

# WiFi Positioning by Optimal k-NN in 3GPP Indoor Office Environment

Sung Hyun Oh  
Dept. Electronic Engineering  
Korea Polytechnic Univ.  
Siheung, Korea  
osh119@kpu.ac.kr

Jeong Gon Kim\*  
Dept. Electronic Engineering  
Korea Polytechnic Univ.  
Siheung, Korea  
jgkim@kpu.ac.kr

**Abstract**— The most important issue in the LBS(Location Based Service) industry is to accurately estimate the user's location to provide various location-based services. In the case of an outdoor environment, relatively high positioning accuracy may be provided through a GPS(Global Positioning System) or the like. However, the application of the GPS is limited in an indoor environment due to problems such as propagation loss. Therefore, in this paper, a technology for positioning a user using WiFi(Wireless Fidelity) communication applied to a general indoor environment is studied. First, a fingerprinting scheme that provides relatively high accuracy in combination with an RSSI(Received Signal Strength Indicator) is applied to perform user positioning. At this time, after arranging each RP(Reference Point) in the offline step, the RSSI value is measured to build a fingerprinting database. After, in the online step, the k-NN(k-Nearest Neighbor) algorithm, a technique of supervised learning, is applied by measuring the RSSI value of the fingerprinting database and the actual user's location. At this time, the initial search area of the PSO(Particle Swarm Optimization) algorithm is limited by deriving the closest RP from the actual user. After that, the particles are distributed in a limited area to finally determine the user's location. Through simulation, it can be confirmed that when k-NN and PSO are jointly used, improved positioning accuracy is obtained compared to the existing schemes.

**Keywords**—LBS(Location Based Service), Indoor Positioning, k-NN(k-Nearest Neighbor), PSO(Particle Swarm Optimization), Wi-Fi(Wireless Fidelity)

## I. INTRODUCTION

With the rapid development of mobile communication technology, the LBS(Location Based Service) industry is attracting attention. In general, LBS may be requested for personal or public purposes. The main examples are for customers to find the store they want by themselves in large and complex shopping malls, to support firefighters in case of a fire in a building, or to provide discount information at large marts. Conventionally, it is possible to provide relatively high positioning accuracy in an outdoor environment based on GPS (Global Positioning System) technology[1]. However, there is a limit to the application of GPS technology due to problems such as propagation loss due to the complicated radio wave environment in the indoor environment. Therefore, to solve this problem, technologies that provide high positioning accuracy based on communication technologies applicable in indoor environments such as WiFi(Wireless Fidelity), Bluetooth, and UWB (Ultra-Wide Band) became an important research subject[2].

In addition, technologies such as IoT(Internet of Things), Bigdata, and AI(Artificial Intelligence), which are the core

\*: Corresponding Author

technologies of the 4th industry, can be fused and applied to the LBS industry. Most people own a smartphone, an IoT device. Big data technology can store and use vast amounts of data. AI technology has the advantage of being able to quickly process complex calculations. When these three technologies are convergent applied, it is possible to provide each user with the optimal location accuracy in real-time.

As mentioned above, mobile communication technologies for indoor positioning that are currently generally used include WiFi, Bluetooth, UWB, and the like. And in the existing sensor positioning technology, there are techniques based on the range and methods that do not use the range. Among them, in general, most of the technology based on the range is applied. Among them, positioning technology based on RSSI(Received Signal Strength Indicator) is the most commonly used because it can obtain high positioning precision at a low cost when used in combination with a fingerprinting algorithm[3].

Existing studies related to these indoor positioning methods are as follows. In [4], the positioning accuracy was improved by limiting the MLE(Maximum Likelihood Estimation)-based PSO(Particle Swarm Optimization) scheme, and in [5], a method combining ANN(Artificial Neural Network) and PSO was proposed to estimate the user's location. In [6], a method of estimating the user's location through the re-sampling process using a particle filter was proposed, and in [7], a method that effectively converges RSSI fingerprinting and MF(Magnetic Field) fingerprinting was used. The above literatures proposed various approaches for indoor user positioning, but they did not consider both positioning accuracy and processing time at the same time.

