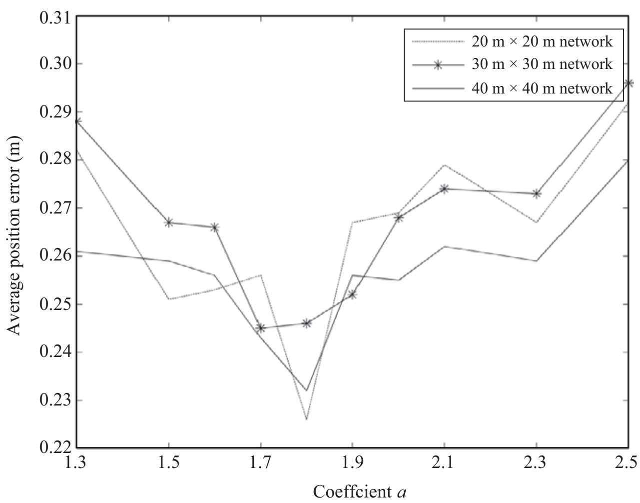

FIGURE 1 Distance between adjacent reference points is 1 m in different networks

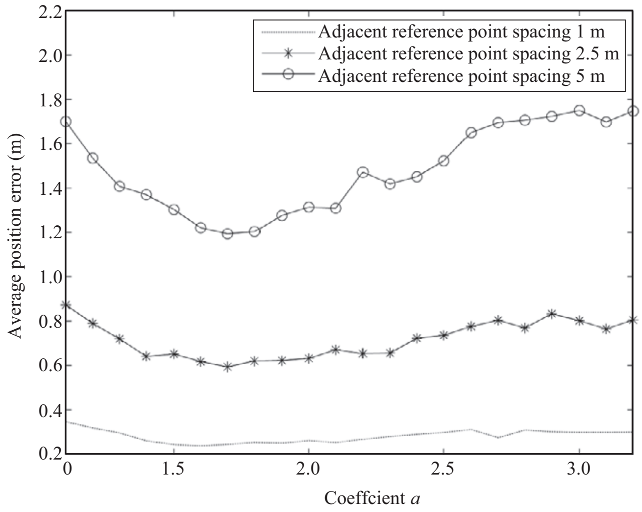

FIGURE 2 Different distances between adjacent reference points in 50 m × 50 m network

The simulation results demonstrate that the optimal coefficient is 1.7 or 1.8 in different situations, and a value of 1.7 is more frequently used.

4.2 | Optimal threshold TH in EKNN algorithm

We set up the same networks to find the best fixed threshold of the EKNN algorithm. The simulation results are used to compare with other algorithms.

Figure 3 shows the position errors obtained using EKNN algorithms in different networks. The optimal thresholds are different in different networks, and the performances change when the distances between two adjacent RPs are different. Figure 4 shows the position errors in a

