공학 석사 학위 논문

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컴퓨터 공학부
송 웅 섭

송웅섭의 석사 학위논문을 인준함

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Abstract

Indoor Localization Method Using UWB Trilateration and WiFi Fingerprinting in Mixed LOS/NLOS Environment

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Recently, indoor localization draws a lot of attention. Application examples of indoor localization are smart factories, smart homes, etc., which are used for user convenience or safety. Among several indoor localization technologies, the indoor localization technology based on UWB ranging is receiving great interest due to its high accuracy. However, in the case of UWB ranging, the indoor localization error increases as the ranging error increases in the Non-Line-of-Sight (NLOS) situation where obstacles exist. In order to improve the localization accuracy in mixed environment of LOS / NLOS, we propose a new positioning method that combines the UWB ranging-based localization method and WiFi fingerprinting method. The proposed method reduces the average and the worst localization error by utilizing the strengths of the existing UWB ranging-based localization method and WiFi fingerprinting method. To calculate the localization error, the experiment is divided into two environments where LOS is relatively well maintained and an environment that is not. The localization accuracy of proposed method are compared to that of existing methods. Experimental results show that the conventional positioning method, UWB trilateration, has an average positioning error of 0.8m and WiFi fingerprinting of 1.44m, whereas the proposed method shows a positioning error of 0.64m. Additionally, the UWB trilateration is 3.7m for the worst positioning error and 5.83m for WiFi fingerprinting, whereas the proposed method is 2.05m, showing that the positioning error has reduced. As a result, the experimental results show that the proposed method is an effective method to improve localization accuracy in a mixed LOS/NLOS environment.

keywords : Indoor localization, indoor positioning, UWB, WiFi, Fingerprinting, Trilateration, NLOS, LOS
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Chapter 1
Introduction

Recently, indoor positioning has received a lot of interest in various fields. There are several use cases using indoor positioning information such as patient tracking in hospitals, factory and logistics automation, indoor navigation for customers in shopping malls, and emergency situation management such as fire in smart buildings[1-8]. In each use case, a different level of localization accuracy is required, and at most, a localization error of about 2 meters to 10 cm is required. In this situation, indoor localization methods using various wireless communication protocols such as WiFi, BLE, RFID, and UWB are used[9]. WiFi uses protocols such as 802.11, the channel frequency is 2.4Ghz or 5Ghz, and the bandwidth of each channel can be 20MHz~80MHz according to the user's desired setting. WiFi fingerprinting is widely used for indoor localization by characterizing the radio signal with respect to certain position.[10][11] WiFi fingerprinting has two phases so called offline phase and online phase. In the offline phase, the characteristics of the radio signal for a specific location are stored and made into a database called a radio map. Additionally, in the offline phase, a learning model such as DNN is trained with the radio map. In the online phase, the characteristics of the measured radio signal and the radio map are compared to predict where the radio signal with the most similar characteristics is measured. Since the WiFi fingerprinting method uses WiFi APs for communication, there is no additional AP installation cost, so it is cost-effective and has the advantage of being robust against the influence of Non-Line-of-Sight(NLOS) by indoor obstacles. The positioning error of WiFi fingerprinting is within 2m.[9][12] Next, there is a BLE-based proximity measurement method called iBeacon. Once, the iBeacon receiving device calculates the distances to the transmitting devices by calculating the RSS values, the calculated distances are used by positioning algorithms such as trilateration. The localization error using iBeacon is about 3 meters[6][8]. However, if the LOS environment is not maintained, the error of distance measurement becomes large, resulting in a large positioning error. RFID is another positioning method. In the case of positioning using RFID, it is cost-effective because RFID communication equipment is inexpensive, but on the other hand, it has a high positioning error of several meters[6]. Lastly, there is a positioning method using the UWB 802.15.4z communication protocol.. In the case of positioning using UWB, positioning error of about 10cm is shown, which is lower than that using other communication protocols. In the case of distance measurement using UWB, there is no interference from other communication media, but the distance measurement error for people or steel structures increases.[12][13] Therefore, when UWB is used for indoor positioning, there is a problem that the localization accuracy decreases in a complex structured environment such as a museum or a factory rather than a general office like environment.

In this paper, we propose an indoor positioning method that combines UWB trilateration and WiFi fingerprinting. The proposed method has robustness to NLOS environment, which is an advantage of WiFi fingerprinting, and high positioning accuracy, which is an advantage of UWB ranging-based trilateration. Through the experiment, the proposed method showed an effective positioning method in an environment in which LOS/NLOS are mixed. The main contributions of this paper are as follows:

- We present a indoor localization method that combines two well known methods, UWB trilateration and WiFi fingerprinting, for mixed LOS/NLOS environment.
- The proposed method has improved localization accuracy when it is compared to traditional trilateration or fingerprinting. We show the experimental results in real-world environment.
- The proposed method uses typical 4-layer DNN based WiFi fingerprinting to show the generality of the method. However, we expect that the method with different communication medium(i.e., BLE, RFID) or different learning model(i.e., CNN, Capsnet) be effective.

After this, this paper is composed as follows. In section 2, we present the proposed system model.. Next, we explain an overview of the proposed method and implementation details in section 3. In section 4, we introduce the metric and experiment environment used in the experiment. In section 5, we analyzes the results of localization in the previously introduced environment. Finally, we conclude in section 6.

Chapter 2
System model

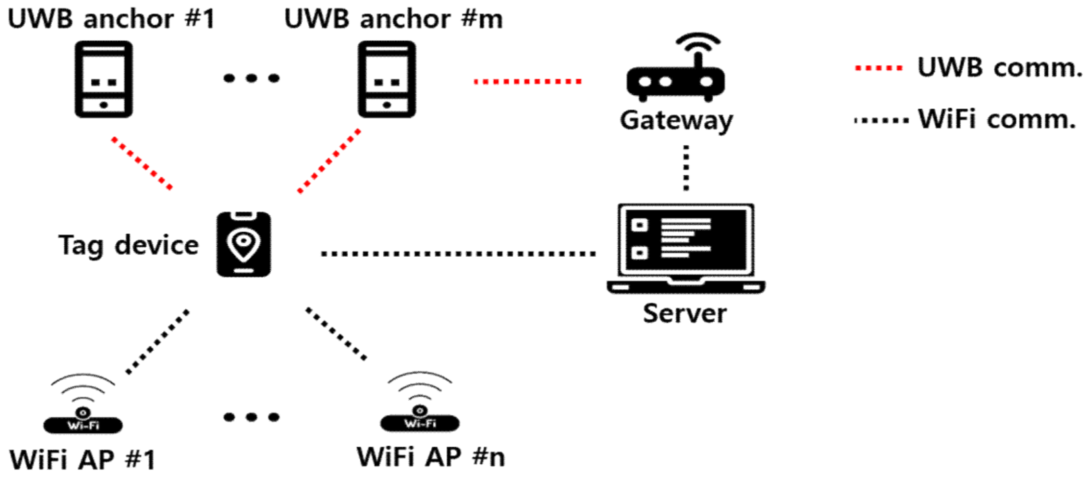

Figure. 1. System model

The proposed system model is divided into a part connected using UWB and a part connected using WiFi. In the case of parts connected by UWB, devices capable of UWB communication are connected using the 802.15.4z protocol, and are intended for indoor positioning using UWB ranging. For the part connected by WiFi, the 802.11b/g/n 2.4Ghz WiFi protocol is used, and it is intended for indoor positioning using WiFi fingerprinting.

