Evaluation of Area Detection Method Using Machine Learning

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Abstract: In recent years, mobile LBSs are gradually achieving mainstream market acceptance along with increasing usage of smartphone applications. One of the most popular LBSs is check-in services. GPS is the most popular method of area detection for outdoor environment to implement this check-in service. Although many kinds of area detection methods for indoor environment have been proposed, these methods have the problem that the new infrastructure for area detection needs to be installed. In order to solve this problem, an area detection method using a machine learning algorithm through Wi-Fi has been proposed. In this paper, to clarify the most suitable machine learning algorithm for area detection, three methods are evaluated. Specifically, area detection performance and hardware requirements are compared using the nearest neighbor, pattern recognition and histogram method. The result of the evaluation shows that the histogram method of area detection performance is high and hardware requirement is low. Therefore, it was found that the histogram method is the most suitable for area detection.

1. Introduction

In recent years, mobile LBSs (Location-Based Services) are gradually gaining mainstream market acceptance along with the increased use of smartphone applications[1]. There are many types of LBS. Specifically, they are: navigation and mapping services, local search and information services, social networking and entertainment services, recreation and fitness services, and tracking services.

The most popular LBSs are check-in services[2] like Forsquare[3], MyTown[3], Facebook Places[3], Loopt[3] and Gowalla[3]. A check-in service is one in which a user enters a predefined area and the system recognizes that the user has checked in and provides information to the user for every area. Check-in services are required to detect the area where the user is. GPS (Global Positioning System) is the most popular method of area detection for outdoor environment (i.e. GeoFence[4]). Many kinds of area detection methods for indoor environment are proposed using Wi-Fi (Wireless Fidelity)[5], ultrasound[5], infrared[5] and IMES (Indoor Messaging System)[6]. But these methods have the problem that a new infrastructure must be installed for area detection.

In order to solve this problem, area detection methods using existing Wi-Fi AP (Access Point) have been developed[7]. The Wi-Fi technique is the popular; Wi-Fi APs are used all over the world. However, there is the problem that the accuracy of area detection is degraded for multi-path in Wi-Fi area detection method.

An area detection method using a machine learning algorithm has been developed that uses as an advantage characteristics of the area of complex radio propagation environment due to multi-path[8][9]. Collecting RSSI (radio signal strength indicator) samples at every area as learning samples clarifies characteristics of the radio environment at every area like Figure 1. When the characteristics of an observation sample are similar to the characteristics of learning samples at the area, the system recognizes that the user is in the area. Using the method, an area can be detected using the radio environment without having to be customized, and without being affected by multi-path phenomenon.

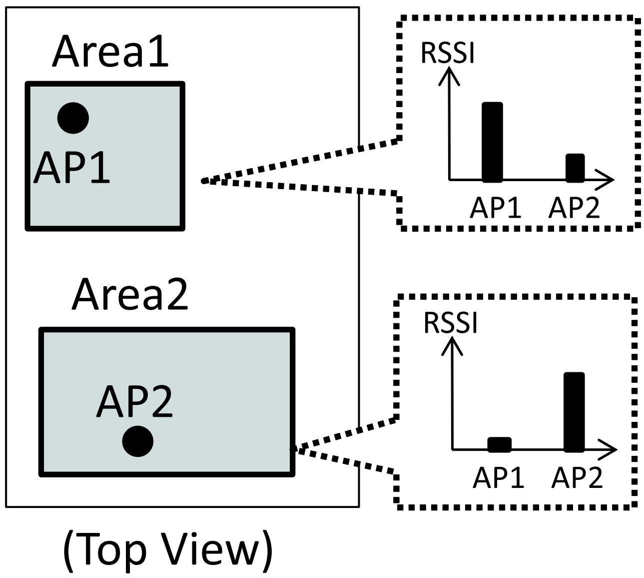

Fig. 1 Characteristics of RSSI at the Areas

To detect the area correctly, it is necessary to run the high-performance area detection method like the pattern recognition method. However, the detection engine like the pattern recognition method might be too powerful for area detec-

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tion using RSSI. Furthermore, the area detection method using a machine learning algorithm runs on the mobile terminal, so hardware requirements like processing time and memory usage are important. From the above, in this paper, three types of engines have been selected. They are: nearest neighbor method because it is a lightweight and low-performance engine; histogram method because it is a middleweight and middle-performance engine; and a pattern recognition method because it is a heavyweight and high-performance engine. These engines were evaluated for their area detection performance, for their hardware requirements. The performance characteristics of each engine have been clarified. By the result of the evaluation, optimal use of each engine has been clarified.

2. Area Detection Method with Machine Learning

There are three types of machine learning algorithm. They are: supervised learning, semi-supervised learning, and unsupervised learning. The discussion of area detection method is limited to supervised learning in this paper. Learning sample for area detection consists of BSSID (Basic Service Set Identification), RSSI and area name. To get the learning sample, a measurer walks around each area with a mobile terminal installed with the Wi-Fi RSSI measuring application. The mobile terminal records the RSSI, BSSID and the name of walked area. Machine learning is implemented using the area name as a correct label, RSSI and BSSID data as learning sample. By comparing the learning sample and observation sample which is RSSI and BSSID data, the area where the user is located was detected.

