Machine learning method for location estimation at various altitudes using multiple items of sensed information in indoor environment

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SUMMARY In an indoor environment, it is difficult to receive radio waves directly from satellites which hinders accurate location estimation by satellite signals. Meanwhile, mobile communication propagation channels suffer from fading and shadowing, so estimation of indoor locations by using only the received signal power of a radio wave is inaccurate as well. Sensed information (e.g., temperature, humidity, illuminance) is often location dependent, and a location can be estimated accurately if such information is used in addition to the received signal power. The use of machine learning for an optimization algorithm has been shown to be promising. In this paper, we apply machine learning for indoor location estimation at various altitudes using multiple items of sensed information. We propose two types of neural networks, a two-dimensional neural network and a nearest node neural network, and experimentally evaluate them in an actual building. The results indicate that location estimation using the nearest node neural network has a greater coincidence probability than that using the two-dimensional neural network.

keywords: *location estimation, machine learning, ZigBee, sensed information, IoT.*

1. Introduction

The demand for accurate location estimation has been increasing as applications that use location information become more commonplace [1], [2]. Receiving radio waves directly from satellites is difficult in an indoor environment, which hinders location estimation using satellites signals (e.g., GPS [3]). Because mobile communication propagation channels suffer from fading and shadowing, the estimation of indoor locations [4]–[6] by using only the received signal power of a radio wave tends to be inaccurate.

Advancements in IoT technology have made it possible to collect sensed information (e.g., temperature, humidity, and illuminance) on a widespread basis. Sensed information is often location dependent, and a location can be accurately estimated if such information is used in addition to the received signal power.

The use of machine learning [7]–[9] for an optimization algorithm has been shown to be promising. We previously proposed applying machine learning for indoor location estimation using multiple items of sensed information and showed that the machine learning method achieves a higher coincidence probability and a smaller standard deviation of error than that of the MMSE method [10][11].

The demand for accurate location estimation is increasing not only for same altitude areas but also various altitudes ones (e.g., buildings). As the number of different altitudes increases, utilizing the machine learning method becomes more complicated. At various altitudes in an indoor environment, e.g., different floors of a building, altitude and distance can be estimated by machine learning in the same manner as in [10][11]. Because there are many sensor nodes at known locations, it is also possible to estimate the nearest sensor node [4][12]. In this paper, we study the effect of neural network structure on location estimation at various altitudes in an indoor environment. We propose two different structures, a two-dimensional neural network and a nearest node neural network, and experimentally evaluate them in an actual building.

2. Machine Learning Location Estimation Method

A neural network is a network constructed by combining many artificial neurons called "cells." A cell subtracts a bias value from the sum of the weighted input signals and outputs the difference via an output function. In our study, the location is estimated from corridors at various altitudes (floors) in a building. Thus, we consider a two-dimensional output layer. The proposed neural network with two output layers is shown in Figure 1, where I is the number of input signals, and M is the number of cells of an intermediate layer. This neural network structure can also output a distance where no sensor nodes are placed as estimated values.

If there are many sensor nodes whose locations are known, the nearest sensor nodes can be found by comparing the sensed information obtained by those sensor nodes and the moving sensor node. Figure 2 shows the proposed nearest node neural network which outputs the likelihood value of each fixed sensor node whose location is known.

The output signal $h_{m,n}$ from the intermediate layer m-th cell to the output layer n-th cell is expressed as the following equations using a sigmoid function $f(x)$:

$$h_{m,n} = f(u_{m,n}), \tag{1}$$

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

$$u_{m,n} = \sum_{i=1}^{I} x_i w_{i,m,n} - v_{m,n}, \tag{3}$$

where x_i is the i-th input signal, $w_{i,m,n}$ is the weight of the intermediate layer m-th cell from the i-th input signal to the output layer n-th cell, and $v_{m,n}$ is the bias value of the intermediate layer m-th cell to the output layer n-th cell. Because a sigmoid function is used as the output function,

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the data must be normalized so that the absolute value of the input signal value is 1 or less. The output signal o_n of the output layer n-th cell can be expressed as:

$$o_n = f(u_n), \tag{4}$$

$$u_n = \sum_{m=1}^{M} h_{m,n} wo_{m,n} - vo_n, \tag{5}$$

where $wo_{m,n}$ is the weight of the output layer n-th cell from the intermediate layer m-th cell signal, and vo_n is the bias value of the output layer n-th cell.