Each of the devices in the system model is as follows. In the case of UWB anchors, m number of anchors are installed at known locations to perform UWB ranging to tag, and the measured ranging values are transmitted to the gateway. Gateway transmits the ranging values received from UWB anchors to the server. There are n total WiFi APs installed and transmits beacon to tag. Tag is a mobile device capable of UWB communication and WiFi communication, such as the Galaxy Note 20, iPhone 11, and iPhone 12, and is the target of indoor positioning. Tag collects RSS values of beacons transmitted by WiFi APs and transmits them to the server using WiFi communication. The server locates the tag using the UWB ranging values and RSS values received from the gateway and tag.

Chapter 3
Proposed Method

3.1 Overview of proposed method

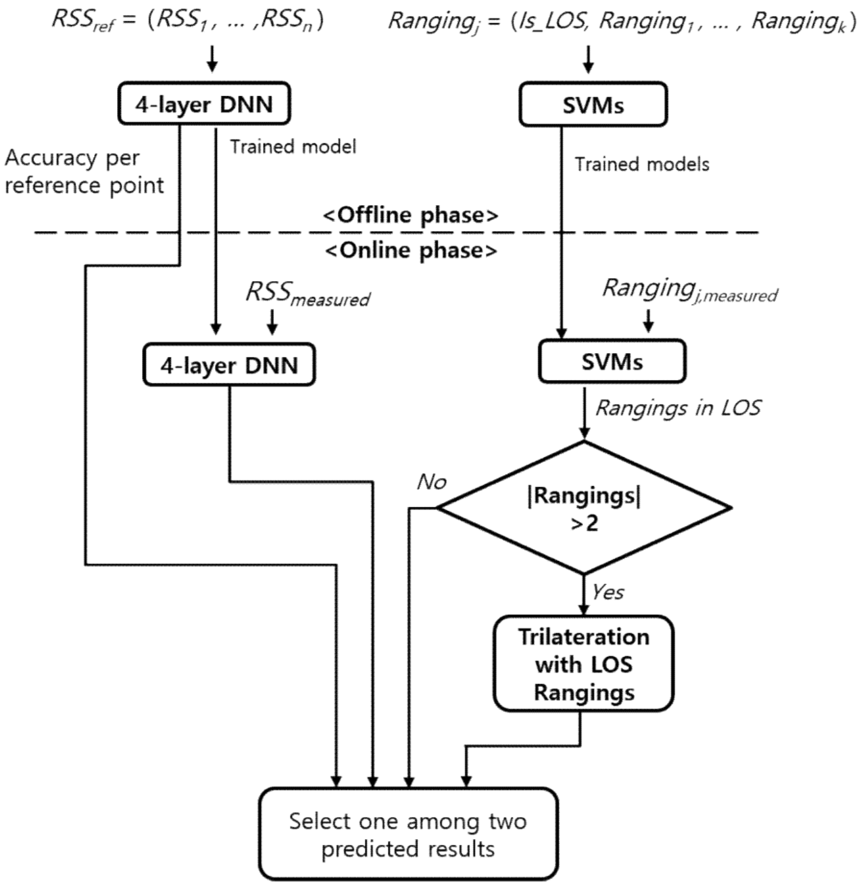

Figure. 2. Overview of proposed method

The proposed indoor localization method is divided into three parts. The three parts are divided into a WiFi fingerprinting part, a UWB trilateration part, and a selection part that combines two independent positioning methods. The WiFi fingerprinting part delivers two pieces of information to the selection part. The first information transmitted from the WiFi fingerprinting part is the accuracy of prediction for each reference point calculated in the offline phase, to the selection part. Then, in the online phase, the trained DNN model is used to predict the position of the tag, and the positioning result is delivered to the selection part as second information. In the UWB trilateration part, LOS/NLOS classification is performed for UWB ranging, and trilateration is performed with the ranging classified by LOS. LOS/NLOS classification uses a support vector machine (SVM), a type of supervised learning ML model. The format of the value used for training of the i-th SVM is $Rangings_j$ = {Is_LOS, $Ranging_1$, ... , $Ranging_k$}. When training a total of m SVMs, the target value of each j-th SVM is Is_LOS and its features are the mean, variance, kurtosis and skewness for k range values of the j-th anchor and a tag. Next, in the online phase, the $Rangings_{j,measured}$ is used to determine whether the distance between the j-th anchor and the tag is LOS, and the format of $Rangings_{j,measured}$ is {$Ranging_1$, ... , $Ranging_k$}. If the $Rangings_{j,measured}$ is classified as LOS, the mean value of the $Rangings_{j,measured}$ is determined as the distance between the j-th anchor and tag. When the number of distances classified as LOS is 3 or more, trilateration is performed using only distances classified as LOS. Trilateration is not performed when the number of LOS distance is less than 3. In the last part, the selection part, the tag is localized with the information collected from the previous two parts.

