

VLC Positioning by DNN via WkNN in Indoor Environment

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Abstract— With the recent development of mobile communication systems, the rapid development of smart devices and internet of things (IoT) technology, and the expansion of the field of application is taking place. One of these application fields is location-based services (LBS). LBS is a technology that provides various services based on a user's location. However, it is very important to accurately position the user to provide such a service. In the case of an outdoor environment, relatively high positioning accuracy may be provided through a global positioning system (GPS) 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, we propose a method for accurately positioning a user's location in an indoor environment based on visible light communication (VLC) and artificial intelligence (AI) technology. The proposed scheme proceeds as follows. First, a fingerprinting database is constructed based on the channel characteristics of VLC. Next, the approximate location of the user is obtained by applying a weighted k-nearest neighbor (WkNN). Thereafter, the received signal strength (RSS) value between each access point (AP) and the user equipment (UE) and the user's approximate location derived through WkNN are used as inputs to the deep neural network (DNN) model to perform learning. The trained DNN model outputs the actual user's location. Through the simulation results, it can be confirmed that the proposed scheme in this paper achieves precise positioning accuracy compared to the existing scheme.

Keywords— *Indoor Positioning; Location Based Service(LBS); Visible Light Communication(VLC); Artificial Intelligence(AI); Deep Neural Network(DNN)*

I. INTRODUCTION

With the recent development of mobile communication technologies such as 5G, technologies related to smart devices and the internet of things (IoT) have become a key issue. Among them, the location-based service (LBS) is being actively researched as a way to provide convenience using a user's smart device. In the case of LBS, there are various application fields such as indoor navigation, customer support at large marts, navigation in airport terminals, and firefighter support in case of fire. However, to provide these services, precise positioning accuracy is required [1].

In the case of an outdoor environment, the user's location can be positioned relatively accurately based on the global positioning system (GPS). However, when a user's location is determined based on GPS in an indoor environment, a problem

of propagation loss occurs due to obstacles and walls in the indoor environment [2]. Propagation loss makes it impossible to determine the exact location of the user indoors. To solve this problem, indoor positioning methods use technologies such as wireless-fidelity (Wi-Fi) [3], ultra-wide band (UWB) [4], Bluetooth [5], and visible light communication (VLC) [6] that can be used indoors are being studied.

VLC technology provides the advantages of a long lifespan and high efficiency based on the light emitting diode (LED) and can perform both communication and lighting functions indoors. In addition, since the visible light band is used instead of the radio frequency band, it enables communication even in an environment where RF-based wireless communication is impossible [7]. Based on these advantages, VLC can be applied to more fields than the existing RF method to perform positioning. In addition, representative positioning methods include angle of arrival (AoA), time of arrival (ToA), time difference of arrival (TDoA), received signal strength (RSS), etc. Among them, many studies are being conducted to apply RSS together with fingerprinting in an indoor environment[8].

In [6], studied a method for positioning the user's location in an indoor VLC environment. First, a fingerprinting database was built and a k-nearest neighbor (kNN) was applied, and the weighted k-nearest neighbor (WkNN) was proposed in an extended way. WkNN is a method in which a weight concept is added to the existing kNN and is a technique for deriving the final location of a user based on proximity. The authors of [6] evaluated the performance of the scheme through simulation, and when the number of sample points was 625, the positioning error was 0.2 m or less. As such, as the number of sample points increases, precise positioning is possible, but problems such as fingerprinting map maintenance and processing time increase when applying WkNN occur in real environments.

Therefore, in this paper, we conducted a study on the improvement of positioning accuracy and processing time based on artificial intelligence (AI) technology in an indoor VLC environment. First, a database (DB) is built by measuring the RSS value of the same x and y coordinates as the location of each access point (AP) by applying the fingerprinting technique. In this case, the number of sample points is the same as the number of LED APs. Thereafter, the approximate location of the real user has been estimated through a WkNN. Finally, the approximate user location obtained through the application of

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WkNN and the real user's RSS values is learned together as inputs to the deep neural network (DNN) model to derive the positioning results.

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 in detail. Subsequent section 4 describes the parameter values and results used in the simulation. Section 5 concludes this paper.

II. SYSTEM MODEL

This section describes the system model used to evaluate the performance of the proposed scheme. The used system model is shown in Fig. 1[6].

