Novel Dynamic KNN with Adaptive Weighting Mechanism for Beacon-based Indoor Positioning System

Chong-Yi Yang, Yi-Wei Ma, Jiann-Liang Chen, Chia-Ju Lin, Wei-Lun Lee

Department of Electrical Engineering, National Taiwan University of Science and Technology, Taiwan
chongyi.yang@gmail.com, yiweimaa@gmail.com, lchen@mail.ntust.edu.tw, tiffany.lin666@gmail.com, nicolas0.094me@gmail.com

Abstract

This work proposes a novel dynamic K Nearest Neighbor (KNN) with an adaptive weighting (DKNN-AW) mechanism that performs beacon-based indoor positioning. Four cases are used to prove that DKNN-AW (Dynamic KNN algorithm with Adaptive Weight algorithm) is better than KNN (k-Nearest Neighbors algorithm), KNN-W (KNN with Weight algorithm), DKNN (Dynamic KNN algorithm) and DKNN-W (Dynamic KNN with Weight algorithm). The experimental results demonstrate that, in terms of approximate positioning accuracy, the proposed mechanism outperforms exiting mechanism such as KNN, DKNN, KNN-W and DKNN-W.

Keywords: Indoor positioning, Bluetooth Low Energy (BLE), Fingerprinting

1 Introduction

As science and technology advance, the number of mobile devices is increasing rapidly, resulting in the widespread use of Location-Based Service (LBS) applications. LBS is a general class of computer program-level service that utilizes location data to control positioning related features. However, the accuracy of indoor positioning is strongly influenced by signal interference problems that are associated with environmental factors. Improving indoor positioning accuracy is critical.

Along with the broad and rapid development of communications industry, the field of wireless communications is developing a novel low-power technology called Bluetooth 4.0. Bluetooth 4.0 solves the high power problem, and is able to push data from the system to neighboring users. On the other hand, there is a huge breakthrough in the development of LBS positioning systems. Also, the GPS technology, which is suitable for outdoor environments, has matured [1-2]. Now, the field of wireless communications includes many positioning products, such as Beacon [3-5] and Light Emitting Diode (LED) [6-8]. Therefore, collecting and analyzing the Received Signal Strength Indication (RSSI) is an important issue.

GPS is able to provide the accurate position, velocity and time of mobile devices over most (about 98%) of the Earth's surface. However, the GPS is easily influenced by shelter. Therefore, it does not work well in indoors. Commonly used indoor positioning media involve Wi-Fi, LED, ZigBee, Bluetooth, infrared, ultrasound, and optical and magnetic fields. Common indoor positioning methods include the Received Signal Strength (RSS) method, the Time of Arrival (TOA) method, the Time Difference of Arrivals (TDOA) method and the Angle of Arrival (AOA) method. Common indoor positioning algorithms include Fingerprint, KNN, Triangulation, LANDMARC and Weights [9-10]. The advantage of fingerprinting is that its system contains two phases – the offline phase and the online phase. In the offline phase, data are collected into a database. In the online phase, the target collects the RSSI value of the beacon or Wi-Fi device and finds out the offline data. The advantage of k-NN is that it uses fingerprint technology. The system filters out the k training points, and then calculate the mean value of these training points. Overcoming environmental interference and improving indoor location accuracy are important issues in the field of indoor positioning.

In general, indoor positioning algorithms determine the user location using two methods: distance based methods, and fingerprinting based methods. In distance based methods, the user's position can be determined by calculating the distance between the user and at least three Access Points (APs) using triangulation method, on the other hand, in fingerprinting based methods, a radio map created in the training phase can be deployed to calculate the user's position. However, the accuracy of these algorithms must now be improved. Therefore, in this work, Bluetooth 4.0 Beacon positioning technique is used with the Fingerprint and KNN positioning algorithms to locate the prediction points. In this work, DKNN-AW is used

*Corresponding Author: Chong-Yi Yang; E-mail: chongyi.yang@gmail.com
DOI: 10.3966/160792642019092005024

to determine whether the weighting mechanism is needed in the calculation, and uses the dynamic KNN method to filter out useless reference points. Finally, the proposed weighting mechanism is utilized to obtained average error distance between the target device and the reference point.

The remainder of the paper is organized as follows. Section 2 surveys related knowledge and studies related to localization concept. Section 3 introduces the proposed dynamic KNN with adaptive weighting mechanism. Its implementation and performance are analyzed in Section 4. Finally, conclusions are given in Section 5.

2 Related Works

In recent years, as mobile devices have become more common and wireless communication technologies have become more sophisticated, advanced information and communication technologies have been developed to integrate various sensors into mobile devices to provide a wide range of services and to facilitate the rapid development of location-based services (LBS), which have attracted attention worldwide. Today's Location-based Services include tracking, navigation, route planning, Information Access, social media, games and advertising services; these are used by shopping centers, parking lots, exhibition centers, airports and homecare facilities. Since these applications must be built with require highly accurate indoor positioning, the accurate and efficient collection and processing of indoor location information has become critical.

Therefore, the GPS positioning system is not useful for indoor positioning services because of the signal is influenced by physical effects associated with the indoor environment, such as refraction, scattering and reflection effects, reducing the positioning accuracy. In indoor positioning, common signal sources include Wi-Fi, ZigBee, Bluetooth, infrared, ultrasound and RSSI. Traditional positioning methods such as ToA and TDoA calculate the target's location from the signal's ToA. However, the signal is vulnerable to environmental effects, which increase positioning error. Therefore, most positioning methods use RSSI to calculate the distance between the Access Point and the target [11-12].

The ToA technology synchronizes the time at both the transmitting facility and the receiving facility, so the travelling time of the signal can be accurately obtained and the distance between the facilities can be calculated. Presently, two types of ToA exist one involves measuring the length of the one-way path of the signal; the other involves measuring the length from the round-trip of the signal [13-14].

