Study of Low-Power Indoor/Outdoor Seamless Positioning System

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Abstract: In recent years, services that use positional information have spread widely and quickly thanks to the popularity of smart-phones. Service for both outdoors and indoors, like those for commercial complexes have been started. As the outdoor positioning technology, known as GPS, is mainly used. The indoor positioning technology ranges from Wi-Fi to IMES. Among these, an Indoor/Outdoor Seamless Positioning System is being studied and developed. An era in which positioning is possible without regard to one being indoors or outdoors is fast approaching. One of the issues of seamless indoor/outdoor positioning is the difficulty of switching because of the different technologies used either indoors or outdoors. Furthermore, there is the issue of high power consumption if outdoor GPS is used. Therefore, the authors considered solving these issues by enabling the use of the same technologies indoors and outdoors. One indoor positioning is room-level localization. This technology detects an area where one is located. First, positioning target areas are defined. Second, the learning data of Wi-Fi in these areas is collected. Thereafter, characteristics can be obtained thereby detecting the area. Therefore, the authors consider that this technology can be applied outdoors. However, in such a case, there are issues to be overcome. They include how to collect learning data, how to define an area, and determining the relationship of both amounts of learning data and its precision. The authors believe that this technology can be adopted by using a feature that obtains characteristics in order to detect the area using the same sample count even when the area size is different. This paper verifies the relationship of area size, amount of learning data, and precision rate by evaluation, and reports on the results of evaluations and future issues.

1. Introduction

In recent years, many location-based services (also known as LBS) that use position information have rapidly spread due to the popularity of smart-phones. For example, a safety service that notifies drivers by sending the positions of people to a vehicle, a navigation service that guides the driver to an intended destination, or a service that is based a person’s walking history.

Until now, these services are used mainly outdoors, utilizing GPS. However, these days, these are considered both outdoor and indoor like commercial complex or station yard or the like. For example, there are services that notify the appropriate information and prompt a visit and a purchase knowing the behavior of people in commercial complex. There is also the navigation service, though it is generally unavailable indoors.

These services can be categorized into positioning only when using a terminal such as when a user wants to know his current position, like that commonly used in navigation, and constant positioning even when the user is not using a terminal, such as for a walking history.

GPS is mainly used as an outdoor-positioning technology. This is a system that receives signals from several satellites (among several tens of GPS satellites) orbiting the earth in space, to ascertain the position of the receiving terminal. The current state of the art for positioning precision is on the order of approximately 20-30 m. However, further improvements are anticipated in new technologies like the quasi-zenith satellite system [1] both at home and abroad. GPS is an essential function for mobile terminals like smart-phones. It is adopted for use by various services. For example, route guidance navigation, services to record a hiker’s trajectory, like life log, and functions where photos can be by adding positioning information to the mobile terminal, and social networking service (SNS), such as Foursquare. However, power consumption when using GPS is generally higher on smart-phones, than that of other devices. For that reason, it is not a problem as long as the service, like taking a picture or SNS, is used only temporarily. Conversely, it is unsuitable for services that utilize continuous positioning, such as the walking trajectory described above. Furthermore, because GPS uses satellite signals, it cannot be used where those signals are interrupted, such as underground or indoors, or similar locations.

Conversely, studies of indoor positioning have been performed. Large-scale demonstration experiments have been conducted at commercial complexes. There have been a plurality of methods for indoor positioning technologies; some methods used wireless LAN (Wi-Fi) [2], IMES (Indoor MEssaging System) [3, 4], sound wave [5] and visible light communication (VLC) [6].

Indoor positioning using Wi-Fi that has become essential to the function of mobile terminals like the smart-phone just like GPS, has attracted attention. Indoor positioning using Wi-Fi is ubiquitously available. There are fewer and fewer places where Wi-Fi radio waves cannot be detected. Wi-Fi access points (AP) are now commonly installed in schools and offices for communication. Some carriers have even installed AP anywhere it is convenient, such as train or bus stations or even in cafés in recent years. In addition, indoor positioning using Wi-Fi is suitable for continuous positioning, because power consumption when using the Wi-Fi is smaller than that when using GPS. There are major two methods adopted for Wi-Fi positioning. One is a method of calculating the position using triangulation. This method identifies the positions of AP in advance, and then calculates the position by using RSSI (Received Signal Strength Indicator) or TOF (Time of Flight). Another method called fingerprint is shown in Figure 1. This method determines multiple points in the positioning area, and creates a database of

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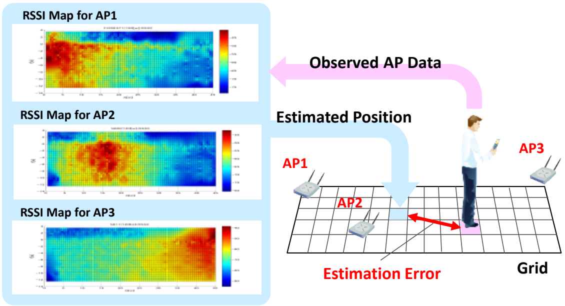

Figure 1. Wi-Fi Positioning of Fingerprint Method

measured RSSI at each point. Finally, it estimates the position using the observed RSSI. The installation cost of indoor positioning using Wi-Fi is very inexpensive because it can make use of pre-installed APs and receivers are mounted on most smart-phones. However, the triangulation method must ascertain each position of all APs. For that reason, maintenance is too difficult. In the fingerprint method, it takes a long time to learn all the points.

