Design and Implementation of WiFi Indoor Localization based on Gaussian Mixture Model and Particle Filter

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***Abstract*— Up to now Scene Analysis has been based on the WiFi location estimation technique and it has been necessary to have a large scale database and a large amount of calculation. We propose a WiFi estimation method that uses little data or calculation. First of all we apply Gaussian Mixture Model to represent the large scale WiFi database to decrease the WiFi data by no less than 95%. Secondly, we apply Particle Filter to adjust the possible calculation quantity needed for the location estimation technique. As experimental result, we achieved real-time location estimation within 6~10m. Another important issue for Scene Analysis technique is the high cost of operation of the previous WiFi observation. Accordingly crowdsourcing approach was used, employing as system where some users could contribute and other uses could share. The ideal system is a composition of the Web and mobile terminal. WiFi data observed by mobile terminals is uploaded to a Web server where it is managed and integrated into GMM and large scale operations are carried out on data and calculations. When the lightweight modeled data is downloaded to the mobile-terminal, the mobile terminal then has the ability to carry out real-time location estimation independently.**

Keywords-component; WiFi Localization, Scene Analysis, Gaussian Mixture Model, Particle Filter, Crwodsourcing

I. Introduction

This research aims to estimate the indoor locations of mobile terminals in real-time using WiFi information. Additionally, the function can be applied in any building in the real world. Location estimation methods such as WiFi, RF tags, infra-red, IMES etc. are also proposed [1-10]. Among these methods, WiFi is said to be more advantageous in terms of infrastructure cost as existing WiFi access points (APs) that are already widely installed in homes and public facilities can be used.

In this research, Scene Analysis [4,8,10] is adopted as the indoor location estimation method. Scene Analysis is a method whereby the scenes at multiple points within a region are observed and then data corresponding to those scenes and the observation points are collated in a database. By comparing the current WiFi environment with the database, the point that is considered the most similar is then taken as the current location. As this method takes into account the effect of reflected and dispersed waves, coupled with the possibility of a higher accuracy compared to other methods by narrowing the distances between the observation points, it is therefore considered to be the most suitable indoor method where there are many obstacles.

In order to estimate the location accurately in real-time using a single mobile terminal, it is necessary to limit the computational complexity to a level that is possible for real-time processing by using a light-weight database. However, conventional methods of location estimation using Scene Analysis require large amounts of data and computational complexity. As indoor WiFi radio waves are not attenuated by the same amount due to the presence of walls and obstacles, it is preferable that the WiFi environment be measured in advance with as narrow an interval as possible so as to improve the accuracy of the estimated location. Now, the amount of data collected increases proportionately with the number of observation points. For conventional methods, the larger the number of WiFi APs in use and the wider the estimation range, the larger is the amount of computational complexity required and therefore the load imposed on the mobile terminal also becomes proportionately larger.

Another problem with Scene Analysis is the high labor cost involved in collecting fingerprints. The system needs to be notified of the location of each observation point and these needs to be recorded repeatedly at narrow intervals together with the radio observation information at that time.

In order to resolve these problems, we propose a WiFi location estimation method that allows the computational complexity to be adjusted accordingly using a light-weight database. Under the proposed method, we approximated the radio wave distribution observed beforehand for each AP into one Gaussian Mixture Model (GMM) to achieve large data compression. We also used a Particle Filter (PF) to estimate the indoor location from the GMM groups obtained. As the

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computational complexity depends on the number of particles, real-time location estimation becomes possible for even mobile terminals if the number of particles is adjusted.

Furthermore, in order to resolve the problem of high labor cost in collecting fingerprints, we introduced the crowdsourcing method [11] and built a system named indoor.Locky whereby the work can be distributed among multiple users. This system is equipped with a floor map posting function so that it can be used in any arbitrary system. Due to the seamless connection with outdoor location services, it is also equipped with floor maps and latitude / longitude functions.

The composition of this paper is as follows. First of all, Chapter 2 provides an overview of the problems faced by current research up till now. Next, in Chapter 3, we propose the location estimation method using GMM and PF, then perform several experiments on the accuracy of the estimated location and data compression ratio in Chapter 4. Chapter 5 describes indoor.Locky which provides the foundation for the WiFi indoor location system based on crowdsourcing while Chapter 6 provides a summary and some future issues.

II. Related Work

Most of the existing location estimation methods using WiFi are classed as Triangulation [1,9], Proximity [3,5] and Scene Analysis [4,8,10] methods. Among these, Scene Analysis is considered effective in estimating the indoor location accurately. Triangulation is a location estimation method that uses the radio propagation characteristics and relative locations from known standard locations. Because of the many walls and obstacles indoors, this method is said to be difficult to use as the radio waves are not attenuated according to the distance characteristics due to the influence of reflected and dispersed waves. The Proximity method is used to determine roughly which standard point is in the vicinity of the location estimation target. This method is deemed insufficient as indoor location estimation generally requires a high degree of accuracy. Scene Analysis estimates the location by performing scene observation at multiple points within the estimation zone and collects data corresponding to each scene and observation point (fingerprint). This method creates a database that takes into account the influence of reflected and dispersed waves. By narrowing the distance between observation points, it is capable of making more accurate estimations than other methods and is thus more suitable for estimating location indoors. In this research, location estimation is performed based on the RSSI-based Scene Analysis.

