

Accuracy Evaluation of Indoor Positioning by Received Signal Strength using Deep Learning

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Abstract—In this paper, we examined indoor positioning systems that combine the deep learning technology with the fingerprint using the received signal strength indicator(RSSI) of Wi-Fi. Because the fingerprint method used previously recorded data, positioning can be performed considering effects in actual indoor environments to obtain a high-precision result compared to other methods that use theoretical formulas. The accuracy of deep learning depends on data shaping and learning methods. Therefore, this study aimed to compare existing methods' accuracy by determining compatible shaping and learning methods. The effectiveness of the proposed method was demonstrated by comparing it with the existing methods.

Index Terms—Deep Learning, Indoor Positioning, RSSI, Fingerprint, Demonstration Experiment

I. INTRODUCTION

In recent years, the positioning functions installed on mobile terminals have been used in various domains, such as social media, games, and navigation systems. Besides, the Internet of Things has become more popular in the industrial field, and with the increasing automation of factories, the importance of accurately measuring the position of machines and components is increasing [1].

The Global Positioning System(GPS), a global satellite positioning system, is used for positioning. However, because this system uses radio waves from satellites, its positioning accuracy decreases in indoor environments where the radio waves cannot reach efficiently. There is a growing demand for positioning systems in indoor environments, such as navigation systems in suburban commercial facilities(i.e., shopping malls), analysis of customer behavior in facilities, and accurate determination of the location of parts and products in factories. Therefore, Indoor MESSaging System(IMES) was developed as an indoor positioning technology, integrated with GPS, to ensure high affinity and positioning accuracy. IMES enables indoor positioning by installing an IMES transmitter that transmits signals similar to GPS. Similar radio wave formats enable seamless positioning both indoors and outdoors, but require dedicated equipment, which increases the installation cost. Therefore, research on positioning systems using Wi-Fi, Bluetooth, and other networking technologies with low installation costs is being actively conducted [2]–[6], [8], [9].

Typical positioning methods that use Wi-Fi include methods that utilize the arrival time of radio waves, arrival angle, and radio field intensity. The methods that use the arrival time and arrival angle have high accuracy but they require a dedicated antenna; therefore, it is difficult to use them. In

contrast, it is easy to use the method that utilizes the radio wave intensity because it uses the property by which radio waves attenuate with distance and it does not require any dedicated equipment. In an ideal environment, the strength and distance of the received radio waves are proportional; however, in practical applications, the radio waves are greatly attenuated owing to the effects of fading. Therefore, their positioning accuracy is very poor. To solve these problems, the approaches of proximity method, triangulation method, and fingerprint method, among others, are used. Although the Triangulation method and Proximity method are easy to use, it is difficult to consider the reflection and attenuation of radio waves in the estimated area, and it is difficult to perform highly accurate positioning. On the other hand, the Fingerprint method uses data observed in advance at any point in the estimation area, so it is possible to perform estimation considering reflection and attenuation. However, with the Fingerprint method, the estimated position to be output is the point measured in advance, so detailed estimation is not possible. Xiaoxuan Lu et al. implemented machine learning techniques on the received signal strength of Wi-Fi and achieved an average error of 2.94 [m] within an area of $35.1 \times 16.6 [m^2]$ [5]. Also, in the study by Tasaki et al., a mean error of 0.96 [m] was achieved in an area of $3 \times 6 [m^2]$ by using a Convolutional Neural Network(CNN) regression model with a compass sensor for the received signal strength of Bluetooth Low Energy(BLE) [6].

In this research, we aim for highly accurate positioning while achieving fine position estimation within the estimation area by combining the existing method, the Fingerprint method, with deep learning technology.

II. PREVIOUS WORKS OF POSITIONING METHODS

This section describes the indoor positioning method using the strength of the radio waves received from the Wi-Fi [7]–[9].