IMES [3, 4] is also called indoor GPS. IMES employs the same frequency band and modulation scheme as GPS. IMES notifies the terminal of the positioning information by sending a signal that includes the latitude, longitude, and floor information from a transmitter which is installed in the ceiling. Indoor/Outdoor seamless positioning system with GPS has been studied. The IMES Consortium [4] aims at disseminating IMES as the world standard for indoor positioning.

A positioning method that uses sound waves [5] has a sound generator that sends sound waves that include the ID; the terminal receives the sound waves via a microphone and converts the ID into position information.

A positioning method that uses VLC [6] has the ID set in the light emitted from a lighting fixture equipped with a signal control system; the terminal receives and converts that into position information.

In addition, the positioning methods by Bluetooth, Near Field Communication (NFC), ultrawideband (UWB) have been studied. In particular, iBeacon [7] by Apple has attracted attention. iBeacon has a feature for detecting when a terminal is in the vicinity of the device using Bluetooth Low Energy (BLE) when the terminal receives the beacon of BLE.

These methods involve much expense and time to put into practical use. Because it is necessary to setup a new transmitter and receiver, most smart-phones are not equipped with this.

A rich amount of indoor positioning technologies have been proposed and therefore indoor/outdoor seamless positioning [8] has attracted attention for utilizing LBS both indoors and outdoors without the user being aware. This technology uses GPS outdoors and uses its own indoor positioning technology indoors. This system switches methods if it detects movement from indoors to outdoors and starts GPS. If it detects movement from outdoors to indoors, it starts indoor positioning. By doing that, continuous positioning is possible without the user being concerned about whether they are indoors or outdoors. Particularly, in the case of IMES [9], it can be used if the device has a supported receiver, because the frequencies and modulation schemes of GPS and IMES are the same. However, power consumption is high so it is not suitable for long-term use. In the case of using a different technology, such as Wi-Fi or sound waves indoors, it is necessary to switch the method by judging whether the terminal has moved indoors or outdoors. Therefore, there are problems associated with switching when the user moves indoors and outdoors. For example, the effect of multipath can cause satellite signals to be detected, so even if the user has moved from outdoors to indoors, GPS position information will be obtained, but the terminal cannot switch methods. For that reason, the authors believe the problems of power consumption and method-switching can be solved by utilizing indoor Wi-Fi positioning outdoors.

Wi-Fi positioning outdoors has been considered to be difficult to implement because that system must be able to identify AP positions, to collect more learning data, and process a large amount of data for mobile terminals. The authors have been conducting research and development of a room-level localization technology that estimates where the user is located. One of the methods of that technology is a probability distribution method. This method is better than other methods in terms of the amount of learning, the amount of processing, and its overall performance. For that reason, the authors believe that it might also be applied outdoors.

There are some issues when an indoor positioning technology is applied outdoors. These issues include how to collect learning data; how to define an area (such as the size or its name) at that time; and how much data to collect. In addition, how precisely can data be obtained at that time? The authors considered that it is possible to apply indoor positioning in the outdoors by using the feature that obtains characteristics to detect the area using the same number of samples even if the area size in the probability distribution method is different. The authors verified the validity of this idea through field trials using the actual equipment in the outdoor.

This paper describes the indoor positioning technology of Wi-Fi in Section 2, the proposed scheme in Section 3, evaluations and considerations in Section 4 and offers a conclusion in section 5.

2. Related Work

2.1 Room-level Localization

The authors studied room-level localization using Wi-Fi indoor. Room-level localization is a technology for estimating an area where the user is located by learning the RSSI of Wi-Fi observed in each predefined area. For example, in Figure 2, an area was defined as a meeting room and an office. AP1 is installed in the meeting room, and AP2 is installed in the office. In the meeting room, RSSI of AP1 is observed strongly, but RSSI of AP2 is observed weakly. Conversely, in the office, the RSSI of AP2 is strong, while the RSSI of AP1 is weak. This technology estimates the area by using the differences in the RSSI.

The room-level localization uses various methods. These methods include k-Nearest Neighbor (k-NN) Method, Pattern

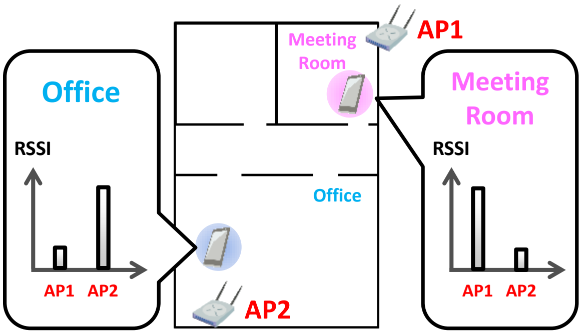

Figure 2. Example of Observed RSSI

Matching (PM) Method [10], and Probability Distribution (PD) Method [11]. K-NN determines the area by finding k that is the nearest RSSI of the observed RSSI, and counts the area which has the nearest RSSI (Figure 3c). PM uses a Support Vector Machine [10]. It determines the area by setting a discriminant boundary line between the two areas (Figure 3a). Finally, PD [11] determines the area by creating the histogram of RSSI on the each AP, and calculating the likelihood of each area (Figure 3b). [12] clarifies PD to be the best balanced method of the three by the evaluating area detection performance, hardware requirement, collection time of learning data.