In order to estimate the real-time location accurately in an indoor WiFi environment, we have to resolve the following two points. The first one concerns the problem of the data volume. Many observation locations are required for accurate location estimation and the data volume increases in proportion to the number of observation points. The second problem is the issue with the computational complexity. Although Bayesian estimation method is proposed as a location estimation method using Scene Analysis [2], computational complexity becomes very large when estimating the location in a large floor as it calculates the most likely location among all the candidate points.

In recent years, the crowdsourcing approach has been attracting much attention. This is a method whereby the workload that cannot be processed automatically using computer due to high labor cost is shared among many users. The world maps in OpenStreetMap are also built by users based on this approach [12]. Through the participation of many users in information collection and content creation, the labor cost for each person can be lowered and large-scale media creation is made possible. The effectiveness of WiFi observations made in advance based on crowdsourcing has already been demonstrated in several research studies [13-16]. One major issue with Scene Analysis is the high labor cost required to make observations of WiFi information in advance. If it is outdoors, the observation terminal can simply be located on a running car or bicycle since the radio observation information can be linked with the absolute coordinates obtained by GPS. However, GPS cannot be used indoors. Therefore, the system needs to be notified of the location of each observation point and these needs to be recorded repeatedly at narrow intervals together with the radio observation information at that time. By sharing this workload among multiple users, the labor cost for each person can be lowered

Conventional crowdsourcing systems [13-16] are not suitable for use in an actual environment for the following two reasons. The first one is that it cannot be used for any arbitrary building as it cannot register the building information and floor map. The second reason is that a seamless connection between indoors and outdoors is not possible. While most location services commonly in-use today are based on geographical coordinates (latitude, longitude), conventional crowdsourcing systems return the location in terms of floor map coordinates.

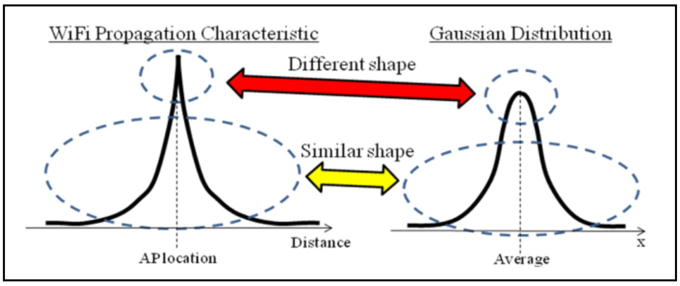

Figure 1. Difference of the shape between WIFI path loss model and Gaussian distribution

III. WiFi Indoor Localization

To enable real-time location estimation using limited resources and mobile terminals, low data volume and low computational complexity need to be achieved. The location estimation method proposed in this paper using a Particle Filter (PF) and model created based on Gaussian Mixture Model (GMM) is able to satisfy both these conditions at the same time.

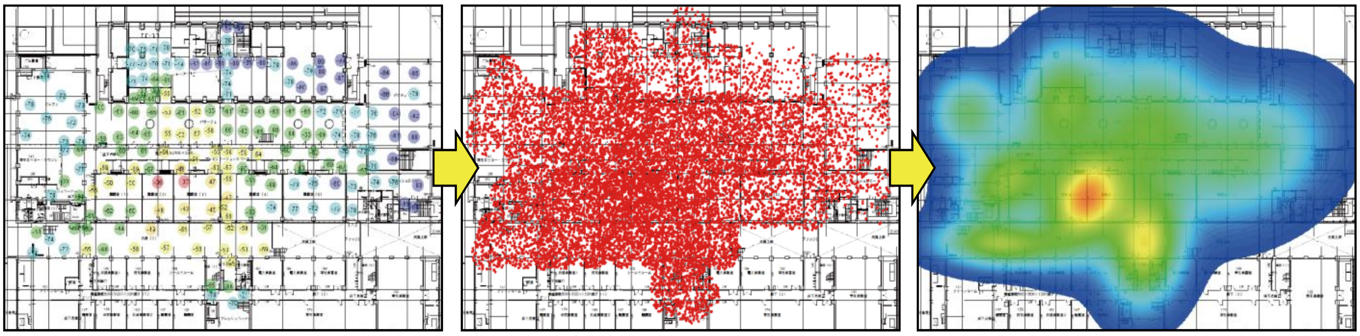

Figure 2. Procedure of modeling. (Left) RSSI, (Center) Convergence of points, (Right) GMM (8 mixture)

A. Data Compression using Gaussian Mixture Model

The volume of data obtained using advance observations in a WiFi environment depends mainly on the number of observation points and number of observations at each point. The information observed at a certain point in the target floor is a list of the BSSID and RSSI. BSSID is the AP's unique ID. RSSI is receives signal strength indication, and the unit is dBm. When the floor under observation is large, the data volume increases if observations are made at narrow intervals for accurate location estimation.

In this research, a model of the radio wave distribution for each AP is approximated into 2-dimensional GMM. As shown in the schematic diagram on the left of Fig. 1, it is known that the intensity varies by a large amount around the AP [9]. On the other hand, Gaussian distribution as shown on the right of Fig. 1 shows that there are no large changes in density near the average value. However, the position that Gaussian distribution cannot approximate the figure is limited to quite near position to the AP, so that the effect seems to be low. Therefore, although the radio wave transmission characteristics of the WiFi cannot be completely represented using GMM, there is no problem in using GMM proximity since only the area extremely close to the AP will show a large proximity influence.