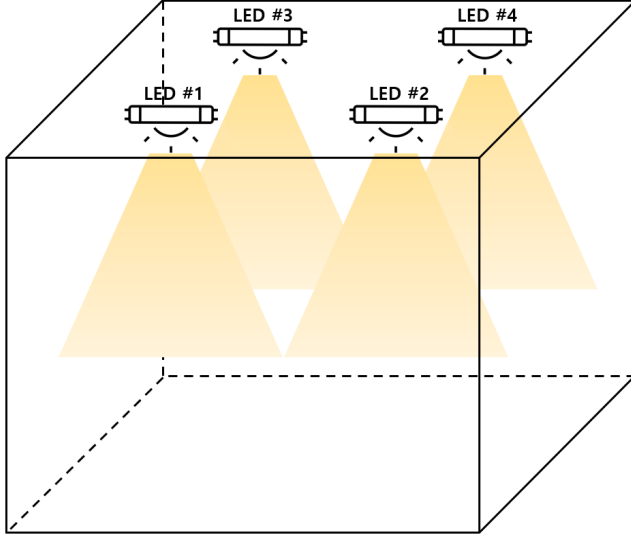


Fig. 1. Indoor Visible Light Communication Environment[6]

The size of the indoor room environment used for the evaluation of the proposed scheme in this paper is 5m×5m×3m of space. At this time, it is assumed that the LED AP is deployed on the ceiling at a height of 3m from the floor. In this model, 4 LED APs are used, and each bulb has a transmitted light power of 10W and a half-power half-angle of exactly 60 degrees. In addition, the user equipment (UE) is set to move around at a height of 0.7m, considering that the user is a human being. The UE has a photodiode (PD) active area of 1cm² and moves parallel to the floor.

Next, we analyze the visible light channel characteristics in the above environment. In this paper, we use a line-of-sight (LOS) environment with no obstacles between the transceivers. The LOS path is shown in Fig. 2. As shown in Fig. 2, the distance, which is a parameter for calculating RSS from the LED AP in the LOS environment, is called d , and the angle is called θ . In this system, since the UE assumes an environment that moves parallel to the floor, the incident angle ψ has the same value as the irradiation angle θ . So, RSS from LED AP can be obtained as eq.1.

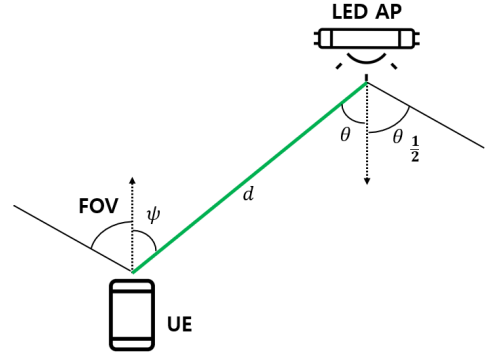


Fig. 2. LOS channel model between of LED AP and UE

$$h_j^i = \begin{cases} P_t \frac{A(m+1)}{2\pi d^2} \cos^m(\theta) T_s(\psi) C(\psi) \cos(\psi), & 0 \leq \psi \leq \psi_c \\ 0 & \psi \geq \psi_c \end{cases} \quad (1)$$

where, P_t is the transmit power of the LED, m is the Lambertian order, A is the detector area of the receiver, and d is the distance between the AP and the receiver. $T_s(\psi)$ denotes an optical filter gain, $C(\psi)$ denotes an optical concentrator gain, ψ_c and denotes a field of view (FOV) of the receiver. In the next section, we describe the proposed method for locating the user's location based on the RSS value.

III. PROPOSED POSITIONING SCHEME

This paper builds an RSS DB in the offline step using the fingerprinting technique and estimates the approximate location of the actual user equipment(UE) by applying WkNN in the online step. In this case, the estimated coordinates are used as inputs of the DNN model together with the RSS value of the actual UE, and the coordinates of the actual UE are used as the output. Fig. 3 shows the system configuration diagram of the proposed scheme in this paper.