3.2 WiFi fingerprinting part of proposed method

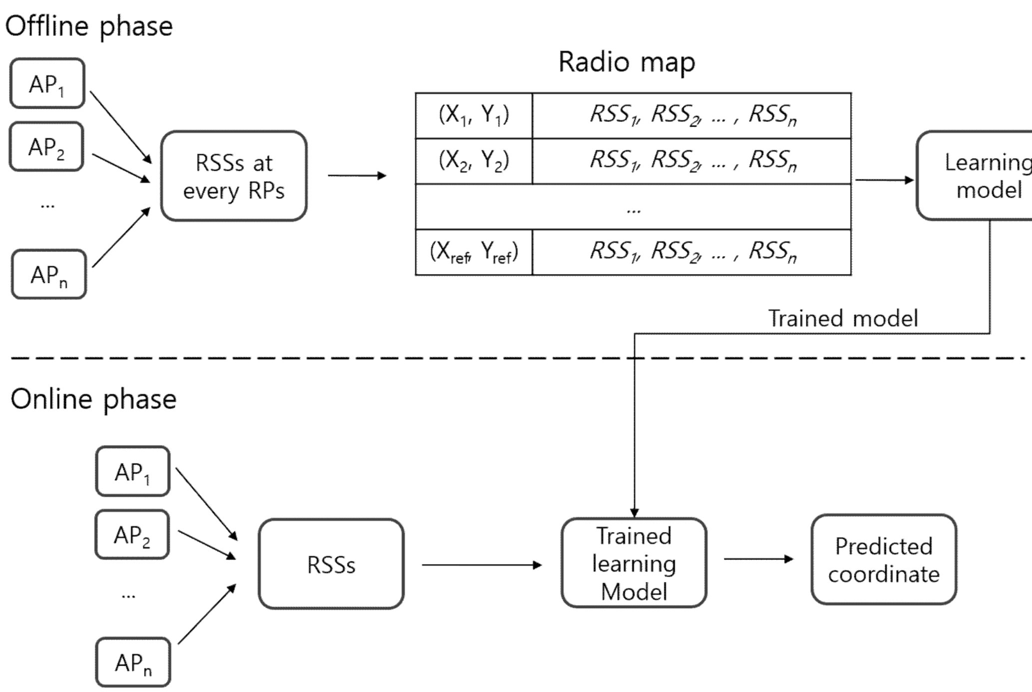

Figure 3. Online and offline phase of WiFi fingerprinting

WiFi fingerprinting characterizes the radio signal with respect to certain position. The fingerprinting in the proposed method uses the RSS of beacons sent by n number of WiFi APs. WiFi fingerprinting is divided into offline phase and online phase as shown in Figure 3. First, in the offline phase, a radio map is constructed by measuring the RSS values of beacons received from APs at known locations called reference points(RPs). The learning model is trained with the constructed radio map. The accuracy per reference point is calculated with trained model and the equation is shown below.

$$Accuracy\ per\ ref.\ point = \frac{The\ number\ of\ correct\ prediction}{The\ number\ of\ prediction\ at\ one\ ref.\ point} \qquad (Eq.\ 1)$$

The accuracy per reference point obtained using the above equation is transferred to the selection part. In the online phase, the tag measures the RSS value from APs and sends the measured value to the server. The server predicts which reference point the tag location will be using the trained learning model, and the coordinates of the predicted reference point become the tag location using WiFi fingerprinting. The tag location predicted by WiFi fingerprinting is also transferred to the selection part like accuracy per reference point. In this paper, a typical 4-layer DNN used for fingerprinting is used. The 4-layer DNN has 512, 256, 128 and 64 nodes per layer, ReLu is used as the activation function, and the dropout value is 0.3. DNN is trained using a radio map where the target value is the index of the reference point, and the feature is the RSS values measured per reference point.

3.3 UWB trilateration part of proposed method

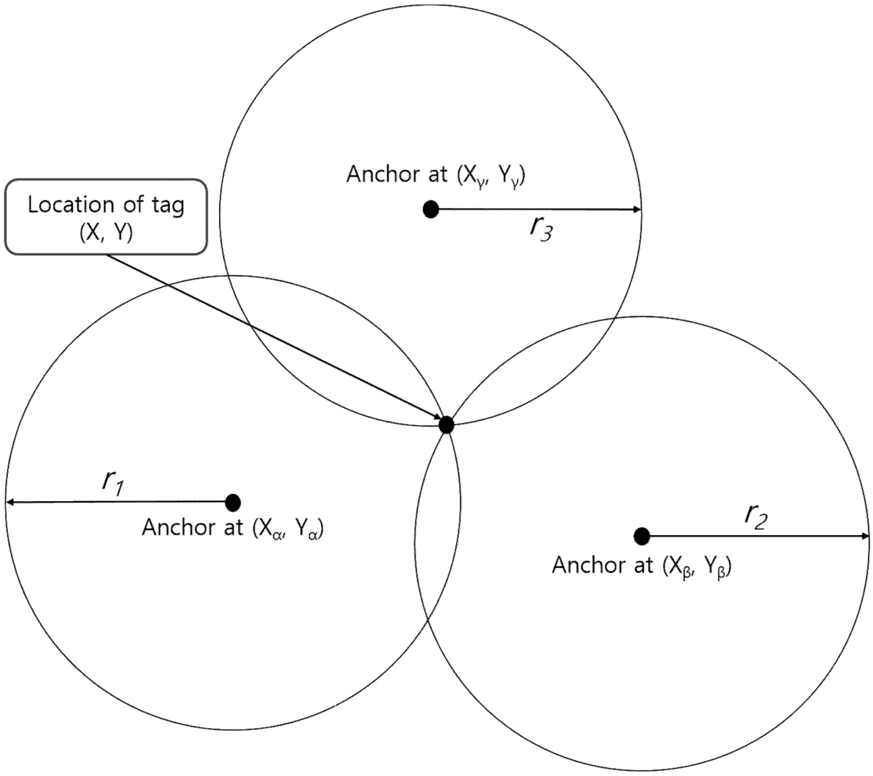

Figure 4. UWB ranging based trilateration

UWB trilateration is an indoor positioning method based on UWB ranging as shown in Figure 4. The trilateration method uses the distance between the tag and the anchors installed in fixed locations. Trilateration calculates the position of the tag by solving the system of equations shown below.

$$\begin{aligned}(X - X_\alpha)^2 + (Y - Y_\alpha)^2 &= r_1^2 \\ (X - X_\beta)^2 + (Y - Y_\beta)^2 &= r_2^2 \\ (X - X_\gamma)^2 + (Y - Y_\gamma)^2 &= r_3^2\end{aligned} \qquad (Eq.\ 2)$$

The solution of equation 2 is the intersection of the circles in Figure 4. Theoretically, it is possible to obtain accurate location of tag by solving the system of equations above. However, due to the radio wave-based UWB ranging characteristic, it may be difficult to get an intersected point of circles due to an error in the ranging value. Therefore, the position of the tag is calculated by using the Least-square sum(LSS) method.[14][15][16] The LSS method predicts the optimal tag position by using the position of anchors and the distance measurement value of the anchors and the tag. The optimal position of a tag using the LSS method is calculated by solving the following equation.

$$\begin{aligned}&(P_j - P_{tag})^T (P_j - P_{tag}) = (Distance_{j,tag})^2 \\ &S(P_{tag}) = \sum_{j=1}^{m} [\,(Distance_{j,tag})^2 - (Ranging_j)^2\,]^2 \\ &P_{tag,optimal} = \arg\min_{P_{tag}} S(P_{tag}) \qquad (Eq.\ 3)\end{aligned}$$

P_j is a coordinate where the j-th anchor is installed, and P_{tag} is a coordinate where the tag can be located. Assuming that the P_{tag} is located at an arbitrary coordinate, the distance between the tag and the j-th anchor can be obtained by the formula of the Euclidean distance. When the $Ranging_j$ is the actually measured distance between the j-th anchor and the tag, equation 3 can be used to calculate the sum of the errors between the Euclidean distance and the measured distance. The LSS method calculates the P_{tag} with the minimum sum of errors and selects the its position as the position of the tag.