The definition of GMM is shown below. Equation (1) expresses a 2-dimensional Gaussian distribution and contains the average μ and scattered co-variance matrix $\mathbf{\Sigma}$. A GMM with a K number of overlapping Gaussian distributions is expressed by (2) and (3). π_k is known as a mixing coefficient and expresses the weight of each mixing element (Gaussian distribution). Like (3), the total of all the mixing coefficients is equal to one. The shape of the 2-dimensional GMM is determined by the individual Gaussian distribution average, scattered co-variance matrix and mixing matrix. If the linearly-mixed weighted coefficients of each Gaussian distribution average and scattered co-variance are adjusted using a sufficient number of Gaussian distributions, any arbitrary and continuous density function can be approximated.

$$N(\mathbf{x}\,|\,\mu,\mathbf{\Sigma}) = \frac{1}{2\pi\sqrt{|\mathbf{\Sigma}|}}\exp\{-\frac{1}{2}(\mathbf{x}-\mu)^{\mathsf{T}}\mathbf{\Sigma}^{-1}(\mathbf{x}-\mu)\} \tag{1}$$

$$p(x) = \sum_{k=1}^{K}\pi_k N(\mathbf{x}\,|\,\mu_k,\mathbf{\Sigma}_k) \tag{2}$$

$$\sum_{k=1}^{K}\pi_k = 1 \tag{3}$$

The radio wave distribution of each of the K number of AP observed on the target floor is approximated using GMM. GMM is expressed as a list of the following information: mixed number of Gaussian distributions; and average, scattered co-variance matrix, mixing coefficient of each Gaussian distribution. Based on this, the data volume after transforming to GMM depends mainly on the number of APs within the target floor and not on the number of observation points.

The process for creating the model is as follows. First of all, transform the WiFi RSSI data (left side of Fig. 2) for a certain AP into a point distribution on a 2-dimensional planar surface (center of Fig.2). Next, using an EM algorithm, estimate the GMM (right side of Fig. 2) from the 2-dimesional distribution. The model is created by following this process for all floors and all APs.

First of all, transform the point distribution on the 2-dimensional diagram (the higher RSSI, the higher is the point density) as shown in the center of Fig. 2 into an intermediate format for creating a model of the collected WiFi information. Here, divide the control regions according to the observation points, and then transform it into a point distribution by scattering the number of points corresponding to the value of the radio wave intensity at each control region. The control region for each observation point is divided up using Voronoi diagram [18] such that the respective control regions do not overlap and there is no blank space between the regions.

The number of points S_n located in each Voronoi region V_n is determined using (4) based on the surface area M_n of the region and the radio wave intensity α_n on the observation points controlling that Voronoi region.

$$S_n = (\alpha_n + R)\frac{M_n}{\arg\min(\mathbf{M})} \tag{4}$$

This thesis assumes that the minimum radio wave intensity considered is -90dBm and that the points are distributed only when α_n is larger than -90dBm. Parameter R is a constant value for converting the RSSI into a positive number. Argmin is a function to return the surface area of the smallest Voronoi regions among the observation points. Finally, by randomly selecting v_m number of coordinates in the region V_n and locating the points at those coordinates, this is transformed into the point distribution as shown in the center of Fig. 2.

From the point distribution, an EM algorithm is used as a method to estimate the GMM. EM algorithm is one of iterative methods and known as powerful method to estimate stochastic model parameters using maximum likelihood estimation. EM algorithm is also known as the estimation method of GMM parameters [17]. There are two step called step E (expectation) and step M (maximization). Assuming the 2-dimensional point distribution as $\{\boldsymbol{x}_1, \ldots, \boldsymbol{x}_N\}$, the matrix becomes *N-2* matrix $\mathbf{X}$ with the *n*-th row as $\mathbf{x}_n^T$ and the log likelihood function is expressed as follows using (2).

$$\ln p(\mathbf{X} \mid \pi, \mu, \boldsymbol{\Sigma}) = \sum_{n=1}^{N} \ln\{\sum_{k=1}^{K} \pi_k N(\mathbf{x}_n \mid \mu_k, \boldsymbol{\Sigma}_k)\} \tag{5}$$

Here, the GMM parameters of each Gaussian distribution (average μ_k, scattered co-variance matrix $\boldsymbol{\Sigma}_k$, mixing coefficient π_k) are estimated by maximizing (5). The GMM mixing coefficient is assumed to be set manually. The EM algorithm consists of two updating steps known as Step E and Step M and calculates the log likelihood function in (5) and repeats Step E and Step M until it satisfies the convergence standard.

First of all, initialize the average, scattered co-variance matrix and mixing coefficient of each Gaussian distribution. In order to reduce the number of iterations until it satisfies the convergence standard, do not set the initial values randomly but use a K-means algorithm to set them. Create a cluster of the 2-dimensional point distributions using K-means (cluster number: *K*) and use the sample average and sample co-variance of each cluster as the initial values of the average and scattered co-variance matrix of each Gaussian distribution. Use the ratio of the number of points belonging to each cluster as the mixing coefficient.