In this chapter, three types of area detection methods with machine learning are described in detail below.

2.1 Nearest Neighbor Method

Nearest Neighbor Method [9] is based on measuring the Euclid distance between the observation and learning sample. The learning sample which is the smallest distance between the observation sample was searched. The area name where the searched learning sample was obtained indicates the location of user. Figure 2 shows the example of area detection using the Nearest Neighbor method. In this example, it is assumed that the access points AP1 and AP2 are clearly observed in Aera1 and Area2. Figure 2 shows the distribution of the learning sample plotted on a graph. The Sample S in Figure 2 shows the observation sample which is scanned RSSI data in order to detect the area where user is located.

The processing of area detection with nearest neighbor method is described below. Initially, the learning sample of the smallest Euclid distance was extracted between the observation sample S.

For Figure 2, the learning sample which is the closest to the observation sample S is S1. The learning sample S1 was corrected at Area1, so that the location of the user is determined the Area1.

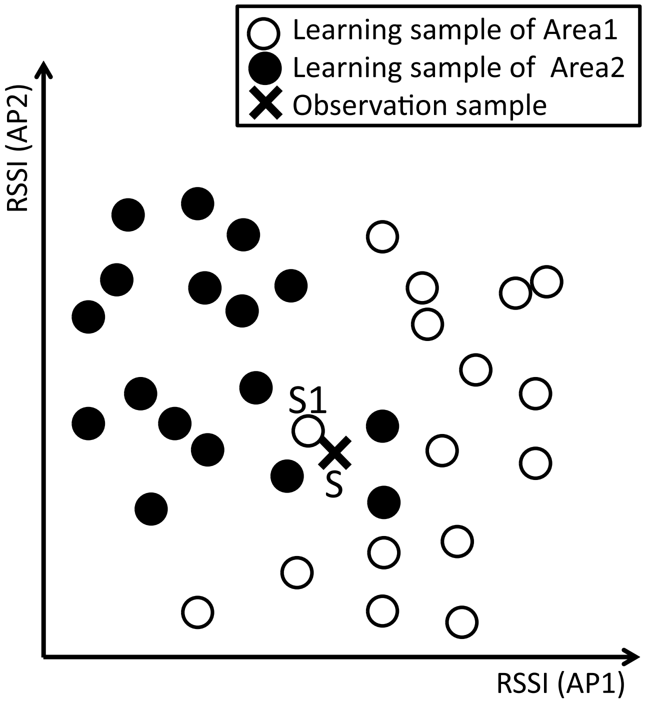

Fig. 2 Example of Area Detection Using Nearest Neighbor Method

The Proximity location technique using Wi-Fi (i.e. Wireless Andrew [5]) is one of the nearest neighbor method. The sending beacon unit with the highest RSSI is searched, so that the location of the mobile terminal determined that mobile terminal is near to the sending beacon unit. The leaning samples defined the maximum values of each axis. For Figure 2, the learning sample which is the closest to the observation sample S is the sample of axis AP1. The access point of AP1 is located at Area1, so the RSSI of AP1 is the highest, and therefore the location of the user is determined as the Area 1.It is deduced that the nearest neighbor method is a light algorithm because it is not necessary to calculate complex expressions. Particularly, the proximity location method is a lighter algorithm. This is because that the amount of calculations does not depend on the number of learning sample, or the number of areas.

2.2 Pattern Recognition Method

The pattern recognition method is based on the calculating of boundaries between the clusters of scanned learning samples of each area. The feature vector is defined that the vector of feature quantity is RSSI of each area. The RSSI sample scanned at each area is plotted in the feature vector space. A similar RSSI sample is scanned at the same area, so the cluster of the scanned RSSI sample is created at each area in the feature vector space. The pattern recognition method using feature vector space like support vector machine (SVM) [10] calculates the boundaries between the clusters for each area and judges whether the observed RSSI sample is the right or left side of the boundary.

Figure 3 shows an example of area detection using the pattern recognition method. The situation of Figure 3 is