In this paper, trilateration using only the LOS ranging values is called Filtered_LSS, and the method using both LOS and NLOS of the ranging values is called LSS. Filtered_LSS distinguishes whether the measured ranging value is LOS using SVM. Ranging value measured by j-th anchor in the offline phase is $Rangings_j$ = {*Is_LOS, Ranging*$_1$*, Ranging*$_2$*, ... Ranging*$_k$}, and *Is_LOS* is set as 1 when k ranging values are LOS and set as 0 when NLOS. The target of SVM is *Is_LOS*, and mean, variance, skewness, and kurtosis are used from k number of ranging values. The formulas that calculate skewness and kurtosis are described in equation 4.

$$\begin{aligned}&Skewness[X] = \frac{E[(X-\mu)^3]}{E[((X-\mu)^2)]^{3/2}} \\ &Kurtosis[X] = \frac{E[(X-\mu)^4]}{E[((X-\mu)^2)]^2} \qquad (Eq.\ 4)\end{aligned}$$

In the online phase, trained j-th SVM classifies whether $Rangings_{j,measured}$ = {*Ranging*$_1$*, Ranging*$_2$*, ... Ranging*$_k$} is in LOS condition. If the $Rangings_{j,measured}$ is LOS, the mean value of k ranging values becomes the distance between j-th anchor and the tag. If there are three or more LOS anchor-tag pairs, Filtered_LSS is performed with the mean value of ranging value in each pair.

3.4 Selecting part of proposed method

▪ Algorithm of Proposed Method

Offline phase
- input : RSS_{ref}, $Rangings_j$
- output : Trained DNN model, Acc. of trained DNN model w.r.t ref. point, Trained SVM models

While DNN_traninging_done = *false* ***do***
  Training DNN model
end while
While SVM_traning_done = *false* ***do***
  Training SVM_j for *j*-th anchor using $Rangings_j$
end while
Calculate accuracy of trained DNN model w.r.t. reference point

Online phase
- input : $RSS_{measured}$, $Rangings_{j,measured}$, $\tau_{\text{threshold}}$
- output : predicted coordinate of tag
- initialize : $LOS\_count \leftarrow 0$, $LOS\_ranging\_set \leftarrow \varnothing$

For each $Rangings_{j,measured}$ ***do***
  $Is\_LOS \leftarrow SVM_j(Rangings_{j,measured})$
  if $Is\_LOS = 1$ ***then***
    $LOS\_count \leftarrow LOS\_count + 1$
    $LOS\_ranging\_set \leftarrow LOS\_ranging\_set \cup \text{Mean}(Rangings_{j,measured})$
  end if
end for
Predicted reference point ← Trained_DNN_model($RSS_{measured}$)
if accuracy at predicted reference point $> \tau_{\text{threshold}}$ ***OR*** *LOS_count* is smaller than 3 ***then***
  return coordinate of predicted reference point
else
  UWB trilateration result ← Filtered_LSS(*LOS_ranging_set*)
  return coordinate of UWB trilateration result
end if

Figure 5. Algorithm of proposed method

Select part chooses between the results of two independent positioning methods, WiFi fingerprinting and UWB trilateration. There are two pieces of information to use when making a selection. The first information is the accuracy per reference point measured after the learning model has trained in the offline phase of WiFi fingerprinting. In the case of the classification method using DNN like models, even if it is a single trained model, the classification accuracy is different for each class.[17][18] Therefore, the accuracy of fingerprinting prediction is different for each reference point. In order to use only the results of fingerprinting with high accuracy for the final positioning, the pre-determined threshold and the accuracy per reference point of the predicted reference point are compared. If accuracy of the predicted reference point is lower than the threshold, the fingerprinting result is not used for final positioning. The second information is the number of LOS anchor-tag pairs, which are classified through SVM. The tag position is calculated using the Filtered_LSS method when there are 3 or more LOS ranging values. In the selection part, when the number of LOS ranging values is less than 3 or the accuracy of the predicted reference point through the trained model is higher than the threshold value, the positioning result of fingerprinting is selected as the position of the tag. In other cases, the tag location is determined using the Filtered_LSS method.

Chapter 4
Experimental environment

4.1 LOS environment

Figure 6. Experimental site in 1st case

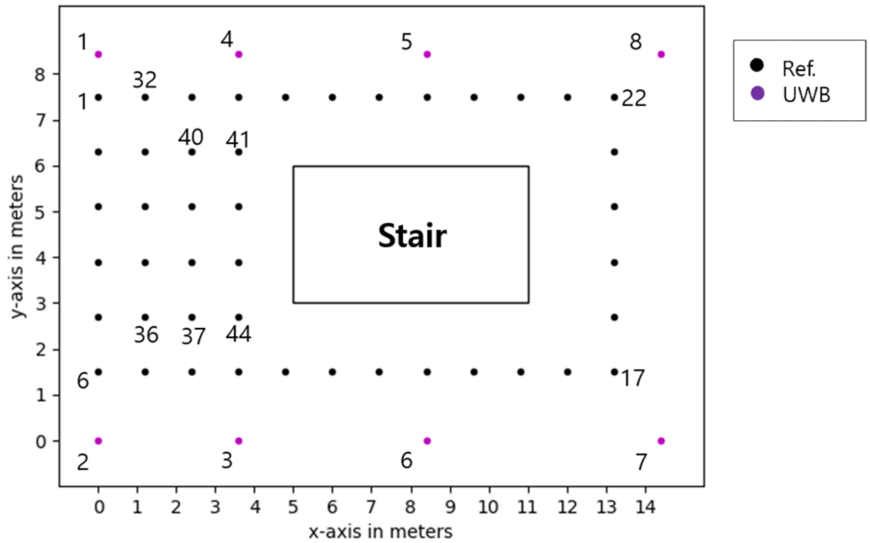

Figure 7. The floorplan of 1st case

The experimental environment is divided into an environment in which LOS is well maintained and an environment in which it is not. Figure 6 shows environment of the first case where LOS is well maintained. This place is the entrance to the 2nd floor of Seoul National University 302 building, and the size of the place is 14m x 9m. The place is selected for a place with few obstacles to simulate a similar office environment. There is a stair in the center of the experiment site and a few people pass by during the experiment. In Figure 7, reference points are designated at 1.2m intervals, and the total number of reference points is 44. Eight UWB anchors are installed across the area.

