Automated Wi-Fi Sample Management System considering User Trajectory

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Abstract: Wi-Fi-based indoor positioning methods have been attracting the attention of researchers because of the low deployment cost due to the ubiquity of Wi-Fi signals transmitted from access points in various places. Wi-Fi fingerprinting-based positioning method needs a Wi-Fi radio environment map, which consists of absolute position data associated with observed Wi-Fi radio information in advance. The map has to be periodically updated with the latest Wi-Fi radio information because Wi-Fi access points are susceptible to be newly placed, removed, and moved, and it takes huge maintenance cost. To address this issue, we propose a method to automatically create and update the map by extracting the staying and the moving periods of a user from accelerometer data daily captured with the user's smartphone. Wi-Fi radio information associated with geographic locations are collected and updated automatically in each period. Evaluation experiment results demonstrated that the positioning accuracy was more than 90% with the granularity of 4 m. Regarding the staying period, the classification accuracy of Wi-Fi samples created at user's stay points were 97 %, while the accuracy of path identification was 95% for the paths longer than 14.4 m in the moving period.

1. Introduction

Wi-Fi-based indoor positioning methods have been attracting the attention of researchers because of the low deployment cost due to the ubiquity of Wi-Fi signals transmitted from access points in various places. Wi-Fi fingerprinting-based positioning method needs a Wi-Fi radio environment map, which consists of absolute position data associated with observed Wi-Fi radio information in advance. The map has to be periodically updated with the latest Wi-Fi radio information because Wi-Fi access points are susceptible to be newly placed, removed, and moved, and it takes huge maintenance cost.

In this paper, we propose a method to automatically manage Wi-Fi samples depending on user's behavioral characteristics using data from accelerometer and Wi-Fi signal information collected for a certain period of time by the user's smartphone. We classify the states of the user into staying and moving based on the user's walking steps detected by the accelerometer, and then manage Wi-Fi samples according to the period of staying or moving.

In the staying period, Wi-Fi samples, which include BSSID, ESSID, RSSI, and the frequency of observation, are created and associated with the stay point. If similar Wi-Fi samples are created, the positioning accuracy will decrease because there is the possibility of wrong Wi-Fi sample being selected. Therefore, a new Wi-Fi sample is not created and only updated if similar sample is found among the many existing Wi-Fi samples. The samples can adapt to Wi-Fi environmental changes in this manner.

In some cases, however, Wi-Fi samples can be created at the same stay point due to Wi-Fi radio signal fluctuation, and it is required to be prevented. It is known that there are "ill-behaved access points" such as mobile routers, which decrease the positioning accuracy, and therefore needs to be removed from Wi-Fi samples. In other cases, Wi-Fi samples cannot be created properly at different stay points while a user is moving due to the fixed threshold value of creating Wi-Fi samples, and it needs to be resolved by allowing the creation of many samples first with the weak threshold value then filter some samples with the strong threshold value followed by the localization performed with the filtered Wi-Fi samples. These processes are performed at fixed intervals.

In the moving period, Wi-Fi signal information cannot be associated with the observed positions because Wi-Fi signal can be observed at each scan and each observed position is unknown and different from each other. We propose to associate each scan with Wi-Fi signal information of the scan. The Wi-Fi signal information associated with each scan is named "scan Wi-Fi sample." Normal Wi-Fi sample is created in a staying period, while the scan Wi-Fi sample is created in a moving period. Since the number of similar scan Wi-Fi samples can be large, the size of the scan Wi-Fi samples needs to be properly restricted.

In the rest of this paper, we detail our approach, explain the evaluation of our proposed method, and conclude.

