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LETTER

Fingerprint localization using data from different radio environments

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Abstract This study evaluated an indoor location estimation method using a wireless local area network (LAN). The Fingerprint method was used as a location estimation technique. This method can estimate the current location based on the received signal strength indicator and media access control address obtained from the wireless LAN access points. However, this method is greatly affected by changes in the radio propagation environment, and the presence or absence of obstacles reduces the location estimation accuracy. This paper proposes a database developed by measuring data of different radio propagation environments. The environment was experimentally confirmed to change with the opening and closing of doors and the direction of radio wave measurement.

Keywords: Fingerprint, localization, convolutional neural network
Classification: Navigation, guidance and control systems

1. Introduction

This paper proposes a Fingerprint method using a received signal strength indicator (RSSI) measured from wireless local area network (LAN) access points (APs). This method compares a database (DB) and user data (UD). The DB is produced by measuring an RSSI in advance. The UD is produced by measuring the RSSI at the time of location estimation. The point with the most similar data is the estimated location.

However, there is a problem. The measured RSSI changes even at the same location, and localization accuracy decreases if the DB and UD radio environment change. Changes in the radio environment can be divided into permanent and temporary. The new installation of fixed walls or fixtures makes permanent changes. The DB needs to be updated, and several studies have been conducted [1, 2].

The opening and closing of doors or human presence cause temporary changes, which reduce the estimation accuracy. Automating location information to changing environmental dynamics using sensors [3] is expensive. This study aimed to improve the localization accuracy using DBs measured in multiple environments. Experiments were conducted focusing on changes in the radio wave environment due to the opening and closing of doors [4], and on the radio wave environment when the direction of the radio wave measurement was changed.

The person measuring the radio wave is holding the Android smartphone in front of the chest. The “direction of radio wave measurement” indicates the direction of the person measuring the radio wave.

This paper proposes two methods. One is learning with data from different radio environments, which aims to maintain accuracy regardless of the user’s radio environment. The second method is learning after selecting APs, which aims to maintain accuracy even if the environments of DB production and location estimation are different.

2. Indoor localization by the Fingerprint method

2.1 Fingerprint method for localization

The Fingerprint method compares the DB and UD. The service providers set the reference points in advance on a map and measure the AP information (MAC address and RSSI of each AP). The data is called a DB. AP information called UD is measured when a user estimates a location. The UD measured was compared with the DB. The most similar reference point was the estimated location. A convolutional neural network (CNN) was used for comparison.

2.2 Fingerprint method using a CNN

The service providers produce a CNN model before the users estimate a location. DB is used as train data to develop a CNN model. The input data for CNN is a square matrix reflecting the AP location. First, the service providers divide the map into a grid and fill the positions where the APs are located with the RSSI measured from the APs and fill the unfilled positions with -100 dBm. Each of these values is normalized from zero to one and used as CNN input data. The output for a CNN is the user existence probability for each reference point [5].

When a user estimates a location, the UD is input into a CNN model produced by the service providers. The point with the highest existence probability is the estimated location of the user.

3. Proposed methods

This paper proposes a method for learning CNNs using data measured in multiple environments.

3.1 Learning data from different radio environments

Data in different radio environments were measured to produce DBs to improve the accuracy using all DBs which were measured in different radio environments, were used as training data for the CNN. In this experiment, we created different radio environments by two different ways. The methods were to open and close doors and to change the

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direction of the radio wave measurement.

In the experimental environment, environments in which all six doors are open/closed are denoted as "open"/"closed" respectively. The environments when the direction of the radio wave measurement is east, west, south, north and south is denoted as "north," "east," "south" and "west," respectively.

This paper proposes six methods (a)–(f) for learning DBs which were measured in different radio environments.

(a) A CNN learns DBs. The output layer outputs the existence probability of each point independent of the radio environment. This method is the simplest of the proposed methods.

(b) A CNN learns DBs. The outputs are the existence probability of each point for each radio environment. In method (b), data trained with different environments are used as different labels, even if these are measured at the same points.

(c) A CNN learns two labels, points, and radio environments, using two softmax functions. This is called multitask learning. CNN can capture mutually beneficial features by learning two types of labels, points, and radio environments.

(d) In the proposed method (a), SE-net learns DBs instead of CNN. A squeeze-and-excitation (SE)-block is added after the first convolutional layer of the CNN. CNN using a SE block is called a SE-net. Each channel is output equally in the convolutional layer of CNN. However, in a SE-net, the valuable channels are emphasized, and the interaction between channels can be represented. What is done in the SE block is shown below [6].