Next, using the average, scattered co-variance matrix and mixing coefficient for each of the mixing element at that point, calculate the load factor in Step E. The load factor expresses the extent of the collection data that the mixing element *k* bears and is expressed using (6).

$$\gamma(z_{nk}) = \frac{\pi_k N(\mathbf{x}_n \mid \mu_k, \boldsymbol{\Sigma}_k)}{\sum_{i=1}^{K} \pi_i N(\mathbf{x}_i \mid \mu_i, \boldsymbol{\Sigma}_i)} \tag{6}$$

In Step M, the average, scattered co-variance matrix and mixing coefficient of each Gaussian distribution are updated using the load factor calculated in (6). The updating formula is as shown below.

$$N_k = \sum_{n=1}^{N} \gamma(z_{nk}) \tag{7}$$

$$\mu_k = \frac{1}{N_k} \sum_{n=1}^{N} \gamma(z_{nk}) x_n \tag{8}$$

$$\boldsymbol{\Sigma}_k = \frac{1}{N_k} \sum_{n=1}^{N} \gamma(z_{nk})(x_n - \mu_k)(x_n - \mu_k)^T \tag{9}$$

$$\pi_k = \frac{N_k}{N} \tag{10}$$

The parameter updating procedures Step E and Step M will always increase the log likelihood function in (5). When the log likelihood function or the variations in each parameter become smaller than the threshold, the EM algorithm is deemed to have converged. Repeat Step E and Step M as long this convergence condition is not satisfied. In this research, a variance of less than 10% in the log likelihood function is assumed as the convergence condition. The right side of Fig. 2 shows the transformed GMM using the actual 2-dimensional point distribution shown in the center of Fig. 2.

B. Real-time Localization using PF

We will describe how location estimation is performed using the GMM. We adopt PF as a technique to estimate the optimal solution for the current location based on the GMM and WiFi information observed at a particular point. PF is a type of chronological order filtering method that can handle any arbitrary probability density function. PF is also adopted by several researches for GMM-based object tracking [19,20]. Selecting multiple sequential states in several hundred to several thousand particles, the weighted average was estimated as sequential states and then tracked based on the likelihood of all the particles.

In order to realize location estimation in real-time using a mobile terminal, the computational complexity needs to be restrained and PF is able to satisfy this constraint. The computational complexity of PF depends on the number of particles *N* and since it is expressed by O(*N*), the computational complexity can be adjusted using *N*. However, if the number of particles is too few, sufficient estimation accuracy cannot be obtained and when there are too many, the computational complexity becomes too large. As a result, the computational complexity needs to be reduced as much as possible while still maintaining the estimation accuracy. Preliminary experimental results indicate that a particle number of between 200 and 300 is the most optimal in indoor location estimation.

The WiFi observation data O^t at time *t* is expressed by a combination of the BSSID β^t and RSSI α^t. The aggregate of the *N* number of particles A^t at time *t* is expressed using particle a^t_n, floor ID $Floor^t_n$, coordinate p^t_n and $weight^t_n$.

$$O^t = \{o^t_1, \ldots, o^t_M\} \tag{11}$$

$$o^t_m = (\beta^t_m, \alpha^t_m) \tag{12}$$

$$A^t = \{a^t_1, \ldots, a^t_N\} \tag{13}$$

$$a^t_n = (Floor^t_n, p^t_n, Weight^t_n) \tag{14}$$

Location estimation algorithm using PF is performed according to the following 5 steps.

1) Particle Initialization

Here, it is assumed that the floor ID and coordinates of each particle are randomly determined and that the user holding the mobile terminal does not to maintain its initial location. In order to equalize the existence probability of each particle, the weight at time *0* $Weight^0_n$ is set as given in the formula.

2) Particle movement

Next, the coordinate p^t_n is updated as each particle is moved in a random direction by a random distance d between 0 and D. D needs to be set at an appropriate distance depending on the interval between the estimation steps and movement speed of the user. For example, assuming a person is walking at a brisk pace, and the location is estimated at 1 second interval, setting D as 5 - 6 m in 1 second can cover the rest state to the brisk walking state. For particle a^t_n where the weight $weight^t_n$ at time t is below the sub-threshold value, that particle is moved from the floor $Floor^t_n$ to which it belongs to a random coordinate of a potential transition floor. When there are multiple potential transition floors, this is randomly determined. The potential transition floors include the current floor as well. Based on this, it is possible to prevent a situation where the location estimation straddles multiple floors and the particle is caught in the furthest areas and cannot be moved to an accurate location. In this thesis, the sub-threshold value of the movement weight between floors is assumed to be 10%

3) Weight updating (WiFi Observation)

The weight $weight^t_n$ of each particle a^t_n after movement is updated using the likelihood function e^t_n. From Fig. 1, since the variation in RSSI versus distance becomes larger in areas where the RSSI is large (distance from AP is short), the estimation accuracy can be improved by using only APs with large RSSI. Sometimes interference may occur in the WiFi radio waves due to the influence of the mobile terminal and other APs and therefore the reception of WiFi radio waves may not be always stable. As a result, sometimes there may be no reception from APs that should have been observable in the first place and sometimes only extremely weak signals can be received. The influence from wave interference can be reduced by estimating the location using the RSSI and model of only those APs where reception is stable and the intensity is above the sub-threshold value. First, extract from the observation data O^t (o^t_0,..., o^t_i) those BSSIDs (β^t_0, ..., β^t_j) whose wave intensities are above the sub-threshold value R. If there are none, select the BSSID whose reception intensity is the strongest. The preliminary experimental results indicate that the location estimation accuracy improved the most when the sub-threshold value R is set in the region of -70dBm.

