DNN-based Positioning with Optimum Input Parameter in Indoor VLC LOS/NLOS Environment

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***Abstract*— Accurate indoor positioning has been a major research topic in recent years. Indoor positioning solutions using radio frequency(RF)-based communication technologies have been used such as WiFi and. However, RF-based technology is difficult to provide the accurate positioning due to the rapid change in the received signal from the movement of obstacles and people in an indoor environment. Therefore, in this paper a visible light-based communication is adopted for user positioning. In addition, in view of two aspects of positioning accuracy and positioning processing time, deep neural network(DNN) was applied to perform the precise positioning. For the DNN model, hyperparameter optimization was considered to achieve high accuracy and fast processing time. The trained DNN model is designed to output the user's three-dimensional actual position, and it can be seen from the simulation results that the proposed method achieves more precise positioning than the existing method.**

Keywords*— *Indoor Positioning, Visible Light Communication, Fingerprinting, Weighted k-Nearest Neighbor, Deep Neural Network

I. Introduction

High-precision, low-cost and wide application range of indoor positioning technology is the core of indoor location-based services, and is a major research topic based on broad market prospects and social values. In general, global positioning system(GPS) is used for positioning in outdoor environment since it enables relatively precise positioning. However, accurate indoor positioning is impossible for GPS signals received indoors due to propagation loss from the obstacles and walls [1]. Hence, there were many efforts to achieve precise indoor positioning without GPS technology. [2].

Most of these studies are based on wireless communication technology and positioning algorithms. They include popular short-range RF-based technologies such as WiFi [3], Bluetooth [4], and ultra-wide band(UWB) [5]. Although the positioning accuracy of RF-based communication technology is somewhat limited, the advantages of them are clear in view of the cost and complexity[6]. However, in the RF-based communication technology, the positioning accuracy is greatly reduced due to interference from the frequency saturation problem. In order to overcome this problem, VLC technology has been studied. VLC technology can perform both lighting and communication functions by performing communication based on LEDs [7-8]. Classic positioning algorithms include angle of arrival(AoA), time of arrival(ToA), time difference of arrival(TDoA), and received signal strength(RSS). AoA achieves relatively accurate positioning accuracy, but requires high computational complexity and ToA and TDoA require strict synchronization. On the other hand, although RSS shows relatively low positioning accuracy, it can be improved when used together with fingerprinting in an indoor environment [9]. In addition, the fingerprinting has been verified as an applicable positioning technique in an indoor environment [10].

Researches related to VLC-based indoor positioning are as follows. The authors of [11] proposed an improved method for the k-nearest neighbor(kNN). A fingerprinting data base(DB) was constructed based on a total of 625 reference point(RP)s in an indoor environment of 5m×5m×3m. Thereafter, the user's RSS is measured in the online stage, and kNN is performed with the value of the fingerprinting DB. Afterwards, weighting was applied based on the similarity to improve the location error. In [12], performance analysis of the existing triangulation technique was attained in the VLC environment. As for the environment in which the performance was evaluated, the positioning results were compared when only the directed path was considered and the non-directed path was considered together. The authors confirmed that the positioning error increases when non-directed paths are considered together. In [13], the authors proposed a method to improve the position error from two aspects. One is the selection of the LED signal. Since the reflected wave gives an error to the positioning result, a method of limiting the number of the strongest signals among the signals received by the user has been proposed. Another way is to reduce the distance between the LED bulbs. This can improve the positioning accuracy because the light power distribution becomes uniform when the LED arrangement becomes dense in the indoor environment. However, when many LEDs are arranged in a narrow environment, there will be an increase of the.

Therefore, we propose DNN based positioning with optimized input parameter in an VLC indoor environment. We assume that finger-freezing, weighted k-nearest neighbor(WkNN) and deep neural network(DNN) techniques are applied to enhance the accuracy. The optimization of the DNN model, provides in view of two aspects of positioning accuracy and the reduction of processing time. The positioning process can be divided into two main categories. Fingerprinting and WkNN are the steps to build the input data set of the DNN, and the DNN outputs the user's 3D coordinates based on the input values.

The fingerprinting technique requires a large number of RPs to achieve precise positioning accuracy. However, as the number of RPs increases, it is difficult to construct in an actual environment and it results in the processing speed is much lowered. The DNN using the WkNN method proposed in this paper can greatly reduce the number of RPs in constructing a fingerprinting map through the DNN model. In addition, precise positioning is achieved by correcting the positional error of WkNN. The performance was evaluated on the overall channel considering the non-directed path as well as the directed path together. For non-directed path, only the first reflected wave is considered. The simulation results show that the proposed technique achieves the highest positioning accuracy in the overall channel.