Therefore, in this paper, we propose a method for estimating the user's location based on WiFi communication in the indoor environment suggested by 3GPP(Third Generation Partnership Project)[8]. The core of the proposed method is to effectively limit the initial search area of PSO through k-NN(k-Nearest Neighbor), an AI(Artificial Intelligence) technology. To this end, initially, RSSI values for a specific RP(Reference Point) are collected based on a fingerprinting technique. Then, k-NN techniques are applied between the RSSI value of the real user and the fingerprinting database value to derive k RPs closest to the user. The derived k points may be used to limit the initial search area of the PSO. At this time, we conduct the simulation by changing the k value and analyzing the positioning accuracy performance according to the k value.

The overall structure of this paper is as follows. Section 2 describes the system model. Section 3 describes the indoor positioning method proposed in this paper. Subsequent section 4 describes the parameter values and results used in the

simulation. Finally, Section 5 draws the conclusion of this paper.

## II. SYSTEM MODEL

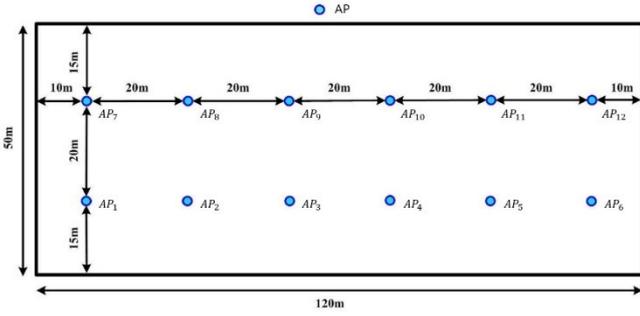


Fig. 1. Indoor environment suggested by 3GPP

The environment considered in this paper is shown in Fig.1[7]. Fig.1 shows the indoor environment suggested by 3GPP and has a size of  $120m \times 50m$ , with a total of 12 APs(Access Point) deployed. The distance between each AP is set to  $20m$ .

In the suggested environment, it communicates based on WiFi and locates the user by using the RSSI value between each AP and the UE(User Equipment). In this case, the RSSI value can be obtained as in (1) below.

$$RSSI_d = 10 \log(P_0) - 10u \log\left(\frac{d}{d_0}\right) + N \quad (1)$$

where,  $RSSI_d(dBm)$  and  $P_0(dBm)$  are the received power between the AP and the user for each distance  $d$  and  $d_0$ .  $u$  is the path loss exponent, and  $N$  is the noise.

## III. PROPOSED POSITIONING SCHEME

The positioning method proposed in this paper is shown in Fig. 2. The proposed scheme locates the user's location by sequentially applying the fingerprinting scheme, k-NN algorithm, and PSO. At this time, the core idea is to limit the initial search area of PSO through a k-NN algorithm.

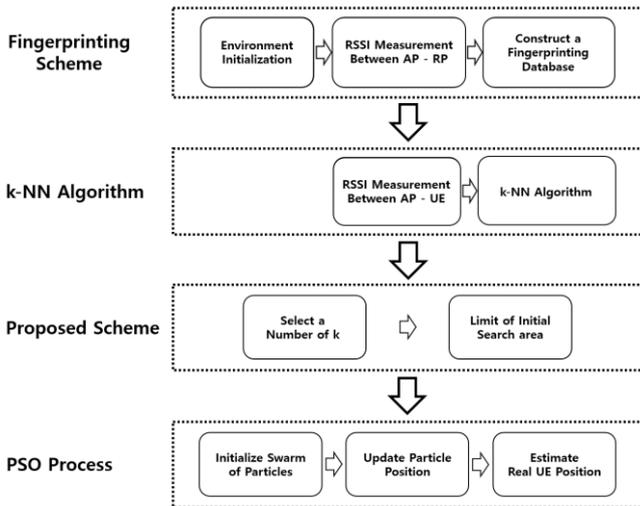


Fig. 2 Block diagram of the proposed scheme

As shown in Fig. 2, the proposed method uses three single algorithms fused. First, the fingerprinting scheme is performed in the offline step. The fingerprinting scheme measures the RSSI value from all APs in each RP. A