The PD method is briefly described below. Figure 3b is a graph of learning data showing a distribution of RSSI of AP1 and AP2 observed in the meeting room and the office. The red points are the distribution of RSSI observed in meeting room, and the blue points are the distribution of RSSI observed in the office. In each axis, the frequencies of each strength (ex. 5 dBm intervals) of RSSI are shown. For example, this method calculates the likelihood of each area in the following order, when the receiver observes RSSI at an unknown area like the S in the center of Figure 3b.

1. Calculating the likelihood by observed RSSIs of the learned APs;
2. Calculating the likelihood by unobserved RSSIs of the learned APs;
3. Calculating the likelihood by observed RSSIs of the unlearned APs; and
4. Calculating the likelihood of the area by the product of 1, 2, and 3.

In this case, no calculation of the 2 and 3, the determination of area is performed in the calculations below.

P (office | S) = p2・p3 = 2/17・5/17 = 0.035

P (meeting room | S) = p1・p4 = 3/16・2/16 = 0.023

Since result is P (office | S) > P (meeting room | S), the office is determined the estimated area in this case.

The amount of learning data is related to area detection performance of room-level Localization. The accuracy rate is low if there is a low number of samples. Conversely, the accuracy rate increases as the number of samples increases. In the room-level Localization of PD, it is necessary that a sufficient frequency distribution is generated in order to distinguish the area and other areas. In [12], PD needs 6 samples per square meter at least from experimental result of the number of samples which generate sufficient frequency distribution in the case of the number of resolutions which is 12.

Defining the results of the amount of learning data as 100%, Figure 4 shows the change in accuracy rate when varying the amount of learning data. From these results, the accuracy rate is becoming a constant from approximately 25% of the amount of learning data in the PD method. It was learned that it is acceptable for approximately 1/4 of the number of samples than the actual number.

Because of this, the authors adopted the PD method which is the best balanced in terms of learning time, processing time, and memory usage in order to process by the mobile terminal in proposed indoor/outdoor seamless positioning.

