International Journal of Innovative Computing, Information and Control
Volume **8**, Number **3(B)**, March **2012**
ICIC International ©2012 ISSN 1349-4198
pp. 2301–2312

LOCALIZATION OF WIRELESS LAN CLIENT IN MULTISTORY BUILDING BASED ON LAYERED NEURAL NETWORK

Tomohiro Umetani[1], Tomoya Yamashita[2] and Yuichi Tamura[1]

[1]Department of Intelligence and Informatics
[2]Graduate School of Natural Science
Konan University
8-9-1 Okamoto, Higashinada, Kobe, Hyogo 658-8501, Japan
{ umetani; tamura }@konan-u.ac.jp; mn024017@center.konan-u.ac.jp

Received March 2011; revised July 2011

Abstract. *This paper describes a method for localizing wireless mobile clients in multistory buildings using a public wireless LAN system. Data pertaining to the physical positions of personal electronic devices or mobile robots are important for information services and robotic applications. By integrating the data and stored information about objects and places, people and robots can be provided with information about device locations. This paper presents a localization method for a wireless LAN client in a multistory building with a wide open-ceiling area based on the fingerprinting method. The proposed method uses public wireless LAN access points that are installed throughout the building. The application of this method involves the assumption that the human or robot carrying the mobile client moves horizontally on each floor in the building. The method simultaneously estimates the position of the mobile client and its floor number. Experimental results show that the proposed method is feasible.*

Keywords: Localization, Wireless LAN, Multistory building, Neural network

1. **Introduction.** Data pertaining to the physical positions of personal electronic devices or mobile robots are important for information services and robotic applications. In this case, the personal electronic devices or mobile robots require the physical positions in the indoor environment such as most buildings and plants; they are generally large and multistoried. Data on the physical positions of mobile agents such as workers with personal electronic devices or mobile robots are important. For example, such information makes it possible to perform surveillance and maintenance tasks. By integrating the data and stored information about objects and places, people and robots can be provided with device location information [1].

Many types of localization services have been presented for personal devices and mobile robots [2, 3]. However, the localization method is generally costly and requires special devices. Therefore, a localization method that uses only a few devices is desirable for practical applications such as mobile robot navigation or information services for users with mobile phones.

This paper describes a method for localizing wireless mobile clients in a multistory building using a public wireless LAN system. This method uses the public wireless LAN access points installed throughout a multistory building. Figure 1 shows the scheme for the localization of people and robots carrying wireless LAN clients. The method assumes that the humans and robots with the mobile wireless LAN clients move only horizontally on any given floor of the building and that they do not change the height of the device while moving on a given floor.

Currently, the global positioning system (GPS) is used for the outdoor localization of a mobile client carried by a human or mobile robot [4, 5, 6]. However, it is difficult

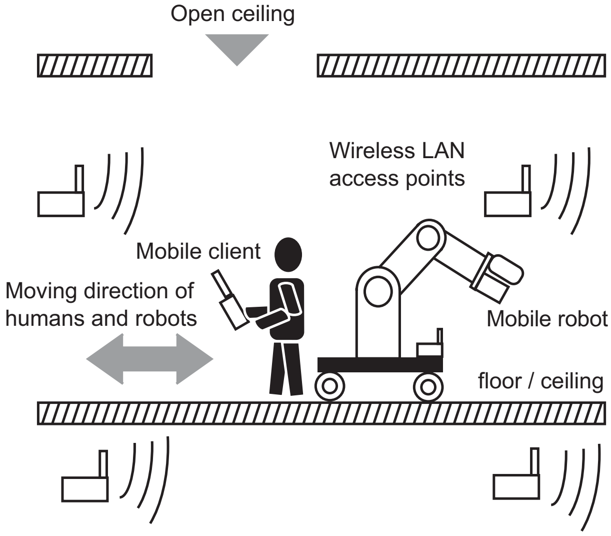

FIGURE 1. Localization of wireless LAN client in multistory building with open ceiling spaces. People and robots move only horizontally on each floor of the building.

to estimate the global position of the mobile client in a multistory building because the GPS is not suitable for indoor localization. In indoor localization systems, radio frequency identification (RFID) tags are commonly used [7]; these systems require that a person or a robot has an RFID reader. Mobile robots can estimate their own position and orientation using a dead-reckoning method and image recognition [8]. In indoor environments, it is difficult to uniquely estimate the global position and orientation of an object because of the symmetrical structure of buildings. In addition, the position-tracking method used for mobile robots is not suitable for the localization of personal devices because the device is moved by the person or robot carrying it.