fingerprinting database is built based on the measured RSSI value. In the online step, RSSI between the UE and each AP is measured. The measured values apply the k-NN algorithm based on the fingerprinting database. By applying the k-NN algorithm, it is possible to derive k RPs closest to the UE. The derived k RPs are used to limit the initial search area of PSO. Limiting the initial search area of PSO is the core idea of this paper. If the initial search area is limited, the convergence time of the PSO process can be shortened and high positioning accuracy can be achieved.

PSO, performed in a limited search area, is an intelligent evolutionary computation algorithm that finds the location of a UE based on intelligent particles. PSO has advantages such as few parameters, simple implementation, and high positioning accuracy [8,9]. In PSO, particles share information and search for an optimal point. Since each particle determines the direction of movement based on shared information, the information of all particles must be updated periodically. The subsections below look at each step in detail.

### A. Fingerprinting Scheme

The fingerprinting scheme is a method of constructing a database by measuring the RSSI value at a specific location. Recently, indoor environments such as airports, large stadiums, high-rise buildings, and large department stores have become wider and more complex. Therefore, when building a fingerprinting database in an indoor environment, big data technology that can store a large number of RSSI samples is required. In this paper, a simulation-based fingerprinting technique was performed. First, the RP is placed in a specific location within the environment considered in the system model. Thereafter, each AP calculates an RSSI value for each RP based on (1). A fingerprinting database  $DB_F$  is built based on the calculated values. The constructed fingerprinting database  $DB_F$  can be expressed as (2) below.

$$DB_F = \begin{bmatrix} h_1^1 & \dots & h_1^m & \dots & h_1^M \\ \vdots & & \vdots & & \vdots \\ h_r^1 & \dots & h_r^m & \dots & h_r^M \\ \vdots & & \vdots & & \vdots \\ h_R^1 & \dots & h_R^m & \dots & h_R^M \end{bmatrix} \quad (2)$$

where,  $h_r^m$  represents an RSSI value between the  $m$ -th AP and the  $r$ -th RP. Thereafter, the  $DB_F$  value is used to estimate the real user's position in k-NN algorithm.

### B. k-NN Algorithm

The k-NN is one of the supervised learning algorithms that finds k closest data in feature space with random input. In other words, it is to find the k most adjacent RPs from the user's location. The k-NN algorithm is a method without a learning process, and when new data comes in, it selects neighbors by measuring the distance between existing data. Because k-NN does not build a model separately, it is also called Instance-based Learning. In k-NN, there are Euclidean Distance and Manhattan Distance as distance measurement methods. In this paper, we apply the method of deriving the adjacent RP based on the commonly used Euclidean Distance. A method of deriving the closest RP from the user is as follows.

First, the RSSI value for the user's location is measured in the online phase. The measured value can be expressed as follows.

$$H_u^{RSSI} = [h_u^1, h_u^2, h_u^m, \dots, h_u^M] \quad (3)$$

where,  $h_u^m$  is the RSSI value between the  $m$ th AP and the user UE  $u$ . Assuming the measured user's RSSI value as new data, the closest RP is derived by calculating the Euclidean Distance with the fingerprinting database value.

$$d_{u,r} = \|H_u^{RSSI} - DB_F\| = \sqrt{\sum_{m=1}^M (h_u^m - h_r^m)^2} \quad (4)$$

where,  $d_{u,r}$  denotes the Euclidean Distance between UE  $u$  and RP  $r$ , and the smaller the value, the closer UE  $u$  and RP  $r$ . Thereafter, the initial search area of the PSO algorithm is limited based on the  $k$  nearest RPs.

### C. PSO Algorithm

PSO is an intelligent evolutionary computational algorithm proposed by James Kennedy and Russell Eberhart in 1995 and can derive an optimal solution by distributing particles within the search area. The specific process of the PSO algorithm is as follows.