The structure of this paper is as follows. Section 2 describes the system model. Section 3 describes the proposed positioning method. Section 4 describes the parameter values used in the simulation and the simulation results. Finally, Section 5 presents a conclusion and discussion.

II. System Model

This section describes the system model used for performance evaluation of the proposed scheme. The model consists of a directed path channel and a non-directed path channel. Two models are used to calculate the received optical power. The positioning scheme is applied based on the total optical power.

First, the optical power characteristics received by the UE in an indoor environment are analyzed. The directed path channel and the non-directed path channel are considered together. In this case, the first reflected wave was considered for the non-directed path. The directed path can be represented as Fig. 1. As shown in the fig. 1, the distance between the AP and the user equipment(UE) is d, and the angle received by the UE is called θ. As mentioned earlier, since the UE moves parallel to the floor, the angle of incidence and the angle of irradiation have the same value. Therefore, the directed path RSS of the u-th UE from the i-th AP can be obtained as in (1).

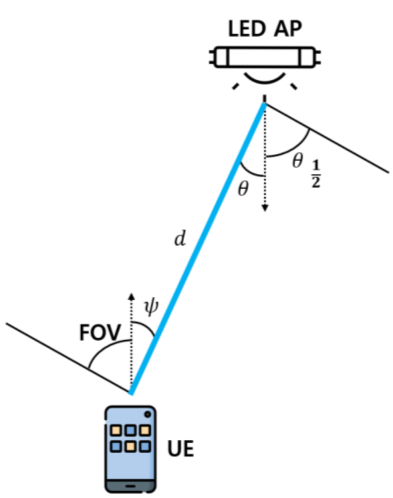

Figure 1. Directed path channel model between of AP and UE.

$$h_{u,directed}^{i} = \begin{pmatrix} P_t \frac{A(m+1)}{2\pi d^2} cos^m(\theta) T_s(\psi) C(\psi) \cos(\psi), & 0 \le \psi \le \psi_c \\ 0 & \psi \ge \psi_c \end{pmatrix} \quad (1)$$

where, P_t is the transmission power of the AP, m is the Lambertian order, A is the active area of the UE, and d is the distance between the AP and the UE. And $T_s(\psi)$ is the optical filter gain, and $C(\psi)$ is the optical concentration gain. In addition, ψ_c means the field of view(FOV) of the UE.

Next, the non-directed path can be represented as in Fig. 2. As can be seen in the figure, the non-directed path considers the first reflected wave. In this case, the distance from the AP to the reflection point is called d_1 and the incident angle is called α, the distance from the reflection point to the UE is called d_2 and the reflection angle is called β. In addition, θ_r refers to the irradiation angle from the AP to the wall, and ψ_r refers to the angle at which the UE receives optical power from the wall. Based on this, RSS from the i-th AP through the non-directed path of the u-th UE can be obtained as in (2).

$$h_{u,non-directed}^{i} = P_t \frac{A(m+1)}{2\pi d_1^2 d_2^2} \rho cos^m(\theta) dA_{wall} \cos(\alpha) \cos(\beta) T_s(\psi_r) C(\psi_r) \cos(\psi_r) \quad (2)$$

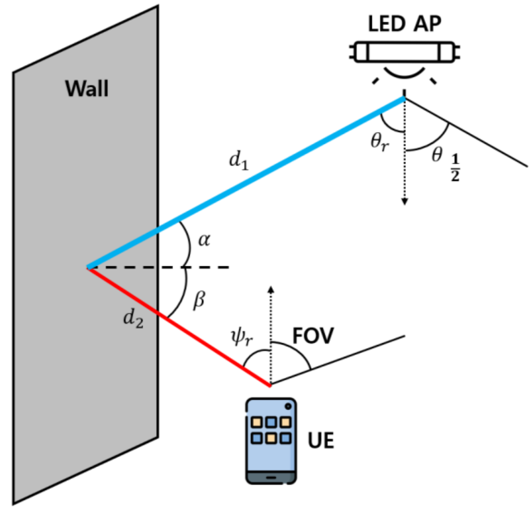

Figure 2. non-directed path channel model between of AP and UE.