Next, determine the estimated RSSI γ^t_{ni} on each GMM for every extracted BSSID β^t_i for each particle a^t_n.

$$r^t_{ni} = GMM(a^t_n, \beta^t_i) \qquad (15)$$

Based on this, the BSSID β^t_i related existence probability for the particle a^t_n can be determined in the GMM. A 1-dimensional Gaussian distribution is used for the likelihood function e^t_n. When the standard deviation of this Gaussian distribution is too small, the e^t_n peak is too sharp, and consequently the particle is stuck in a far area and cannot be moved to its correct location. However, as seen in the preliminary experimental results, this phenomenon could be avoided by setting the standard deviation in the region of 5.

Since the extracted BSSID number is j, the likelihood function e^t_n is determined as follows.

$$e^t_n = \prod_{i=1}^{j} p^t_i \qquad (16)$$

Lastly, normalize the particle weight such that the sum of all the particle weights equals 1. The weight is updated using the constant C as follows.

$$Weight^t_n = \frac{e^t_n + C \cdot Weight^{t-1}_n}{\sum_{i=1}^{N}(e^t_i + C \cdot Weight^{t-1}_i)} \qquad (17)$$

The constant C refers to the extent the weight in the previous step is inherited. In this thesis, in order for a particle to easily break out of a point in a far area where it has converged to, C is set at a small value of $1.0*10^{-15}$.

4) Resampling:

In particle resampling, all particles are moved to the coordinates of other particles. In order to determine the particle at the destination point, the weight of each particle is treated as a probability where that particle has been chosen to be the destination point. In order to avoid too many particles existing at the same coordinates, random walks at small distances are added. Based on the above, many particles end up being relocated around particles with large weights.

5) Presentation of the estimated Location

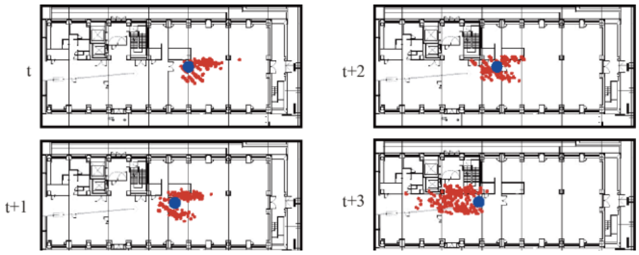

Figure 3. Visualization of the location estimation.

The coordinates of each particle are presented to the user together with the floor map (Fig. 3). Large blue points are locations where the terminal actually exists and the multiple small points are the particles. From Fig. 3, it can be seen that most of the particles exist in the vicinity of the actual terminal location indicating that the location estimation has been performed normally. After presenting the location, return to Step 2 and estimate the location at time t+1.

IV. EVALUATION

A. Evaluation of Data Compression

In this section, the extent of the data compression after transforming to GMM is evaluated.

The actual WiFi observation information on the first and second floors of the electronic data center in Nagoya University was observed. The area of each floor was about 5000m^2. The observation points were set at 1m intervals with

187 points on the first floor and 139 points in the second floor. 30 observations at 1 second interval were carried out at each point. The amount of time taken for the WiFi observation was about one and a half hours for each floor. Before creating the model, APs where RSSI above the sub-threshold value was not observed at any point were excluded. This thesis set the sub-threshold value of the RSSI of the APs that were to be excluded from the model creation experientially at -70dBm. When creating the model, the mixed coefficient of the GMM was manually determined.

Table 1 shows a comparison of the AP number and text data volume before and after the model creation. The data volume compression ratio refers to the ratio of the data volume after removing APs with low RSSI to the data volume after creating the model. Based on this, the data volume can be said to have been reduced to 99.81% after the model was created. Nonetheless, the model created in this thesis uses the average of 30 WiFi measurements at one observation point. If one observation at one point is used, the data volume before the model creation is reduced to 1/30 of the average. In this case, the data volume compression ratio as a result of creating the model is about 95%.

TABLE I. COMPARING OF THE AMOUNT OF DATA

	# AP	# AP (except for low RSSI)	Data amount before modeling	Data amount before modeling (except for low RSSI)	Data amount after modeling	Compressibility ratio
1F	207	22	45288KB	12169KB	22KB	99.82 %
2F	241	12	50663KB	5643KB	13KB	99.77 %
Total	448	34	95951KB	17812KB	35KB	99.81 %

TABLE II. PARAMETERS OF EXPERIMENTS

Particle Number	300
Max moving distance of a particle	6m
Standard deviation of likelihood function	5
RSSI Threshold	-70dBm

B. *Evaluation of Localization*

The accuracy and real-time nature of the estimated location was evaluated using the collected data in this section.

First, we will provide a comparison of the estimated accuracy using the proposed method and other conventional methods. 2 conventional methods were selected. One of the two methods uses the Bayesian estimation method [2]. The other estimates the location from the virtual location distribution of the WiFi APs and uses the radio transmission characteristics to determine the location of the terminal. Based on the preliminary experimental results, the parameters used in the proposed method are set as shown in Table 2.