Time Difference of Arrival (TDOA) is an electronic method that is used in direction finding and navigation, in which the ToA of a particular signal, at physically separate receiving stations with precisely synchronized time references, is calculated. First, the transmitting device sends the first signal A, whose propagation velocity is V_A, and the transmission time T_0 is recorded. As soon as the receiving device receives signal A, the arrival time T_1 is recorded. Then, the transmitting device sends another signal, B, whose propagation velocity is V_B, and whose transmission time T_2, is recorded. As soon as the receiving device receives signal B, the arrival time T_3 is recorded. Finally, the distance between the transmitting device and the receiving device is calculated using the following equation [15-17].

$$d = |((T_3 - T_1) - (T_2 - T_0)) \times \frac{V_B \times V_A}{V_B - V_A}| \quad \textbf{(1)}$$

Angle of Arrival (AoA) is a method for determining the direction of propagation of a radio-frequency wave by measuring the difference between the received phases at individual elements of the antenna array. In the AoA method, neither software nor hardware has to be updated to perform positioning calculations, and the accuracy is high. However, the greatest shortcoming of the AoA method is that the antenna is not able to actually measure an angle, so a directional antenna array must be installed at each base station, which increases the cost [18-19].

RSSI is a metric of the power in a received radio signal and is measured in dBm. A represents the received RSSI when the distance between the receiving device and the transmitting device is 1m; n is the Propagation Exponent, and d is the distance between the receiving device and the transmitting device [20-21].

Trilateration is the process of determining absolute or relative locations of points by the measurement of distances using the geometry of circles, spheres or triangles. Trilateration uses at least three known reference points close to the target device as centers of circles; finds the intersections of these circle, and calculates the center of these intersection points, which is the location of the target device [22].

Fingerprinting performs positioning by comparing a received signal pattern and a training pattern in the fingerprint database. First, in the offline phase, the current RSSI pattern that is most similar to those stored in the fingerprint is assumed to be the location of the target device. Then, the location of the target device is calculated using the received signal and the training patterns in the fingerprint database [23-24].

The Cell of Origin (COO) positioning method is a mobile positioning technique for finding a cellular telephone system's cell location. This method compares the strengths of signals from all base stations within the receiving range of a target device; retrieves the location of a base station from a database, and transmits the location information to the target device.

The COO positioning method is not very accurate, as the majority of mobile network cells are projected from an antenna with an angle of 120°, giving a signal coverage area with the base station at one corner, rather than the center; but it is simple to implement [25].

Dead Reckoning (DR) takes the previous location of the target device as a reference point in positioning. However, the shortcoming of the method is that the errors accumulate, so every single positioning uses the previous positioning result as a reference. Whenever the positioning result does not match the target's actual location, the repeated effects on subsequent positioning results generate an enormous decline in positioning accuracy. Therefore, Dead Reckoning is better suited to use in an inertial positioning system [26-30].

3 The Proposed Novel Dynamic KNN with Adaptive Weighting Mechanism (*DKNN-AW*)

The Novel Dynamic KNN with Adaptive Weighting Mechanism (*DKNN-AW*) that is developed herein in the indoor positioning system, as presented in Figure 1. The system includes a beacon, a mobile device and a managing server. The managing server, which calculates the RSSI using a filter, threshold and weighting module, and sends the target device's location information from the server to the target. The four major modules of managing server were threshold module, weighting module and filtering module. The threshold module is part of the function of the dynamic k-NN mechanism, which defines the range of all threshold values. The weighting module dynamically adjusts the weights used in the weighting mechanism. The filtering module is also part of the function of the dynamic k-NN mechanism. It filters out useless reference points and reserves useful reference points for the system. The association module connects with the mobile device.

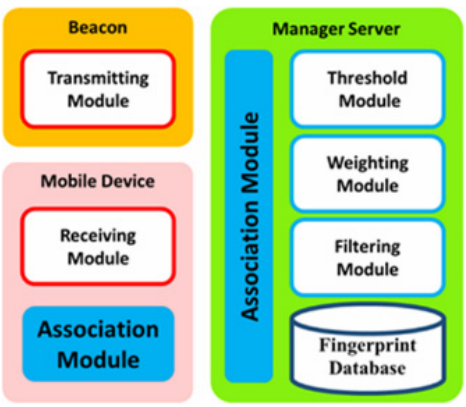


Figure 1. Proposed DKNN-AW system architecture

Figure 2 shows the experimental field, in which eight beacons are deployed, is 8m long and 5m wide. Figure 3 shows the deployment of the reference points. The interval between each pair of reference points is 1m. The user of a mobile device measures the RSSI at each reference point.

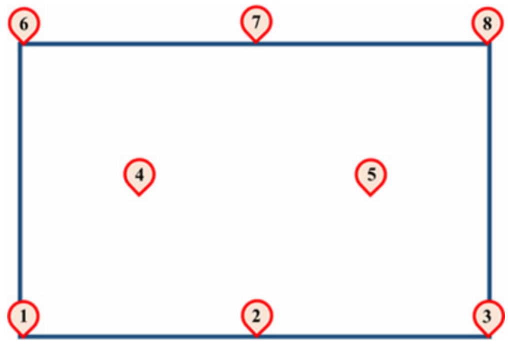


Figure 2. Schematic diagram of the beacons

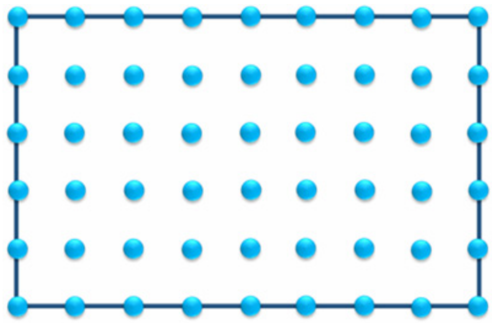
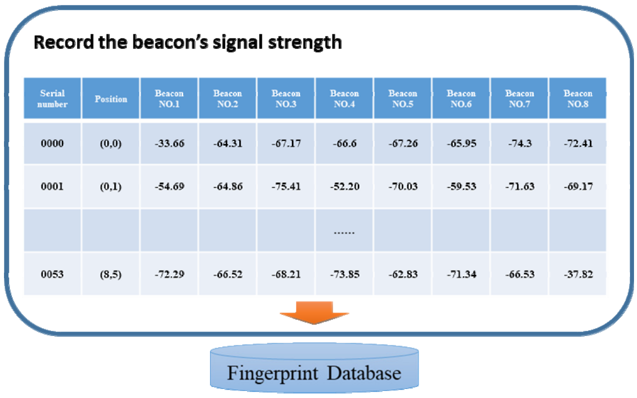


Figure 3. Schematic diagram of reference points

In the offline phase, the target device collects the beacon's RSSI at each reference point, and sends the data to the managing server. The managing server stores the fingerprint database, and ranks the positions of the target devices according to their corresponding Euclidean distances, as which is shown in Figure 4. The fingerprint database provides information including the beacon's location, RSSI and historical data. The system uses the information in the fingerprint database to locate the target by the DKNN-AW mechanism when the system is online. Figure 5 presents the indoor positioning system process sequence in the offline phase.