We focus on the use of a wireless LAN for localization in indoor environments because this method does not require special devices for locating a personal mobile device. The proposed method simultaneously estimates the position of the mobile client and the floor number. Most studies have focused on the determination of the two-dimensional horizontal position of a mobile wireless client on a floor [9, 10]. Because many buildings and plants are multi-storied, the determination of the position and floor is important when performing indoor localization with a single localization system. The floor number should be estimated by the estimation system, without the need for another sensor such as an altitude meter.

In this paper, we illustrate the operation of a measurement system using a movable carriage to obtain the relation between the position in the building and strength of the received signals from the wireless LAN access points. An estimation system based on a layered neural network is built to evaluate the relation between the position in the building and signal strength. The position of the wireless LAN client is determined by the proposed estimation system using the strengths of the received signals from the wireless LAN access points obtained at various points in the building. Experimental results show that the proposed method is feasible.

2. **Localization of Wireless LAN Client in Multistory Building.** This section provides an overview of the method used for the localization of a wireless LAN client in a multistory building. Other studies related to the localization of wireless LAN clients are

also summarized. Then, the outline of the localization method for multistory buildings based on a neural network is explained.

2.1. **Related studies.** Numerous wireless indoor positioning techniques and systems have been proposed [11, 12]. Bahl and Padanabhan presented a localization method based on the nearest neighbor algorithm and a propagation model for the signals from wireless LAN access points [13]. They showed that the value of the received signal strength identifier (RSSI) is more useful than the signal-to-noise ratio. Each of their test data measurements was averaged from 20 samples. They showed the effect of the distances between the mobile client and wireless LAN access points.

Ladd et al. presented a localization method based on Bayes' rule [14]. Their probabilistic signal strength distribution was frequency-based. The state space of the estimated position was discrete, and the received training data signals at each position were averaged. To improve the localization accuracy, their estimation results were combined based on the hidden Markov model. Their experimental data showed the effectiveness of a tracking method based on the hidden Markov model.

M. N. Borenović and A. M. Nešković presented a localization method based on a neural network [15]. They proposed the space partitioning of the measurement area. Their method classified the subspace of a two-dimensional area based on a neural network; it then estimated the continuous position of the wireless LAN client in this subspace. They used one-shot measurements of the signal strength from the wireless LAN access points for the training data and test data.

2.2. **Localization of wireless LAN client based on neural network.** There are many wireless indoor positioning techniques and systems. The proposed method simultaneously estimates the position of the mobile client and the floor number using a probabilistic model. We use a neural network to localize the wireless LAN client because of the floor classification requirement and properties of the output values. The characteristics of the proposed method are described as follows:

- The estimation system classifies the floor number in a multistory building with wide open-ceiling spaces. In a building with open-ceiling spaces, no significant signal strength attenuation between floors is expected. The floor number should be estimated by the estimation system, with no need for other sensors such as an altitude meter. The floor number detection is related to the space partitioning of the measurement area [15]. Our method is different because we deal with floor number classification in a building that has wide open-ceiling spaces; the communication areas of wireless LAN access points are overlapped widely. The signal strength does not attenuate significantly between floors in a building with open-ceiling spaces.
- The output value for the wireless LAN client is the continuous position; it is suitable to use as the input value for the other application.
- For both the training and validation data, one-shot measurements are applied. For mobile client applications, it is better to keep the measurement time for the acquisition of the signal strength short.

In the following sections, we introduce the measurement system used for data collection. Then, the estimation model for the floor number and position of the wireless LAN client is explained. Finally, a localization experiment is explained to show the feasibility of the method.