Figure 4 shows a graph comparing the estimation accuracy of the various methods. The horizontal axis shows the error between the estimated result and the actual location while the vertical axis shows the proportion of correct estimations against the overall number performed. Comparing the proportion where the estimated error is less than 10m among the various methods, the base estimation method was the lowest at about 15%, the virtual AP method about 50% while that for the proposed method was the highest at 88%. Based on this, it has been shown that the proposed method is more accurate in estimating the location indoors compared to other methods.

The accuracy of the estimated location using the various

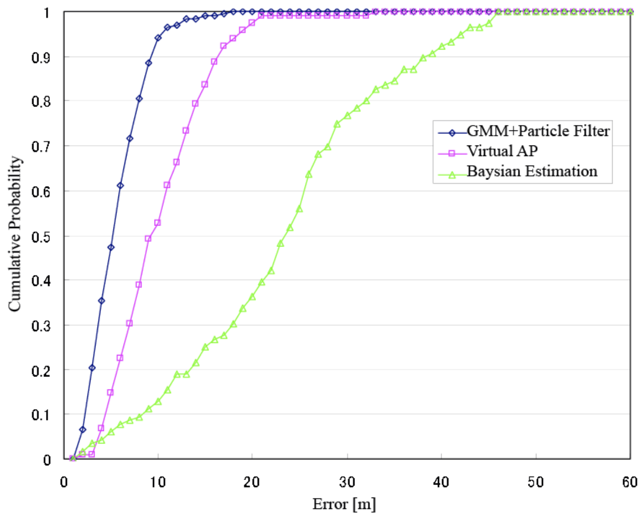

Figure 4. Comparing graph of the accuracy of each location estimation method

methods as obtained from the experimental results was studied. As a preliminary step using Bayesian Estimation, the RSSI at points that were not observed was supplemented using the observed RSSI. However, it was not possible to overcome the constraints posed by the building walls and thus scenes were supplemented using only the distance characteristics. Moreover, as it was not possible to express the continuity according to the estimation steps using base estimation, this resulted in the low accuracy. On the other hand, as the proposed method uses a PF that is a chronological order filtering technique, it can express the continuity of the estimation steps thereby resulting in the higher accuracy. The median of the error is about 6m¸ and the probability that the estimation error is less than 10m is about 90%. The reason for the low accuracy using the virtual WiFi APs is believed to be because the influence of reflected waves due to the walls and obstacles has not been factored in. On the other hand, as the proposed method takes into account the influence of walls and obstacles by adopting the Scene Analysis methods, highly accurate estimation is thus possible.

Next, the real-time nature of the method is evaluated. Equipping the actual device with the location estimation function using GMM and PF, it has been verified that location estimation in real-time is possible. An iPad (processor: A4, memory: 256MB) was used. Using this, estimation at 1 second intervals for up to about 2000 particles was possible. As the optimal number of particles is about 200 to 300, it can be said that processing in real-time is therefore sufficiently possible.

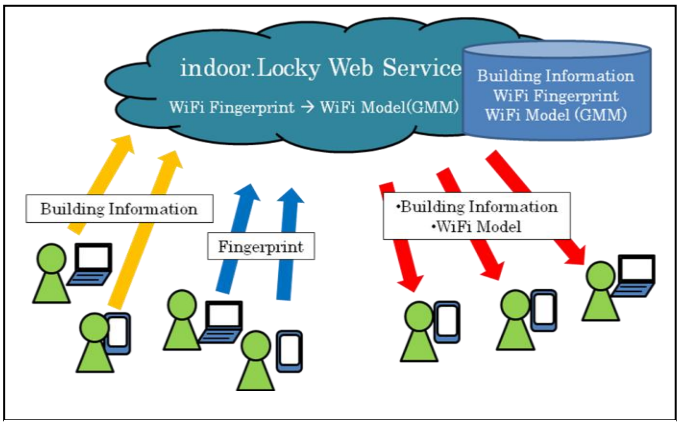

Figure 5. Abstract of indoor.Locky platform

V. INDOOR.LOCKY

In this chapter, we will describe the system named indoor.Locky as the foundation for an indoor location estimation system that can be used in the real world. In order to use the location information in any building, crowdsourcing approach based on the cooperation of general users is adopted so that the workload for the indoor WiFi observations can be shared among multiple users. Furthermore, this system can be used for location estimation in any building and by connecting it to an outdoor GIS.

indoor.Locky consists of the following three elements. 1: A web service for the integration and management of WiFi information and building information that has been posted by the user. 2: Client software operating on the mobile terminal. 3: API for the use of the location information by any application. The client software is suitable for use in PC and iPhone / iPad. The web service uses the Google App Engine.

A summary of this system is shown in Fig. 5. Each user uses a terminal that has been installed with the indoor.Locky client software. Based on the following process, the location information in any building can be used.

A) Users enter the building and floor information (building information)

B) Users perform the WiFi observation on each floor and uploads the information

C) The web service integrates the uploaded observation data and transforms it into a GMM on the spot (WiFi model)

D) Users download the WiFi model and building information into the terminal and use the real-time location estimation function.