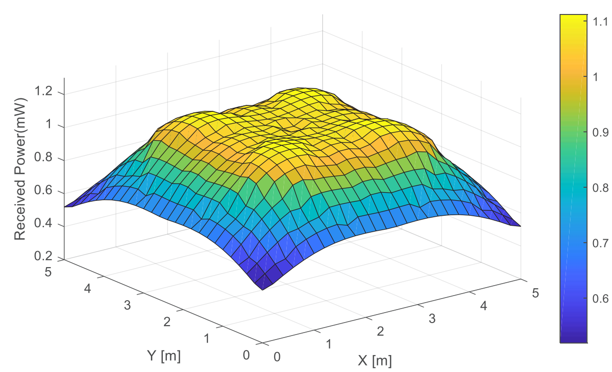

Figure 3. RSS distribution of overall channel.

where, dA_{wall} is the surface element of the wall and ρ is the reflectance of the wall. Further, the range of ψ_r is $0 \le \psi_r \le \psi_c$. Then, based on (1) and (2), the total RSS received by the UE is the same as (3) and the RSS distribution is as shown in Fig. 3.

$$h_{overall} = h_{directed} + h_{non-directed} \quad (3)$$

III. Proposed Positioning Scheme

This section describes the proposed indoor positioning scheme in detail. First, the indoor environment for positioning performance evaluation is shown in Fig. 4. As can be seen in the fig. 4, the size of the indoor environment is $5m \times 5m \times 3m$ and an empty space is assumed. Total of 4 LED access point(AP)s are uniformly arranged at a height of 3m and the light power of each AP is 10W., The height of the UE is assumed to be 0.7 m and they are randomly located in indoor environment. In addition, the UE has a photodiode(PD) active area of $1cm^2$ and moves parallel to the floor in any direction.

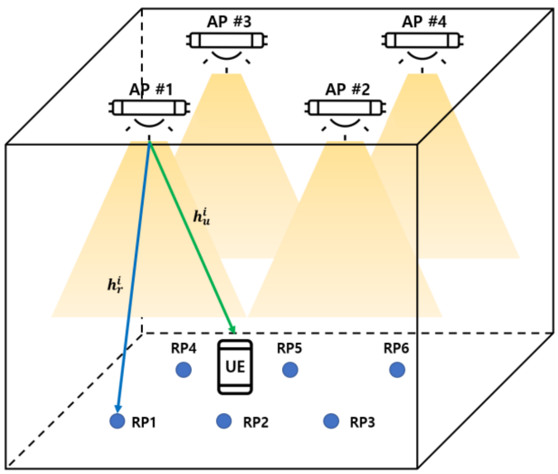

Figure 4. Indoor Environment concept with number of 4 APs.

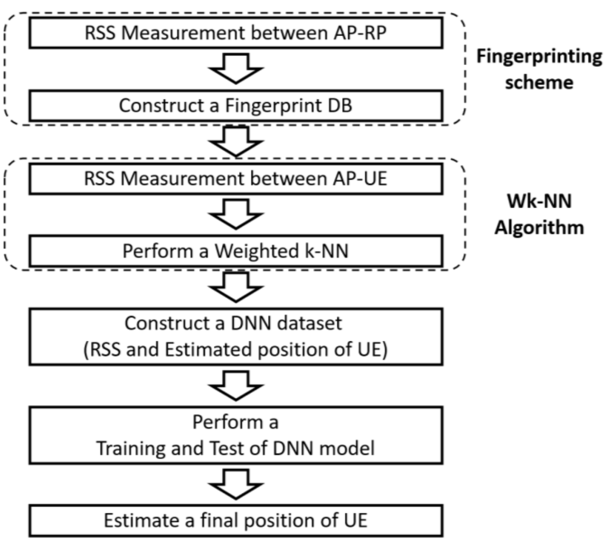

Figure 5. Block diagram of proposed system

The proposed positioning scheme consists of three steps, fingerprinting, WkNN and DNN, and the system block diagram is shown in Fig. 5. As can be seen in the fig. 5, the fingerprinting technique is performed first. In the fingerprinting technique, RSS is measured from the AP in each RP. The measured RSS value is stored in the fingerprinting DB. The RSS value of the RP stored in the DB is used later when performing WkNN. After completing the fingerprinting DB construction, it measures the RSS received from the AP to position the UE. The measured RSS value of the UE is used in the fingerprinting DB and WkNN. Approximate positioning of the UE is possible through WkNN. At this time, as the number of RPs of the fingerprinting technique increases, precise positioning is possible through WkNN, but it also increases the processing time. Therefore, in this paper, we propose a method to set the input of the DNN model to solve this problem.