3. **Data Collection.** This section provides an overview of the system used for determining the location of an object in a building and the strengths of the signals received from the wireless LAN access points in the building. First, our experimental testbed is

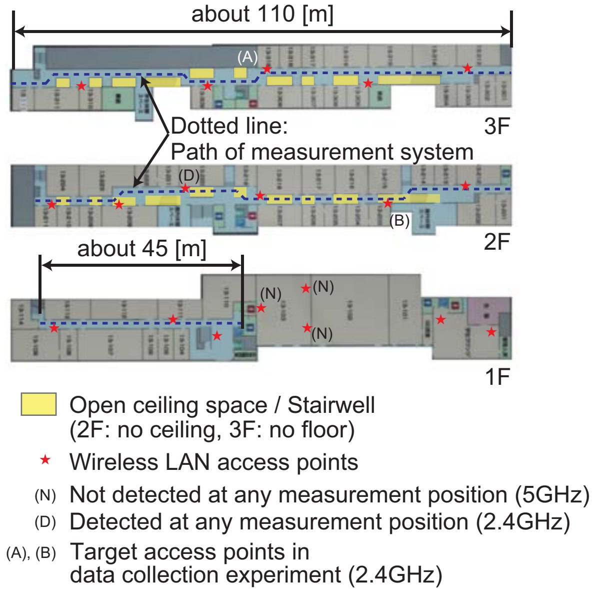

FIGURE 2. Experimental environment

described, and then the measurement system is explained. Finally, we explain the data collection method and discuss the impact of the floor number on the signal strengths from the wireless LAN access points.

3.1. **Experimental environment.** Our experimental testbed was Building #13 at Konan University. This building has three stories. Figure 2 shows the building layout. The dotted lines indicate the paths along which the wireless LAN client was carried. The corridor on each floor runs in the east-west direction. The corridors on the second and third floors are approximately 110 [m] long, whereas the corridor on the first (ground) floor is approximately 45 [m] long.

Public wireless LAN access points (Cisco Aironet 1210) are located in the corridors and large rooms of the building. There are a total of 19 access points: eight, six and five access points on the first, second and third floors, respectively. The wireless LAN access points utilize the following standards: IEEE 802.11a, 802.11b and 802.11g. We identified each public access point using the extended service set identifier (ESSID). We used the signal strengths received from these public wireless LAN access points.

We assumed that the wireless LAN client was moving along the length of the corridor on each floor, as the width of the corridor is considerably smaller than its length. The estimation parameters for localization were the floor number and the displacement of the wireless LAN client from the wall at the eastern edge of the building. It was difficult to detect the floor number based on the signal strengths from the wireless LAN access points because there are several open-ceiling spaces on the third floor of the building. Therefore, we considered the problem of setting up and building a measurement system to measure the trends in the strengths of the received signals.

3.2. **Measurement system.** We built a measurement system to record the signal strengths from the wireless LAN access points. Figure 3 shows the system configuration. The wireless LAN client was used to obtain the received signal strength indicator (RSSI) values for different places in the building. A roller encoder unit was used to determine the locations of points by dead reckoning. A microcontroller was used to count the encoder pulses to measure the distance from the initial point.

FIGURE 3. Measurement system

We used an ICOM SU-50W as the wireless LAN client and an Arduino microcontroller to measure the distance by counting the pulses from the encoder. The wireless LAN client supported the IEEE 802.11a, 802.11b and 802.11g standards. In addition, we used a rotary encoder, OMRON E6B2-CWZ6C (60P/R), to determine the instantaneous distance of the LAN client from the eastern edge of the building. This encoder was connected to a rubber tire with a diameter of 60 [mm]. The wireless LAN client, roller encoder, microcontroller, and PC were positioned on a mobile carriage. The notebook PC was placed on a cardboard box to prevent the signals received from the wireless LAN access points from being influenced by metal objects.

3.3. **Data collection.** We recorded the relations between the position of the wireless LAN client in the building and the signal strengths received from the wireless LAN access points using the assembled movable carriage.

The position of the wireless LAN client was estimated relative to the wall on the eastern side of the building. For the first measurement on each floor, the displacement from the wall was measured using a laser distance meter (Leica DISTO D3). The position of the wireless LAN client was considered to be the origin of the distance meter. After initializing the displacement, the position of the wireless LAN client was estimated using dead-reckoning.