A. *Registration of Building Information*

First, enter the building information used for the location estimation from the Web browser. Figure 6 is the building registration screen. Enter the building name and number of floors above and below the basement into the form and using Google Maps, register the coordinates of a representative point of the building. Next, register the floor map of each floor of the

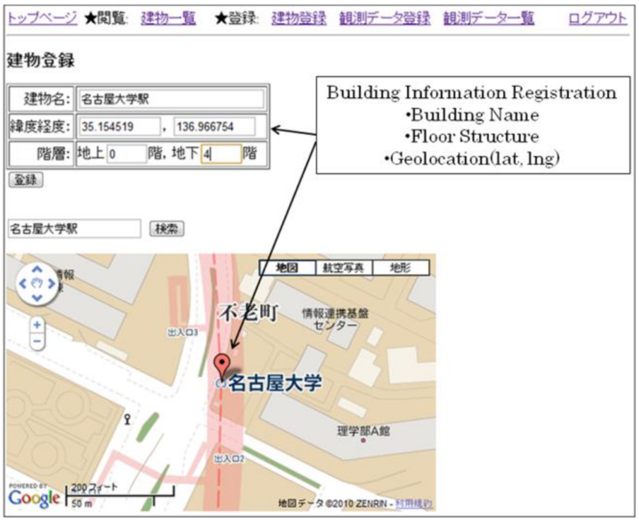

Figure 6. Building Information Registration

building. As most buildings generally do not make public their detailed floor map data such as CAD data, a picture of the floor map displayed in the building can be taken using a camera and then the image is uploaded.

The management of floor images posted by the user is presented here. First of all, the display of floor maps is generally not standardized. It is not necessary to have one image for each floor and the same floor image can be used for multiple floors. For example, in Fig. 7 the second storey and mezzanine converge to a single floor image. Sometimes multiple floors may also collapse into one. In reality, a point in the middle second storey is a location that is surrounded by a dotted line. Also, instead of being depicted in a planar surface, sometimes it can also be represented 3-dimensionally as shown in Fig. 8.

The floor images are managed as shown below according to units known as floor regions. Each floor region is created by designating 3 or more points in the floor image. On the right side of Fig. 9, a section of the second floor in the train station is taken as a single floor region (a pin is shown at the peak with the region bordered by the lines between the peaks). When multiple floors exist for a single floor image, create multiple floor regions. This way, we can resolve the issue of multiple floors existing in a single floor image and create 3-dimensional floor maps that are trapezoidal and diamond-shaped and also polygonal floor regions. Next, select the floors corresponding to each respective floor region. In addition, use the mouse cursor to enter into the Google Maps the geographical coordinates corresponding to the peaks of the polygonal floor region so as to map them to a geographical coordinate system (right side of Fig. 9). By performing an affine transformation of the floor region, an inter-conversion between the coordinates in the floor image and geographical coordinates can be achieved. Even if multiple floors collapse into a single floor image as shown in Fig. 7 so as to match the latitude and longitude according to each region, we can still map the coordinates of each floor region correctly to the geographical coordinates. The mapping of the peaks of the floor region with the geographical coordinate system is not a requirement and is only carried to determine the mapping function correctly. Display of location information using geographical coordinates is limited to floor regions that have already been mapped with the geographical coordinate system.

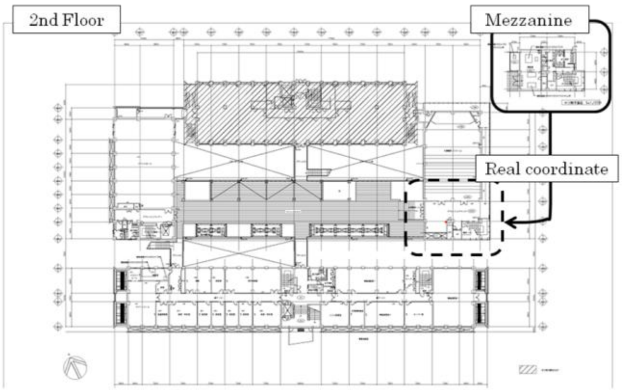

Figure 7. An example of floor map. Physical relationships of these floors are not consistent