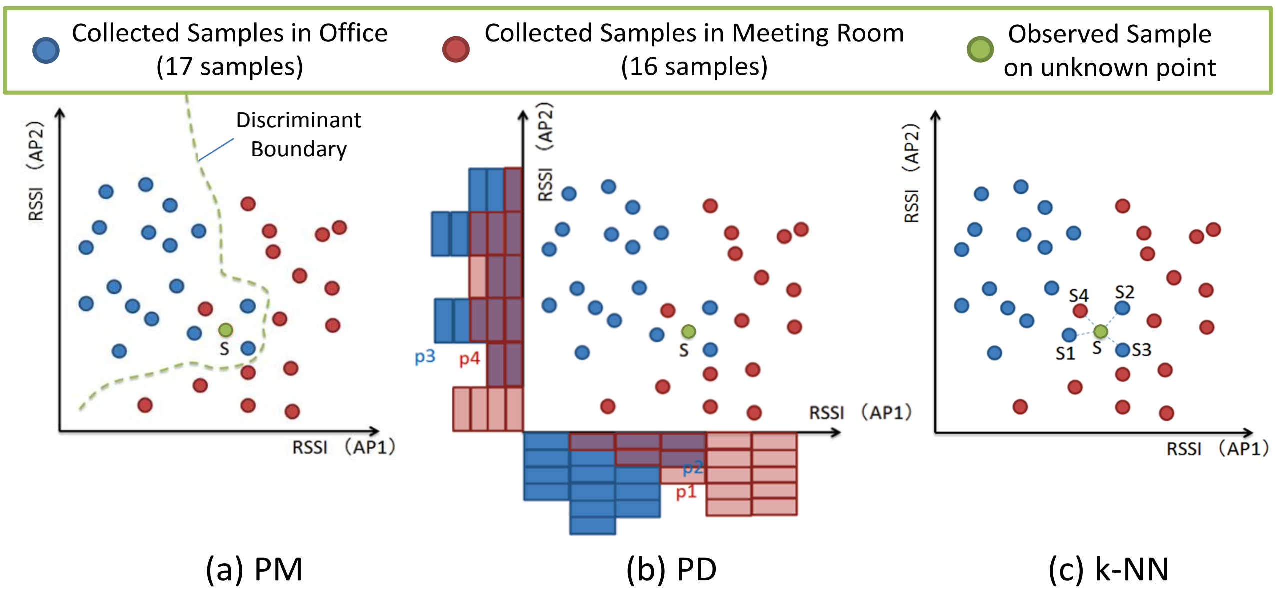

Figure 3. Room-level Localization Using Each Method

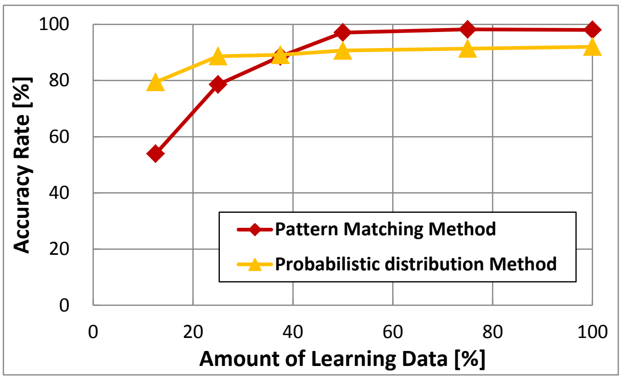

Figure 4. Relationship of Amount of Learning Data and Accuracy Rate

3. Proposal Method

Therefore, the authors believe that applying the indoor room-level localization technology of PD method to the outdoors may overcome the issues of switching indoors and outdoors and reducing power consumption by reducing the use of outdoor GPS. For that reason, to apply this indoor technology outdoors, the following problems must be considered.

- How to collect the learning data
- How to decide the area name
- How to decide area size

3.1 Indoor/Outdoor Seamless Using the Probability Distribution Method

In indoor positioning, an administrator defines the area, and collects the learning data for the area. However, it is difficult to collect the learning data because the outdoor range is very wide. In addition, another reason is also the learning data isn't collected by a lot of users because there is a tendency not to want to disclose their own information.

Therefore, the authors actualize the outdoor positioning using PD method by limiting the use of area used frequently by the individual user and collecting the learning data by associating the GPS information to Wi-Fi information in the individual user.

Figure 5 shows a flowchart of the indoor/outdoor seamless positioning including the feature that collects the learning data. A description of the flowchart is below.

1. Scan the Wi-Fi information;
2. Implement indoor positioning using the scan results;
3. Notify the area of indoor if the result is indoor and return 1;
4. Implement outdoor positioning using the same scan results if there is no indoor learning data;
5. Notify the area of outdoor if the result is outdoor and return 1;
6. Implement GPS if there is no outdoor learning data;
7. Create the outdoor learning data by associating GPS information to Wi-Fi information as the area name that position information; and
8. If GPS information isn't obtained because of a timeout, the learning data isn't created and the system returns to 1.

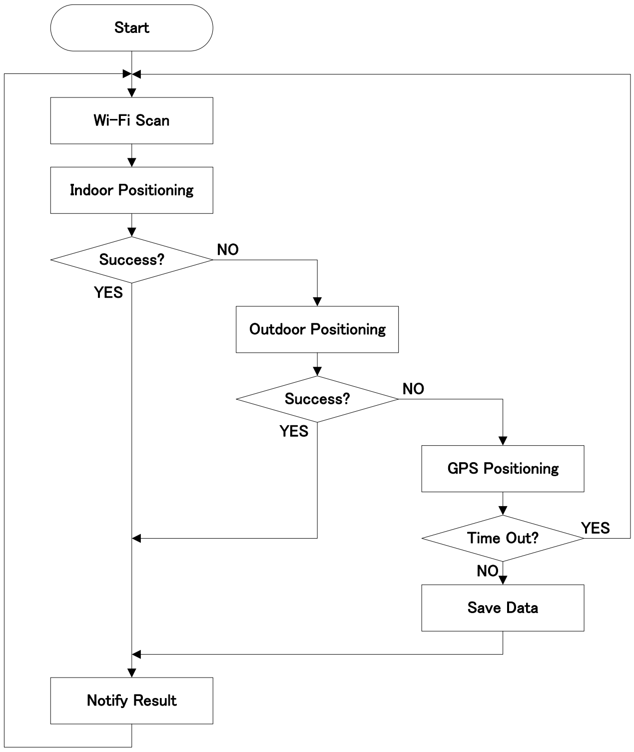

Figure 5. Flowchart of Indoor/Outdoor Seamless Positioning

3.2 Area Name by Aggregating of Names

All area names must be defined in the indoor positioning. The issue is how to decide the area name outdoor. The area name is decided by aggregating names and rounding the latitude and longitude of positioning information of GPS. Figure 6 shows an example of aggregating names. The three positioning information belongs to the same area by aggregating names.

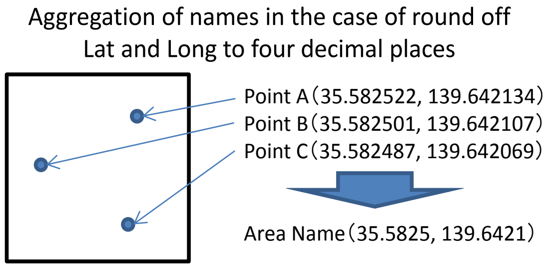

Figure 6. Example of Aggregation of Names

3.3 Enhanced Area Size by Number of Samples

The area is not so widely defined by administrator. There is the issue of how to decide the area size. This is because it is unclear how people move in the outdoors. In [12], the sample of the learning data for generating the characteristics in order to distinguish the area and other areas needs at least 6 samples or 1/4 than the actual number of cases of resolutions which is 12.