1. Average pixel values as representative values for each channel using global average pooling.
2. Represent nonlinear relationships between channels using a fully connected layer.
3. Express the information value of a channel as 0–1 using a sigmoid function.

The amount of information of an RSSI, which is sensitive to the radio environment, can be improved using the SE-net property of highlighting information on the necessary channels. By doing so, it is hoped that CNN would successfully learn data from different radio environments.

(e) In the proposed method (b), SE-net learns DBs instead of CNN.

(f) In the proposed method (c), SE-net learns DBs instead of CNN.

3.2 Learning after selecting APs

There are APs with significant variations in RSSI at the same point due to changes in the radio environment. The CNN may not learn well because of this AP. The proposed method selects APs with large RSSI fluctuations because of the changes in the radio environment and eliminates them from the CNN input data for learning. The APs are selected in order of the difference in RSSI due to changes in the radio environment at the same point using the Euclidean distance and cosine similarity to evaluate the RSSI difference. The two methods are expressed using Equations (1) and (2), respectively.

$$d(\boldsymbol{x},\boldsymbol{y}) = \sqrt{(x_1 - y_1)^2 + \cdots + (x_n - y_n)^2} \tag{1}$$

$$\cos(\boldsymbol{x},\boldsymbol{y}) = \frac{\boldsymbol{x} \cdot \boldsymbol{y}}{\|\boldsymbol{x}\|\|\boldsymbol{y}\|} \tag{2}$$

4. Verification

In this experiment, we created different radio environments by two different ways in a building with multiple rooms and corridors surrounded by metal walls and doors. The methods were to open and close doors and to change the direction of the radio wave measurement.

The change in the radio environment due to the opening and closing of a door is denoted as Situation 1.

The change in the radio environment due to the direction of the radio wave measurement is denoted as Situation 2.

Table I Verification condition

(a) Measurement condition (Situation 1)

Num. of points	39 points (3 m interval)
Num. of measurements	train data: 50 times/points test data: 10 times/points
Num of APs	44

(b) Measurement condition (Situation 2)

Num. of points	28 points (3 m interval)
Num. of measurements	train data: 40 times/points test data: 10 times/points
Num of APs	38

4.1 Learning with data from different environments

The proposed method (a)–(f) in Section 3.1 was validated. In Situation 1, the train data was measured in two radio environments, open and close, and test data were measured by changing the number of open doors from zero to six.

In Fig. 1, the dotted line shows the CNN trained on the data from a single radio environment. A CNN, which learns DBopen only, is denoted as CNNopen, and a CNN, which learns DBclose only, is denoted as CNNclose. The solid line shows the CNN trained on the data from two environments using the proposed methods.

In Situation 2, the train data was measured in four radio environments: north, east, south and west, and test data were

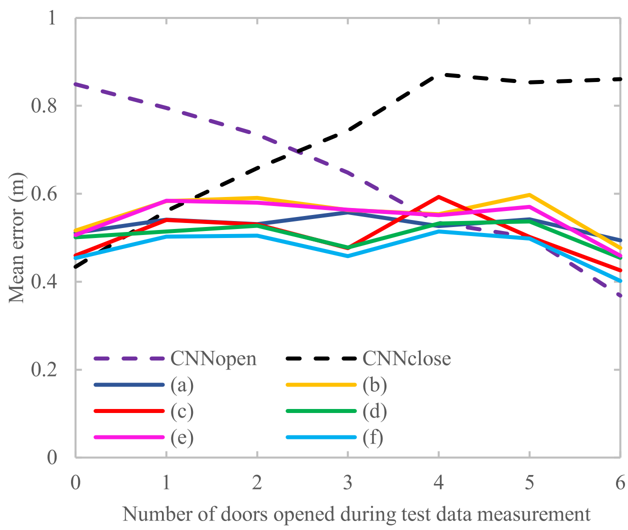

Fig. 1 Mean error of proposed method (Situation 1)

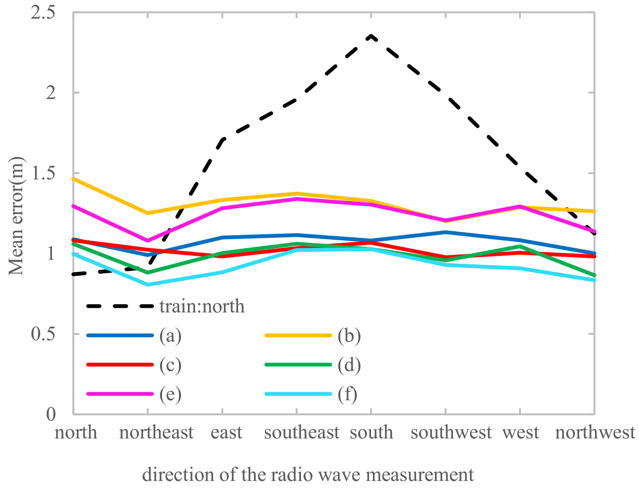

Fig. 2 Mean error of proposed method (Situation 2)

measured in eight measurement directions.