The RSSI values obtained for the wireless LAN access points were obtained by scanning the basic service set identifiers (BSSIDs) for the positions of the points. Next, we prepared a list of wireless LAN access points, whose BSSIDs were stored in the wireless LAN client. At the same time, RSSI values were obtained for each wireless LAN access point. We chose the signal indicators received from the public wireless LAN access points from a set of obtained data based on the name of the ESSID. The RSSI values were converted into signal strengths [dBm]. We then ordered the measurement data according to the floor number, displacement of the moving carriage, and received signal strengths.

We moved the movable carriage by several tens of centimeters and recorded the received signal strengths. This procedure was repeated until the movable carriage reached the wall on the western side of the building, with data obtained for each floor.

At each measurement point, the measurement system detected 10 – 30 signals from the wireless LAN access points, with not all the access points detected in all parts of the building. A total of 35 signals were received from the access points in the data collection experiment. Only three signals were not detected in the data collection experiment. These

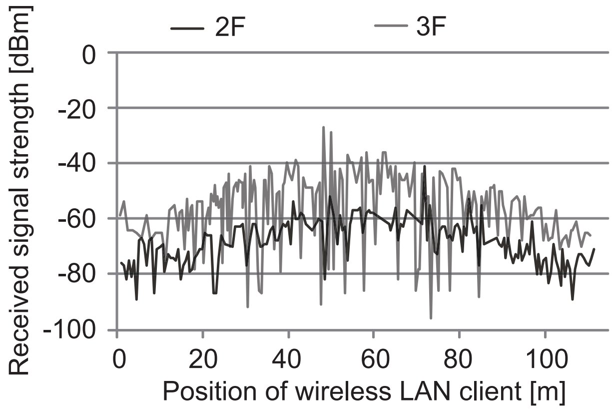

Figure 4. Signal strength [dBm] from access point (A) (see Figure 2) on each floor in building

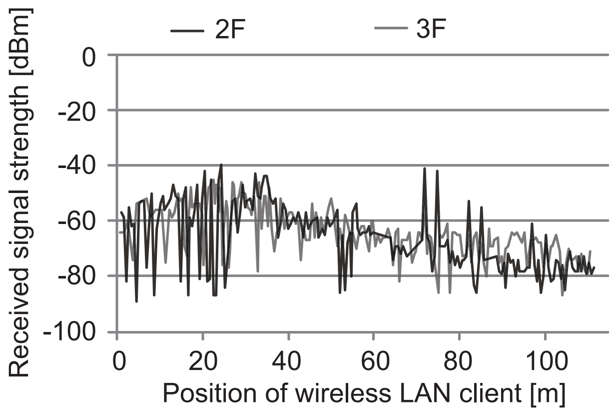

Figure 5. Signal strength [dBm] from access point (B) (see Figure 2) on each floor in building

were the signals from access points on the first floor. The signal from one access point on the second floor could be detected at any measurement point in the building. In the localization experiment, the input values for the received signals from the access points that were not detected were set to a specified value.

Figures 4 and 5 show that the relations between the received signal strengths for wireless access points (A) and (B), shown in Figure 2, on different floors but at the same location. The horizontal axis indicates the displacement of the wireless LAN client from the eastern wall, whereas the vertical axis indicates the received signal strength. We can see that the received signal strengths from several wireless LAN access points are different for each floor. Some of the received signal strengths for a particular floor from particular wireless LAN access points were attenuated by the floors and ceilings in the building. The accuracy of the localization estimation could be improved by taking this attenuation into account.

On the other hand, as seen in Figure 5, the strengths of several signals were the same on the second and third floors because of the open-ceiling space of the building. In this case, the distance between the access point (B) and the same location on different floor is the same. Access point (B) is located on the open-ceiling area. The signals were not significantly attenuated.

