Location Estimation Applying Machine Learning Using Multiple Items of Sensed Information in Indoor Environments

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Abstract— Receiving radio waves directly from satellites is difficult in an indoor environment, making accurate location estimation by satellite signals difficult. Since mobile communication propagation channels suffer from fading and shadowing, estimating accurate locations in an indoor environment by using only the received signal power of a radio wave is also difficult. We have previously proposed a minimum mean square error (MMSE) location estimation method using multiple items of sensed information as well the received signal power and shown that its estimation errors are smaller than those of the conventional method using only the received signal power. Machine learning has recently become attractive as an optimization algorithm, and in this paper we propose to apply machine learning with a back propagation method for indoor location estimation using multiple items of sensed information. Our proposed machine learning location estimation method is experimentally validated and compared with the MMSE method. The machine learning location estimation method was found to reduce the standard deviation of the location estimation error and increase the probability that the estimated distance is within 2.5 m of the actual distance.

Keywords— location estimation, machine learning, back propagation, ZigBee, sensed information, temperature, illuminance, humidity.

I. INTRODUCTION

As applications that use location information become commonplace, the demand for accurate location estimation is increasing [1], [2]. However, receiving radio waves directly from satellites is difficult in an indoor environment, making location estimation with satellites (e.g., the GPS [3]) difficult. Since mobile communication propagation channels suffer from fading and shadowing, providing accurate location estimation in an indoor environment [4]–[6] by using only the received signal power of a radio wave is difficult.

Because of the development of IoT technology, sensing technology is now widely used. Sensed information, e.g., temperature, humidity, and illuminance is frequently location dependent, and accurate location estimation can be provided if such items of information are used in addition to received signal power. We therefore previously proposed a method for estimating locations by using the above multiple items of sensed information [7], [8].

Our previously proposed minimum mean square error (MMSE) method [8] estimates the location by minimizing the mean square error between multiple items of sensed information and the information in a database that expresses relationship between location and multiple items of sensed information. We validated the proposed MMSE method by showing experimentally that it is more accurate than the conventional method using only the received signal power.

Machine learning [9]–[11] is becoming attractive as an optimization algorithm, and in this paper we propose to apply machine learning with a back propagation [12] method for indoor location estimation using multiple items of sensed information. We also evaluate the effectiveness of our proposal experimentally.

II. BACK PROPAGATION METHIOD

Back propagation (BP) method is one of the weight updating methods for a neural network. A neural network is a network constructed by combining a lot of artificial neurons which are called cells. The cell subtracts the bias value from the sum of the weighted input signals, and outputs the difference via an output function. In the BP method, the weights and bias values of cells are updated using the error between the output signal and a desired signal.

An example of a neural network is shown in Figure 1, where I is the number of input signals and N is the number of cells of an intermediate layer. Here, the output signal h_n of the n-th cell is expressed as the following equations using a sigmoid function $f(u)$:

$$h_n = f(u_n) \tag{1}$$

$$f(u) = \frac{1}{1+e^{-u}} \tag{2}$$

$$u_n = \sum_{i=1}^{I} x_i w_{n,i} - v_n \tag{3}$$

where x_i is the i-th input signal, $w_{n,i}$ is the weight of the n-th cell for i-th input signal, and v_n is the bias value of the n-th cell. Output signal o of the neural network can be expressed as follows:

$$o = f(u_k) \tag{4}$$

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$$u_k = \sum_{n=1}^{N} h_n w_{k,n} - v_k \quad (5).$$

The weight $w_{k,n}$ of output layer can be updated as follows:

$$w_{k,n} \leftarrow w_{k,n} + \alpha \cdot o \cdot (1-o) \cdot h_n \cdot E \quad (6)$$

where α is a learning coefficient and E is an error expressed as

$$E = o_t - o \quad (7)$$

where o_t is a desired signal. The weight $w_{n,i}$ of the intermediate layer can be updated as follows.

$$w_{n,i} \leftarrow w_{n,i} + \alpha \cdot o \cdot (1-o) \cdot h_n \cdot (1-h_n) \cdot w_{k,n} \cdot E \cdot x_i \quad (8)$$

The bias values v_k and v_n can be updated as special weights of $h_n = -1$ and $x_i = -1$ for equations (6) and (8) respectively.

