Location/Area Estimation Based on Multi-Class Classification with DNN Using RSSI of Wireless LAN

Shota Miyagoshi
School of Engineering
University of Fukui
Fukui, Japan
shota-m@network.fuis.u-fuki.ac.jp

Tomonori Yokono
School of Engineering
University of Fukui
Fukui, Japan
tomonori-y@network.fuis.u-fuki.ac.jp

***Abstract*—In this report, we propose a location/area estimation based on multi-class classification with deep neural network (DNN) using RSSI of wireless LAN. In the proposed method, a location and an area can be estimated by using DNN. We evaluate the performance of our proposed method. From numerical examples, we show that our proposed method is effective to estimate the location and area using RSSI of wireless LAN.**

Keywords—Location Estimation, Area Estimation, RSSI, Wireless LAN, Multi-Class Classification, Deep Neural Network

I. Introduction

The demand for location information is becoming more critical due to the emerge of map applications and augmented reality (AR) [1]. It is expected that the location can be estimated from the radio signal received from access point (AP) of wireless LAN and base station (BS) of cellular systems is promising [2,3]. However, the multipath fading channel degrades the performance of location estimation, resulting low accuracy. The challenge in [1] aims to verify if the AI/Machine Learning (ML) aided localization utilizing receives signal strength indicator (RSSI) observed at the terminal can achieve a similar accuracy as the GPS-based localization.

Here, AI/ML is effective for the location estimation from RSSI of wireless LAN. Nevertheless, it is not easy to determine the only appropriate location even if AI/ML is used. Moreover, for some context-aware applications [4, 5], the determination of an appropriate location is not needed, just the determination of an appropriate area is adequate.

Therefore, in this report we propose a location/area estimation based on multi-class classification with deep neural network (DNN) using RSSI of wireless LAN. In the proposed method, a location and an area can be estimated by using DNN. At first, we divide the map into small areas for location estimation. Our DNN model predicts which area contains the measurement points. We solve the location estimation problem as a classification model instead of a regression model. In a regression problem, a single value is output as the prediction result, but in a multi-class classification problem, the prediction result is the probability that each area contains a measurement point, which means that there are multiple candidates. It is expected the multi-class classification problem is effective to estimate an appropriate area not an appropriate location.

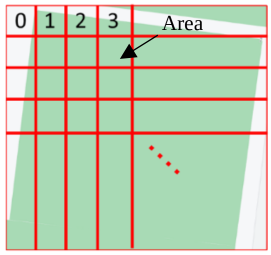

Fig. 1. Division of map into areas.

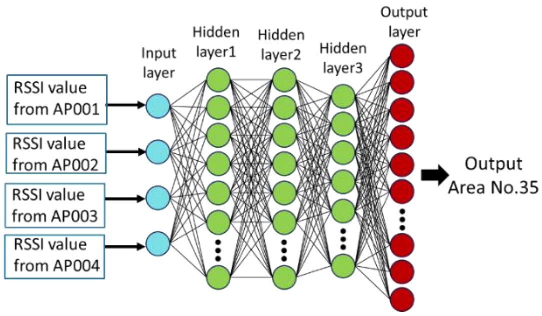

Fig. 2. Proposed DNN model.

We evaluate the performance of our proposed method in two cases. In this performance evaluation, we estimate the location of 13 measurement points from only RSSI of wireless LANs. From numerical examples, we show that our proposed method is effective to estimate the location and area using RSSI of wireless LAN.

II. Proposeed Multi-Class Classification with DNN

In this section, we explain our proposed multi-class classification with DNN. In our proposed method, at first, a map whose size is about 50 m $\times$ 50 m is divided into multiple areas as shown in Fig. 1. Then, a number is added into each area. In the following, a map is divided into $51 \times 68 = 3468$ areas. The size of each area is about 1.0 m $\times$ 1.0 m. Here, we consider the location estimation problem as the area estimation problem with multi-class classification. This area estimation problem becomes closer to the location estimation problem when the number of areas is much large.

In our DNN model, as shown in Fig. 2, the input is the RSSI values of the four access points. The output is the probability that each area contains a measurement point. The output is the probability that the measurement point is included in each area, and the area with the highest probability

Layer	Activation function
Hidden layer1	ReLU
Hidden layer2	ReLU
Hidden layer3	ReLU
Output layer	softmax

Fig. 3. Activation function for our DNN.