The variance in the received signal strength for a specific position was large because of the multipath interference of the received signal. In addition, the received signal strength

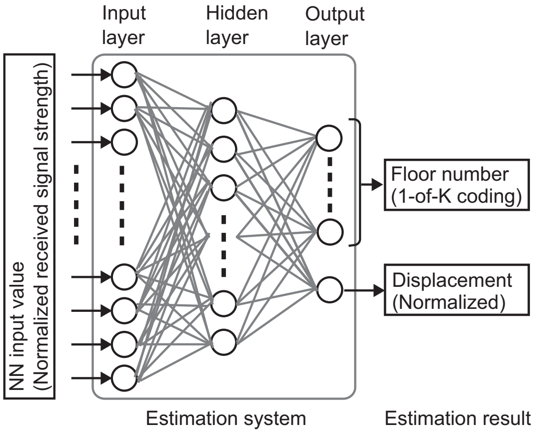

FIGURE 6. Structure of estimation system based on neural network

had strong nonlinearity. We used a layered neural network to estimate the position and floor number of the wireless LAN client.

4. **Estimation of Position and Floor Number Using Neural Network.** This section describes the construction of the neural-network-based estimation system. Figure 6 shows the construction of a position estimation system based on supervised learning. To estimate the position and floor number of the mobile client, we used a layered neural network, which is described as follows:

$$y_k = \phi\left(\sum_{j=0}^{M} w_{kj}^{(2)} \sigma\left(\sum_{i=0}^{D} w_{ji}^{(1)} x_i\right)\right) \quad (k = 1, \ldots, N) \tag{1}$$

$$y_{N+1} = \sum_{j=0}^{M} w_{N+1,j}^{(2)} \sigma\left(\sum_{i=0}^{D} w_{ji}^{(1)} x_i\right) \tag{2}$$

where y_k is an element of output vector $\boldsymbol{y}$, that is, the floor number is expressed by a 1-of-K coding scheme and the position on the floor is estimated by the system; x_i is an element of input vector $\boldsymbol{x}$, the signal strength; and $w_{kj}^{(2)}$ and $w_{ji}^{(1)}$ are the weight parameters of the neural network. N is the number of floors in the building. M is the dimension of the hidden layer of the neural network, and D is the number of wireless LAN access points used for the location experiment. $\sigma(a)$ is a logistic sigmoid function

$$\sigma(a) = \frac{1}{1 + \exp(-a)}, \tag{3}$$

and $\phi(a_k)$ is a softmax transformation

$$\phi(a_k) = \frac{\exp(a_k)}{\sum_j \exp(a_j)}. \tag{4}$$

Note that x_0 and $\sigma\left(\sum_{i=0}^{D} w_{0i}^{(i)} x_i\right)$ are the bias parameters, which are both set to 1. In addition, note that each element of input vector $\boldsymbol{x}$ and output vector $\boldsymbol{y}$ is normalized to the interval [0, 1].

We used an error back-propagation method to tune the parameters of the position estimation system [16].

5. **Localization Experiment.** This section describes a localization experiment conducted in Building #13 at Konan University. First, we introduce the experimental setting used for the estimation of the position and floor number of the wireless LAN client. Next, the experimental results are discussed. Finally, the estimation accuracy of the proposed system is discussed.

5.1. **Experimental setting.** We constructed the layered neural network described in the previous section to estimate the displacement and floor number of the wireless LAN client. The number of received signals, or parameter D, was 35 out of a total of 38 BSSIDs. The dimension of input vector, $\boldsymbol{x}$, was 35. The dimension of output vector, $\boldsymbol{y}$, and the training data set vector, $\boldsymbol{t}$, was 4. The dimension of hidden layer vector M was set to 10, 15, 20 and 25. We set the tuning parameter for the back-propagation method, $\epsilon = 0.1$. The initial values of the weight parameters of the network, $w_{kj}^{(2)}$ and $w_{ji}^{(i)}$, were set at random with a uniform distribution; the range off the initial values of the weight parameters had the interval $[-0.3,\ 0.3]$. The iterations for network training were experimentally set at 30,000.

Input vector $\boldsymbol{x}$ was set as follows. Subscript K is the identifier number of the wireless LAN access point identified by the BSSID. The strength of received signal r_k is restricted, $-100 \leq r_k \leq 0$ [dBm], and we suppose that an element of the input vector, x_k, is given by

$$x_k = -\frac{r_k}{100}. \tag{5}$$

If the wireless LAN client does not obtain the signal strength for wireless LAN access point k at the position, we set $x_k = 1.0$.