The authors thought that it might be possible to obtain the characteristics of the area with the same number of samples with a fixed number of resolutions in the any size of area. For example, the area size of Figure 6 is 11 meters by 9 meters. In this area size, about 150 samples are needed to distinguish this area from other. The authors attempted to verify whether the characteristics can be obtained with the same number of samples

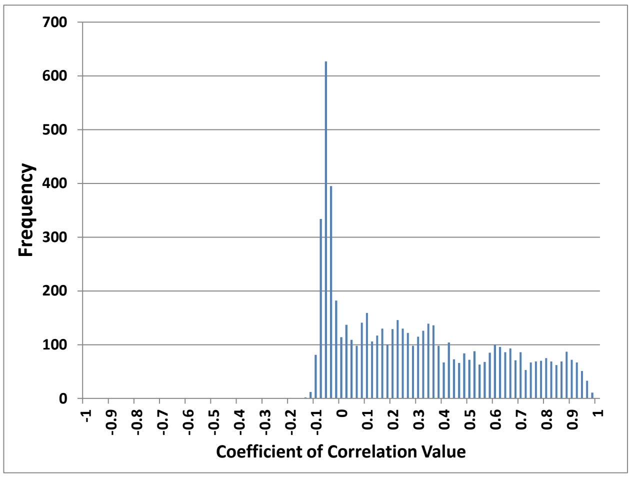

Figure 7. Frequency of Coefficient of Correlation Values

in a size that is three times that, specifically 33 meters by 27 meters. In order to determine the learning data collected in two adjacent areas are similar, the authors correlated each sample of two areas. The results are shown in Figure 7. The horizontal axis represents the correlation coefficient. It means that the sample is not similar as the correlation coefficient close to 0 or less. It also means that the sample is similar as a correlation coefficient close to 1. The vertical axis represents the frequency of correlation coefficients obtained. It can be confirmed in Figure 7 that the characteristics can be obtained from the sample of correlation coefficient is close to zero in many cases.

In addition, it is thought that the characteristics of an area can be obtained with a small number of samples because the set of RSSI representing that area is very simple from the fact that the difference does not appear to performance of PM method and PD method in the room-level localization.

When collecting learning data outdoors, it is not possible to collect that data all at once; it is also thought that there are many initial false-positives because it is not possible to obtain the characteristics of the area that has a small number of samples. Therefore, it was considered that it might be possible to reduce the number of false-positives because the characteristics of the area can be obtained by integrating with the surrounding area and gathering the learning data until that is accumulated for the area of original size.

4. Evaluation

However, it is unclear that whether the PD method can be used outdoors under the assumptions described above. Because the distance from user to the AP is very different indoors and outdoors, therefore the amount of RSSI change indoors and outdoors is different.

For that reason, the authors conducted experiments to verify the relationships among the amount of learning data, the area size, and the accuracy rate in the proposed method.

4.1 Experimental Environment

Outdoors, there are many different environments such as residential and urban areas. However, it is considered that the effects on RSSI caused by such differences are small compared those indoors. For that reason, the experiments were performed on roads near the Fujitsu Kawasaki Factory. Figure 8 shows the experimental course is about 1 km from Point A (Fujitsu Kawasaki Factory's rear gate) to Point B (in front of Fujitsu Laboratory's lobby). Learning data of 20 times was obtained in 10 days assuming going to work and returning home. Evaluation data was also obtained for one round trip.

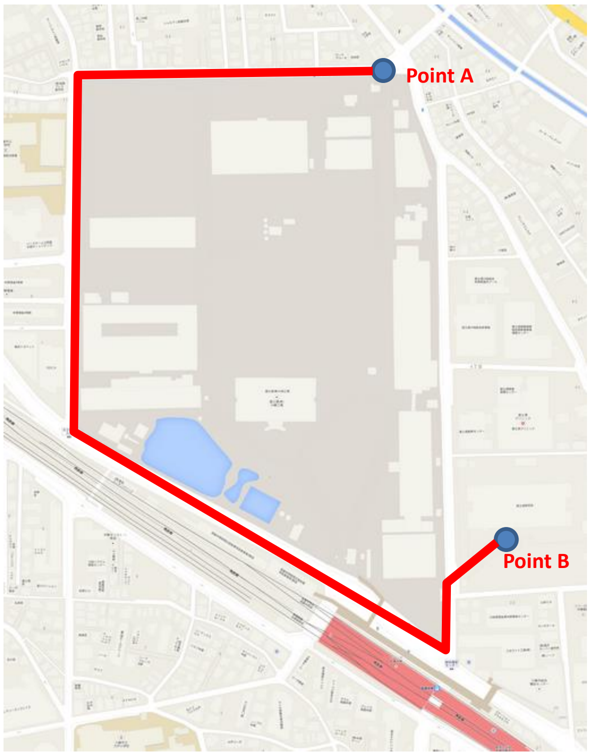

Figure 8. Experimental Course

Area size is 4 patterns of following.

- Area Size 1: 11 meters by 9 meters
- Area Size 2: 33 meters by 27 meters
- Area Size 3: 55 meters by 45 meters
- Area Size 4: 110 meters by 90 meters

For example, in the case of the Area Size 1, a position information such as the following left is obtained, and rounded off to four decimal places (the following right).