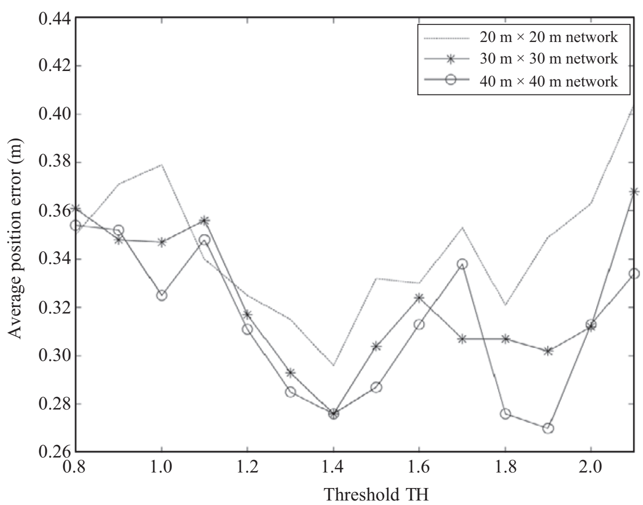

FIGURE 3 Average error values for different thresholds

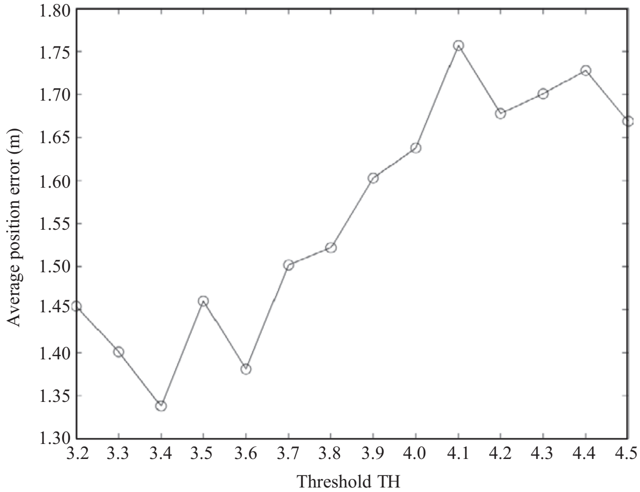

FIGURE 4 Average error values for different thresholds in 50 m × 50 m network

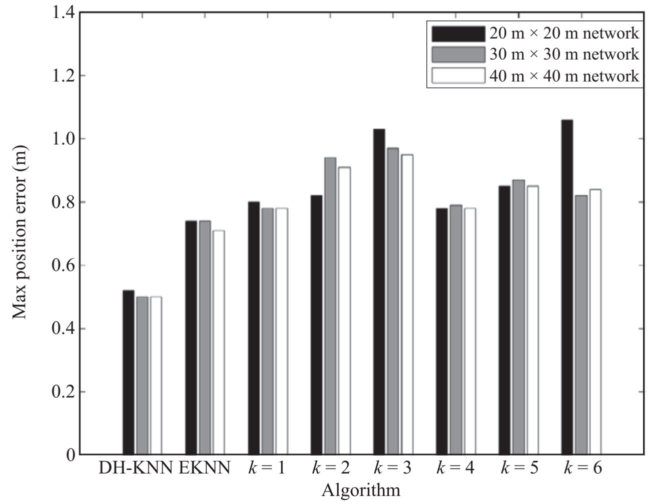

FIGURE 6 Maximum position errors of different algorithms

50 m × 50 m network when the distance between two adjacent RPs is 5 m.

4.3 | Comparison of different algorithms

We compare the proposed algorithm (DH-KNN) with EKNN and weighted KNN (EKNN, k is 1, 2, 3, 4, 5, and 6) algorithms. The performances of different algorithms are considered when the distance between two adjacent RPs is 1 m in three different networks. The simulation results are shown in Figures 5 and 6.

Figure 5 shows the average position error of different algorithms in different networks. It is clear that DH-KNN outperforms EKNN and WKNN. The performance of WKNN is the worst. We performed many experiments, and the results show that the average errors of DH-KNN decrease by 11.2% to 13.5% and 22.2% to 27.9%, respectively, compared with those of EKNN and WKNN.