Serial number	Position	Beacon NO.1	Beacon NO.2	Beacon NO.3	Beacon NO.4	Beacon NO.5	Beacon NO.6	Beacon NO.7	Beacon NO.8
0000	(0,0)	-33.66	-64.31	-67.17	-66.6	-67.26	-65.95	-74.3	-72.41
0001	(0,1)	-54.69	-64.86	-75.41	-52.20	-70.03	-59.53	-71.63	-69.17
					......				
0053	(8,5)	-72.29	-66.52	-68.21	-73.85	-62.83	-71.34	-66.53	-37.82

Figure 4. Schematic diagram of the fingerprint database

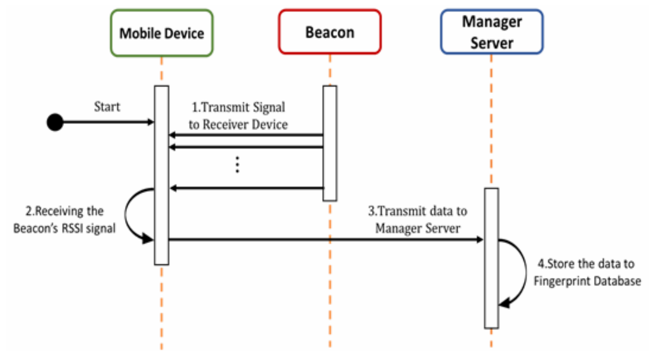


Figure 5. Schematic diagram of process sequence in the offline phase

Figure 6 shows the flow diagram of the indoor positioning system online. In the online phase, the dynamic k-NN mechanism involves the following three processes; calculate the Euclidean distance; filter the useful k-NN points, and calculate the k-NN points' values. The dynamic weight adjustment mechanism is composed of the following three processes; determine the type of weight used in the weight adjustment mechanism for further calculations; calculate the range of threshold values, and calculate the target's location.

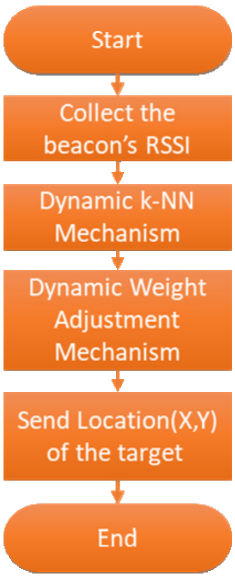


Figure 6. Flow diagram – Online

3.1 Indoor Positioning Algorithms – Online

In the online phase, the indoor positioning system adopts three mechanisms: the dynamic k-NN mechanism, the threshold mechanism, and the dynamic weight adjustment mechanism. The system collects the beacon's RSSI, which is shown in Figure 7. The target collects the beacons' RSSI values and stores them in the fingerprint database. The managing server calculates the target device's location and returns the location information to the target.

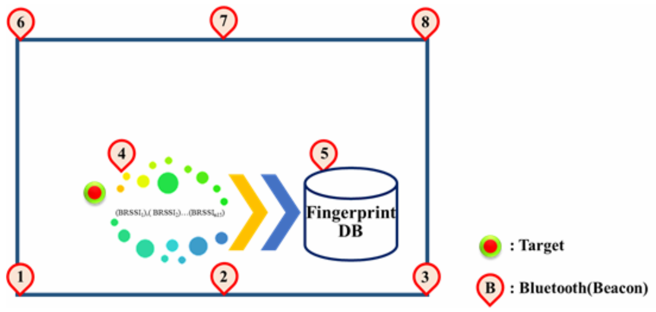


Figure 7. Beacon's RSSI collection

3.2 Dynamic k-NN Mechanism

After receiving the RSSI of the beacon, the managing server calculates the offline data using the Euclidean distance equation (2), in which "d" represents the Euclidean distance of the target device from the reference point and "n" is the number of beacons. The managing server ranks the positions of the KNN points in order of the corresponding Euclidean distances, as shown in Figure 8.

KNN points(At (0,0))

Position	Euclidean Distance	Rank
(0, 0)	7.15694538	1
(0, 1)	13.55909777	2
(1, 0)	22.29402135	3
(1, 1)	25.73221176	4
⋮	⋮	⋮
(8, 5)	55.84059821	54

K = The points of the data top K

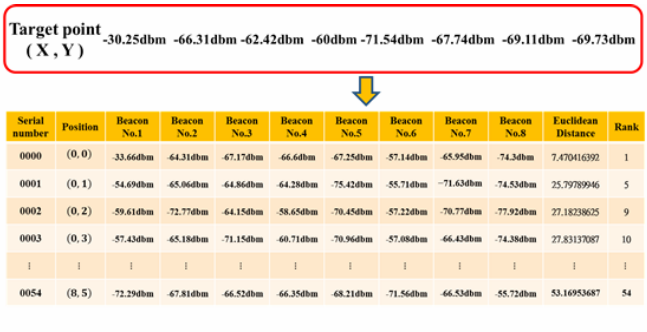
Figure 8. Euclidean distance calculation

$$d(RSSI_{target}, RSSI_{reference}) = \sqrt{\sum_{i=1}^{n}(RSSI_{target_i} - RSSI_{reference_i})^2} \quad (2)$$

The system then selects the best four points for further calculations, and checks whether these four points are within the dynamic k-NN range. Finally, the managing server transmits the data that have been filtered out by the dynamic weight adjustment mechanism. Figure 9 presents the filtered results.