The core idea of this paper is to use the positioning results of WkNN as input to the DNN model. As mentioned earlier, in the case of WkNN, the more use the reference points, the higher get the positioning accuracy, but it results in the huge increase of the processing time. Hence, in this paper, even if we greatly reduce the number of RPs, the approximate location of the UE obtained through WkNN can be used together as an input to the DNN model. This can reduce the processing time of WkNN by reducing the number of RPs and also shorten the total processing time based on the fast processing speed of DNN. In addition, precise positioning accuracy can be achieved through optimization of the DNN model. For this purpose, , the RSS value received by the UE and the approximate positioning result obtained through WkNN as input to the DNN model were used for indoor positioning. The DNN model was set to provide the UE's three-dimensional coordinates as an output value.

A. *Fingerprinting technique*

The fingerprinting technique is most commonly used among indoor positioning techniques. When used together with RSS, it can achieve high positioning accuracy compared to existing techniques. The fingerprinting technique consists of two steps. First, the offline stage is a stage of collecting RSS data based on RP. RP means specific coordinates, and RSS from each AP is measured at the coordinates. As the number of RPs increases, more precise positioning can be achieved. However, there is also a disadvantage that the processing time increases as the number of RPs increases. Hence, when we determine the number of RPs initially, two aspects should be considered in view of positioning accuracy and total processing time. In this paper, the number of RPs is set to 16. The rationale for this is explained later in the simulation section. RSS measured at each RP is stored in the fingerprinting DB, the fingerprinting DB can be represented as follows.

$$H_{DB} = \begin{pmatrix} h_1^1 & \cdots & h_r^1 \\ \vdots & \ddots & \vdots \\ h_1^i & \cdots & h_r^i \end{pmatrix}_{I \times R} \tag{4}$$

where, h_r^i means RSS between the i-th AP and the r-th RP. The constructed fingerprinting DB is later used to determine the approximate position of the user based on WkNN.

B. *Weighted k-Nearest Neighbor*

WkNN is a method in which weights are added to the existing kNN. In kNN, the positioning accuracy is improved by giving higher weights to RPs with high proximity. The algorithm is performed in the following order. First, the kNN algorithm can set the neighbor data based on the Euclidean distance, which is generally used for positioning. The Euclidean distance between the UE and the RP can be calculated as follows.

$$d_{u,r} = \sqrt{\sum_{i=1}^{I}(h_u^i - h_r^i)^2} \tag{5}$$

where, h_u^i represents the RSS value between the i-th AP and the u-th UE. Then, based on the Euclidean distance $d_{u,r}$, the weight $w_{u,r}$ and approximate coordinates X_e, Y_e, Z_e of the UE is obtained as follows.

$$w_{u,r} = 1 - \frac{d_{u,r}}{\sum_{r=1}^{R} d_{u,r}} \tag{6}$$

$$X_e = \frac{\sum_{r=1}^{R} w_{u,r} x_r}{\sum_{r=1}^{R} w_{u,r}},\ Y_e = \frac{\sum_{r=1}^{R} w_{u,r} y_r}{\sum_{r=1}^{R} w_{u,r}},\ Z_e = \frac{\sum_{r=1}^{R} w_{u,r} z_r}{\sum_{r=1}^{R} w_{u,r}} \tag{7}$$

When the approximate coordinate estimation of the UE is completed through the above process, the WkNN is finished and an input data for training the DNN model is constructed.

C. Deep Neural Network

DNN is one of the supervised learning methods and can be applied to various applications depending on the input/output data set. In this paper, a DNN model is applied to improve the accuracy of indoor positioning. The input/output data for training the DNN model is configured as follows.

$$Input\ Data = (h_u^i, X_e, Y_e, Z_e),\ \ i = 1,2, \dots I. \tag{8}$$

$$Output\ Data = (X, Y, Z) \tag{9}$$

where i means the number of the AP that transmits a signal. The input of the DNN model uses the RSS values and positioning results of the UE from WkNN algorithm. The output of the DNN model can be the final coordinates of the UE. Table 1 shows the detailed structure of the DNN model designed in this paper. Also, the DNN model solves the overfitting problem by applying the drop-out technique to each layer and improves the generalization performance of the model. And, the proposed DNN model uses the Adam optimizer.