We set training vector $\boldsymbol{t} = [t_1\ t_2\ t_3\ t_4]^T$ as follows: t_1, t_2 and t_3 indicate the floor number as expressed by the 1-of-K coding scheme; for example, in a case where the measurement point is the second floor, $[t_1\ t_2\ t_3]^T = [0\ 1\ 0]^T$. t_4 indicates the displacement of the moving carriage, d_M, and we set $t_4 = d_M/120$.

We set output vector $\boldsymbol{y} = [y_1\ y_2\ y_3\ y_4]^T$ as follows: y_1, y_2 and y_3 indicate the floor number as expressed by the 1-of-K coding scheme. y_4 indicates the displacement of the moving carriage, d_E, and we set $d_E = 120y_4$.

The number of data points in the training data set was 600 (1F: 200, 2F: 200 and 3F: 200), and the number of data points in the validation data set was 450 (1F: 150, 2F: 150 and 3F: 150).

5.2. **Experimental results.** Figure 7 shows the relation between the estimated position and the real position of the wireless LAN client where $M = 20$. The horizontal axis indicates the number of collected data points, and the vertical axis indicates the displacement of the wireless LAN client. The thick line indicates the estimation result, and the gray line indicates the measured displacement. The obtained data from #1 to #150 correspond to the first floor and those from #151 to #300 correspond to the second floor. The data from #301 correspond to the third floor.

Table 1 shows the classification of the estimated distance on the basis of the error between the estimated and measured values, where $M = 20$. In addition, Figure 8 shows the cumulative rate for the estimation error of the position of the wireless LAN client. The horizontal axis shows the error distance, while the vertical axis shows the cumulative rate. The average estimation error is 8.27 [m], and the root mean square (RMS) error for the estimation result is 11.70 [m].

From Table 1, it is observed that the number of estimated values with an estimation error smaller than 5 [m] is 210 out of a total of 450 values. The number of estimated

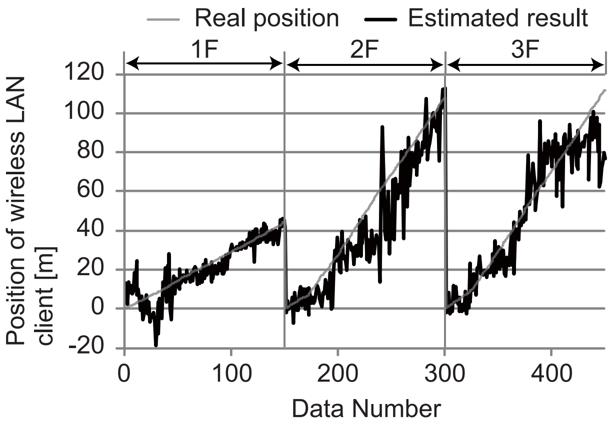

Figure 7. Estimation result for position of wireless LAN client ($M = 20$)

Table 1. Estimation error ($M = 20$)

Error range	Estimated data points	Cumulative frequency
Less than 3 [m]	129	129
3 – 5 [m]	81	210
5 – 10 [m]	90	320
10 – 20 [m]	92	412
Over 20 [m]	38	450

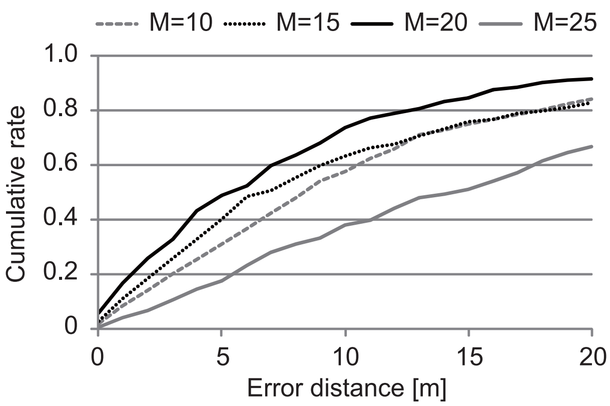

Figure 8. Cumulative rate for error distance of estimation result

Table 2. Uncertainty in estimation result; average error and root mean square for each floor ($M = 20$)

	Average error [m]	Median error [m]	Root mean square (RMS) error [m]
1st floor	5.14	3.81	7.03
2nd floor	10.65	7.63	14.13
3rd floor	9.04	6.86	12.72
Total	8.28	5.83	11.70

values with an estimation error smaller than 10 [m] is 320. Table 2 shows the estimation error, median error, and root mean square (RMS) for each floor, where $M = 20$.