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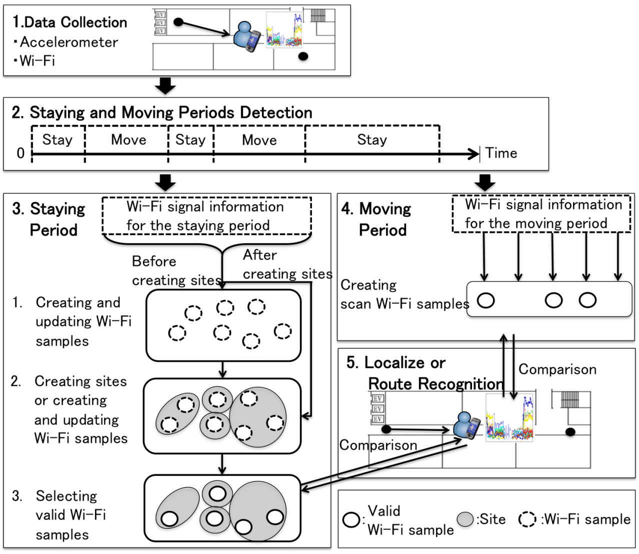


Fig. 1 System Concept Diagram

2. System Overview

The overview of the proposed system is illustrated as a concept diangram in **Fig. 1**. We assume the offline data processing after the data acquisition from accelerometer and Wi-Fi device.

First, a user's walking step is detected using the data from accelerometer. If the walking step is detected continuously in a certain period of time, the period is detected as moving period; otherwise, the period is detected as staying period.

In the staying period, a Wi-Fi sample is created if the similarity between new Wi-Fi signal information and existing Wi-Fi samples is lower than threshold α. Wi-Fi samples are created as many places a user stay as possible by setting α large. Wi-Fi sample is updated with new Wi-Fi signal information if similarity is larger than threshold β. In some cases, however, Wi-Fi samples are created at the same stay point due to the Wi-Fi radio signal fluctuation. We need to limit creating samples at the same stay point. In addition, we need to remove ill-behaved access points such as mobile routes to prevent decreasing the positioning accuracy.

Therefore, we introduce the concept of "site," which represents a set of Wi-Fi samples from the similar Wi-Fi radio environment observed for a certain period of time. Site can limit the creation of samples at the same stay point and remove ill-behaved access points. Wi-Fi samples are created by using α. Although Wi-Fi samples are created by using α, α is too large to accurately localize a user's stay point. Therefore, Wi-Fi samples are selected by using α', which is smaller than α. The selected Wi-Fi samples are named and become available to be used for localization. Data collection continues for localization, and the same process is performed after a certain period of time. In that case, newly observed Wi-Fi signal information is compared to all sites. If a site is similar to the new Wi-Fi signal information, the information is compared to Wi-Fi samples of the site.

In the moving period, a scan Wi-Fi sample is created at each scan. However, the accuracy of localization could decrease because the scan Wi-Fi samples created at sequential scans are similar. Therefore, some scan Wi-Fi samples are not created if new Wi-Fi signal information observed at one scan is similar to existing scan Wi-Fi samples.

Finally, localization is performed with available Wi-Fi samples and scan Wi-Fi samples.

3. Classifying Staying and Moving Period

User's walking step is calcurated by using data from accelerometer of the user's smartphone. We applied a walking step detection algorithm[15], where a walking step is detected if the difference between the maximum and minimum value of the accelerometer's smoothed synthesized value of three axes is above a certain threshold. If the user's walking step is continuously observed in a certain period of time, the period is classified as a moving period; otherwise the period is classified as a staying period.

4. Wi-Fi Samples Management in the Staying Period

Wi-Fi sample is created when Wi-Fi signal information is newly observed during the staying period. Wi-Fi sample consists of BSSID, ESSID, RSSI, FREQUENCY, and OBSERVEDTIME fields. BSSID and ESSID are identifiers for Wi-Fi access points, while RSSI is the received signal strength of each access point calculated by averaging all the observed data during the staying period. FREQUENCY is the number of observations during the staying and OBSERVEDTIME is the accumulated time of staying periods. Eq.(1) is a mathematical formula for "virtual distance," which is used to verify the similarity of samples. Wi-Fi sample is created if the virtual distance between new Wi-Fi signal information and existing Wi-Fi samples is larger than threshold α, while Wi-Fi sample is only updated with new Wi-Fi signal information if the virtual distance is smaller than threshold β.