4.2 NLOS environment

Figure 8. Experimental site in 2nd case

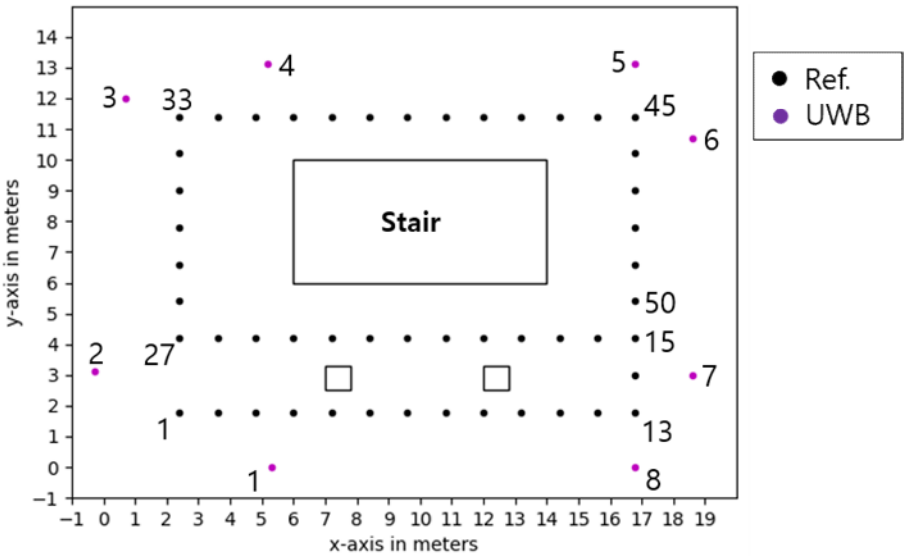

Figure 9. The floorplan of 2nd case

The second experimental site is where the LOS is not well maintained. The place is the lobby on the 1st floor of Seoul National University Building 302 and the size of the place is 21m x 15m. This is a place that simulates environments where LOS maintenance is difficult such as factory and warehouse. In the second experiment, a greater number of people pass by than in 1st environment. The size of the stairs in the center is larger than the 1st case and ATM machine and other items are loaded under the stairs. In addition, there are two concrete pillars size of 0.8m x 0.8m each. There are 50 reference points at 1.2m intervals and the number of installed UWB anchors is 8.

4.3 Experimental metric

Localization is performed 30 times for each reference point in the two experimental sites and the Euclidean distance error resulting from the localization is called the Euclidean distance error per reference point. The mean value is the average value of Euclidean distance errors for all reference points, and the variance is the variance of Euclidean distance errors for all reference points. In the worst case, it refers to the largest value among Euclidean distance error value per reference point. The experimental results in different experimental sites are analyzed using mean, variance and worst value.

Chapter 5

Experimental Results

5.1 Experimental results in LOS environment

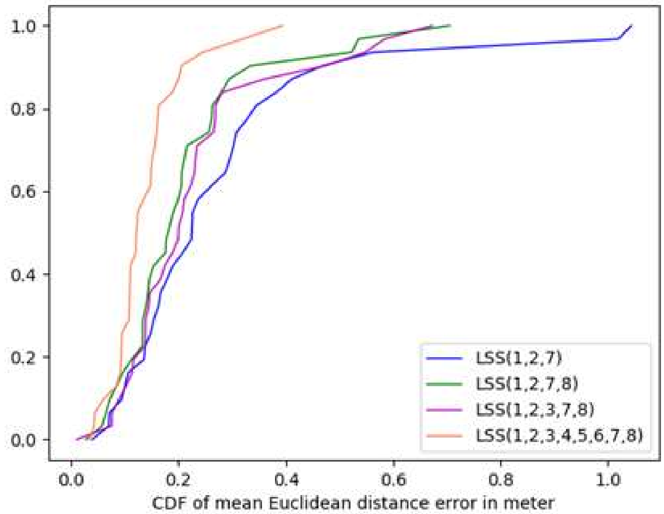

Figure 10. CDF of Euclidean error for all RPs when LSS is applied with different anchor sets in 1st case

Table I. Mean, variance, worst value when LSS is applied with different anchor sets in 1st case

Method/ Anchor index	Mean	Variance	Worst
LSS (1,2,7)	0.2779	0.0535	1.0438
LSS (1,2,7,8)	0.2099	0.0212	0.7048
LSS (1,2,3,7,8)	0.2086	0.0204	0.5995
LSS (1,2,3,4,5,6,7,8)	0.139	0.0056	0.3939

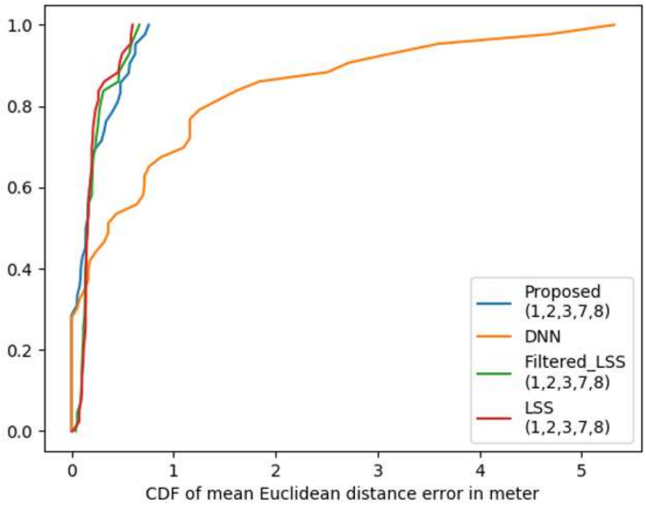

Figure 11. CDF of Euclidean error for all RPs when different methods are applied in 1st case

Table II. Mean, variance, worst value when different methods are applied in 1st case

Method/ Anchor index	Mean	Variance	Worst
Proposed (1,2,3,7,8)	0.2093	0.0508	0.7567
DNN	0.9001	1.6282	5.3198
Filtered_LSS (1,2,3,7,8)	0.2216	0.0263	0.6647
LSS (1,2,3,7,8)	0.2086	0.0204	0.5995