A. Triangulation Method

In this method, estimation is performed using the relative positional relationship from a reference point (Wi-Fi) whose position is known. The distances from three or more reference points are used for estimation. It is assumed that the terminal observes the received radio wave intensity $\{\alpha_1, \alpha_2, \dots, \alpha_n\}$ from the APs $\{AP_1, AP_2, \dots, AP_n\}$ at position $T(x_t, y_t)$. It should be noted that in the Centroid method, the position

T of the terminal can be obtained by equation (1) using the known AP positions (x_1, y_1) to (x_n, y_n) . However, the method does not take into account the received signal strength indicator(RSSI) value from Wi-Fi.

$$T(x_t, y_t) = \left(\frac{\sum_{i=1}^n x_i}{n}, \frac{\sum_{i=1}^n y_i}{n} \right) \quad (1)$$

The radio waves observed by the terminal are stronger because they are closer to the AP. Thus, if the AP information with the stronger received radio wave intensity is used, the positioning accuracy would be improved. Therefore, the weight of the radio wave intensity is substituted in equation (1). Seidel's model is used as the weighting model. In Seidel's model, the RSSI value $\alpha_i[\text{dBm}]$ at distance $r_i[\text{m}]$ is expressed using equation (2). Let α_0 be the RSSI value observed at r_0 and n be a parameter to be set due to the physical environment's obstacles.

$$\alpha_i = \alpha_0 - 10n \log_{10} \left(\frac{r_i}{r_0} \right) \quad (2)$$

Solving equation (2) for r_i yields equation (3).

$$r_i = 10^{(\alpha_0 - \alpha_i)/10n} \quad (3)$$

Using equation (3) as a weight, equation (1) is expanded as follows.

$$(x_t, y_t) = \left(\frac{\sum_{i=1}^n \frac{x_i}{10^{(\alpha_0 - \alpha_i)/10n}}}{\sum_{i=1}^n \frac{1}{10^{(\alpha_0 - \alpha_i)/10n}}}, \frac{\sum_{i=1}^n \frac{y_i}{10^{(\alpha_0 - \alpha_i)/10n}}}{\sum_{i=1}^n \frac{1}{10^{(\alpha_0 - \alpha_i)/10n}}} \right) \quad (4)$$

It should be noted that in the triangulation method, the position of the terminal is estimated using the reference point data and equation (4).

B. Proximity Method

This method is used to estimate the APs closest to the terminal by utilizing information related to the connection status and received signal strength of the APs. Because the estimation algorithm is simple, and the reference point information denotes the estimated position, this method's accuracy is low. If there are multiple APs with different BSSIDs, the terminal measures the AP's received signal strength and estimates the range covered by the strongest AP as the terminal position. Because the terminal only needs to hold the AP location information and BSSID in advance, the system can be easily constructed. The error varies depending on the estimation region, but they are generally in the range of 50 to 100 [m].

C. Fingerprint Method

In this method, radio wave information of wireless LAN at various places (coordinates) within the measurement range is observed and recorded in advance. A model for indoor positioning is formed. The radio wave information is the information of the received radio wave strength from each AP and the source AP's identification number. Since the radio waves transmitted from the AP have the property of being attenuated depending on the distance, the radio wave information at

each coordinate is different and becomes unique. Therefore, when estimating the position, the positioning target terminal uses the radio wave information at the current location and compares it with the position estimation model formed to obtain the position information corresponding to the radio wave information measured at the current location. This method finds and estimates the closest radio wave information among the position estimation models measured in advance. Since a model, including reflection and attenuation in the region, is formed, it is an estimation method that does not consider reflection and attenuation. The positioning accuracy varies depending on the number of registered position estimation models, and the number of radio field strengths received from the AP. Since reflection and attenuation are not considered, more accurate positioning is possible than the Triangulation method and Proximity method [11], [12].

III. OUR POSITIONING METHODS

The Fingerprint method is a more accurate positioning method than the Triangulation method and Proximity method, but since the position measured in advance is output, fine positioning cannot be performed. Therefore, we think that fine positioning can be performed by combining the Fingerprint method with deep learning technology.

A. System Model

Figure.1 illustrates the process of learning and position estimation.