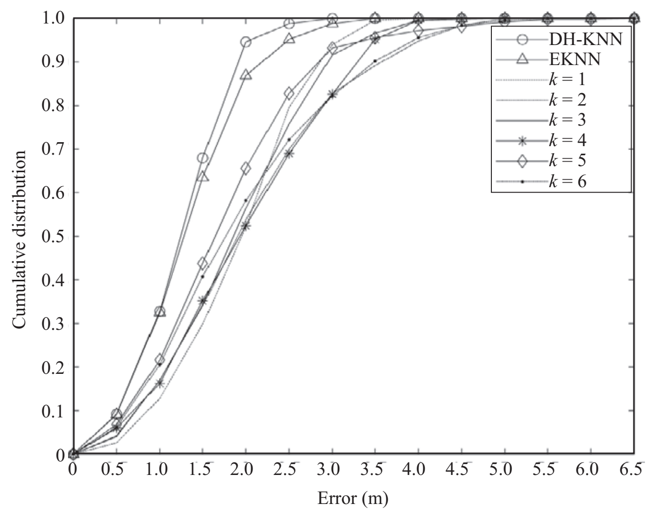

FIGURE 7 Cumulative percentage in 50 m × 50 m network

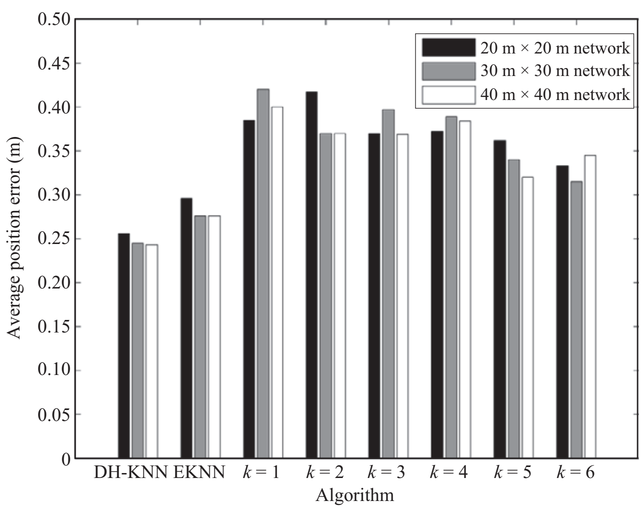

FIGURE 5 Average position error for different algorithms

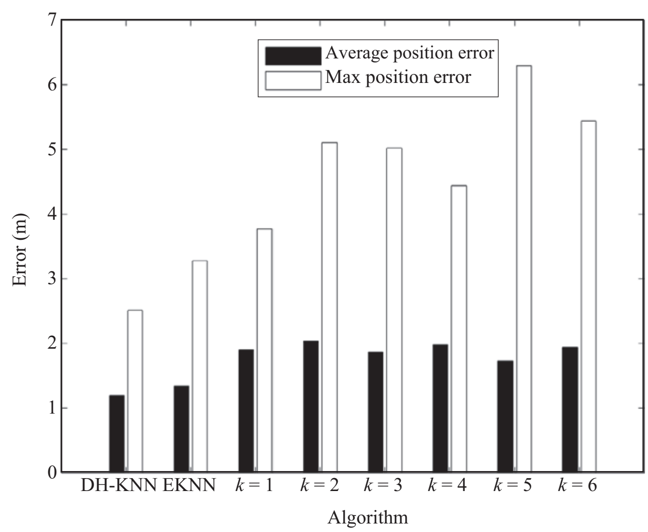

FIGURE 8 Average error and maximum error of different algorithms

TABLE 1 Position error in different locations.

Position coordinates	DH-KNN	EKNN	$k = 1$	$k = 2$	$k = 3$	$k = 4$	$k = 5$	$k = 6$
(23.7,1.8)	1.74	1.74	2.22	1.74	**0.90**	2.07	3.41	2.25
(12.8,5.4)	0.71	0.71	2.24	0.71	2.33	**0.70**	0.89	0.85

Figure 6 demonstrates the average position error of different algorithms in different networks. It clearly shows that performance of DH-KNN is better in the indoor scenario. The performance of EKNN and WKNN is about the same. A large number of experiments show that the maximum errors of DH-KNN improve by 29.6% to 32.4% and 33.3% to 37.8%, respectively, compared with those of EKNN and WKNN.

The performances of different algorithms were compared when the distance between two adjacent RPs is 5 m in a 50 m × 50 m network. Figure 7 shows the cumulative percentage of different algorithms. The simulation results show that the highest cumulative location error distribution of DH-KNN is 94.6%, and it is 86.9% in EKNN and 65.6% in WKNN (k is 5).

Figure 8 shows the position errors obtained under the same conditions for different algorithms. The simulation results clearly show that the position accuracy of DH-KNN is higher than the value for other algorithms. Compared with EKNN and WKNN (k is 5), the average position error of DH-KNN improves by 10.8% and 31.1%, respectively, and the maximum position error of DH-KNN reduces by 23.5% and 38.4%, respectively.

Figures 6 and 8 show that the maximum position error of DH-KNN is about half the distance of two adjacent RPs. The maximum position error is 0.52 m when the distance is 1 m, and 2.51 m when the distance is 5 m.

There is a dynamic K in the EKNN algorithm, but its threshold is fixed. It is inconvenient for use because its threshold is not the same in different scenarios. The position accuracy of DH-KNN is higher than other classical algorithms because it uses a dynamic K value. However, it cannot use the optimal K to estimate each position. Some simulation results are shown in Table 1.

5 | CONCLUSIONS

The KNN algorithm selects the fixed K-value nearest neighbors based on the Euclidean distance to the location estimation. However, its position accuracy is not high. In this paper, we proposed a modified KNN algorithm (DH-KNN) that selects the best nearest neighbors dynamically using a dynamic threshold. The dynamic threshold is the minimum Euclidean distance between the signal strength of the measured point and the signal strength of RPs multiplied by a fixed coefficient a. Simulation results show that the optimal fixed coefficient, a, is 1.7. Compared with EKNN and WKNN, the performance of the proposed DH-KNN is shown to be optimal. The average localization errors of DH-KNN have the smallest values. The average localization accuracy is better than 10.8% and 22.2% compared with EKNN and KNN, respectively. The maximum localization errors therefore decreased by 23.5%.

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