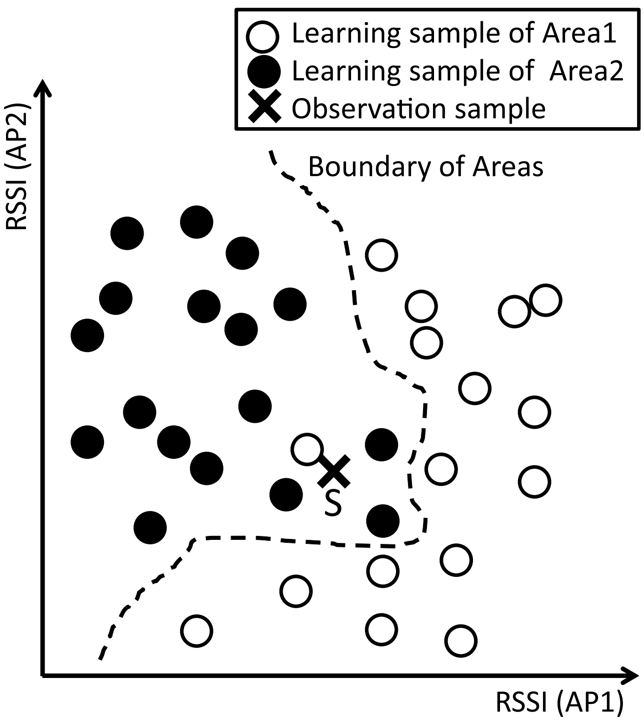

Fig. 3 Example of Area Detection Using Pattern Recognition Method

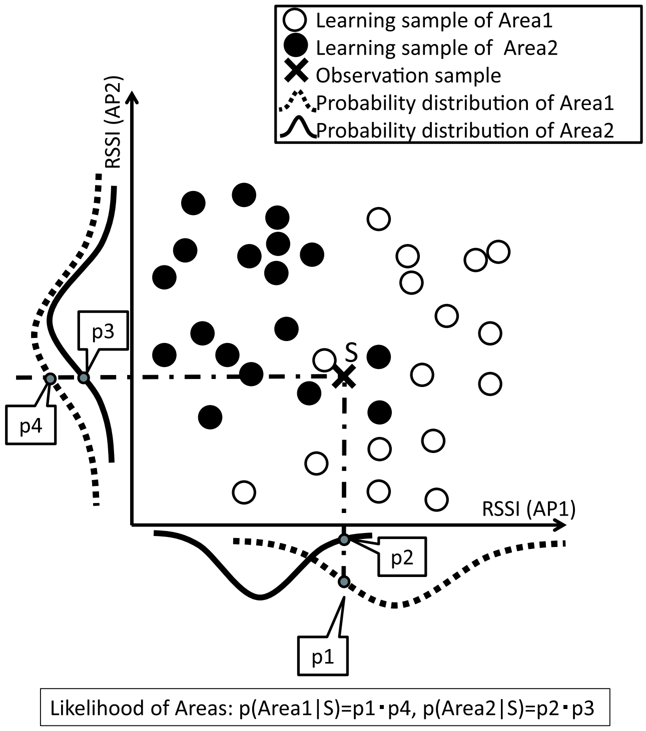

Fig. 4 Example of Area Detection Using Parametric Histogram Method

the same as Figure 2. The RSSI samples corrected at Area 1 and Area 2 are plotted in the feature vector space. SVM is saved as the area model to determine the parameters that defines the boundaries indicated by the dotted line in Figure 3. Since the observation sample S is the left side of the boundary, it is determined that the user is at Area 1.

It is deduced that the pattern recognition method is a heavy algorithm because it requires calculation of complex expressions. Another reason is that the processing times increase exponentially as the number of areas increases because SVM uses a combination search algorithm for area detection.

2.3 Histogram Method

The histogram method [8] is based on calculating a likelihood of a user existing in an area from probability distribution of the RSSI frequency histogram. The RSSI frequency histogram created by the learning data is converted to the probability distribution of RSSI. When the observation sample of RSSI is scanned, the likelihood of the area is calculated with the probability distribution that was previously created. The histogram method is classified into two methods, specifically, the parametric method [8] and the non-parametric method [11].

The parametric method is based on the idea that the distribution of RSSI is assumed to be Gaussian distribution. The learning samples of RSSI corrected at each area is applied to a Gaussian distribution. The parameter of the RSSI distribution which is the mean and covariance is calculated at each area to estimate the RSSI probability Gaussian distribution. The likelihood of the area is calculated using observation samples of RSSI and RSSI probability Gaussian distribution.

Figure 4 shows an example of area detection using parametric method. The situation of Figure 4 is same as Figure 2. Firstly, the covariance and mean of learning sample corrected at Area 1 and Area 2 are calculated and the RSSI probability Gaussian distribution is estimated using the covariance and mean of learning sample. Thereafter, the likelihoods of Area 1 and Area 2 are calculated using observation sample S and RSSI probability Gaussian distribution of Area 1 and Area 2. Finally, the area of the highest likelihood is selected in the candidate location. In the example of Figure 4, the area of highest likelihood is Area 2, so the user is determined to be in Area 2.

However, the parametric method is not suitable for area detection using RSSI because the value of RSSI is constantly changing by being affected by interference to radio wave propagation and the way the mobile terminal is held. Therefore, the RSSI distribution is not represented by Gaussian distribution.