First, the particles in the swarm perform the initialization process. The initialized particles are randomly distributed in the search area, and the location of the UE is estimated. In the PSO, all particles repeat the process of finding the optimal solution estimated as the actual location of the UE. During the search, each particle shares its optimal position,  $pbest$ , and its optimal position,  $gbest$ , within the cluster. Particles are searched based on  $pbest$  and  $gbest$  to derive an optimal solution. The algorithm terminates when the maximum number of iterations is reached or the target accuracy is achieved. The parameter changes of each particle according to the repetition are shown below.

$$V_p(t+1) = wV_p(t) + c r [pbest_p(t) - x_p(t)] + c r [gbest(t) - x_p(t)] \quad (5)$$

$$X_p(t+1) = X_p(t) + V_p(t+1) \quad (6)$$

$$w = w_{max} - \frac{t}{T}(w_{max} - w_{min}) \quad (7)$$

where,  $V_p(t)$  is the velocity of the  $p$ -th particle in the  $t$ -th iteration,  $X_p(t)$  is the position of the  $p$ -th particle in the  $t$ -th iteration. In addition,  $c$  is an acceleration coefficient,  $w$  is an inertia coefficient, and  $r$  is an arbitrary coefficient of contraction.  $t$  represents the current number of iterations, and  $T$  is the total number of iterations of the PSO algorithm.

As above, while the particles perform repetitions, the PSO process is terminated when the preset target accuracy or the maximum number of repetitions is reached. After the PSO process is finished, the position of the particle having the most optimal solution becomes the estimated position of the UE. The process of the proposed technique is described in detail in Algorithm 1.

#### Algorithm 1: Proposed Positioning Algorithm

**Result:** Location of user  
 Environment Initialization  
 Distribute the RP at a specific location within the area for  $m = 1:M$   
 where,  $M$  is the total number of Wi-Fi APs  
 Measure Wi-Fi AP  $m$  and each RP's RSSI value  
 End

Fingerprinting database  $DB_F$  construction for  $m = 1:M$

Measure Wi-Fi AP  $m$  and UE's RSSI value

End

Construction  $H_u^{RSSI}$  with measured values

Weighted fuzzy matching with  $DB_F$  and  $H_u^{RSSI}$

Deriving the  $k$  RPs closest to the UE and obtaining a limited area

Randomly distribute particles over a limited area

For  $t = 1:T$

PSO algorithm implementation

End

Obtain the position of the particle with the most optimal fit and use it as the UE's estimated position

## IV. SIMULATION SETUP AND RESULTS

A simulation was performed based on MATLAB 2017b to evaluate the performance of the proposed scheme. The main parameters used in the simulation are summarized in Table I.

TABLE I. SIMULATION PARAMETER

Parameter	Value
Room size	120m × 50m
Distance between reference points	3, 6, 9 m
Number of iteration	10,000
Number of AP	12
Transmit Power of AP	20 dBm
Number of Particle	10
$c, r, w_{min}, w_{max}, T$	2, 0.3, 1, 0.4, 10
$k$ Value	3, 4, 5

As can be seen in Table 1, in this paper, user positioning is performed based on the indoor environment suggested by 3GPP. The size of the suggested indoor environment is 120m × 50m. To evaluate the positioning performance, the simulation is repeated a total of 10,000 times. The built environment is shown in Fig. 3.