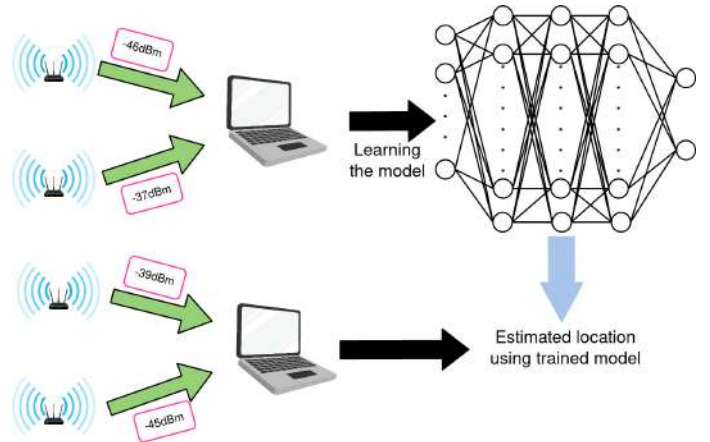


Figure 1. Learning process and position estimation process

The receiving terminal receives the received signal strength indicator value and SSID from each access point. The receiving terminal measures the strength of the received radio wave from the area's access point about once every 5 seconds. Learning and estimation are performed using the received signal strength indicator value and SSID. In this paper, eight access points(APs) are installed in a room with dimensions of $7 \times 3.765[\text{m}^2]$. The APs use the TP-Link Archer C5400, and the RSSI values are measured using NetSpot, developed by Etwok.

The experimental environment is demonstrated in Figure.2 and 3. In this paper, the grid size is set to 1 [m], and it

is divided into 28 cells. The red dot in Figure.3 represents the center of each square and measures the training data, verification data, and test data. The blue dot represents an arbitrary point, and only the test data is measured.

In the model, the strength of the radio wave received from each Wi-Fi is input (example: [-50, -40, ..., -38]), and the coordinates [x, y] of each input are learned. When a new radio field intensity dataset is received, position estimation is performed using the learned model.



Figure 2. Experimental environment

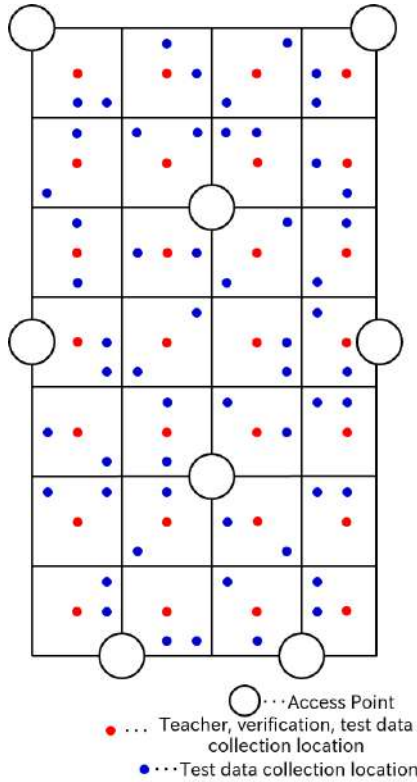


Figure 3. Outline of the experimental environment

In this paper, we used the Fingerprint method as a positioning method that uses the RSSI. A network model is

created by supervised learning using the observed RSSI value as input by associating a label with the receiving terminal position. Subsequently, the position is estimated from the network model's output that has learned the observed received signal strength indicator value.

B. Data Shaping

TABLE I presents a part of the measurement data.

TABLE I. PART OF MEASUREMENT DATA

Date	Signal (dBm)	Channel	Security	PHY mode
2020/03/11 15:58:21	-52	11	WPA2 Personal	n
2020/03/11 15:58:28	-51	11	WPA2 Personal	n
2020/03/11 15:58:31	-50	11	WPA2 Personal	n
2020/03/11 15:58:38	-51	11	WPA2 Personal	n
2020/03/11 15:58:41	-52	11	WPA2 Personal	n
2020/03/11 15:58:44	-51	11	WPA2 Personal	n
2020/03/11 15:58:47	-52	11	WPA2 Personal	n
2020/03/11 15:58:52	-57	11	WPA2 Personal	n
2020/03/11 15:58:57	-50	11	WPA2 Personal	n
2020/03/11 15:59:02	-53	11	WPA2 Personal	n
2020/03/11 15:59:07	-49	11	WPA2 Personal	n
2020/03/11 16:00:00	-50	11	WPA2 Personal	n
2020/03/11 16:00:04	-58	11	WPA2 Personal	n
2020/03/11 16:00:09	-	-	-	-

The collected data are shaped to ensure that the network model is easy to learn. The SSID and Signal(dBm) values of each instance of data are extracted, and a label is assigned to them. If the data instance represents a loss, the model does not learn, and the time series data with the loss are deleted.