The non-parametric method is based on the idea that distribution of RSSI is not assumed to be Gaussian distribution. Figure 5 shows an example of area detection using non-parametric method. The situation of Figure 5 is the same as that depicted in Figure 2. The learning sample of RSSI is plotted on a graph and the RSSI observation frequency histogram is described along the coordinate axis. At the learning phase, the histogram is created and saved as RSSI model of areas. At the area detection phase, the likelihood of each area is calculated with the observed samples and the histogram. For Figure 5, when the sample S is observed, the likelihood of Area 1 and Area 2 is calculated as shown below. The likelihood of Area 1 is multiplied by the

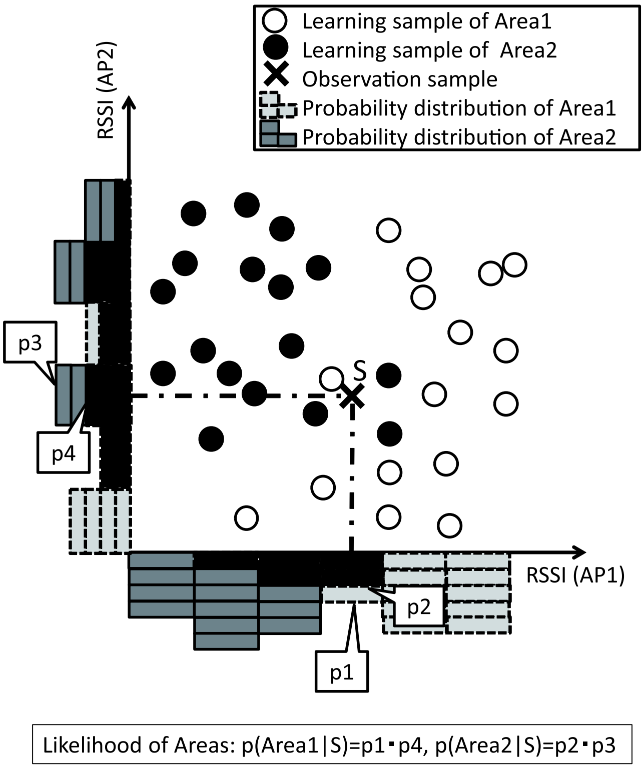

Fig. 5 Example of Area Detection Using Non-parametric Histogram Method

probability calculated with the histogram of AP1 and AP2. In the same way, the likelihood of Area 2 is calculated. The likelihood of Area 1 is higher than Area 2, so the location of the user is determined to be Area 1.

In this paper, a non-parametric method is evaluated as the histogram method because it is predicted that the non-parametric method is more suitable for area detection than parametric method. It is deduced that the histogram method is a middleweight algorithm. The likelihoods of each area are calculated with simple expressions. Therefore, the calculation amount of the histogram method is greater than the nearest neighbor method (proximity) and smaller than the pattern recognition method.

3. Evaluation of Area Detection Method

3.1 Situation of Evaluation

In this chapter, the area detection performance of area detection methods is evaluated using a proximity algorithm as nearest neighbor method, SVM as the pattern recognition method, and non-parametric algorithm as the histogram method. The area detection performance is defined as area detection performance and hardware requirement.

The hardware requirement of area detection method is one of the important elements of mobile LBS. To implement the mobile LBS, an area detection method is processed on mobile terminal. If the area detection method requires a high-performance mobile terminal, power consumption increases. For that reason, the area detection method which is suitable for mobile LBS requires that the hardware requirement is low-level (a light algorithm) and area detection performance is high.