The weight $w_{i,m,n}$ of the intermediate layer m -th cell from the i-th input signal to the output layer n-th cell can be updated as follows.

$$w_{i,m,n} \leftarrow w_{i,m,n} + \alpha \cdot x_i \cdot v_{m,n}, \tag{6}$$

$$v_{m,n} \leftarrow h_{m,n} \cdot \left(1 - h_{m,n}\right) \cdot w_{i,m,n} \cdot E_n \cdot o_n \cdot \left(1 - o_n\right), \tag{7}$$

where α is a learning coefficient, and E_n is the error of the output layer n-th cell.

The weight $wo_{m,n}$ of the output layer n-th cell from the intermediate layer m-th cell can be updated as:

$$wo_{m,n} \leftarrow wo_{m,n} + \alpha \cdot E_n \cdot o_n \cdot \left(1 - o_n\right) \cdot h_{m,n}, \tag{8}$$

$$E_n = o_n - t_n, \tag{9}$$

where t_n is the teacher data of the output layer n-th signal.

After a set of learning data is input to a neural network, the weights and bias values of all cells are updated by the procedure described above. This learning process is performed for all sets of learning data, and the neural network iteratively learns more than 10^8 times.

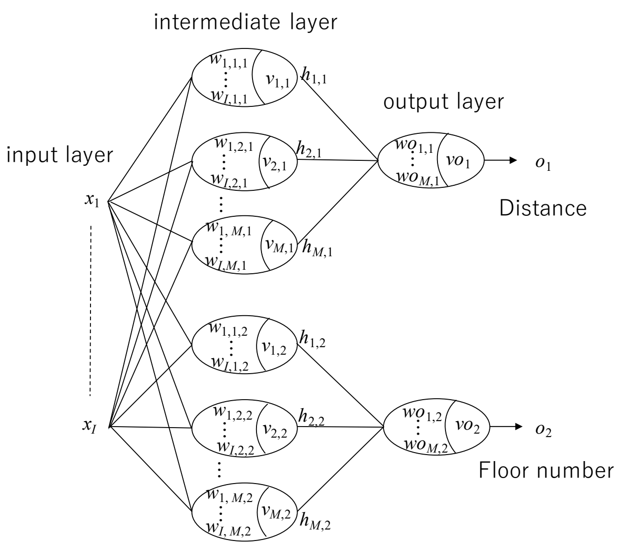

Fig. 1 Two-dimensional neural network.

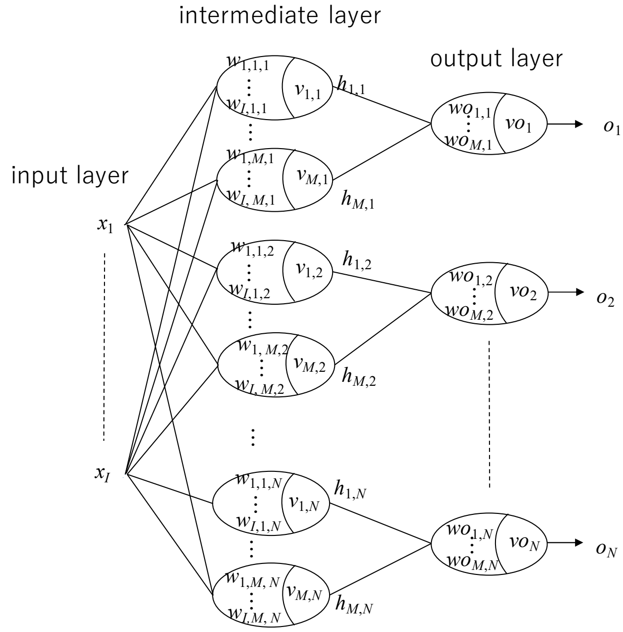

Fig. 2 Nearest sensor node neural network.