(35.582551, 139.642134) -> (35.5826, 139.6421)

4.2 Experimental Result

Figure 9 shows the changes of the number of areas and registered APs in the learning data. The horizontal axis represents the data acquisition date and going to work (A) or returning home (B) in the day. The vertical axis represents the number of areas and registered APs. For Area Size 1, the number of areas is increased to approximately 5.7 times from 131 areas of day 1 A to 744 areas of day 10 B in the learning data of 10 days. For Area Size 2, the number of areas is increased to about 2.5 times. For Area Size 3, the number of areas is increased to about 2 times. For Area Size 4, the number of areas is increased to about 1.6 times. The number of registered APs is increased to about 2.8 times from 206 APs to 582 APs.

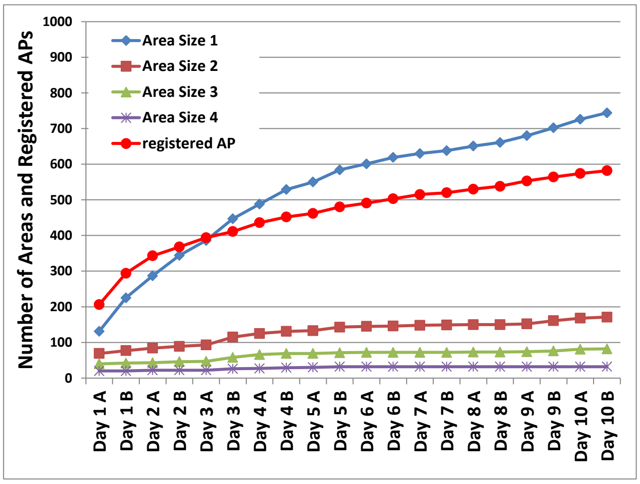

Figure 9. Transition of Number of Areas and Registered APs

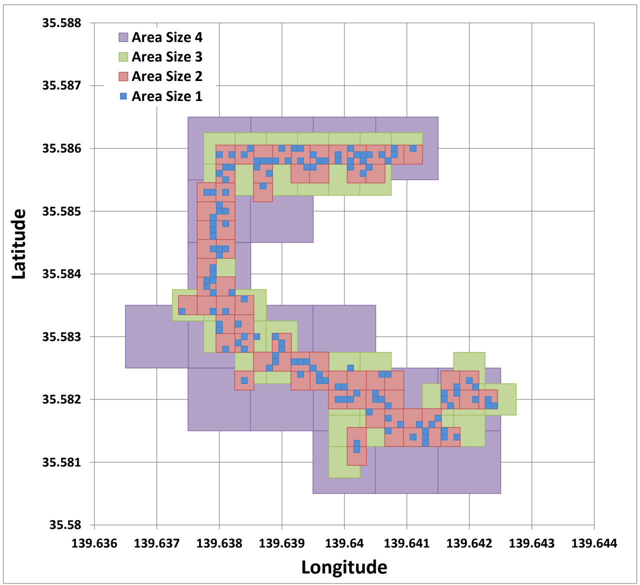

Figure 10. Areas by Learning Data of Day 1 Going to Work

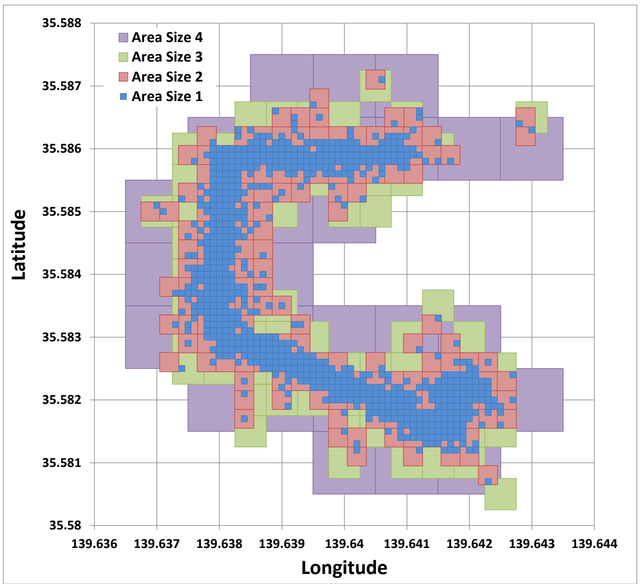

Figure 11. Areas by Learning Data of Day 10 Returning Home

Figure 10 is a graph for visualizing the areas of the learning data generated in day 1 A. Figure 11 is a graph for visualizing the areas of the learning data generated in day 10 B. The horizontal axis represents longitude, and the vertical axis represents longitude. The areas other than Area Size 1 cover the entire experimental course, but the area of Area Size 1 didn't cover all in the learning data of day 1 A. Conversely, the experimental course is covered with area of the area size of all in the learning data of day 10 B. However, the area is also created in the location that is not actually walked.

Figure 12 shows the change of the maximum number of samples in registered areas. The number of areas registered reached a sufficient number within 10 days. Conversely, the maximum number of registered samples characterizing the area is 33 for area size 1. This is 1/5 of the required number of samples, which is 150. For Area Size 2, the maximum number of samples is 102 samples. A little extra time was needed for collection. For Area Size 3, the number of samples has been reached 150 samples at day 7 B, and the maximum number of samples is 161 samples at day 10 B. For Area Size 4, the number of samples has been reached 150 samples at day 4 B, and the maximum number of samples is 356 samples at day 10 B. However, this number is the number of registered area has the maximum number of samples, so other areas have less number of samples.