In the 1st case environment, two experiments are conducted. Firstly, the localization accuracy with different number of anchors when using LSS is shown in Figure 10 and Table I. Figure 10 shows the Euclidean errors measured at all reference points in CDF when using LSS for different anchor sets. Table I shows the mean, variance, and worst value of Euclidean error values measured at all reference points. From the experimental results, it is shown that the Euclidean error decreases as the number of anchor increases. When the use case requires high localization accuracy at the cm level[5], it is suitable for installing more anchors to obtain better localization accuracy in such environment. In the second experiment, the positioning accuracy of the different positioning methods is compared. The results of 2nd experiment is shown in Figure 11 and Table II. When the fingerprinting method is executed, the result shows that mean is 0.9m, the variance is 1.6m and the worst is 5.3m. The remaining three positioning methods have similar level of mean and variance values. When looking at the worst, the error of the propose method increases by 0.1m compared to the Filtered_LSS method. When looking at the results of the experiment conducted in an environment where LOS is relatively well maintained, the three methods proposed, LSS, and Filtered_LSS are better than WiFi fingerprinting.

5.2 Experimental results in NLOS environment

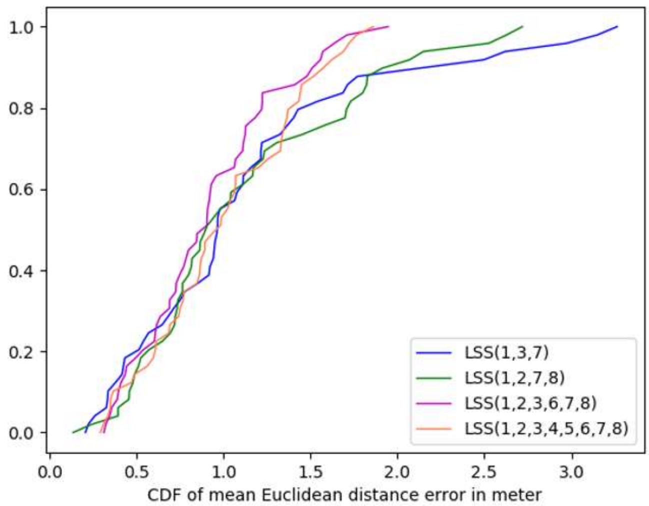

Figure 12. CDF of Euclidean error for all RPs when LSS is applied with different anchor sets in 2nd case

Table III. Mean, variance, worst value when LSS is applied with different anchor sets in 2nd case

Method/ Anchor index	Mean	Variance	Worst
LSS (1,3,7)	1.1196	0.5571	3.2626
LSS (1,2,7,8)	1.1051	0.4002	2.7177
LSS (1,2,3,6,7,8)	0.9055	0.1648	1.9468
LSS (1,2,3,4,5,6,7,8)	0.9956	0.1862	1.8609

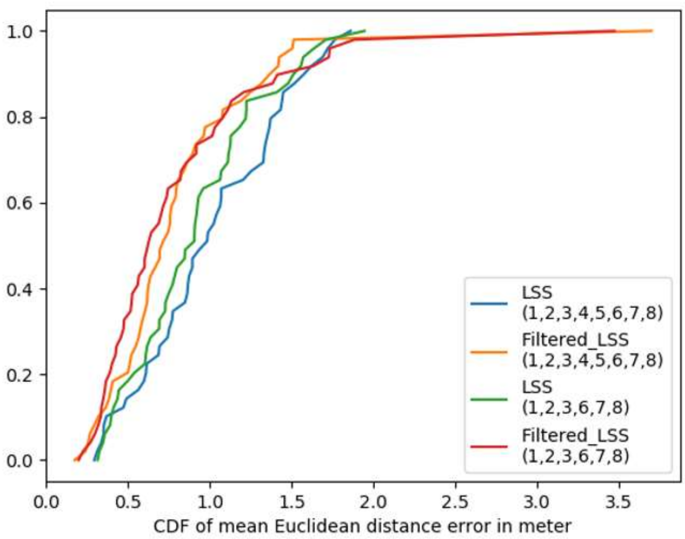

Figure 13. CDF of Euclidean error for all RPs when LSS and Filtered_LSS are applied in 2nd case

Table IV. Mean, variance, worst value when LSS and Filtered_LSS are applied in 2nd case

Method/ Anchor index	Mean	Variance	Worst
LSS (1,2,3,4,5,6,7,8)	0.9956	0.1862	1.8609
Filtered_LSS (1,2,3,4,5,6,7,8)	0.8089	0.2963	3.7024
LSS (1,2,3,6,7,8)	0.9055	0.1648	1.9468
Filtered_LSS (1,2,3,6,7,8)	0.7918	0.3273	3.4758

According to the experimental results of 1st case, where the LOS was well maintained, both the LSS method and the Filtered_LSS method showed high positioning accuracy. However, as a result of applying both methods in 2nd case where the LOS is not well maintained, there is a limit to the improvement of positioning accuracy. According to the experimental results of Figure 12 and Table III, even if the same LSS method as in the 1st case is applied, the mean value does not improve as the number of installed anchors increases unlike the 1st case. When the number of anchors installed is 6 to 8, the mean value even increases. The Filtered_LSS method shows that the mean value is improved than that of the LSS method, but in the case of worst value, the accuracy decreases very much in Table IV. The reason for the drop in the positioning accuracy of the Filtered_LSS method is when the LOS/NLOS classification of the SVM makes wrong decision. Therefore, according to the positioning results of LSS and Filtered_LSS, there is a disadvantage that the mean value does not sufficiently decreases or the worst value increases.

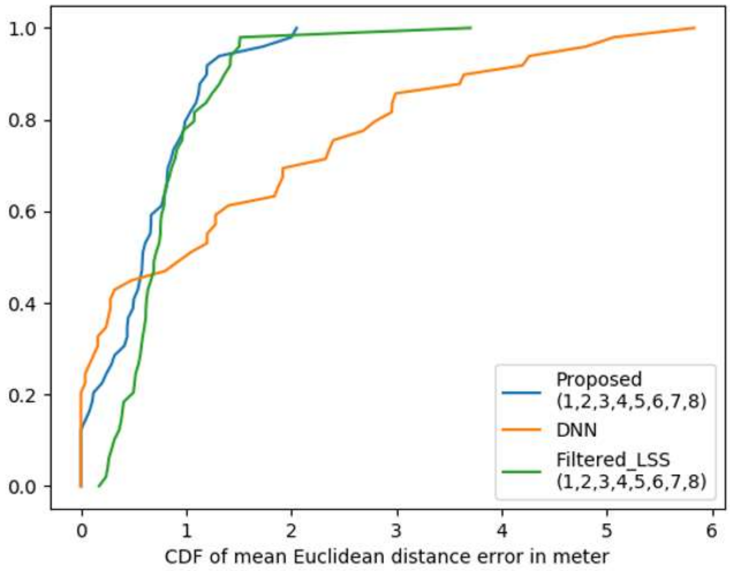

Figure 14. CDF of Euclidean error for all RPs when different methods are applied in 2nd case