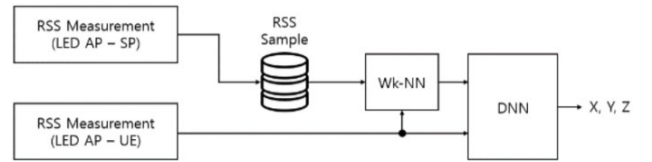


Fig. 3. Block Diagram of Proposed System

First, it is assumed that the fingerprinting technique uses a total of i LED APs and j sample points (SP). Each SP measures the RSS value for each AP. After that, the Fingerprinting DB is built based on the measured RSS value. The constructed Fingerprinting DB F_{DB} can be expressed as follows.

$$F_{DB} = \begin{pmatrix} h_1^1 & \cdots & h_j^1 \\ \vdots & \ddots & \vdots \\ h_1^i & \cdots & h_j^i \end{pmatrix}_{I \times J} \quad (2)$$

where, h_j^i means the RSS value between the i -th AP and the j -th SP, can be obtained through eq.1.

When the Fingerprinting DB construction is completed, the RSS value of the actual UE is measured in the online step. Then, the WkNN is performed using the measured values and the Fingerprinting DB of eq. 2. WkNN is a method that improves performance by adding a weight concept to the existing kNN. In this paper, the kNN based on the Euclidean distance is applied, and the Euclidean distance $D_{u,j}$ between the SP and the UE can be calculated as eq. 3.

$$D_{u,j} = \sqrt{\sum_{i=1}^I (h_u^i - h_j^i)^2} \quad (3)$$

where, h_u^i means the RSS value between the i -th AP and the u -th UE. Then, based on the Euclidean distance $D_{u,j}$, the weight $w_{u,j}$ is obtained as follows.

$$w_{u,j} = 1 - \frac{D_{u,j}}{\sum_{j=1}^J D_{u,j}} \quad (4)$$

Next, approximate coordinates X_e, Y_e, Z_e of the UE can be estimated with the obtained weight.

$$X = \frac{\sum_{j=1}^J w_{u,j} x_j}{\sum_{j=1}^J w_{u,j}}, \quad Y = \frac{\sum_{j=1}^J w_{u,j} y_j}{\sum_{j=1}^J w_{u,j}}, \quad Z = \frac{\sum_{j=1}^J w_{u,j} z_j}{\sum_{j=1}^J w_{u,j}} \quad (5)$$

where, X, Y , and Z represent the actual coordinates of the UE. After, a data set for training the DNN model is established. Fig.4 shows the input/output of the data set for training the DNN model and the configuration diagram of the DNN model.

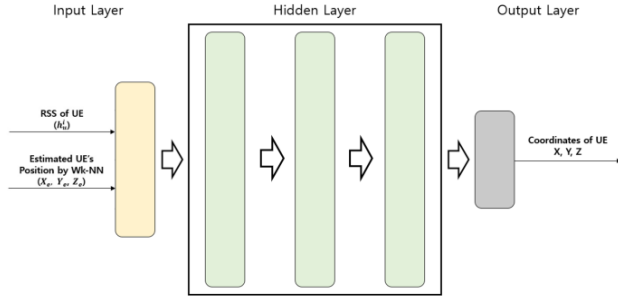


Fig. 4. DNN model configuration diagram and input/output data

TABLE I. DETAILED STRUCTURE OF THE DESIGNED DNN MODEL

Layer Name	Input/output	Activation
Input Layer	7/140	ReLU
Drop Out1	0.4	-
Hidden Layer1	140/100	ReLU
Drop Out2	0.4	-
Input Layer2	100/50	ReLU
Drop Out3	0.4	-
Input Layer3	50/20	ReLU
Drop Out4	0.4	-
Output Layer	20/3	Sigmoid

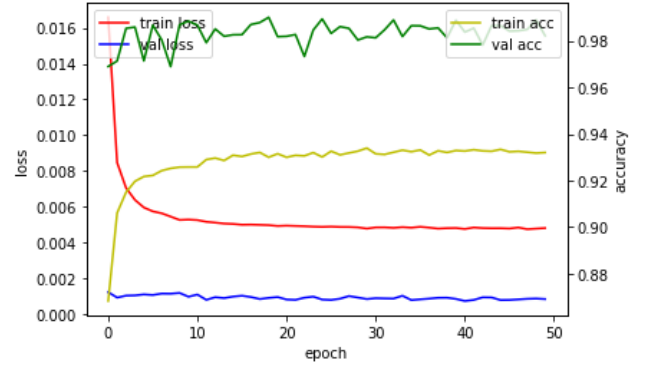


Fig. 5. DNN model training results

As shown in Fig. 4, the input of the DNN model uses the UE's RSS and WkNN positioning results from each LED AP. The output of the DNN model outputs the final coordinates of the UE. The DNN model solves the overfitting problem by applying the drop-out technique to each layer and improves the generalization performance of the model. The detailed structure of the DNN model is shown in Table 1.