3. Experiment

All sensor nodes used in the experiment contained a ZigBee TWE-lite DIP radio module [13] and a sensor. The specifications of the ZigBee module are shown in Table 1. Figure 3 shows an overview of the sensor nodes. Sensor TSL2561 [14] measures illuminance, and sensor SHT-21 [15] measures 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

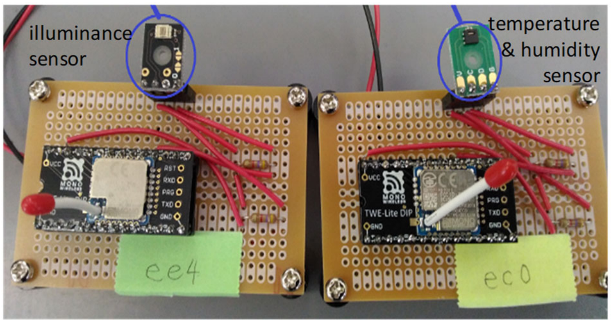

Fig. 3 Overview of sensor nodes.

As shown in Figure 4, the experiment was performed on the fourth to sixth floors of Building 3 at the Yagiyama Campus of Tohoku Institute of Technology. Three access points (APs) were fixed at the navy circle shown on the Figure 4 and connected to a PC. Five fixed sensor nodes C (indicated by red circles) were placed at 5-m intervals on each floor. The sensor nodes measured multiple items of sensed information, i.e., temperature, humidity, and illuminance. A moving sensor node E (green triangle) also measured the same items while moving at each place. The measurement duration was 5 minutes each location, and the items acquired by each sensor node were transmitted every 10 seconds and recorded on the PC connected to the AP by using a Tag Viewer [16]. The items obtained by all fixed sensor nodes were used as teacher data for machine learning. After learning the teacher data, the location of the moving sensor node was estimated using the learned neural networks.

Fig. 4 Experimental layout.

4. Experimental Results

We then used both proposed neural networks for location estimation. The received signal power at three APs and the three items of sensed information (temperature, humidity, illuminance) were used as the input signal. Because the sensed information was time varying, the receiving time was also used for input signals for the neural networks. Thus, the number of input layers I was 7. For the two-dimensional neural network (Figure 1), one output layer output the distance from an AP, and the other output the number of floors. Because there were 15 fixed sensor nodes, the number of output layers N was 15 in the nearest node neural network (Figure 2). In the training process of both neural networks, 3600 data sets were used as the teacher data, and training was carried out for more than 10^8.

Figure 5 shows the coincidence probability between the estimated location and actual location. In the case of the two-dimensional neural network, it was assumed that the estimated location coincided with the actual location when the difference between the estimated distance and the actual distance was smaller than 2.5 m, and the estimated floor number is coincident with the actual floor number. To validate the learning process, the location of the fixed sensor node was also estimated by using the original learning data. As seen in Figure 4, the coincidence probability was almost 100% when the locations of the fixed sensor nodes were estimated, indicating the validity of the learning process for both neural networks.

When the location of the moving sensor node was estimated, the coincidence probability using the nearest node neural network was 72.5%, which is higher than that using the two-dimensional neural network (37.8%). The reason for this can be considered bellow. When using the two-dimensional neural network, both the distance from the AP and the number of floor must be estimated correctly. Furthermore, there are 3 different number of floors for the same distance from the AP, and 5 different distances from the AP for the same number of floors. On the other hand, when using the nearest node neural network, it can estimate the location correctly only to find the cell with the highest likelihood value among the cells corresponding to each node, resulting in a higher coincidence probability.

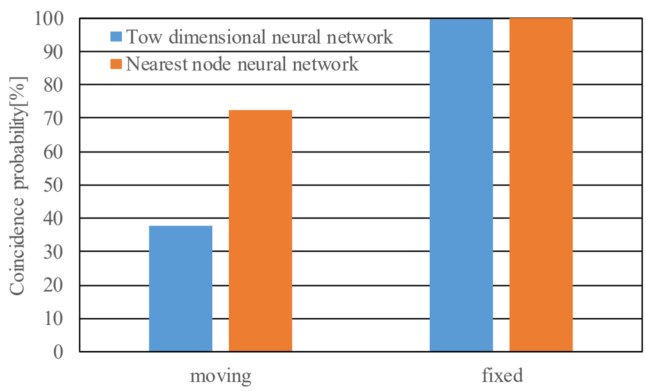

Fig. 5 Coincidence probability between estimated and actual locations.

5. Conclusions

We proposed a two-dimensional neural network and a nearest node neural network which use multiple items of sensed information for location estimation. The neural networks were experimentally evaluated for various altitudes in an indoor environment. The results indicated that the location estimation using the nearest node neural network yields a higher coincidence probability than that using the two-dimensional neural network.

Acknowledgments

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