Table V. Mean, variance, worst value when different methods are applied in 2nd case

Method/ Anchor index	Mean	Variance	Worst
Proposed (1,2,3,4,5,6,7,8)	0.6423	0.2532	2.0509
DNN	1.4402	2.5482	5.83
Filtered_LSS (1,2,3,4,5,6,7,8)	0.8089	0.2963	3.7024

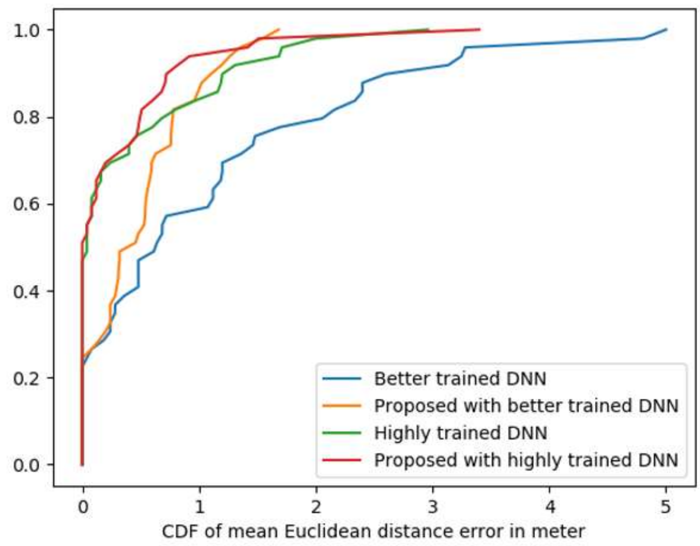

Figure 15. Proposed method using differently trained DNNs in 2nd case

Table VI. Mean, variance, worst value when proposed method using differently trained DNN models in 2nd case

Method	Mean	Variance	Worst
Better trained DNN	1.0656	1.5436	5.0
Proposed with better trained DNN	0.4793	0.2003	1.6815
Highly trained DNN	0.372	0.4204	2.96
Proposed with highly trained DNN	0.2875	0.3344	3.4

Figures 14 and Table V show the positioning errors of the proposed method, DNN and Filtered_LSS method in 2nd environment. DNN represents the learning model in WiFi fingerprinting. The proposed method in Table V used the DNN and Filtered_LSS methods in the same table. The proposed method has improved mean value compared to the LSS method in Table IV, the Filtered_LSS method, and the DNN method in Table V. Worst value is improved over DNN and Filtered_LSS and becomes similar to LSS. It is shown that proposed method improves the mean and worst value compared to LSS, DNN, Filtered_LSS according to the experimental results in both cases. Even if the proposed method uses a DNN with different positioning capabilities instead, the same result is obtained. The better trained DNN in Figures 15 and Table VI has the same structure as the DNN in Table V. However, it is a model that improves positioning accuracy by increasing the number of training epochs. In particular, in the case of highly trained DNN, it is a model in which the number of epochs is trained until the positioning accuracy is no longer improved, which means the most ideal training result that can be obtained from a given DNN structure and data. The higher the positioning performance of the DNN, the higher the positioning performance with proposed method tends to be improved, which can be seen in the experimental results in Figure 15 and Table VI. The reason why the positioning performance of the propose method is improved is that the fingerprinting method is a classification problem that predicts an appropriate reference point for the input radio signal. Classification problems using DNN have different classification accuracy for each class which is reference point. In the proposed method, only the class with high prediction accuracy per class is used for positioning, so the positioning accuracy is improved. Therefore, the proposed method can be applied even if it has a different model structure like CNN instead of a DNN structure, or other communication media such as BLE instead of WiFi are used.

Chapter 6
Conclusion

Indoor localization has attracted great interest recently. Indoor localization has various use cases from hospitals, factories, and warehouse environments that require positioning errors within few meters to smart cities that require cm level positioning errors. The UWB ranging-based positioning method which has a high localization accuracy of the order of cm has drawn attention among the indoor localization methods using various communication media. The positioning method using UWB ranging has a positioning error of about 10cm in an ideal situation such as an LOS environment. However, LOS and NLOS environments are mixed in general indoor environment due to obstacles. Since UWB ranging error increases as the more obstacles exist, the localization error as increases. In particular, it is difficult to improve positioning accuracy by increasing the number of UWB anchors or by classifying LOS/NLOS of rangings in environment with large impact of NLOS. Therefore, there is a need for a way to improve the positioning error in the LOS/NLOS situation. In this paper, we improved the positioning accuracy in LOS/NLOS environment by using WiFi fingerprinting method and UWB trilateration. The experimental results shows that the proposed method improves positioning accuracy in mixed LOS/NLOS environment. Additionally, the proposed positioning method is expected to be applicable to a fingerprinting method using other communication protocols (i.e., BLE, UWB).

Bilbliography

[1] S. Sadowski and P. Spachos, "RSSI-Based Indoor Localization With the Internet of Things," in *IEEE Access*, vol. 6, pp. 30149-30161, 2018, doi: 10.1109/ACCESS.2018.2843325.

[2] N. Macoir, J. Bauwens, B. Jooris, B. Van Herbruggen, J. Rossey, J. Hoebeke, and E. De Poorter, "UWB Localization with Battery-Powered Wireless Backbone for Drone-Based Inventory Management," *Sensors*, vol. 19, no. 3, p. 467, Jan. 2019. DOI: 10.3390/s19030467 .

[3] J. Zhang, P. V. Orlik, Z. Sahinoglu, A. F. Molisch and P. Kinney, "UWB Systems for Wireless Sensor Networks," *Proc. of the IEEE*, vol. 97, no. 2, pp. 313-331, Feb. 2009, DOI: 10.1109/JPROC.2008.2008786.

[4] M. Murata, D. Ahmetovic, D. Sato, H. Takagi, K. M. Kitani and C. Asakawa, "Smartphone-based Indoor Localization for Blind Navigation across Building Complexes," *2018 IEEE Int. Conf. on Pervasive Computing and Communications (Perfcom)*, Athens, 2018, pp. 1-10, DOI: 10.1109/PERCOM.2018.8444593.