When training a data set whose scales are not uniform among the features, there is a demerit that the training parameters' update becomes slow, and the learning becomes slow. Since data shaping has the merit of reducing the number of steps to find the optimum solution and improving the accuracy, the collected data is shaped by the following method.

1) Standardization

Instead of using the original data, the data features are standardized. Standardization is performed using the following formula. Using the following formula, the features of the data can be converted to 0 on average and 1 on variance.

$$x_{std} = \frac{x - m_x}{s_x}$$

x_{std} denotes the data after standardization, x denotes the data before standardization, m_x represents the average of the data, and s_x denotes a sample standard deviation of the data.

2) Normalization

This operation converts the range of the feature values to a predefined range, i.e., [0, 1] or [-1, 1]. In this paper, assuming that the range is set to [0,1], the transformation of x_i can be expressed by the following equation.

$$x_{norm,i} = \frac{x_i - x_{min}}{x_{max} - x_{min}}$$

$x_{norm,i}$ denotes the normalized data, x_{min} and x_{max} represent the minimum and the maximum values of the dataset, respectively. Consequently, the minimum and maximum values of the converted data are found to be 0 and 1, respectively, and the values are obtained within [0, 1].

3) Binary conversion

Similar to standardization, the data are converted to a binary sequence such that the model is easy to learn. The absolute value of the data is converted into an 8-bit binary sequence, and learning techniques are implemented on it. An example of converting RSSI data into binary is given below.

$$\begin{bmatrix} -50 \\ -40 \\ -37 \\ -24 \\ -50 \\ -45 \\ -35 \\ -38 \end{bmatrix} \Rightarrow \begin{bmatrix} 00110010 \\ 00101000 \\ 00100101 \\ 00011000 \\ 00110010 \\ 00101101 \\ 00100011 \\ 00100110 \end{bmatrix}$$

C. Learning Model

This section describes the model used in the training. To create a learning model, we used Keras, which can easily construct a network model and implement it with a relatively short source code [10].

1) Classification model

Labels are assigned to the previously measured data. The label shows the probability of existence in each square, and 1 is given only to the square in which the terminal exists among the 28 squares (e.g.: $[y_0, y_1, \dots, y_{26}, y_{27}] = [1, 0, \dots, 0, 0]$). The model extracts features from the input data and outputs the probability of being at each position. The measured data are classified into teacher data and verification data; accordingly, the model is learned and verified. This model can estimate the position in the same way as the Fingerprint method. Therefore, it is considered that fine adjustment is not possible like the Fingerprint method. However, unlike the Fingerprint method, it seems that even abnormal data can be positioned with a certain degree of accuracy.

2) Ensemble learning

This method is used to generate a learning model by fusing multiple models (learners). Multiple models are trained, and finally, the position is estimated by majority voting on each model's output. In this paper, the collected data are divided into six parts and used as training data. Learning is performed by shaping and labeling each dataset to create six learning devices using the six sets of divided data.

3) Regression analysis

In this paper, the position is predicted using the regression that predicts the real value from the given input, which is typical in supervised learning. This time, the received signal strength indicator values received from the eight APs are input, and the coordinates (x, y) are output. When new data are received using the trained model, the position is estimated by calculating (x, y) . By using the regression model, the output is not specified, and the coordinates matched to each data can be output. Therefore, it is considered that highly accurate positioning can be achieved. The hyperparameter of the model are shown below.

- Activation function : relu
- Hidden layer : 5

- Number of hidden layer units : 500
- Learning rate : 10^{-5}
- Optimization function : Adam
- Loss function : mean squared error
- batch size : 128
- epochs : 2000

The existing Fingerprint method has a problem that fine positioning is difficult because the output is fixed to a certain value, but by using the regression analysis model, highly accurate positioning can be expected regardless of the received radio waves.