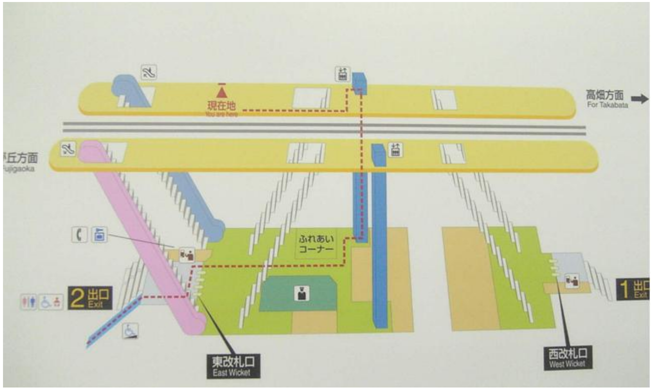

Figure 8. An example of floor map. The floors are as three-dimensionally

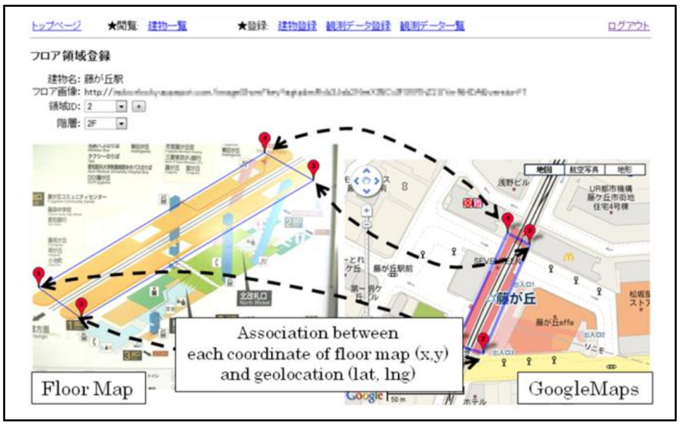

Figure 9. Mapping between a floor area and geographical coordinates.

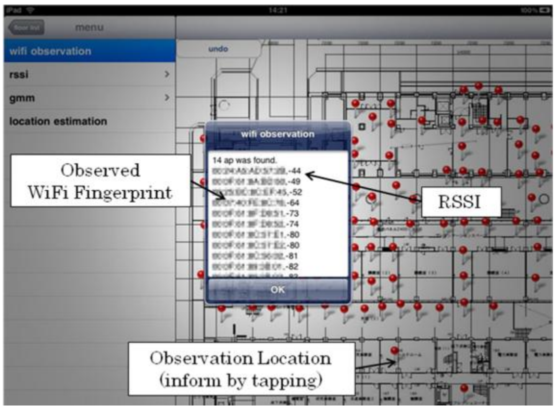

Figure 10. Indoor WiFi observation client (iPad)

B. *WiFi Observation*

The indoor WiFi observation is performed by the user using the client software installed in the terminal. At each observation point where the WiFi observation is performed, the user taps or clicks the floor image to inform the system of his location and record the corresponding WiFi observation information at the position (Fig. 10). A pin is displayed for points that have already been observed by the user or other users and the user repeats the movement and observation for only points where there are no pins shown.

C. *Modeling WiFi observation data toGMMs*

When the user transmits the observation data to the Web service, the Wed Service immediately transforms the data into the WiFi model according to the base station on each floor by making use of the data uploaded by multiple users. When multiple users post observation data from the same floor, the system integrates these multiple observation data and transforms them into the WiFi model. Even when the model transformation is already completed, when new WiFi observation data is posted, the transformation is performed again to update the WiFi model.

Using the technique described in Sec. 3, the GMM mixing coefficient had to be determined manually. However, this function has been automated in the system by allowing more mixing coefficients to be set when there are more observation points for each base station. When there are too few mixing coefficients, complex radio distribution shapes cannot be approximated. Conversely, few failures occur as a result of too many mixing coefficients when approximating simple radio wave distribution shapes. The specific correlation between the number of observations points and mixing coefficients has been determined experientially here.

D. *Utilizing the result of location estimation*

When a user accesses the Web service and downloads the WiFi model, the system is ready to perform real-time location estimation on that floor. When the current location display function in the client is used, the results of the location estimation can be viewed in real-time as a particle distribution (Fig. 10). Any browser and application can access the client through the API to make use of the estimated location (particle center of gravity). The current configuration only allows the use of the estimated location information by browsers and applications which are installed on the same terminal as the client.

As mentioned previously, when the peaks of the floor regions have been mapped with the latitude/longitude coordinates, the estimated location can be obtained not only as coordinates within the floor image but also as geographical coordinates. Coordinates within the floor image are useful for services where the relative positions indoors are important (e.g. indoor navigation, store guide etc). On the other hand, geographical coordinates are useful for many existing outdoor location services that rely on geographical coordinates. Therefore this system is useful for location services that require a seamless connection between the indoors and outdoors.

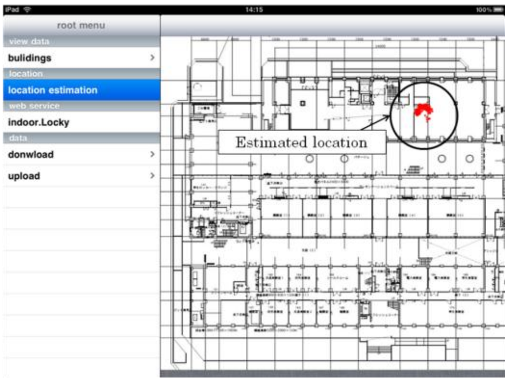

Figure 11. A scene of real-time indoor location estimation (iPad)

VI. CONCLUSION

This paper proposes the adoption of a location estimation method in creating a system with the aim of using a mobile terminal and WiFi technology to determine the indoor location in any building. Under this method, the WiFi data volume using GMM and PF has been reduced by more than 95% with an accuracy of about 6 to 10 m in real-time location estimation. Next, a system based on the proposed method was built in an actual operating environment. This system named indoor.Locky adopts crowdsourcing approach to reduce the labor costs in performing advance observations by sharing the workload among multiple users. By equipping the system with functions to upload floor maps taken by users and map the floor maps to geographical coordinates, the system can be used in any building and also connects seamlessly with outdoors GIS.

Going forward, we are aiming for a public launch with more functions incorporated into the indoor location service. We are also studying how to semi-automatically organize the floor map images posted by users.

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