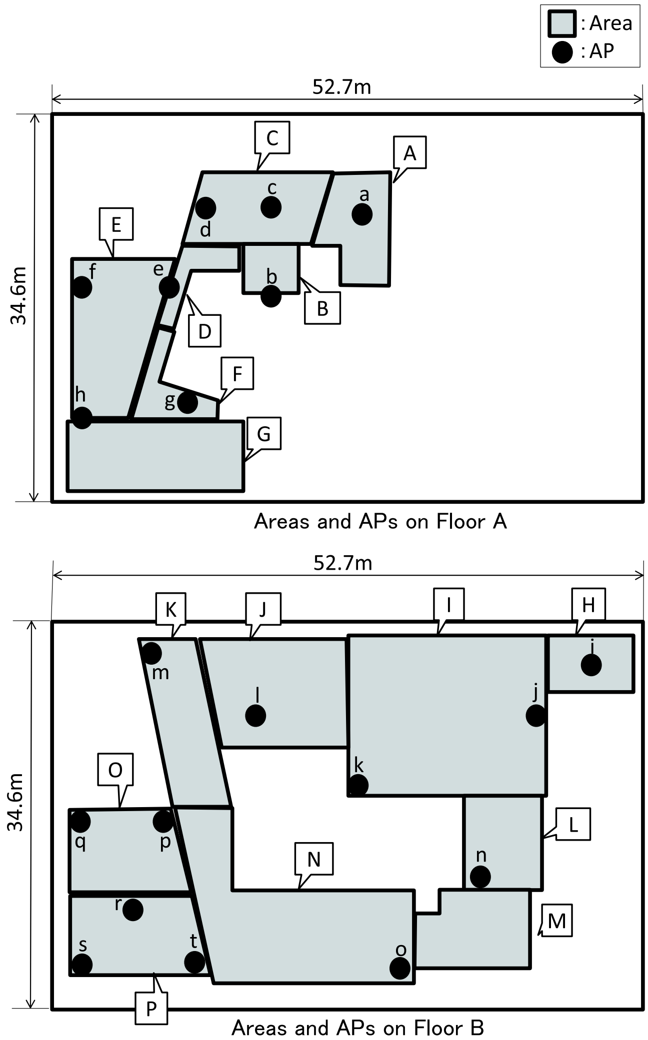

Fig. 6 Evolutional Parameter of Areas and APs

The area detection performance is evaluated using an area detection accuracy rate. The successful sample number of area detections divided by the entire number of samples is the area detection accuracy rate. The hardware requirement is evaluated using the processing time and memory usage. The parameters for evaluation were the number of areas, the number of APs, and the number of learning samples.

Figure 6 shows the environmental parameter of areas and APs. The total number of area is 16, and AP is 20. The parameter of the area and AP are selected at random. The parameter of the learning sample is selected for the specific rate in time series. In this evaluation, the number of learning sample is about 20,000 and the number of observation samples is about 4,000. The leaning samples are obtained at every position and direction in each area. For the evaluation, offline software is developed. Also, the parameter of non-parametric algorithm is set as: number of bins: 12; bin width: 5dB; and RSSI range: -100 to 40dB.

3.2 Evaluation of Area Detection Performance

In this section, the area detection performance (accuracy of area detection) affected by the number of areas, AP, and learning samples is compared to the three area detection

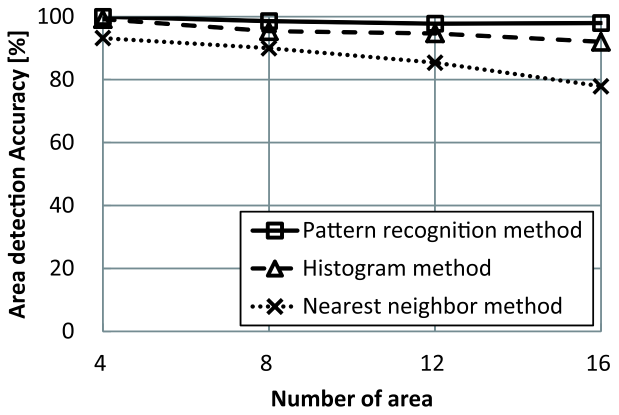

Fig. 7 The Area Detection Accuracy Affected by the Number of Areas

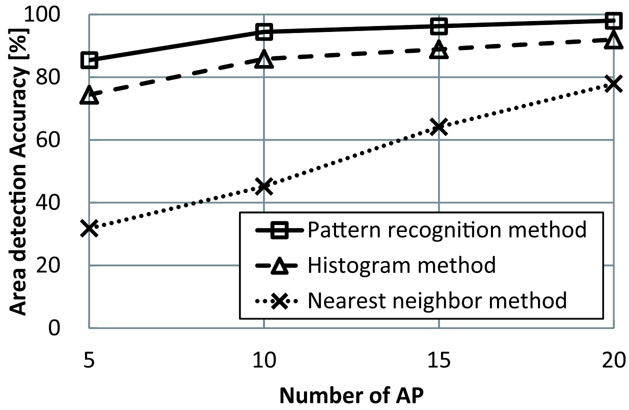

Fig. 8 The Area Detection Accuracy Affected by the Number of APs

methods.

It is predicted that area detection accuracy decreases as the number of areas increases. The reason is that the number of candidate areas whose RSSI characteristics is similar to the correct detection area increases according to the increased number of areas. . Figure 7 shows the evaluation results for area detection accuracy affected by the number of areas. In this evaluation, the number of AP was 20 and the number of learning samples was full. The area detection accuracy of pattern recognition method was 98%, the histogram method was 92%, and the nearest neighbor method was 79% while the number of areas was 16. The area detection accuracy of the three methods decreased according to the increased number of areas, as was expected. While the area detection accuracy of nearest neighbor method gradually decreases according to the number of areas, the area detection accuracy of the pattern recognition and the histogram method decreases little. Furthermore, area detection accuracy of the pattern recognition method is the highest of the three methods regardless of the number of areas. The result of the evaluation provides that area detection of the pattern recognition and the histogram method has high-performance; especially the area detection of pattern recognition method is the highest of the three.