TABLE 3. Relation between floor number determined by measurement and estimation floor number ($M = 20$)

		Estimated floor number		
		1	2	3
Floor number (measured)	1	150	0	0
	2	0	150	0
	3	0	1	149

Table 3 shows the relation between the floor number determined by measurement and the estimated floor number. The rows represent the floor numbers determined from floor measurements, while the columns denote the estimated floor numbers. The diagonal values in the table are the number of times that the estimation system correctly identified the floor number. From Table 3, the number of correct results for floor number identification was 449 out of 450 samples. The ratio of correct results was 99.8 [%]. The correct result ratios for the individual floors were 100 [%], 100 [%] and 99.3 [%], respectively, where $M = 20$. The correct result ratios were 99.1 [%], 99.1 [%] and 98.4 [%], where $M = 10$, 15 and 25, respectively.

5.3. **Discussion.** We have shown the feasibility of using our method based on the received signal strengths from wireless LAN access points for localization and floor identification in a multistory building. From Figures 7 and 8, the estimated positions of the wireless LAN client are related to the measured positions. When the wireless LAN client failed to capture the received signal strength at a position, the localization result had a large estimation error.

From Table 2, the estimation error for the first floor was smaller than that for the other floors. The density of the training data for the first floor was higher than that on the other floors. In addition, the signal strengths from the wireless LAN access points on the other floors were strongly attenuated by the floors and ceilings. From these results, an increase in the sample data for the other floors is needed to improve the localization accuracy.

Table 3 shows that the system identified the floor number correctly using the data captured on each floor of the building. The estimation results show that the estimation system can successfully classify the floor based on the signal strengths from the wireless LAN access points in a building with open-ceiling spaces.

Based on the experimental results, several issues need to be addressed to improve the estimation results:

- The data collection method should be improved. The estimation system requires a much larger quantity of training data consisting of received signal strengths from the wireless LAN access points corresponding to very accurate position data for the wireless LAN client. Future work will include the simultaneous applications of localization and mapping methods by a mobile robot using other sensors [17].
- An evaluation of the received signal strength obtained in the estimation phase is needed. In the proposed algorithm, the estimation error is large in a case where the wireless LAN client fails to obtain the received signal strength at the estimation position.
- The localization of other types of mobile LAN clients such as smart phones is needed. In this study, the same wireless LAN client was used for the data collection and estimation phases of the experiment.

- For sensor-data fusion with other output data and other sensor data, probabilistic models, such as particle filter and linear dynamics models, are widely used; for the sensor-data fusion, not only the position of the client but also the variance of its estimated position is needed. The estimated variance of the client position can be obtained based on the framework of a Bayesian neural network [16]. The parameter tuning method for the estimation system should be improved. An extension of the estimation system for estimating the variance will be discussed.

6. **Conclusions.** This paper proposed a method for localizing wireless mobile clients in multistory buildings; this method involves the use of a public wireless LAN system. A prototype of the data collection system employing a wireless LAN client and a movable carriage with a roller encoder unit was developed.

We showed the feasibility of the proposed method using a localization experiment. From the experimental results, the method was able to estimate the floor number in a multistory building with large open-ceiling spaces in the corridor. On the other hand, the mobile LAN client sometimes failed to obtain the signals from the wireless LAN access points. This data collection failure caused estimation error in the placement and floor number in the building.

A discussion of the experimental results showed the directions for future work. In the data collection phase of the study, an improvement is needed in the data collection of received signal strengths from the wireless LAN access points, corresponding to position data with good accuracy. An evaluation of the obtained received signal strengths used for estimation and the use of a probabilistic localization method are expected to reduce the estimation error. The localization of other types of mobile LAN clients is needed to evaluate the effectiveness of the proposed system. We will develop more accurate and robust methods for indoor localization system using a wireless LAN.