$$dist(F_w, F_c) = \sqrt{\frac{\sum w_c \times (r_w - r_c)^2}{\sum w_{cF_{com}}}} \times \left(\frac{\sum w_{F_{w-com}} + \sum w_{F_c}}{\sum w_{cF_{com}}} + \frac{|\sum w_{cF_{com}} - \sum w_{wF_{com}}|}{\sum w_{cF_{com}}} \right) \quad (1)$$

$$w = \frac{frequency}{maxFrequency} \quad (2)$$

F_w is a set of access points identified with newly observed Wi-Fi signal information and F_c is a set of access points of Wi-Fi samples. F_{com} is the intersection of F_w and F_c. r_w represens the RSSI of each member access point of F_w, while r_c represents the RSSI of each member access point of F_c.w$_{F_w}$, $w_{F_{com}}$, $w_{F_{w-com}}$, and w_{F_c} are the weights of access point according to the value of FREQUENCY calculated with the Eq.(2) so that they can reduce the influence of noisy access points. However, the influence of ill-behaved access points cannot be reduced by the weight value.

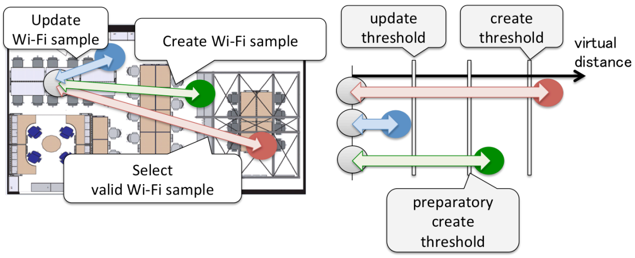


Fig. 2 Three thresholds for virtual distance

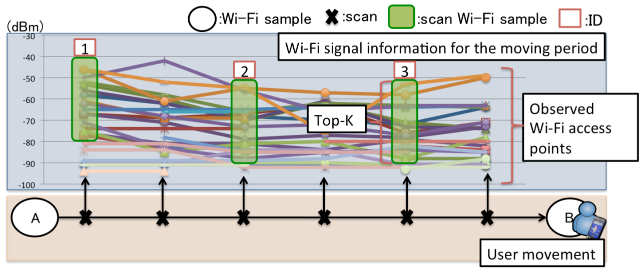


Fig. 3 Scan Wi-Fi samples

We introduce three threshold values for the virtual distance as shown in **Fig. 2**. The first one is "update threshold" β, which has the smallest value, and a Wi-Fi sample is updated if the virtual distance is smaller than the threshold β. The second one is "preparatory create threshold" α, which is larger than the update threshold, and a Wi-Fi sample is created If the virtual distance is larger than the threshold α. The third one is "create threshold" α', which is larger than the preparatory create threshold α, and an available Wi-Fi sample is selected if the virtual distance is larger than the threshold α'.

Wi-Fi samples are managed automatically with the virtual distance and thresholds. The virtual distance is calculated between newly observed Wi-Fi signal information and other existing Wi-Fi samples. Although Wi-Fi sample is updated or created according to the thresholds, several Wi-Fi samples can be created at the same stay point due to the Wi-Fi radio signal fluctuation. We need to somehow avoid creating samples at the same stay point, as well as remove the effect decreased positioning accuracy caused by ill-behaved access points. As such, we employ the method of grouping Wi-Fi samples observed in a similar Wi-Fi radio environment for a certain period time into an entity named Site[7].