IV. SIMULATION RESULTS

In order to prove our hypothesis, we actually collected and tested the data.

TABLE II shows the results of training the classification model described in Section III-C-1 with and without data shaping. TABLE III shows the results of training the ensemble learning described in Section III-C-2 with and without data shaping. TABLE IV shows the positioning accuracy obtained by combining the regression analysis models described in Section III-C-3 with and without each data shaping.

TABLE V compares the position accuracy of the triangulation method with that of the proximity method. In the triangulation method and the Proximity method for comparison. In the triangulation method, the parameters are set to $n = 2.5$, $r_0 = 1[m]$, and $\alpha_0 = -32[dBm]$ based on the empirical rule proposed by LaMarca et al [7], [8]. The estimated position can be represented using equation (5).

$$r_i = 10^{(-32 - \alpha_i)/25} \quad (5)$$

Figure.4 shows a comparison between the most accurate output of the proposed method and the existing method (eg, a combination of classification model and binary conversion). It was found that the accuracy was low when the classification model and ensemble learning were used for position estimation. As proposed in the hypothesis, the regression analysis model realized finer positioning than other methods and achieved improved accuracy. On the contrary, the classification model could not process abnormal data, and when abnormal data was input, it output a value far from the correct output.

TABLE II. CLASSIFICATION MODEL

	Normal data	Standardization	Normalization	Binary
average (m)	3.470	3.447	3.481	3.143
maximum (m)	6.749	6.749	6.749	5.385
dispersion (m^2)	4.094	4.073	4.098	4.206

TABLE III. ENSEMBLE LEARNING

	Normal data	Standardization	Normalization	Binary
average (m)	3.181	3.760	3.169	3.183
maximum (m)	6.749	7.397	6.749	6.749
dispersion (m^2)	4.133	4.465	4.149	4.069

TABLE IV. REGRESSION ANALYSIS

	Normal data	Standardization	Normalization	Binary
average (m)	0.931	0.931	0.930	0.888
maximum (m)	6.677	6.736	6.612	6.658
dispersion (m^2)	0.477	0.489	0.481	0.398

TABLE V. EXISTING METHOD

	Triangulation method	Proximity method
average (m)	1.000	1.348
maximum (m)	6.424	7.000
dispersion (m^2)	0.453	0.544

V. CONCLUSION

This paper investigated indoor location estimation based on the received signal strength using deep learning. We have summarized the position accuracy values when using the regression analysis model, one of the deep learning methods, for some data sets. Consequently, it has been found that the regression analysis model is more accurate than existing methods, such as the triangulation and proximity methods. Moreover, it is evident from TABLE IV that binary conversion exhibits the highest precision in shaping the data, whereas the accuracy of other data shaping methods does not demonstrate any significant change. This result found that it is suitable to convert the RSSI value to a binary number using a regression analysis model in position estimation.

In the future, we will use this result to change the model and parameters of the regression model and combine the regression analysis model with other models to improve the positioning accuracy.

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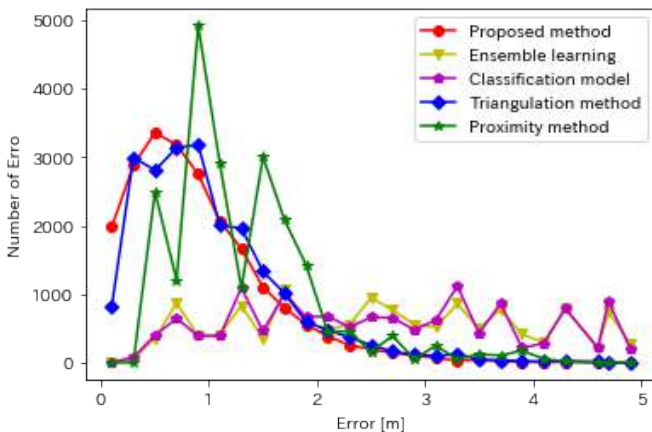


Figure 4. Accuracy comparison of each method

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