In Fig. 2, the dotted line shows the CNN trained only on DB measured in the north direction. The solid line shows the CNN trained on the data from four environments using the proposed methods.

In both situations, the CNN trained on data from a single environment had a smaller mean error if the measurement environment was the same for the train and test data. However, the mean error was large when the measurement environments were different. On the other hand, the proposed method shows that the mean error is small no matter which radio environment is used when the test data is measured.

In particular, the proposed method (c), (d) and (f) has a smaller mean error. The proposed method (c) has a lower mean error than the proposed methods (a) and (b). This indicates that multitask learning is effective.

From the proposed methods (d), (e), and (f), the mean error is smaller with SE-net than with CNN. This indicates that SE-net is effective.

Proposed method (f), which combines proposed methods (c) and (d), has the smallest mean error among the proposed methods. The method combining multitask learning and SE-net was more effective.

4.2 Learning after selecting APs

The APs selection was proposed in Section 3.2. When train and test data were measured in different environments, the mean error of the CNN was compared when APs were selected for each method and when all the APs were used.

In Situation 1, Fig. 3 shows the mean error when the measurement environment is open for the train data and close for the test data.

In Situation 2, Fig. 4 shows the mean error when the measurement environment is north for the train data and south for the test data.

The selection using the Euclidean distance has a lower mean error than when all APs are trained. This indicates that eliminating the APs that are sensitive to radio environments is effective.

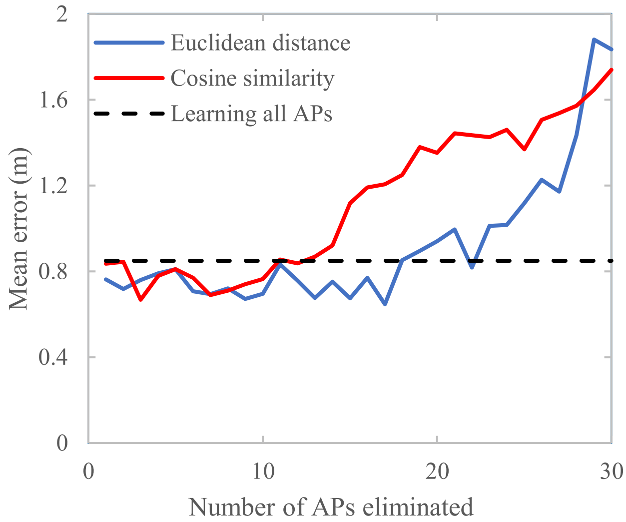

Fig. 3 Learning after selecting APs (train: open, test: close)

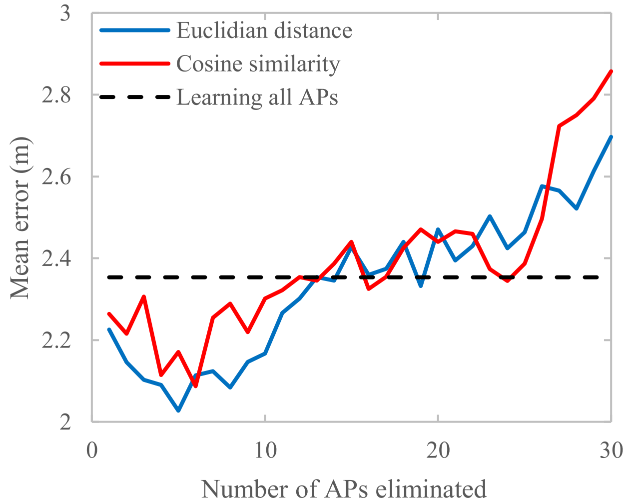

Fig. 4 Learning after selecting APs (train: north, test: south)

5. Conclusion

A problem in Fingerprint localization is that localization accuracy decreases when the radio environment changes between the DB and UD measurements. A method that uses DBs measured in multiple environments was proposed to solve this problem.

The first proposed method trains the DBs measured in multiple environments using various methods. The results show that the accuracy was maintained for data from various radio environments. Among the proposed methods, the method of learning multiple labels with SE-net was the most accurate.

The second method eliminates APs whose RSSI fluctuates significantly because of the changes in the radio environment from the train data. As a result, the accuracy was maintained when the radio environment of the DB and UD measurements were different.

Acknowledgments

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