A set of Wi-Fi samples is selected as a site by sorting in descending order of OBSERVEDTIME and grouping them according to a certain virtual distance calculated with Eq.(1). After the creation, Wi-Fi samples are managed on a per site basis. When new Wi-Fi signal information is observed, it is compared with a representative Wi-Fi sample with the largest OBSERVEDTIME in each site. A site with the smallest virtual distance between the new Wi-Fi signal information and the representative Wi-Fi sample is selected. Then, the virtual distance between the new Wi-Fi signal information and Wi-Fi samples belonging to the selected site is calculated, and the Wi-Fi samples are updated or a new Wi-Fi sample is created according to the calculation result. Finally since Wi-Fi samples are created with a preparatory create threshold value at this stage, valid Wi-Fi samples are determined by selecting Wi-Fi samples at each site in the descending order of OBSERVEDTIME and calculating the virtual distance between the Wi-Fi signal information and valid Wi-Fi samples to find items with the distance larger than the create threshold. Wi-Fi sample is selected as a valid Wi-Fi sample if the virtual distance between the Wi-Fi sample and valid Wi-Fi samples is larger than the create threshold. Valid Wi-Fi samples are re-selected at fixed interval according to the change of user's stay point, such as moving from one seat to other seats in an office.

5. Wi-Fi Samples Management in the Moving Period

Scan Wi-Fi samples are created at each scan like **Fig. 3**. In the case of moving period, unique sequential identifier is allocated to each scan Wi-Fi sample. In addition, access points with Top-K RSSI values are used to eliminate the effect of large signal fluctuations at the access points observed on a moving path.

However, since scan Wi-Fi samples created at sequential scans are highly similar with each other, the accuracy of localization decreases if we adopt these samples. Therefore, we do not create scan Wi-Fi samples if new Wi-Fi signal information of a scan is similar to existing scan Wi-Fi samples. The similarity between the new Wi-Fi signal information and existing scan Wi-Fi samples is is measured in the virtual distance, and scan Wi-Fi sample is created if the virtual distance is larger than create threshold.

6. Localization and the Recognition of the Same Route

In real-time, localization and route recognition are performed with valid Wi-Fi samples and scan Wi-Fi samples. In the staying period, real-time Wi-Fi signal information is compared with sites or valid Wi-Fi samples. Virtual distance between real-time Wi-Fi signal information and sites or valid Wi-Fi samples is calculated. If the distance is smaller than update threshold, the Wi-Fi sample's predefined label name is output as the result of route recognition. In the moving period, real-time Wi-Fi signal information is compared with scan Wi-Fi samples based on routeDistance calcurated with Eq.(3).

$$routeDistance(F_w, F_c) = dist(F_w, F_c) \times diff(N_c, N_p) \quad (3)$$

$$diff(N_c, N_p) = \begin{cases} 1 & (if N_c - N_p = 0) \\ |N_c - N_p| & (otherwise) \end{cases} \quad (4)$$

$$matchRate = \frac{matchCount}{scanCount} \times 100(\%) \quad (5)$$

The dist(F_w,F_c) means virtual distance between F_w and F_c. N_c is the id of the current scan Wi-Fi sample and N_p is the id of previously matched scan Wi-Fi sample. Some routes are selected if the routeDistance is smaller than a

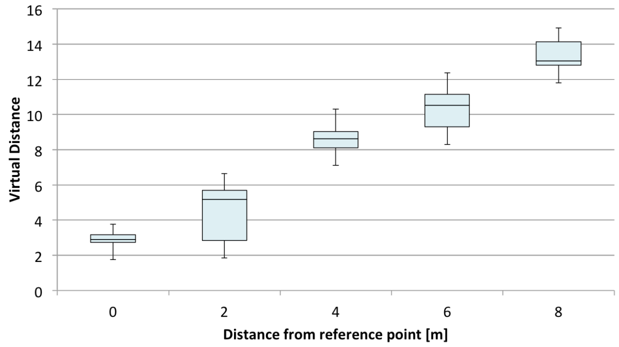


Fig. 4 The relationship between real and virtual distances

certain threshold. The route on which a user is moving is detected among the selected routes by matchRate. The scanCount represents the number of scans during the moving period from a user's start time to the current time. The matchCount is the number of route selection. The route with the highest matchRate is regarded as the same route taken by the user.