After a set of learning data is input to a neural network, all weights and bias values of all cells are updated by the procedure described above. This learning process is performed for all the sets of learning data and iteratively learns until the sum of the squares of the errors falls below the upper limit value of the error.

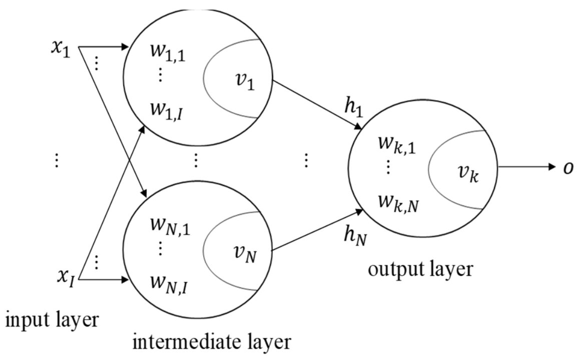

Figure 1. Example of a neural network.

III. Experiment

All the sensor nodes we used had a ZigBee TWE-lite DIP radio module [13] and a sensor. The specifications of the ZigBee TWE-lite DIP radio module are shown in Table 1. Figure 2 shows overviews of the sensor nodes. Sensor TSL2561 [14] can measure illuminance, and sensor SHT-21 [15] can measure temperature and humidity.

Table 1. Specifications of ZigBee TWE-lite DIP radio module.

Radio standard	IEEE 802.15.4
Radio frequency	2.5 GHz
Number of channels	16 channels
Modulation scheme	O-QPSK, DSSS
Transmission rate	250 kbps
Transmit power	+2.5 dBm
Receiver sensitivity	−95 dBm

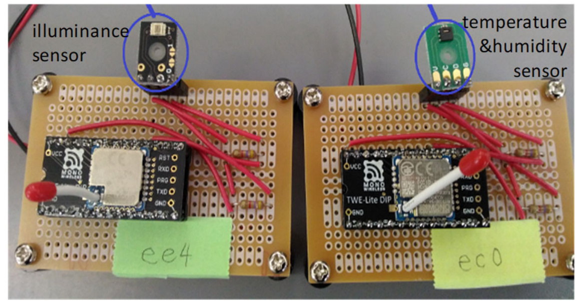

Figure 2. Overview of sensor nodes.

As shown in Figure 3, the experiment was performed on the 3rd floor of the Tohoku Institute of Technology Yagiyama Campus Building 9. The access point (AP) was fixed and connected to a PC. Sensor nodes measured multiple items of sensed information (signal power received from AP, temperature, humidity, illuminance). Fixed sensor nodes were placed every 5 m to 45 m from the AP. The information measured by all of the fixed sensor nodes was sent to the AP every 10 seconds and recorded to the PC by using a Tag Viewer [16]. Learning data consisted of multiple items of sensed information measured at fixed sensor nodes. Machine learning with a BP method was performed using the learning data. A moving sensor node also measured multiple items of sensed information (signal power received from AP, temperature, humidity, illuminance) and moved 0–45 m in 2.5 m steps. The sensed information measured by the moving sensor node was sent to the AP every 10 seconds and recorded. Then these multiple items of information sensed at the moving sensor node were used to estimate the distance between the moving sensor node and the AP. For comparison, location estimation by the MMSE method [8] was also performed. To validate the learning process, the distances between the AP and the fixed sensor nodes were also estimated using the original learning data.

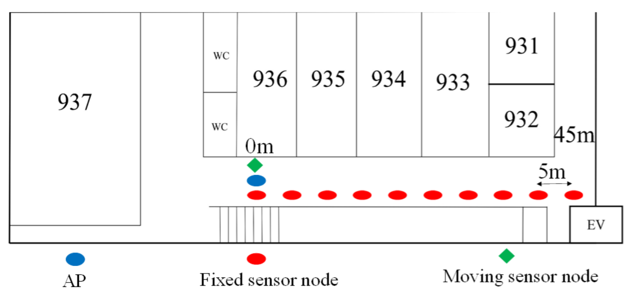

Figure 3. Experimental layout.