From the above results, it is possible to create a sufficient number of areas, but it takes a long time to collect sufficient number of samples for distinguishing the area in a small area. This means that the accuracy rate is low. In the large area, the number of samples which might be able to distinguish the area is collected for 4 days at the earliest.

Figure 13 shows the results of accuracy rate of evaluation data of the course for going to work, and Figure 14 shows the results of accuracy rate of evaluation data of the course for returning home. Accuracy rate of Area Size 1 is not less than 10% on the course for going to work and for returning home. Accuracy rate of Area Size 2 rose about 15% from day 1 A to day 2 B on the course of going to work, but it has decreased gradually from then. On the course for returning home, it has risen to around

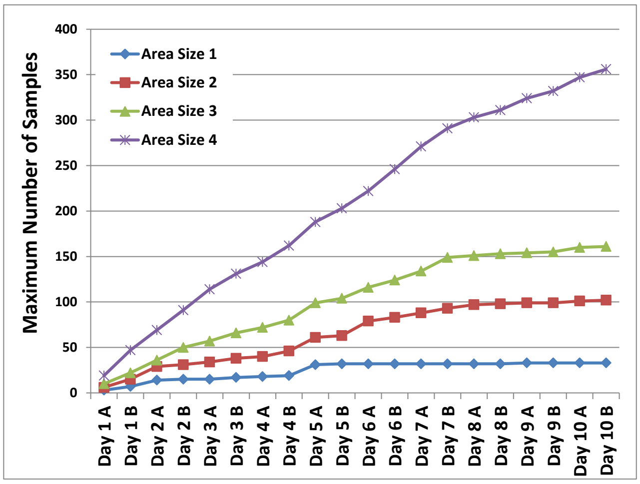

Figure 12. Transition of Maximum Number of Samples on Areas

40% after the learning data of the day 8 A. Accuracy rate of Area Size 3 is around 40% on both courses in the learning data of the day 1 A, it has risen to around 50% after that. The accuracy rate of Area Size 4 is approximately 70% on both courses.

Looking at the results, false-positives can be decreased by increasing the area by integrating small areas for gathering the samples and characterizing the area. However, the accuracy rate hasn't increased in the same area size regardless of fact that the number of the samples also has been slowly increasing in Figure 12. Several reasons can be considered. Initially, it is considered that the number of samples is small. The number of samples is enough in some areas, but the number of samples is not enough for distinguishing the area in other areas. For that reason, the accuracy rate has not increased. Secondly, it is considered the influence of accuracy of GPS information when creating the learning data. There are increasing extra areas by accuracy of GPS information which is poor and registering the similar RSSI to a different area. For that reason, the accuracy rate hasn't increased. Even though the number of samples is increasing, it is considered the influence is reduced because of incorrect data would be buried in the correct data.

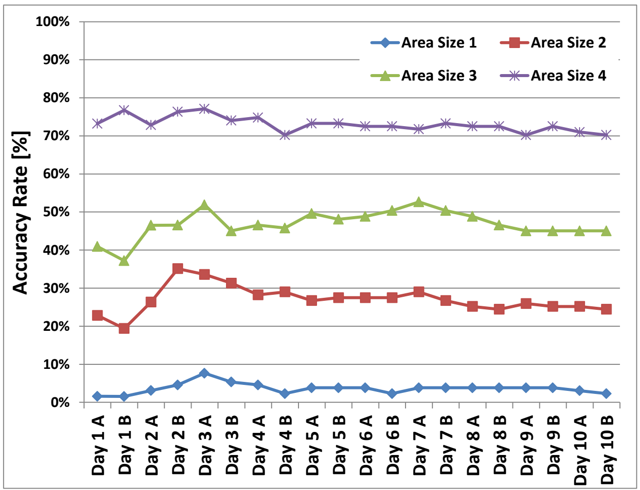

Figure 13. Result of Accuracy Rate with the Course for Going to Work

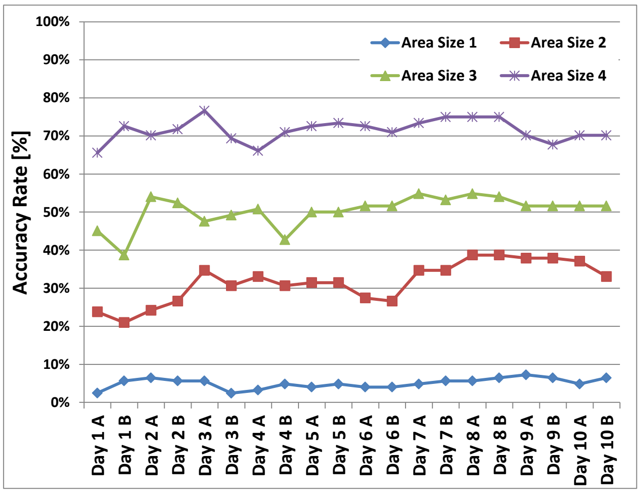

Figure 14. Result of Accuracy Rate with the Course for Returning Home

4.3 Consideration

In field trials, it was confirmed that it is possible to reduce the false-positive and characterize the area with the same number of samples if area size is different.