The proposed DNN model was optimized in terms of two parameters the number of layers and the learning rate. The performance of the optimized DNN model can be explained in detail. The training accuracy of the model was 95.57%, the loss was 0.0021, the test accuracy was 99.37% and the loss was 0.00024. From the training and test results, it can be shown that the training and generalization of the proposed DNN model works reliably.

IV. Simulation and Results

In this section, the parameter determination of the proposed scheme is first described and the performance results are derived and compared.

TABLE I. DETAILED STRUCTURE OF DNN MODEL

Layer name	Number of Node, Activation
Input Layer	7
Hidden Layer1	210, ReLU
Drop out1	0.4
Hidden Layer2	50, ReLU
Drop out2	0.4
Output Layer	2, Sigmoid

A. Determination of parameter

To evaluate the positioning performance of the proposed scheme, the comparison with the conventional scheme was presented in this section. The conventional schemes uses kNN and triangulation scheme and the positioning results of each scheme are used as the input to the DNN model. Then, as shown in Table 2, the number of RPs was set to 16 in consideration of processing time and accuracy.

Thereafter, the DNN model in the proposed scheme can control the number of layers and the learning rate. First, Table 3 shows the performance of the DNN model according to the various number of layers. The number of layers is the total number of layers that consist of input and output pair in DNN model. 4-Layer Structure shows the best performance with a test accuracy of 99.37% and a loss of 0.00024 when the number of nodes per layer is 7-210-50-3. Next, Table 4 shows the performance of the DNN model according to the change in the learning rate. The learning rate was varied to 0.01, 0.005, and 0.001. In this case, the DNN model was based on the 4-Layer Structure as mentioned above. When the learning rate is set to 0.005, it attains the best performance in terms of test accuracy and positioning error. Finally, simulation parameters is described in Table 5. The simulation was repeated 10,000 times in total and was based on MATLAB 2017b and Python 3.7. As mentioned earlier, an empty space of 5x5x3 size was assumed for the indoor environment. Also, 4 APs were used,

TABLE II. COMPARISON WITH CONVENTIONAL SCHEME

Performance	No. RP	Wk-NN	k-NN	Triangulation
Processing time [s]	4	0.00021	0.00019	0.00237
	9	0.00033	0.00026	
	16	0.00048	0.00039	
Positioning error [m]	4	1.687	1.711	1.298
	9	1.324	1.351	
	16	0.812	0.846	

TABLE III. PERFORMANCE ANALYSIS ACCORDING TO THE VARIOUS NUMBER OF LAYERS

Number of Layer	Training/Test Loss	Training/Test Accuracy	Positioning Error [m]
7-Layer	0.234/0.0046	82.07/91.82	0.4104
6-Layer	0.0049/0.00085	93.38/98.32	0.1746
5-Layer	0.0023/0.00025	95.04/99.30	0.0913
4-Layer	0.0021/0.00024	95.57/99.37	0.0898
3-Layer	0.0011/0.0003	97.26/98.4	0.0942

TABLE IV. PERFORMANCE ANALYSIS ACCORDING TO THE VARIOUS LEARNING RATE

Learning Rate	Training/Test Loss	Training/Test Accuracy	Positioning Error [m]
0.01	0.0021/0.00025	95.40/99.14	0.0933
0.005	0.0021/0.00024	95.57/99.37	0.0898
0.001	0.0021/0.00026	95.54/98.65	0.0961

TABLE V. SIMULATION PARAMETER

Parameter	Value
Room size	$5m \times 5m \times 3m$
Number of LED AP	4
Number of RP	16
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

and 16 RPs were assumed based on Table 2. P_t is the characteristic of the transmitter, and $T_s(\psi)$, $C(\psi)$, FOV, A are the characteristics of the receiver.

B. Result of simulation

Fig. 6 shows the positioning error finally derived through DNN. When only the directed path is considered, the DNN model that learned the positioning results of the triangulation technique shows the smallest positioning error. This is because, in the case of the triangulation technique, more precise positioning than WkNN and kNN is possible in a directed path environment. In the case of the overall channel, the positioning accuracy of the three techniques decreases, but it can be seen that WkNN and kNN based on RP achieve higher accuracy than triangulation. Because it performs positioning based on the fingerprinting technique, stability is guaranteed compared to the triangulation technique. In addition, the positioning processing time was improved by minimizing the number of RPs in the indoor environment and the precise positioning performance of 0.0898m was achieved in the overall channel by supplementing the positioning accuracy performance through the DNN model.