3.3 Dynamic Weight Adjustment Mechanism

The system receives the information of the four points within the dynamic k-NN range. The managing server adjusts the weights of these four points, and reduces the weight of the point that is the farthest from the target. The dynamic weight adjustment mechanism



Serial number	Position	Beacon No.1	Beacon No.2	Beacon No.3	Beacon No.4	Beacon No.5	Beacon No.6	Beacon No.7	Beacon No.8	Euclidean Distance	Rank
0000	(0, 0)	-33.66dbm	-64.31dbm	-67.17dbm	-66.6dbm	-67.25dbm	-57.14dbm	-65.95dbm	-74.3dbm	7.470416392	1
0001	(0, 1)	-54.69dbm	-65.06dbm	-64.86dbm	-64.28dbm	-75.42dbm	-55.71dbm	-71.63dbm	-74.53dbm	25.79789946	5
0002	(0, 2)	-59.61dbm	-72.77dbm	-64.15dbm	-58.65dbm	-70.45dbm	-57.22dbm	-70.77dbm	-77.92dbm	27.18238625	9
0003	(0, 3)	-57.43dbm	-65.18dbm	-71.15dbm	-60.71dbm	-70.96dbm	-57.08dbm	-66.43dbm	-74.38dbm	27.83137087	10
⁞	⁞	⁞	⁞	⁞	⁞	⁞	⁞	⁞	⁞	⁞	⁞
0054	(8, 5)	-72.29dbm	-67.81dbm	-66.52dbm	-66.35dbm	-68.21dbm	-71.56dbm	-66.53dbm	-55.72dbm	53.16953687	54

Figure 9. KNN Points Calculation

is composed of three steps. First, the managing server determines the type of weight and checks if the RSSI value of the target device shows that its position is at the same position with the beacon, as shown in Figure 10.

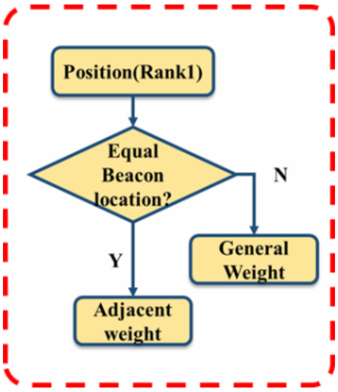


Figure 10. Type of weight decision

Second, the system determines the adjacent weight and calculates the range of thresholds. In the offline phase, the managing server receives the RSSI value from beacons and then adjusts the range of thresholds. The server then sets the weight to 0.1 over the beacon number. The range of thresholds is shown in Figure 11.

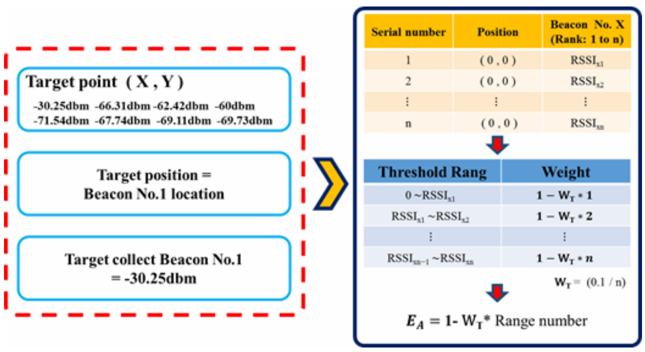


Figure 11. Threshold range calculation

The manager server calculates the target's location by applying the weight mechanism. The weight mechanism uses the Euclidean distance to decide the weight to allocate to every target point. Consider, for example, four points A, B, C and D. The Euclidean distance (between the target device and the reference point) of four points were defined as α, β, γ and δ, where α is the A shortest and following by β, γ and δ. The weight of points A, B, C, D were defined as Equation (3)-(6).

$$E_A = \frac{\frac{1}{\alpha}}{\frac{1}{\alpha}+\frac{1}{\beta}+\frac{1}{\gamma}+\frac{1}{\delta}} \tag{3}$$

$$E_B = \frac{\frac{1}{\beta}}{\frac{1}{\alpha}+\frac{1}{\beta}+\frac{1}{\gamma}+\frac{1}{\delta}} \tag{4}$$

$$E_C = \frac{\frac{1}{\gamma}}{\frac{1}{\alpha}+\frac{1}{\beta}+\frac{1}{\gamma}+\frac{1}{\delta}} \tag{5}$$

$$E_D = \frac{\frac{1}{\delta}}{\frac{1}{\alpha}+\frac{1}{\beta}+\frac{1}{\gamma}+\frac{1}{\delta}} \tag{6}$$

Finally, the manager server calculates the normalization. The weighting of points A, B, C, D were defined as Equation (7)-(10).

$$W_A = \frac{E_A}{E_A + E_B + E_C + E_D} \tag{7}$$

$$W_A = \frac{E_B}{E_A + E_B + E_C + E_D} \tag{8}$$

$$W_A = \frac{E_C}{E_A + E_B + E_C + E_D} \tag{9}$$

$$W_D = \frac{E_D}{E_A + E_B + E_C + E_D} \tag{10}$$

3.4 Indoor Positioning Process Sequence–Online

Figure 12 shows the online program of the indoor positioning system.

The managing server calculates the range of the data collected in the offline phase and filters out the useless reference points. After ranking these devices using the Euclidean distance equation, the system first checks whether the best point is at the location with Rank 1. The managing server defines the range of the data and beacon No.X collects the RSSI signal at its location in the offline phase. Then, the managing server adjusts the range of these data according to the received RSSI and calculates the location of the target using the

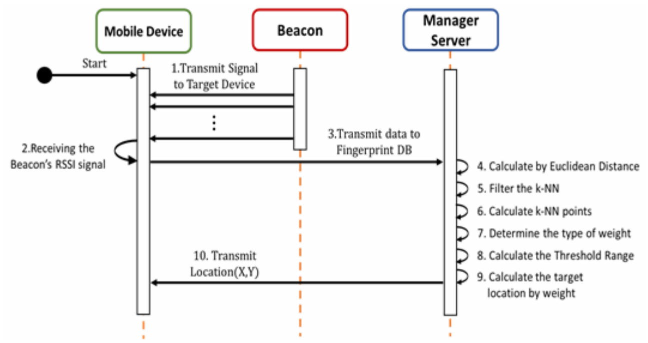


Figure 12. Schematic diagram of process sequence in online phase

proposed weight mechanism in this study. Finally, the managing server transmits the location to the target device.

3.5 Indoor Positioning Database

The indoor positioning database stores the receiver's reference point data and is generated in the offline phase. The system conducts fingerprint positioning in the offline phase before the target device uses the database to perform positioning.