Acknowledgment. This work was supported in part by the Hirao Taro Foundation of the Konan University Association for Academic Research, Japan. We are most grateful to the Education and Research Center for Information Science, Konan University, for the information supplement for localization experiments.

REFERENCES

[1] J. H. Lee and H. Hashimoto, Intelligent space – Concept and contents, *Advanced Robotics*, vol.16, no.3, pp.265-280, 2002.

[2] J. Hightower and G. Borriello, Location systems for ubiquitous computing, *IEEE Computer*, vol.34, no.8, pp.57-66, 2001.

[3] T. Manesis and N. Avouris, Survey of position location techniques in mobile systems, *Proc. of the 7th International Conference on Human Computer Interaction with Mobile Devices & Services*, Sulzurg, Austria, pp.291-294, 2005.

[4] P. Enge and P. Misra, Special issue on GPS: The global positioning system, *Proc. of IEEE*, vol.87, no.1, pp.3-15, 1999.

[5] T. Aoki and S. Sugimoto, Dynamical models for automobile movements, *International Journal of Innovative Computing, Information and Control*, vol.6, no.1, pp.3-14, 2010.

[6] M. Tanikawara, Y. Kubo and S. Sugimoto, Modeling of sensor error equation for GPS/INS hybrid systems, *International Journal of Innovative Computing, Information and Control*, vol.6, no.1, pp.127-138, 2010.

[7] D. Joho, C. Plagemann and W. Burgard, Modeling RFID signal strength and tag detection for localization and mapping, *Proc. of 2009 IEEE International Conference on Robotics and Automation*, Kobe, Japan, pp.3160-3165, 2009.

[8] A. Georgiev and P. K. Allen, Localization methods for a mobile robot in urban environments, *IEEE Trans. on Robotics*, vol.20, no.5, pp.851-864, 2004.

[9] J. Rekimoto, T. Miyaki and T. Ishizawa, LifeTag: WiFi-based continuous location logging for life pattern analysis, *Proc. of the 3rd International Symposium on Location- and Context-Awareness (LoCA2007)*, Oberpfaffenhofen, Germany, pp.35-49, 2007.
[10] S. Ito and N. Kawaguchi, Bayesian based location estimation system using wireless LAN, *Proc. of the 3rd International Conference on Pervasive Computing and Communication Workshop (PerCom 2005 Workshops)*, Kauai Island, HI, USA, pp.273-278, 2005.
[11] H. Liu, H. Darabi, P. Banerjee and J. Liu, A survey of wireless indoor positioning techniques and systems, *IEEE Trans. on Systems, Man, and Cybernetics – Part C: Applications and Reviews*, vol.37, no.6, pp.1067-1080, 2007.
[12] C. G. Lim, X. F. Xu, E. K. Kim and Y. M. Kim, A technique of approximate estimation for localization in wireless sensor networks, *ICIC Express Letters, Part B: Applications*, vol.2, no.2, pp.351-356, 2011.
[13] P. Bahl and V. N. Padmanabhan, RADAR: An in-building RF-based user location and tracking system, *Proc. of IEEE Infocom 2000*, Tel-Aviv, Israel, vol.2, pp.775-784, 2000.
[14] A. M. Ladd, K. E. Bekris, A. P. Rudys, D. S. Wallach and L. E. Kavraki, On the feasibility of using wireless ethernet for indoor localization, *IEEE Trans. on Robotics and Automation*, vol.20, no.3, pp.555-559, 2004.
[15] M. N. Borenović and A. M. Nešković, Positioning in WLAN environment by use of artificial neural networks and space partitioning, *Annals of Telecommunications*, vol.64, no.9-10, pp.665-676, 2009.
[16] C. M. Bishop, *Pattern Recognition and Machine Learning*, Springer, New York, 2006.
[17] S. Thrun, W. Burgard and D. Fox, *Probabilistic Robotics*, MIT Press, Cambridge, Massachusetts, 2006.