It is predicted that the area detection accuracy increases

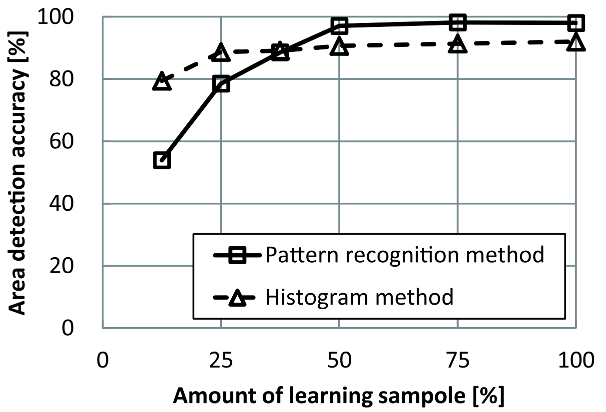

Fig. 9 The Area Detection Accuracy Affected by the Amount of Learning Samples

by the increased number of areas. This is because of the probability of using the AP that can receive the RSSI sample characterizing the area increase. Figure 8 shows the evaluation results for the area detection accuracy affected by the number of APs. In this evaluation, the number of areas was 16 and the number of learning samples was full. The area detection accuracy of the three methods increased according to the increased number of APs as was expected. While the area detection accuracy of the nearest neighbor method gradually decreased by decreasing the number of APs, area detection accuracy of the pattern recognition and the histogram method decreased little. Furthermore, area detection accuracy of the pattern recognition method is the highest of the three methods regardless of the number of areas. The result of the evaluation provides that the area detection of the pattern recognition and the histogram method is high-performance. Particularly, the area detection of the pattern recognition method is the highest of the three.

Considering the installation of the system for applying the LBS, the required number of leaning samples is one of the most important elements. To install the system for LBS, it is necessary to walk around in each area with the mobile terminal to correct the required amount of leaning samples. If the required amount of leaning sample is small, it is easy to install the system for applying the LBS.

The amount of leaning sample is defined by the time of walking around in the area to correct RSSI learning samples divided by the time of scanning RSSI samples at every position and direction in the area. The time of scanning sample at every area and direction in the area is expressed as:

$$t = 0.103 \times S \times s \times n \quad (1)$$

where t is the minutes of scanning at every position and direction in the area; s is the sampling rate of mobile terminal; S is the square measure of area; n is the number of mobile terminals to correct the RSSI samples at the same time;, and the value 0.103 is the parameter determined from experiments.

It is predicted that area detection accuracy will increase by the larger amount of learning samples. This is because the large amount of learning sample enables the characteris-

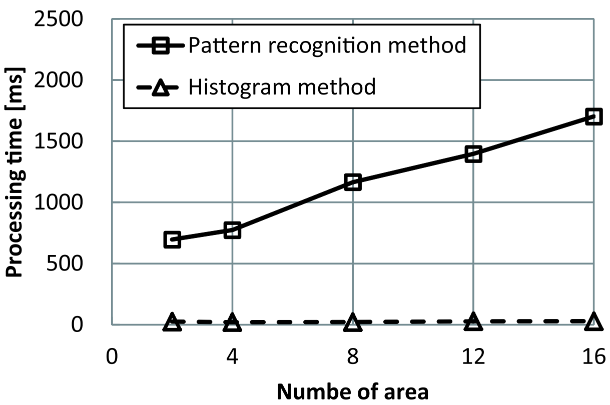

Fig. 10 Evaluation Result of Processing Time

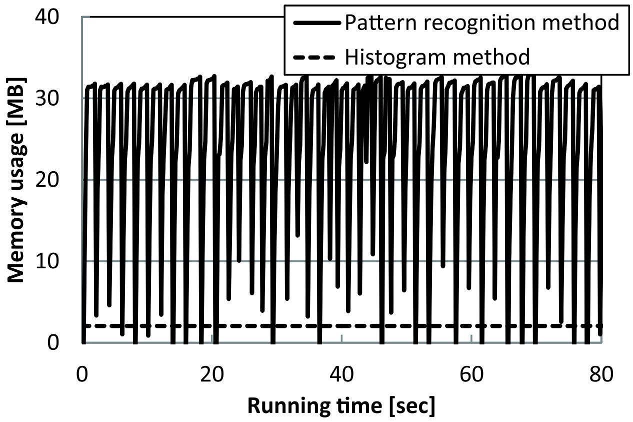

Fig. 11 Evaluation Result of Memory Usage

tics of RSSI in the area accurately to be ascertained. Figure 9 shows the evaluation results for the area detection accuracy affected by the amount of learning samples. In this evaluation, the number of areas used was 16 and the number of APs was 20. In Figure 9, the nearest neighbor method was not evaluated because the learning samples are unnecessary to the proximity algorithm as the nearest neighbor method.

When the amount of learning samples was over 30%, the area detection accuracy of the pattern recognition method was better than the histogram method. However, when the amount of learning samples was under 30%, the area detection accuracy of pattern recognition method was worse than the histogram method. The accuracy of area detection of pattern recognition method decreased when the amount of learning samples was 50%, and the histogram method was 25%. The result of the evaluation provides that the histogram method is not affected by the amount of learning samples, and the histogram method exhibits sufficient area detection performance with fewer samples than the pattern recognition method.