IV. Experimental Results

In this paper, three parameters affecting the learning process of a BP method are determined as follows. The learning coefficient α corresponding a learning speed is determined to be a large value in the range where the learning process converges. The upper limit of the error is set to be a small value in that range while avoiding the error due to the vanishing gradient problem (a phenomenon in which the distributed error becomes too small to update the weights when the number of cells in the intermediate layer is too large or the error of the whole network is too small). The number N of cells in the intermediate layer is determined to be the number that makes the error as small as possible within a range where the error vanishing gradient problem does not occur. In this paper, multiple items of sensed information multiplied by 1/2000 were used as the input signals to the neural network so that the output variable of the neural network was 1 or less in order to use the sigmoid function. Under this learning data used in this paper, when the learning coefficient α is 30, the number N of cells in the intermediate layer is 23, and the upper limit of the error is 0.002, the optimal estimation result is obtained within our retrieved range. The distance between the AP and sensor node is estimated under these conditions. The distance estimation results are shown below.

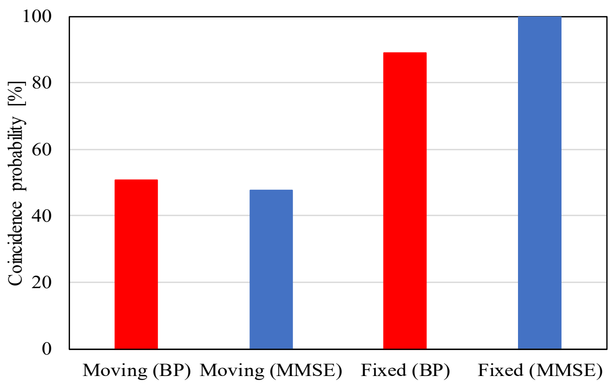

Figure 4. Probability that estimated distance is within 2.5 m of actual distance.

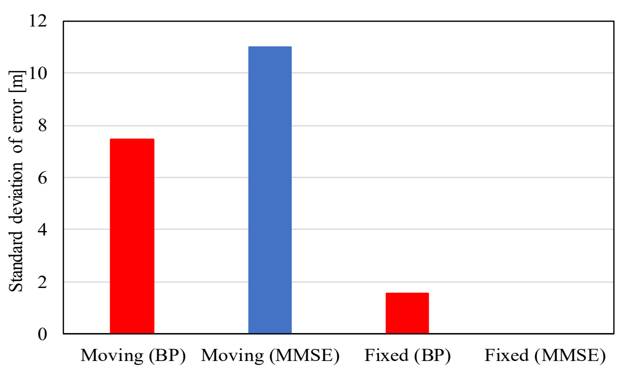

Figure 5. Standard deviation of location estimation error.

Figure 4 shows the probability that the estimated distance is within 2.5 m of the actual distance. Figure 5 shows the standard deviation of the distance estimation error. In order to validate the learning process, location estimation of the fixed sensor node was performed using the original learning data. The coincidence probability of MMSE method is 100%, showing that the MMSE method works well. The theoretical value of the standard deviation of the location estimated error of the BP method is evaluated as follows, using the upper limit of estimation error 0.002, the normalized factor 2000 and the number of learning data 3341.

$$\sqrt{\frac{0.002}{3342}} \cdot 2000 \cong 1.547 \ [m] \tag{9}$$

It is found from figure 5 that the standard deviation of location estimation error of the BP method is about 1.5 m, which is smaller than the theoretical value. Therefore, it is considered that BP learning process works well. In the case of estimating the location of a moving sensor node, the coincidence probability of the BP method is larger than that of MMSE method. And the standard deviation of the location estimation error for the BP method is about 3.5 m less than that for the MMSE method. Therefore, it can be seen that the location estimation of the BP method is more accurate than that of the MMSE method.

V. Conclusions

In this paper, machine learning with back propagation method is applied for indoor location estimation using multiple items of sensed information. In an experiment estimating the location of a moving sensor node, the proposed machine learning method had an about 3% higher coincidence probability and an about 3.5 m smaller standard deviation of error than the MMSE method. Thus the machine learning method can estimate location more accurately than the minimum mean square error method.

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