Fig. 5 shows the accuracy and loss values of the DNN model. As can be seen in the figure, the training accuracy of the model is 93.20%, and the loss value is 0.0048. Then, the test performance has an accuracy of 98.22% and a loss value of 0.0008. Through the training and test results, it can be confirmed that the training and generalization of the proposed DNN model performed well. In the next section, we discuss the positioning simulation of the UE based on the proposed scheme in this paper.

IV. SIMULATION AND EVALUATION

This section describes the parameters used in the simulation and the performance evaluation results. The simulation parameters used are shown in Table 2.

TABLE II. SIMULATION PARAMETER

Parameter	Value
Room size	$5m \times 5m \times 3m$
Number of LED AP	4
Number of SP	4
P_t (Transmit power of AP)	10 W
$T_s(\psi)$ (optical filter gain)	1
$C(\psi)$ (optical concentrator gain)	1.5
FOV (Field Of View)	60°
A (Receiver detect area)	$1cm^2$
Number of simulation iterations	10,000

As shown in Table 2, the size of the indoor environment is $5m \times 5m \times 3m$, and four LED APs are deployed. As described above, the number of SPs is the same as the number of LED APs. In addition, transmit power of AP, optical filter gain, and optical

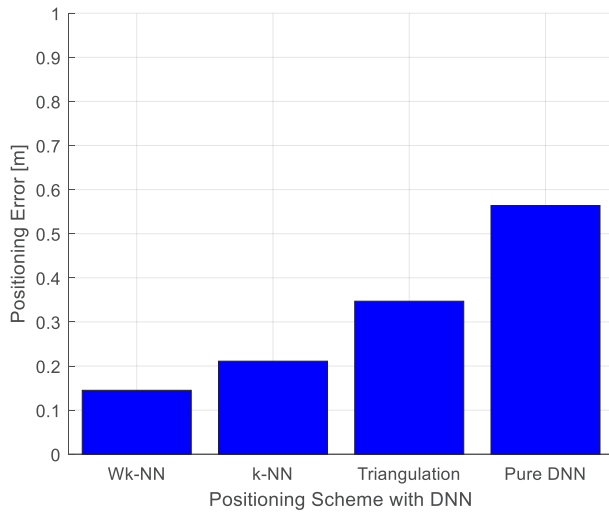


Fig. 6. Comparison of positioning errors of each scheme

concentrator gain, are transmitter characteristics, and FOV and receiver detect area are receiver characteristics.

The simulation was repeated 10,000 times in total and was based on MATLAB 2017b and Python 3.7. In order to evaluate the positioning accuracy performance of the proposed scheme, the positioning results obtained through the conventional kNN and triangulation techniques were learned as the input of the DNN model. The result of comparing the position accuracy is presented in Fig. 6.

Fig. 6 shows the results of comparing the positioning accuracy after learning the approximate positioning coordinates of the UE obtained through the existing triangulation, kNN, and WkNN techniques on the DNN model. As can be seen in the figure, it can be confirmed that the positioning results of the WkNN+DNN technique proposed in this paper are the most accurate. This shows that the positioning accuracy of WkNN is more precise than that of kNN and triangulation, achieving the highest positioning accuracy when used together as an input of a DNN model.

Additionally, in the case of processing time, WkNN confirmed through the simulation of [9] that the processing time increases as the number of reference points increases. However, in the case of a DNN model that has been trained, it has

characteristics that can achieve fast processing time and improve positioning accuracy. Based on this, by reducing the number of reference points in WkNN, processing time can be shortened and accuracy can be improved.

V. CONCLUSION

In this paper, we proposed a method for positioning a user in an indoor environment using Fingerprinting, WkNN, and DNN models based on VLC. The proposed method was compared with the existing method, WkNN, through simulation, and it was confirmed that the proposed method achieved higher positioning accuracy. In the future, we plan to study a method for positioning a user by additionally considering an non line-of-sight (NLOS) scenario in a VLC indoor environment and a method for improving positioning accuracy through parameter adjustment of the DNN model.

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