3.3 Evaluation of Hardware Requirement

In this section, the hardware requirements (processing time and memory usage) are compared and specifications of each method are clarified.

It is predicted that the processing time and memory usage of the nearest neighbor method is much better than the other methods, so the hardware requirements of nearest neighbor method were not evaluated. This is because the calculation for area detection with the nearest neighbor method is quite simple.

Initially, to evaluate the processing time, a change in the processing time with the increased number of areas was measured. It was expected that the processing time will increase as the number of areas increases. This is because the number of times to search the existing user's area will increase by increasing the number of candidates for the detected areas.

Figure 10 shows the evaluation result of processing time. Here, of the evaluation, the number of APs was 20, and amount of learning samples was full. The processing time was measured from the time of loading the model file which is described the characteristics of RSSI in each area to the time to determine the area where the user exists.

The processing time of pattern recognition method increased greatly according to the increase in the number of areas. This is because the pattern recognition method like SVM uses a combination search algorithm for area detection. For that reason, the processing time increased exponentially as the number of areas increased. Conversely, the processing time with the histogram method was little changed by the number of areas. This is because the number of times to calculate the likelihood increased according to the number of increased areas, so the processing time increased linearly. The value of increase in the processing time of the pattern recognition is 71.9 ms/area, and the histogram method was 0.2ms/area. Compared to amount of increase in the processing time in the pattern recognition and histogram methods, it was found that the processing time in the histogram method was just under 1/300 times that of the pattern recognition method. The result of the evaluation clearly shows that the area detection using the histogram method is able to run the area with a light process.

To evaluate the memory usage, memory usage was logged while the area detection software was running. The evaluation used 16 areas. The number of APs was 20, and the entire amount of learning samples was used. Figure 11 shows the evaluation results of memory usage. The memory usage in the pattern recognition method maintains about 30 KB, and decreases greatly to about 0 KB. This is because usage memory is released when the area detection process that loads the observation sample file is completed. Therefore, the memory usage in the pattern recognition method is a maintained value in Figure 11. Figure 11 shows that the memory usage in the pattern recognition method is approximately 30MB and in the histogram method it is about 3MB. In other words, memory usage in the histogram method is approximately 1/10 smaller than that of the pattern recognition method. The evaluation clearly shows that the area detection using the histogram method is able to run in the area with little memory use. Confirming the size of the

Table 1 Summary of Evaluation

Name of Method	Area Detection Performance	Hardware Requirement		Amount of Sample
	Accuracy	Processing Time	Memory Usage	
Pattern Recognition Method	98% (Highest)	71.9ms/area (Long)	30MB (Large)	50% (Large)
Histogram Method	92% (High)	0.2ms/area (Short)	3MB (Small)	25% (Small)
Nearest Neighbor Method	79% (Low)	No Evaluation (Shortest)	No Evaluation (Smallest)	0% (Smallest)

model file of learning sample, the size of model file for pattern recognition method is approximately 2.26MB, and that of histogram method is 3KB in this evaluation. Therefore, memory is used to load the model file.

3.4 Summary of the Evaluation

In this section, the area detection performance of the three methods is evaluated. Table 1 shows the summary of the evaluation results. Area detection accuracy in the pattern recognition and the histogram method is high. Particularly, the pattern recognition method is the highest. The required amount of learning samples in the histogram method is the smaller than the pattern recognition method. Processing time and memory usage of histogram method were smaller than those in the pattern recognition method. The hardware requirement of the nearest neighbor method is not evaluated in this paper. The nearest neighbor method is much simpler than the other methods. Therefore, its hardware requirements are assumed to be the best.

The summary of the evaluation shows that the nearest neighbor method is not the best area detection method for mobile LBS because the area detection accuracy in the nearest neighbor method is low. Although the area detection accuracy of pattern recognition method is the highest, it is necessary that the high-performance mobile terminal runs the area detection method in the pattern recognition method. In view of this, the best of area detection method for mobile LBS is the histogram method.

3.5 Discussion: Effective Use of Pattern Recognition Method

The evaluations in this paper show that the most suitable machine learning algorithm for area detection of mobile LBS is the histogram method. However, the pattern recognition method detects areas more correctly than the histogram method. In this chapter, effective use of the characteristics of the pattern recognition method is discussed. To effectively use the pattern recognition method, an environment that is easy to be mis-detected for the area is expected. Easy mis-detection of an area is defined by a similarity of the radio signal strength .