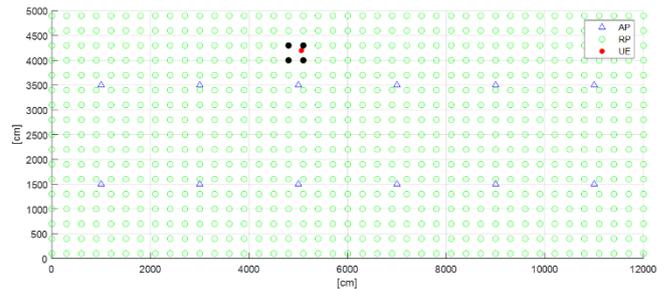


Fig. 3. Indoor environment and RP location realized by simulation

In Fig. 3, the blue triangle is a WiFi AP, and the red circle is a UE, and the green circle is an RP, and the black circles are the  $k$  RPs closest to the UE. A total of 12 APs are uniformly placed in the presented environment. The transmit power of each AP is set to 20dBm, and the interval between APs is 20m. At this time, to apply the fingerprinting scheme, the interval of the RP is arranged by changing it to 3, 6, and 9m. In the simulation, the UE is randomly placed in the suggested environment and the proposed positioning scheme is applied. The initial search area is limited for the PSO process.

Simulations are performed by changing the  $k$  value of the  $k$ -NN algorithm to 3, 4, and 5 to derive a limited area. Afterward, in the PSO process, the particles are initialized using the variables shown in Table 1. In the proposed scheme, the maximum number of repetitions of the PSO was set to a total of 10 times.

TABLE II. POSITIONING ERROR ACCORDING TO K-VALUE

Scheme	Positioning Error [m]		
	Distance between of RP [m]		
	3m	6m	9m
Best Match ( $k = 1$ )	2.380 m	3.134 m	4.416 m
$k$ -NN with $k = 3$	1.380 m	2.076 m	3.211 m
$k$ -NN with $k = 4$	1.227 m	2.019 m	3.102 m
$k$ -NN with $k = 5$	1.231 m	2.322 m	3.526 m

Table 2 shows the positioning error of each scheme according to the change in the RP interval. The best match is a scheme of estimating the coordinate value of the RP with the highest proximity as the coordinates of the UE. In this case, the best match set the value of  $k$  to one in the  $k$ -NN algorithm. In  $k$ -NN,  $k$  values were set to 3, 4, and 5, and simulations were performed. As can be seen from the results, it can be confirmed that the highest positioning accuracy performance is shown when  $k$  values are 3 and 4. This shows that the smaller the initial search area of the PSO algorithm, the higher the positioning accuracy performance.

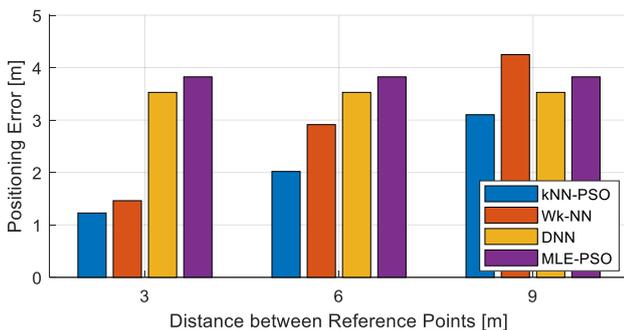


Fig. 4. Positioning Error vs Distance between Reference Points

Fig. 4 is the result of comparing the positioning accuracy between the proposed scheme and the existing scheme.  $k$ NN-PSO is a scheme proposed in this paper and based on the results of Table 2, the  $k$  value is 4. W(Weighted) $k$ -NN is a method of deriving  $k$  adjacent RP, assigning weights through Euclidean distance calculation, and estimating the user's location. MLE-PSO[4] is a method of improving the positioning accuracy by estimating the user's approximate location through the MLE method and then applying the PSO algorithm additionally. A DNN(deep neural network) is a method of estimating a user's location using a feed-forward neural network. As can be seen from the fig.4, it can be seen that MLE-PSO and DNN have a constant positioning error regardless of the change in the distance between RPs. This shows that the two schemes are a method of estimating the user's location without relying on RP. Unlike this, it can be seen that the positioning error of  $k$ NN-PSO and Wk-NN increases as the distance of RP increases. As the result shows, when the distance between RP is 3m, it could be verified that the scheme proposed in this paper achieves the highest

positioning accuracy. This improved the probability of particle convergence by limiting the area in which the actual user may exist to the PSO search area.