In the offline phase, the receiving data from target device in managing server are provided into the system to conduct fingerprinting position methods, as shown in Figure 13.

Serial number	Position	Beacon No.1	Beacon No.2	Beacon No.3	Beacon No.4	Beacon No.5	Beacon No.6		Beacon No.14	Beacon No.15
0001	(0, 0)	-33.66dbm	-52.13dbm	-64.31dbm	-68.29dbm	-67.17dbm	-57.14dbm	···	-66.83dbm	-72.41dbm
0002	(0, 1)	-54.69dbm	-65.06dbm	-64.86dbm	-64.28dbm	-75.42dbm	-55.71dbm	···	-74.53dbm	-69.17dbm
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮		⋮	⋮
0211	(8, 5)	-72.29dbm	-67.81dbm	-66.52dbm	-66.35dbm	-68.21dbm	-71.56dbm	···	-55.72dbm	-37.82dbm

Figure 13. Fingerprint database

4 System Performance Analysis

In this work, indoor positioning is carried out using the proposed method in Section 3 with a PC table, a mobile device, a beacon and a receiver in the experimental area. Finally, the performance of the proposed indoor positioning system is analyzed.

4.1 Experimental Environment

The experimental area is on the third floor of Auden Technology Company and it is 8m long and 5m wide. The eight beacons are placed at point (0, 0), point (0, 5), point (2, 2.5), point (4, 0), point (4, 5), point (6, 2.5), point (8, 0) and point (8, 5), as shown in Figure 14.

4.2 Performance Analysis with DKNN-AW

This section presents the results of the proposed algorithm DKNN-AW. Table 1 and Figure 15 prove that the proposed DKNN-AW is highly accurate. Four

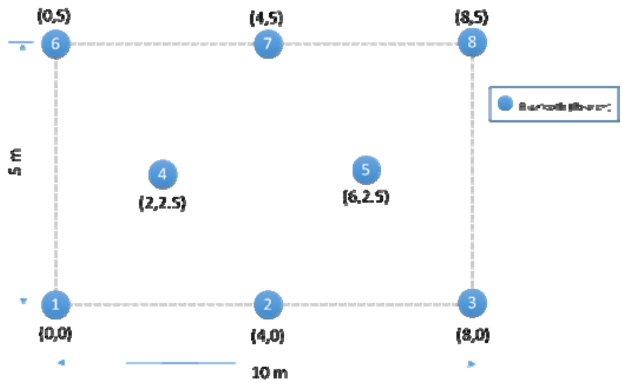


Figure 14. Schematic diagram of positioning environment

Table 1. Average error distance and accuracy of DKNN-AW

	Avg. Error Distance	Accuracy
Average	0.672m	96.46%
CDF (80%)	1.02m	91.83%
CDF (90%)	1.149m	89.64%

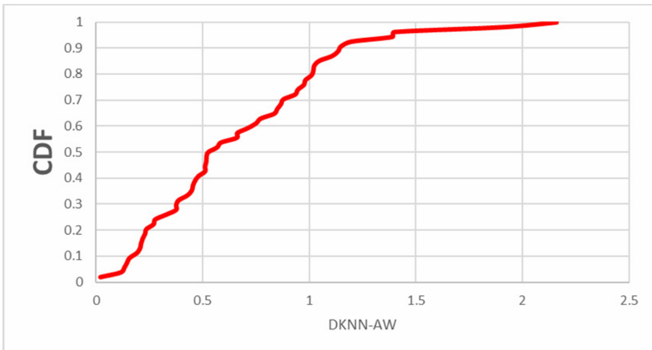


Figure 15. CDF of DKNN-AW positioning methods

cases of the positioning results are considered, and the traditional mechanism and various different filters are applied in the experiment.

These four algorithms are compared with the proposed algorithm. The results presents that the proposed DKNN-AW is the best indoor positioning algorithm. Figure 16 shows these four cases.

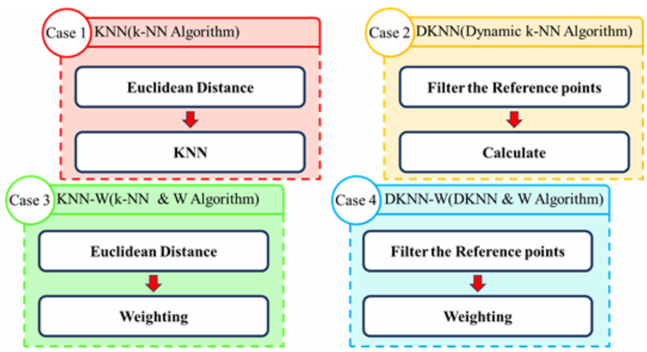


Figure 16. Performance analysis with four cases

4.3 Performance Analysis with Traditional Mechanism

This section describes the traditional mechanism, KNN and compares it with the DKNN-AW mechanism. Table 2 presents the mean error of the distance between the measured position and the actual position and accuracy of the k-NN algorithm. Figure 17 shows cumulative percentage errors obtained using the k-NN algorithm. The results in Table 1, Table 2 and Figure 15, Figure 17 prove that the DKNN-AW is more accurate than the k-NN algorithm. The data demonstrate that the average difference between the measured position and the actual position is approximately 14.4 centimeters. When the CDF reaches 90%, the overall average error is 19.7cm, and the positioning accuracy of the k-NN algorithm is about 9.01%.

Table 2. The analysis of average error distance and accuracy–KNN

	Avg. Error Distance	Accuracy
Average	0.816m	94.78%
CDF (80%)	1.25m	87.73%
CDF (90%)	1.346m	85.77%

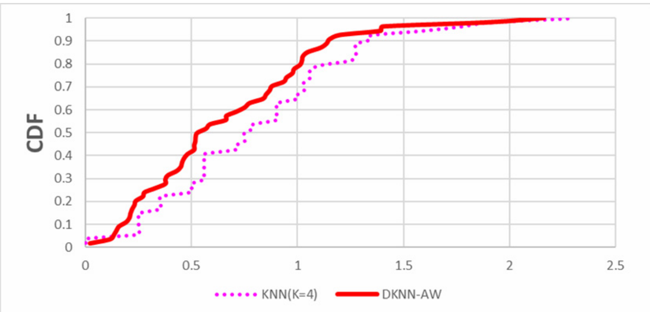


Figure 17. CDF of DKNN-AW and KNN (K=4) positioning methods

4.4 Performance Analysis with Threshold Mechanism

Table 3 present the mean error of the distance between the measured position and the actual position and the accuracy of the DKNN algorithm. Figure 18 shows the cumulative percentage error obtained using the DKNN algorithm. Table 4 and Figure 20 prove that the DKNN-AW is much more accurate than the DKNN algorithm. The data demonstrate that the mean error of the distance between the measured position and the actual position is 11.1cm. When the CDF reaches 90%, the mean error of the distance between the measured position and the actual position is 19.7cm, and the positioning accuracy of DKNN algorithm is about 9.41%.