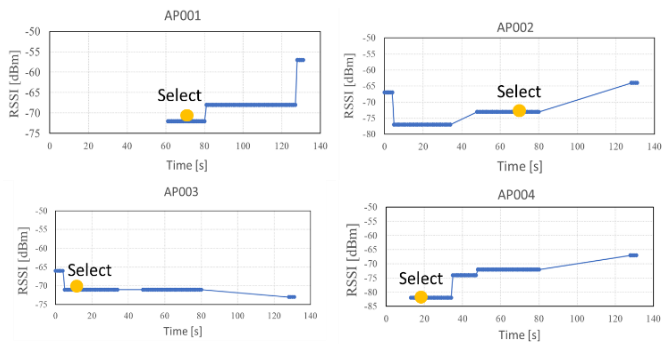

Fig. 4. Random selection of RSSI for training data.

number of units in the input layer is 4 and the number of units in the output layer is 3468.

Moreover, the model consists of three hidden layers; layer 1, layer 2, and layer 3. The layer 1 has 20 units, the layer 2 has 20 units, and the layer 3 has 10 units. For each hidden layer, activation functions are used as shown in Fig. 3. The rectified linear unit (ReLU) function for all hidden layers and the softmax function is used for the output layer.

In our model, the loss function is a multi-class cross-entropy. By using label distribution learning [6], a label is changed into a gaussian distribution whose mean is the value of the label and variance is 1.0.

III. Generation of Training Data

In order to use our proposed location/area estimation based on multi-class classification with DNN, we make a data set from the provided RSSI information.

Figure 4 shows an example of the information of RSSI for four AP. In our method, one value is randomly selected from the RSSI of each access point as shown in Fig. 4. We repeat the random selection 500 times to generate 500 records of training data per measurement point.

IV. Numerical Examples

In this section, we investigate the performance of our proposed method for two data sets. Figure 5 shows a measurement point (label) for each data set. In Fig. 5(a), 13 blue positions are the label of training data and 13 red positions are the label of verification data. On the other hand, in Fig. 5(b), 13 green positions are the label of training data and 13 yellow positions are the label of verification data.

(a) Data set 1 (b) Data set 2

Fig. 5. Two data sets for location estimation

Table 1. Average error and maximum error for two data sets.

	Data set 1	Data set 2
Average error	11.1579971 m	11.8099257 m
Maximum error	24.1497287 m	27.1292539 m

Table 2. Average error and maximum error for data set.

	Data set for Grand Challenge Finale
Average error	13.1439172 m
Maximum error	22.3437030 m

From these data sets, at first, we start the training for the training data, and then we perform the verification from the verification data.

Table 1 shows the average error and maximum error [m] between our estimation and the label. From this table, our proposed method can estimate the location (area) with about 10 m error. The performance of our proposed method is not better than GPS but we can estimate the location/area with only RSSI of wireless LAN.

Finally, we evaluate the performance of our proposed method for the data set for grand challenge finale. Table 2 shows the evaluation result.

V. Discussion

In our proposed method, we use multi-class classification. In this report, we investigate the performance of estimating an area. Therefore, the performance is not so better. However, in the future context-aware application, a wide estimated area may be used. For such applications, our proposed method can estimate an appropriate area with much smaller error than other methods by extending the method. We believe that our proposed method can be used more effectively for the context-aware application.

VI. Conclusions

In this report, we proposed location/area estimation based on multi-class classification with deep neural network (DNN) using RSSI of wireless LAN. In the proposed method, a location and an area can be estimated by using DNN. We evaluated he performance of our proposed method. From numerical examples, we showed at our proposed method is effective to estimate the location and area using RSSI of wireless LAN.

Acknowledgment

We thank to Mr. Y. Qiang for his kind support to make a presentation slide.

References

[1] ITU-ML5G-PS-016: Location estimation using RSSI of wireless LAN, https://challenge.aiforgood.itu.int/match/matchitem/58.

[2] S. Hara and D. Anzai, "Use of Simplified Maximum Likelihood Function in a WLAN-Based Location Estimation" IEEE Conference on Wireless Communications and Networking, pp.1-6, May 2009.

[3] S. Hara, "Statistical estimation theory in localization," IEICE Fundamentals Review, vol.4, no.1, pp.32-37, 2010.

[4] G. Engel, F. Bhatti, T. Greiner, M. Heizmann, and F. Quint, "Distributed and Context Aware Application of Deep Neural Networks in Mobile 3D-Multi-sensor Systems Based on Cloud-, Edge- and FPGA-Computing," in *Proc. IEEE 7th International Conference on Industrial Engineering and Applications (ICIEA)*, Apr. 2020.

[5] D. Da Silva, and R. Sofia, "A Discussion on Context-Awareness to Better Support the IoT Cloud/Edge Continuum," IEEE Access, vol. 8, pp. 193686-193694, 2020.

[6] B. Gao, C. Xing, C. Xie, J. Wu, and X. Geng, "Deep Label Distribution Learning with Label Ambiguity," IEEE Transactions on Image Processing, vol. 26, no. 6, pp. 2825-2838, 2017.