TABLE III. COMPARISON OF PROCESSING TIME OF EACH SCHEME

Scheme	Processing Time [s]
Wk-NN	0.06572
MLE-PSO	0.15314
$k$ -NN-PSO	0.10847
DNN	0.00144

Table 3 shows the algorithm processing time of each scheme. First, the  $k$ NN-PSO scheme and MLE-PSO scheme proposed in this paper have the longest processing time. It can be confirmed that this is related to the time required for the PSO algorithm to converge. In the case of Wk-NN, it can be confirmed that the PSO scheme achieves a shorter processing time than the above two methods in a way that is not applied. In the case of DNN, when learning is completed in the offline stage as one of the supervised learning models, it can be confirmed that the time required for the user's position is the shortest in the online stage. However, since all four schemes may complete the positioning within 1 second, it is judged that the positioning will not be a problem.

## V. CONCLUSION

In this paper, a study was conducted to improve the positioning accuracy of users in the indoor environment suggested by 3GPP. It is based on WiFi communication and uses a fusion of fingerprinting,  $k$ -NN, and PSO algorithms to locate the user. Through the simulation results, it was confirmed that the positioning accuracy varies according to the size of the fingerprinting database built in the offline stage and the  $k$  value in the  $k$ -NN algorithm. In this paper, it was confirmed that the highest positioning accuracy was achieved when the distance between RPs was 3 m and the  $k$  value was 4. In the future, research is planned to improve the positioning accuracy through optimization of the PSO algorithm.

## ACKNOWLEDGMENT

This work was supported by the National Research Foundation of Korea(NRF) grant funded by the Korea government(MSIT) (NRF-2021R1F1A1063845).

This research was supported by the Korea Institute for Advancement of Technology (KIAT) grant funded by the Korea government (MOTIE) (N0002429, The Competency Development Program for Industry Specialists).

## REFERENCES

- [1] S. C. Yeh, W. H. Hsu, M. Y. Su, C. H. Chen, K. H. Liu, "A Study on Outdoor Positioning Technology using GPS and WiFi Networks," 2009 International Conference on Networking, Sensing and Control, Mar. 2009.
- [2] B. H. Kim, M. C. Kwak, J. K. Lee, T. K. Kwon, "A multi-pronged approach for indoor positioning with WiFi, magnetic and cellular signals," 2014 International Conference on Indoor Positioning and Indoor Navigation (IPIN), Oct. 2014.
- [3] N. Li, J. Chen, Y. Yuan, "A WiFi Indoor Localization Strategy Using Particle Swarm Optimization Based Artificial Neural Networks,"

- International Journal of Distributed Sensor Networks, vol. 12, pp. 1-9, Mar. 2016.
- [4] Z. Chong, W. Bo, "A MLE-PSO Indoor Localization Algorithm Based On RSSI," 2017 36th Chinese Control Conference (CCC), Jul. 2017.
  - [5] S. K. Gharghan, R. Nordin, M. Ismail, J. A. Ali, "Accurate Wireless Sensor Localization Technique Based on Hybrid PSO-ANN Algorithm for Indoor and Outdoor Track Cycling," IEEE Sensors Journal, vol. 16, pp. 529-541, Jan. 2015.
  - [6] Z. Yajun, W. Hao, W. Hongjun, "Indoor Navigation System Design based on Particle Filter," 2016 International Conference on Intelligence Transportation, Big Data & Smart City(ICITBS), pp.105-108, Dec. 2016.
  - [7] K. S. Kim, S. H. Lee, K. Huang, "A scalable deep neural network architecture for multi-building and multi-floor indoor localization based on Wi-Fi fingerprinting," Big Data Analytics, vol. 3, pp. 1, Apr. 2018.
  - [8] "Study on channel model for frequencies from 0.5 to 100 GHz (Release14)," 3GPP TR 38.901.
  - [9] H. K. Yu, S. H. Oh, J. G. Kim, "AI based Location Tracking in WiFi Indoor Positioning Application," 2020 International Conference on Artificial Intelligence in Information and Communication (ICAIIIC), Feb. 2020.