Table 3. The Analysis of Average Error Distance and Accuracy- DKNN

	Avg. Error Distance	Accuracy
Average	0.783m	95.18%
CDF (80%)	1.25m	87.73%
CDF (90%)	1.346m	85.77%

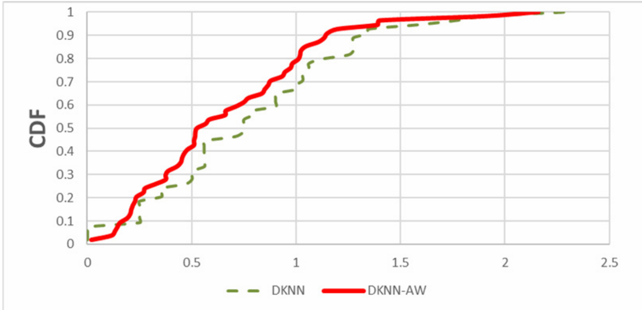


Figure 18. CDF of DKNN-AW and DKNN positioning methods

4.5 Performance Analysis with Threshold Mechanism

Table 4 shows the mean error of the distance between the measured position and the actual position and accuracy of the DKNN-W algorithm. Figure 19 shows the cumulative percentage error obtained using the DKNN-W algorithm. Table 4 and Figure 19 reveal that the DKNN-AW is much more accurate than the DKNN-W algorithm. The data demonstrate that the mean error of the distance between the measured position and the actual position is 9.9cm. When the CDF reaches 90%, the mean error of the distance between the measured position and the actual position is 24.3cm, and the positioning accuracy of the DKNN-W algorithm is about 10.59%.

Table 4. The analysis of average error distance and accuracy–DKNN-W

	Avg. Error Distance	Accuracy
Average	0.771m	95.34%
CDF (80%)	1.048m	91.38%
CDF (90%)	1.392m	84.79%

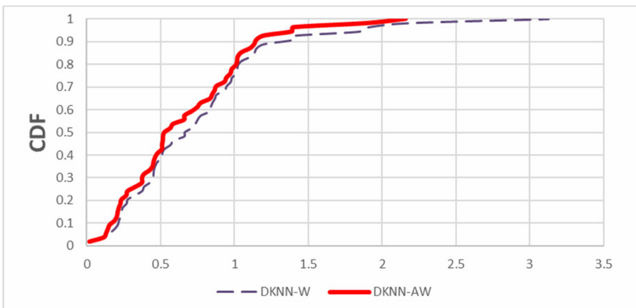


Figure 19. CDF of DKNN-AW and DKNN-W positioning methods

Figure 20 and Table 5 presents the mean error distance between the measured position and the actual position and accuracy of the KNN-W algorithm. Table 5 presents the cumulative percentage errors obtained using the KNN-W algorithm. The data demonstrate that the overall average error in the distance between the measured position and the actual position is 2.7cm. When the CDF reaches 90%, the overall average error is 24.3cm. The positioning accuracy of the KNN-W algorithm is about 9.01%. Therefore DKNN-AW is much more reliable than the hybrid mechanisms.

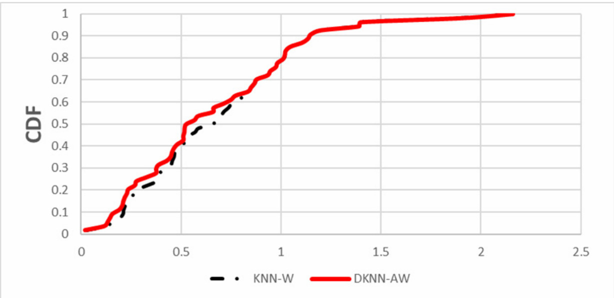


Figure 20. CDF of DKNN-AW and KNN-W positioning methods

Table 5. The analysis of average error distance and accuracy–KNN-W

	Avg. Error Distance	Accuracy
Average	0.669m	96.17%
CDF (80%)	1.012m	86.73%
CDF (90%)	1.392m	84.79%

Three tables show “the best case”, “the worst case” and “general cases”. The “general cases” includes all cases that are considered in this study. Table 6 presents the mean error distance between the measured position and the actual position and accuracy of such positioning method in the best case. Figure 21 presents the cumulative percentage errors in the best case. Table 7 presents the mean error of the distance between the measured position and the actual position and the accuracy in the worst case. Figure 22 shows the cumulative percentage errors in the worst case. Table 8 presents the mean error of the distance between the measured position and the actual position and accuracy across all cases. The results below demonstrate that the mean error of the distance between the measured position and the actual position is 0.711m. The mean error of the distance between the measured position and the actual position in the best case is 0.672m. The mean error of the distance between the measured position and the actual position in the worst case is 0.753m. The DKNN-AW mechanism that is proposed in this study is much more accurate than the other mechanisms.