It has efficacy as a service to determine whether the user is in the area, such as a geo-fencing. Conversely, how is the service like navigation using GPS?

Figures 15, 16 show the results of positioning error against correct position on the evaluation course. The positioning error is calculated by the distance to the correct position. Correct position is calculated by dividing the walking distance by the walking time as being movement at a constant velocity. Red results are positioning error of GPS. Positioning error of going to work is 34.3 m, and returning home is 35.3 m.

On the course for going to work, positioning error of Area Size 2 exceeds the GPS in the learning data of day 2 A. Moreover, positioning error of Area Size 1 in the learning data of day 2 B and Area Size 3 in the learning data of day 3 A exceed the GPS. Positioning error after that also exceeds the GPS. Positioning error of Area Size 4 couldn't exceed the GPS, but it is considered that the results are valid because originally, the area size is large (110 meters by 90 meters).

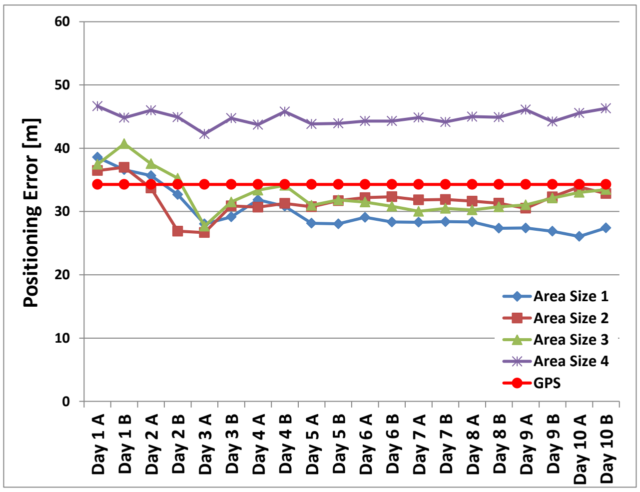

Figure 15. Result of Positioning Error with the Course for Going to Work

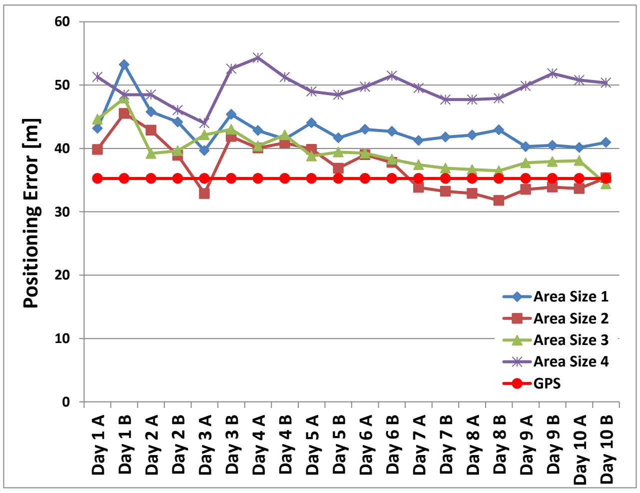

Figure 16. Result of Positioning Error with the Course for Returning Home

On the course for returning home, positioning error of all area size is worse than the course for going to work. Positioning error of Area Size 1 and 4 couldn't exceed the GPS. Positioning error of Area Size 2 exceeds the GPS in the learning data of day 3A and after day 7A. Positioning error of Area Size 3 exceeds the GPS in the learning data of day 10 B. There is a tendency for the accuracy rate to rise in proportion as the learning data increases except Area Size 4.

From the above, it has been verified that the positioning error obtained the accuracy at the same level as the GPS because the closed area which is not the correct area was estimated. In addition, it is considered that the method for outdoors can be switched from GPS to room-level localization because a certain degree of accuracy rate is obtained in the early stages of small number of samples. Moreover, it is not always true that accuracy rate of the smallest area is the best. The accuracy rate of Area Size 2 was the most stable. It is considered that this area size is close to the positioning error of the GPS and that the error of the learning data is small.

5. Conclusion

The authors investigated the application of indoor room-level localization of the probability distribution method to outdoors as a study of the low-power indoor/outdoor positioning system. It was considered that the outdoor method can be used by increasing the number of samples by integrating the some small areas that have small number of samples in the early stages of collecting the learning data because the feature that obtains the characteristics in order to detect the area by same number of samples area size is also different.

It was revealed that it is possible to use the room-level localization of probability distribution method outdoors from the relationships among the area size, the learning data, and accuracy rate on the experiments. Conversely, the positioning error close to the GPS was measured from the learning data for one time. Also, it can be seen that the positioning error is better than the GPS from the learning data of 4-5 times.

In view of the above, it is possible to adopt positioning outdoors using room-level localization of probability distribution instead of GPS. Furthermore, the feasibility a low-power indoor/outdoor seamless positioning was confirmed.

As the future work, the authors will focus on AP changes over time (such as removal and configuration changes etc.) and the effects of mobile APs (such as movement).

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