The similarity of the radio signal strength is represented as the frequency distribution of the correlation coefficients of RSSI. The vector correlation coefficients of RSSI are expressed as:

$$R = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})}\sqrt{\sum_{i=1}^{n}(y_i - \overline{y})}} \quad (2)$$

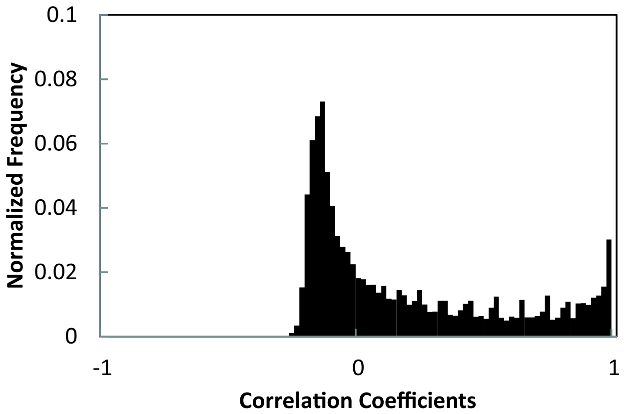

Fig. 12 Example of Frequency Distribution of Correlation Coefficient

where R is the correlation coefficient of RSSI; x is the RSSI vector of Area 1; y is the RSSI vector of Area 2; $\overline{x}$ is the average of RSSI corrected at Area 1; and $\overline{y}$ is the average of RSSI corrected at Area 2. The correlation coefficient is calculated at every RSSI vector of Area 1 and Area 2.

Figure 12 shows an example of the frequency distribution of RSSI correlation coefficients. The shape of frequency distribution in Figure 12 has two peaks when the correlation coefficient is near one and zero. However, the height of the peak near zero is higher than near one. This means that the radio signal strength between the areas is slightly different. The similarity of radio signal strength between areas is indicated by the height of the two peaks. When the peak of the correlation coefficient which is near zero is higher than the one near one, the radio signal strength between the areas is different. When the peak of the correlation which is near one is higher than the one near zero, the radio signal strength between areas is similar.

In this discussion, to compare the mis-detection rate of similar radio signal strength areas and different radio signal strength areas, the pattern recognition method was effective in the environment where mis-detection was easy.

Figure 13 shows that the mis-detection rate using the pattern recognition method and the histogram method when the radio signal strength is similar or different. When the radio signal strength is different, the mis-detection rate in the pattern recognition and the histogram method is almost same. However, when the radio signal strength is similar, the mis-detection rate in the recognition method is smaller than the histogram method. The result shows that area detection using the pattern recognition method in environments with similar radio signal strengths is more suitable

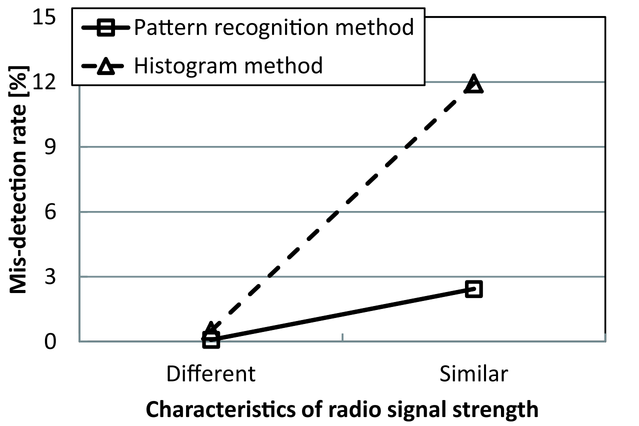

Fig. 13 Mis-detection Rate Affected by the Similarity of Radio Signal Strength

than the histogram method.

In this discussion, it was found that the effective use situation of the pattern recognition method is the environment of similar radio signal strength between areas. In particular, the best area detection method was selected based on the similarity of radio signal strengths. The RSSI sample of each area was corrected in advance. The frequency distribution of the correlation coefficient for each area was calculated using the RSSI sample. The heights of peaks in correlation coefficients which were near zero and near one were compared. When the peak at the correlation coefficient which is near zero was higher than near zero, it indicates that the radio signal strength between areas is similar. Conversely, the peak near one is higher than near zero, it indicates that the strength is different.

When there are many similar areas of radio signal strength, the area is detected using the pattern recognition method. When there are many different areas of radio signal strength, the area is detected using histogram method.

4. Conclusion

This paper described the evaluation of area detection method using a machine learning algorithm in order to clarify the most suitable machine learning algorithm. In this evaluation, area detection performance and hardware requirements of the learning algorithm which was the nearest neighbor, the pattern recognition, and the histogram method were compared. The area detection performance in this evaluation is defined the area detection accuracy. The result of area detection accuracy evaluation shows that the pattern recognition and the histogram method are better. From the evaluation result, it is determined that the pattern recognition method and the histogram method are suitable for area detection. Conversely, the hardware requirement in this evaluation was defined for the processing time and memory usage. The results of processing time and memory usage show that the nearest neighbor and histogram method are better. From the evaluation result, it is determined that the nearest neighbor and the histogram method are suitable for a mobile service. From the description above regarding the evaluation result, it is determined that the most suitable area detection method for mobile LBS is the histogram method.

In future, the authors plan to evaluate optimal parameters of the histogram method for area detection. The parameter is the threshold for the likelihood to judge the detected area or unknown area. The authors also plan that the area detection using the histogram method applies not only indoors but also in outdoor environments in order to implement the seamless area detection system.

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