Table 6. The analysis of average error distance and accuracy–Best case

Algorithm	Avg. Error Distance	Accuracy
DKNN-AW	0.672m	96.46%
KNN	0.816m	94.78%
DKNN	0.783m	95.18%
KNN-W	0.699m	96.17%
DKNN-W	0.771m	95.34%

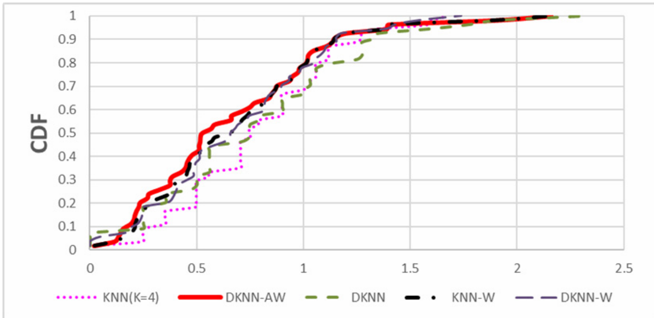


Figure 21. CDF of Best Case

Table 7. The analysis of average error distance and accuracy–Worst case

Algorithm	Avg. Error Distance	Accuracy
DKNN-AW	0.753m	95.55%
KNN	0.876m	93.98%
DKNN	0.82m	94.73%
KNN-W	0.773m	95.31%
DKNN-W	0.848m	94.36%

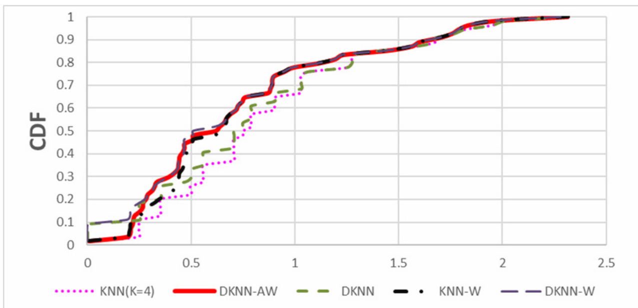


Figure 22. CDF of worst case

Table 8. The analysis of average error distance and accuracy–All cases

Algorithm	Avg. Error Distance	Accuracy
DKNN-AW	0.711m	96.04%
KNN	0.83m	94.6%
DKNN	0.796m	95.03%
KNN-W	0.729m	95.83%
DKNN-W	0.779m	95.24%

5 Conclusion

The benefits of DKNN-AW fall into three categories. First, the dynamic k-NN mechanism in this work can filter reference points and remove low-value reference points. Second, the threshold mechanism enhances the upper value of the weight of reference points. The threshold mechanism accurately determines the target location by analyzing a large number of data. Finally, the weight adaptive mechanism effectively adjusts the ratios among the weights of the reference points. This mechanism improves the upper value of the weight of the reference points by proportional allocation. The proposed DKNN-AW is composed of the dynamic k-NN mechanism, the threshold mechanism and the weight mechanism. DKNN-AW has quite a high accuracy in indoor positioning, and the experimental directional positioning herein demonstrates that it achieves a higher positioning accuracy than existing positioning technologies.

References

[1] A. Tian, D. Dong, D. Ning, C. Fu, GPS Single Point Positioning Algorithm Based on Least Squares, *2013 Sixth International Symposium on Computational Intelligence and Design*, Vol. 2, Hangzhou, China, 2013, pp. 16-19.

[2] M. Yan, C. Xiuwan, X. Yubin, Wireless Local Area Network Assisted GPS in Seamless Positioning, *2012 International Conference on Computer Science and Electronics Engineering*, Vol. 3, Hangzhou, China, 2012, pp. 612-615.

[3] S. Yamaguchi, D. Arai, T. Ogishi, S. Ano, Short Paper: Experimental Study of Long-term Operation of BLE Tags for Realizing Indoor Location Based Service, *2015 18th International Conference on Intelligence in Next Generation Networks (ICIN)*, Paris, France, 2015, pp. 136-138.

[4] A. Iqbal, M. Murshed, On Demand-driven Movement Strategy for Moving Beacons in Sensor Localization, *Journal of Network and Computer Applications*, Vol. 44, pp. 46-62, September, 2014.

[5] M. E. Rida, F. Liu, Y. Jadi, A. A. A. Algawhari, A. Askourih, Indoor Location Position Based on Bluetooth Signal Strength, *2015 2nd International Conference on Information Science and Control Engineering (ICISCE)*, Shanghai, China, 2015, pp. 769-773.

[6] E. Martin-Gorostiza, F. J. Meca-Meca, J. L. Lázaro-Galilea, D. Salido-Monzú, E. Martos-Naya, A. Wieser, Infrared Local Positioning System Using Phase Differences, *2014 Ubiquitous Positioning Indoor Navigation and Location Based Service (UPINLBS)*, Corpus Christ, TX, 2014, pp. 238-247.

[7] Y. Sharma, V. Gulhane, Hybrid Mechanism for Multiple User Indoor Localization Using Smart Antenna, *2015 Fifth International Conference on Advanced Computing & Communication Technologies (ACCT)*, Haryana, India, 2015, pp. 602-607.

[8] L. C. Png, L. Chen, S. Liu, W. K. Peh, An Arduino-based Indoor Positioning System (IPS) Using Visible Light Communication and Ultrasound, *2014 IEEE International Conference on Consumer Electronics-Taiwan (ICCE-TW)*, Taipei, Taiwan, 2014, pp. 217-218.

[9] J. S. Leu, H. J. Tzeng, Received Signal Strength Fingerprint and Footprint Assisted Indoor Positioning Based on Ambient Wi-Fi Signals, *2012 IEEE 75th Vehicular Technology Conference (VTC Spring)*, Yokohama, Japan, 2012, pp. 1-5.

[10] L. M. Ni, Y. Liu, Y. C. Lau, A. P. Patil, LANDMARC: Indoor Location Sensing Using Active RFID, *Proceedings of the First IEEE International Conference on Pervasive Computing and Communications (PerCom 2003)*, Fort Worth, TX, 2003, pp. 407-415.

[11] B. Mukhopadhyay, S. Sarangi, S. Kar, Novel RSSI Evaluation Models for Accurate Indoor Localization with Sensor Networks, *2014 Twentieth National Conference on Communications (NCC)*, Kanpur, Inida, 2014, pp. 1-6.

[12] M. Yassin, E. Rachid, R. Nasrallah, Performance Comparison of Positioning Techniques in Wi-Fi Networks, *2014 10th International Conference on Innovations in Information Technology (INNOVATIONS)*, Al Ain, United Arab Emirates, 2014, pp. 75-79.

[13] Y. Geng, J. He, H. Deng, K. Pahlavan, Modeling the Effect of Human Body on TOA Ranging for Indoor Human Tracking with Wrist Mounted Sensor, *2013 16th International Symposium on Wireless Personal Multimedia Communications (WPMC)*, Atlantic City, NJ, 2013, pp. 1-6.