[5] F. Zafari, I. Papapanagiotou and K. Christidis, "Microlocation for Internet-of-Things-Equipped Smart Buildings," *IEEE Internet of Things Journal*, vol. 3, no. 1, pp. 96-112, Feb. 2016, DOI: 10.1109/JIOT.2015.2442956.

[6] F. Zafari, A. Gkelias and K. K. Leung, "A Survey of Indoor Localization Systems and Technologies," *IEEE Communications Surveys & Tutorials*, vol. 21, no. 3, pp. 2568-2599, 3rd Quart., 2019, DOI: 10.1109/COMST.2019.2911558.

[6] F. Zafari, A. Gkelias and K. K. Leung, "A Survey of Indoor Localization Systems and Technologies," *IEEE Communications Surveys & Tutorials*, vol. 21, no. 3, pp. 2568-2599, 3rd Quart., 2019, DOI: 10.1109/COMST.2019.2911558.

[7] A. Morar, A. Moldoveanu, I. Mocanu, F. Moldoveanu, I. E. Radoi, V. Asavei, A. Gradinaru, and A. Butean, "A Comprehensive Survey of Indoor Localization Methods Based on Computer Vision," *Sensors*, vol. 20, no. 9, p. 2641, May 2020.

[8] A. R. Jiménez and F. Seco, "Finding objects using UWB or BLE localization technology: A museum-like use case," *2017 Int. Conf. on Indoor Positioning and Indoor Navigation (IPIN)*, Sapporo, 2017, pp. 1-8, DOI: 10.1109/IPIN.2017.8115865.

[9] Jiang Xiao, Zimu Zhou, Youwen Yi, and Lionel M. Ni. "A Survey on Wireless Indoor Localization from the Device Perspective," *ACM Comput. Surv.*

vol 49, no. 25, pp. 1-31, Nov. 2016. DOI: https://doi.org/10.1145/2933232.

[10] C. BASRI and A. El Khadimi, "Survey on indoor localization system and recent advances of WIFI fingerprinting technique," *2016 5th International Conference on Multimedia Computing and Systems (ICMCS)*, Marrakech, 2016, pp. 253-259, DOI: 10.1109/ICMCS.2016.7905633.

[11] Li, You et al. "Wireless Fingerprinting Uncertainty Prediction Based on Machine Learning," *Sensors*, vol. 19, p. 324, Jan. 2019, DOI:10.3390/s19020324.

[12] Mendoza-Silva, Germán Martín et al. "A Meta-Review of Indoor Positioning Systems." *Sensors*, vol. 19 p. 4507. Oct. 2019, DOI: 10.3390/s19204507.

[13] Barral, V.; Escudero, C.J.; García-Naya, J.A. "Maneiro-Catoira, R. NLOS Identification and Mitigation Using Low-Cost UWB Devices," *Sensors*, vol 19, p. 3464, Aug. 2019. DOI: https://doi.org/10.3390/s19163464.

[14] Y. Zhou, "An efficient least-squares trilateration algorithm for mobile robot localization," *2009 IEEE/RSJ International Conference on Intelligent Robots and Systems*, St. Louis, MO, 2009, pp. 3474-3479. DOI: 10.1109/IROS.2009.5354370.

[15] Ismail Güvenç, Chia-Chin Chong, Fujio Watanabe, and Hiroshi Inamura. "NLOS identification and weighted least-squares localization for UWB systems using multipath channel statistics". *EURASIP J. Adv. Signal Process 2008*, Jan. 2008. DOI: https://doi.org/10.1155/2008/271984.

[16] V. Barral, C. J. Escudero and J. A. García-Naya, "NLOS Classification Based on RSS and Ranging Statistics Obtained from Low-Cost UWB Devices," *2019 27th European Signal Processing Conference (EUSIPCO)*, A Coruna, Spain, 2019, pp. 1-5, DOI: 10.23919/EUSIPCO.2019.8902949.

[17] M. Z. Afzal et al., "Deepdocclassifier: Document classification with deep Convolutional Neural Network," *2015 13th Int. Con. on Document Analysis and Recognition (ICDAR)*, Tunis, 2015 DOI: 10.1109/ICDAR.2015.7333933.

[18] Shin J., Jung S.H., Yoon G., Han D. "A Multi-Classifier Approach for WiFi-Based Positioning System", in *Electrical Engineering and Applied Computing. Lecture Notes in Electrical Engineering*, 1st ed. Springer, Ao SI., Gelman L., 2011, ch 12, pp. 135-147, DOI: 10.1007/978-94-007-1192-1_12.

요 약

최근 실내 측위는 많은 관심을 끌고 있다. 실내 측위의 적용 사례로는 스마트 팩토리, 스마트 홈 등으로 사용자의 편의나 안전 향상을 위해 사용된다. 여러 실내 측위 기술 중 UWB 거리 측정 기반 실내 측위 기술이 높은 정확도로 인해 관심을 받고 있다. 하지만 UWB ranging의 경우 물체가 존재하는 Non-Line-of-Sight(NLOS) 상황에서의 거리 측정의 오차가 커짐에 따라 ranging을 기반으로 한 실내 측위 오차도 커지게 된다. LOS/NLOS가 혼재된 환경에 의한 측위 오차를 개선하기 위해 UWB ranging 기반 측위 방식과 WiFi Fingerprinting을 결합한 새로운 측위 방식을 제안한다. 제안하는 방식은 LOS/NLOS가 혼재된 환경에서 기존의 UWB ranging 기반 측위 방식이나 WiFi Fingerprinting 방식의 장점들을 활용하여 평균 측위 정확도와 최악의 측위 오차를 개선한다. 측위 오차를 계산하기 위해 LOS가 비교적 잘 유지되는 환경과 그렇지 못한 환경으로 나누어 실험한다. 두 환경에서 측정한 데이터를 사용하여 기존 측위 방식들과 제안하는 측위 방식의 측위 오차를 비교한다. 실험 결과는 기존 측위 방식인 UWB trilateration의 평균 측위 오차가 0.8m이며 WiFi fingerprinting이 1.44m 임에 반해 제안하는 방식은 0.64m의 측위 오차를 보인다. 또한 최악의 측위 오차의 경우 UWB trilateration은 3.7m, WiFi fingerprinting의 경우 5.83m임에 반해 제안하는 방식은 2.05m으로 측위 오차가 개선됨을 보인다. 결과적으로 실험 결과를 통해 제안하는 방식이 LOS/NLOS가 혼재된 환경에서 측위 오차를 개선하는 효과적인 방식임을 보인다.

주요어 : 실내 측위, UWB, WiFi, Fingerprinting, Trilateration, NLOS, LOS
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