To achieve the above positioning results, the processing time of the proposed scheme is as follows. First, when performing WkNN in an environment with 16 RPs, as shown in Table 2, it takes 0.00048s. After that, when the value derived through WkNN is input to the learned DNN model, it takes about 1 to 2 μs to output. Therefore, the DNN model achieves accurate positioning accuracy without significantly affecting the overall processing time because the processing time is very short.

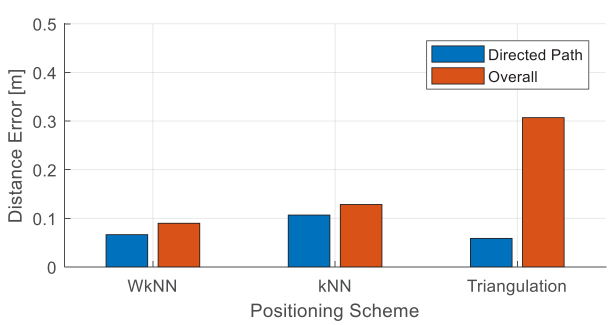

Figure 6. Comparison of positioning errors of each scheme.

V. CONCLUSIONS

In this paper, we proposed a method for positioning a user's location based on a DNN model in an indoor VLC environment. The proposed technique learns the localization results of the existing technique as an input to the DNN model. This can achieve fast processing time and precise positioning accuracy even when the fingerprinting technique is appliedwith a small number of RPs. In the future, we plan to verify the effectiveness of the proposed technique by considering a mobility and implementing a real testbed environment.

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REFERENCES

[1] J. Machaj, P. Brida, R. Piché, “Rank based fingerprinting algorithm for indoor positioning,” 2011 International Conference on Indoor Positioning and Indoor Navigation, pp.1-6, Sep. 2011.

[2] 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.

[3] H. Liu, H. Darabi, P. Banerjee, J. Liu, “Survey of wireless indoor positioning techniques and systems,” IEEE Trans. Syst. Man Cybern. Part C Appl. Rev. vol. 37, pp.1067-1080, Nov. 2007.

[4] A. Alarifi, A. Al-Salman, M. Alsaleh, A. Alnafessah, S. Al-Hadhrami, M. A. Al-Ammar, H. S. Al-Khalifa, “Ultra wideband indoor positioning technologies: Analysis and recent advances,” Sensors, vol.16, pp.1-36, May 2016.

[5] Q. Wang, Y. Feng, X. Zhang, Y. Sun, X. Lu, “IWKNN: An effective Bluetooth positioning method based on Isomap and WKNN,” Mobile Information Systems, vol. 2016, pp.1-11, Nov. 2016.

[6] Y. Zhuang, L. Hua, L. Qi, J. Yang, P. Cao, Y. Cao, Y. Wu, J. Thompson, H. Haas, “A Survey of Positioning Systems Using Visible LED Lights,” IEEE Communications Surveys & Tutorials, vol. 20, pp.1963-1988, Feb. 2018.

[7] Z. Ghassemlooy, W. Popoola, S. Rajbhandari, “Optical Wireless Communications, System and Channel Modeling with MATLAB,” Boca Raton, FL: CRC Press, 2012.

[8] E. D. Kaplan, C. J. Hegarty, Understanding GPS: Principles and Applications, Norwood, MA: Artech House Publishers, 2006.

[9] C. Zhao, H. Zhang, J. Song, “Fingerprint and visible light communication based indoor positioning method,” 2017 9th International Conference on Advanced Infocomm Technology (ICAIT), pp. 204-209, Nov. 2017,

[10] Z. Li, J. Liu, F. Yang, X. Niu, L. Li, Z. Wang, R. Chen, “A Bayesian Density Model Based Radio Signal Fingerprinting Positioning Method for Enhanced Usability,” Sensors, vol. 18, pp.1-18, Nov. 2018.

[11] M. T. Van, N. V. Tuan, T. T. Son, H. Le-Minh, A. Burton, “Weighted k-nearest neighbour model for indoor VLC positioning,” IET Commun., vol. 11, pp. 864-871, Mar. 2017.

[12] N. Mohammed, M. Elkarim. Exploring the effect of diffuse reflection on indoor localization systems based on RSSI-VLC. Available: https://www.osapublishing.org/oe/abstract.cfm?uri=oe-23-16-20297.

[13] W. Gu, M. Aminikashani, P. Deng, M. Kavehrad, “Impact of Multipath Reflections on the Performance of Indoor Visible Light Positioning Systems,” Journal of Lightwave Technology, vol. 34, pp. 2578-2587, Mar. 2016.