[14] A. A. Wahab, A. Khattab, Y. A. Fahmy, Two-way TOA with Limited Dead Reckoning for GPS-free Vehicle Localization Using Single RSU, *2013 13th International Conference on ITS Telecommunications (ITST)*, Tampere, Finland, 2013, pp. 244-249.

[15] R. Kaune, Accuracy Studies for TDOA and TOA Localization, *2012 15th International Conference on Information Fusion (FUSION)*, Singapore, 2012, pp. 408-415.

[16] J. Y. Yoon, J. W. Kim, W. Y. Lee, D. S. Eom, A TDoA-based Localization Using Precise Time-synchronization, *2012 14th International Conference on Advanced Communication Technology (ICACT)*, PyeongChang, South Korea, 2012, pp. 1266-1271.

[17] S. Uebayashi, M. Shimizu, T. Fujiwara, A Study of TDOA Positioning Using UWB Reflected Waves, *2013 IEEE 78th Vehicular Technology Conference (VTC Fall)*, Las Vegas, NV, 2013, pp. 1-5.

[18] J. R. Jiang, C. M. Lin, F. Y. Lin, S. T. Huang, ALRD: AoA localization with RSSI Differences of Directional Antennas for Wireless Sensor Networks, *International Journal of Distributed Sensor Networks*, Vol. 9, No. 3, 529489, March, 2013.

[19] B. D. S. Muswieck, J. L. Russi, M. V. T. Heckler, Hybrid Method Uses RSS and AoA to Establish a Low-cost Localization System, *2013 Fourth Argentine Symposium and Conference on Embedded Systems (SASE/CASE)*, Buenos Aires, Argentina, 2013, pp. 1-6.

[20] S. Shuo, S. Hao, S. Yang, Design of an Experimental Indoor Position System Based on RSSI, *2010 2nd International Conference on Information Science and Engineering (ICISE)*, Hangzhou, China, 2010, pp. 1989-1992.

[21] M. M. Atia, A. Noureldin, M. J. Korenberg, Dynamic Propagation Modeling for Mobile Users' Position and Heading Estimation in Wireless Local Area Networks, *IEEE Wireless Communications Letters*, Vol. 1, No. 2, pp. 101-104,

April, 2012.

[22] S. Alamri, D. Taniar, M. Safar, Indexing Moving Objects in Indoor Cellular Space, *2012 15th International Conference on Network-Based Information Systems (NBiS)*, Melbourne, VIC, Australia, 2012, pp. 38-44.

[23] G. Li, C. Busch, B. Yang, A Novel Approach Used for Measuring Fingerprint Orientation of Arch Fingerprint, *2014 37th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO)*, Opatija, Croatia, 2014, pp. 1309-1314.

[24] O. Zanganeh, B. Srinivasan, N. Bhattacharjee, Partial Fingerprint Matching Through Region-based Similarity, *2014 International Conference on Digital Image Computing: Techniques and Applications (DICTA)*, Wollongong, NSW, Australia, 2014, pp. 1-8.

[25] A. Aboodi, T. C. Wan, Evaluation of WiFi-based Indoor (WBI) Positioning Algorithm, *2012 Third FTRA International Conference on Mobile, Ubiquitous, and Intelligent Computing (MUSIC)*, Vancouver, BC, Canada, 2012, pp. 260-264.

[26] J. A. Jiang, X. Y. Zheng, Y. F. Chen, C. H. Wang, P. T. Chen, C. L. Chuang, C. P. Chen, A Distributed RSS-based Localization Using a Dynamic Circle Expanding Mechanism, *IEEE Sensors Journal*, Vol. 13, No.10, pp. 3754-3766, October, 2013.

[27] N. Miwa, S. Tagashira, H. Matsuda, T. Tsutsui, Y. Arakawa, A. Fukuda, A Multilateration-based Localization Scheme for Ad Hoc Wireless Positioning Networks Used in Information-oriented construction, *2013 IEEE 27th International Conference on Advanced Information Networking and Applications (AINA)*, Barcelona, Spain, 2013, pp. 690-695.

[28] J. Park, D. Lee, J. Park, Digital Map Based Pose Improvement for Outdoor Augmented Reality, *2012 IEEE International Symposium on Mixed and Augmented Reality (ISMAR)*, Atlanta, GA, 2012, pp. 309-310.

[29] A. Chandra, S. Jain, M. A. Qadeer, GPS Locator: An Application for Location Tracking and Sharing Using Gps for Java Enabled Handhelds, *2011 International Conference on Computational Intelligence and Communication Systems*, Gwalior, India, 2011, pp. 406-410.

[30] M. H. Park, W. H. Kim, S. J. Lee, H. C. Kim, GPS-tag for Indoor Location Information and Additional User Information Providing, *2012 14th International Conference on Advanced Communication Technology (ICACT)*, PyeongChang, South Korea, 2012, pp. 894-897.

Biographies

Chong-Yi Yang studied in the Department of Computer Science at I-Shou University, where he received a B.S. degree in 2005; and in the Department of Electrical Engineering, National Cheng Kung University where he received a M.S. degree in 2008. He studies in the Department of Electrical Engineering, National Taiwan University of Science and Technology. He is a director in the department of Project Management, CHT Security, Taipei City 100, Taiwan.

Yi-Wei Ma received the Ph.D. degree from the Department of Engineering Science, National Cheng Kung University, Tainan, Taiwan. He is currently an assistant professor in the Department of Electrical Engineering, National Taiwan University of Science and Technology. His research interests include Internet of Things, digital home network, cloud computing, embedded system, multimedia P2P streaming, and ubiquitous computing.

Jiann-Liang Chen received the Ph.D. degree in Electrical Engineering from National Taiwan University, Taipei, Taiwan in 1989. Since August 1997, he has been with the Department of Computer Science and Information Engineering of National Dong Hwa University. Prof. Chen joins the Department of Electrical Engineering, National Taiwan University of Science and Technology, as a full professor now. His current research interests are directed at cellular mobility management, digital home network and personal communication systems.

Chia-Ju Lin received a M.S. degree in 2016; and in the Department of Electrical Engineering, National Taiwan University of Science and Technology.

Wei-Lun Lee received a M.S. degree in 2015; and in the Department of Electrical Engineering, National Taiwan University of Science and Technology. He is a research and development engineer in the Data Communication Business Group, Chunghwa Telecom Company, Taipei City 100, Taiwan.