7. Evaluations

7.1 Verification of the Distance between Wi-Fi Samples

We verified the distance between Wi-Fi samples and scan Wi-Fi samples. User's position is most finely localized if Wi-Fi samples are created at user's all stay points. However, some Wi-Fi samples are not created to avoid the degradation of localization accuracy due to the high similarity between samples. Therefore, the distance between Wi-Fi samples are evaluated to know the distance for each individual Wi-Fi sample. Fixed-point observation is performed at a reference point and the points 2 m, 4 m, and 8 m away from the reference point for one hour. A Wi-Fi sample is created for each point. We randomly chose the start time among Wi-Fi signal information observed at the reference point, and calculated the virtual distance between feature values created for 5 minutes from the chosen start time and Wi-Fi samples created at each point.

Fig. 4 shows the relationship between real and virtual distance. The virtual distance from the Wi-Fi samples created at the reference point is about 4 at maximum. Whereas, the minimum virtual distance is about 7 at 4 m. It is, therefore, possible to identify Wi-Fi samples if there are at least 4 m between Wi-Fi samples, and we adopted threshold values 5 for α, 7 for α', and 4 for β.

In the moving period, scan Wi-Fi samples are created and the distance between the scan Wi-Fi samples is verified as well. Timestamps are collected when a user pass through check points while the user is moving along a path. **Fig. 5** shows the relationship between the points where scan Wi-Fi samples are created and the time when they are created. The difference between the creation time of scan Wi-Fi samples is 12 seconds at maximum. Suppose the walking velocity of a user is 1.2 m/sec, we can create a scan Wi-Fi sample and determine a walking route if the minimum length is at least

Table 1 Simulation patterns

Pattern name	Description
PatternAC	Points A and C are visited 40%, point B is visited 20%
PatternB	Point B is visited 60%, points A and C are visited 20%
PatternACtoB	Pattern AC is conducted first, patternB is conducted after a certain period of time

14.4 m.

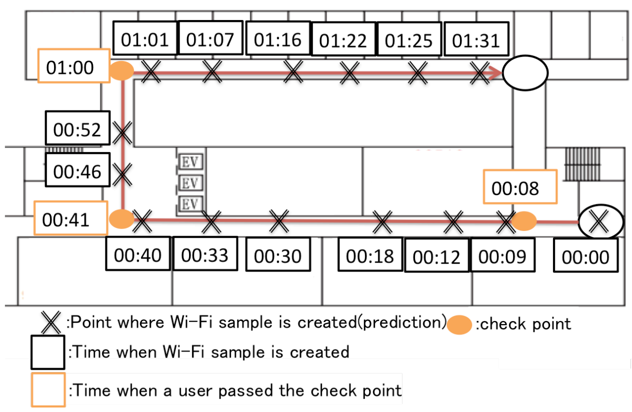


Fig. 5 The relationship between the points where scan Wi-Fi samples are created and the time of creation

7.2 Staying Period Evaluation

The automated management system with two steps is evaluated by a simulation of human behavior. An experiment is carried out in our laboratory. A fixed observation was conducted at three places for two weeks. The three places A, B, and C are illustrated in **Fig. 6**.

We have already verified that the distance over 6 meters between samples is sufficient for accurate positioning, and the distance between A and C is over 6 meters. Whereas the distance between A and B is less than 6 meters, and samples created at A and B are insufficient. The samples created at B and C are insufficient as well.

In the simulation, a user visits each place at 5-minute interval. In addition, Wi-Fi radio signal statistics are collected for 5 minutes. After 5 minutes passed, the user randomly visits other places or stays at the same place. Wi-Fi radio signal statistics are again collected for 5 minutes. The simulation is performed by repeating these steps. This simulation represents a human behavior such as a user keeps staying at one place for 5 minute and then move to another place. A sample is created and updated with Wi-Fi radio signal statistics collected at each place for 5 minutes. Positioning is performed every 5 minutes as well. We prepared a few simulation patterns by changing the transition probability among the places. These patterns are described in **Table 1**.

The Precision and the Recall are calculated by the following formulas for the evaluation.

$$\text{Precision} = \frac{\text{Number of correct system output}}{\text{Number of all positioning}} (\%) \quad (6)$$

$$\text{Recall} = \frac{\text{Number of correct positioning}}{\text{Number of all positioning}} (\%) \quad (7)$$

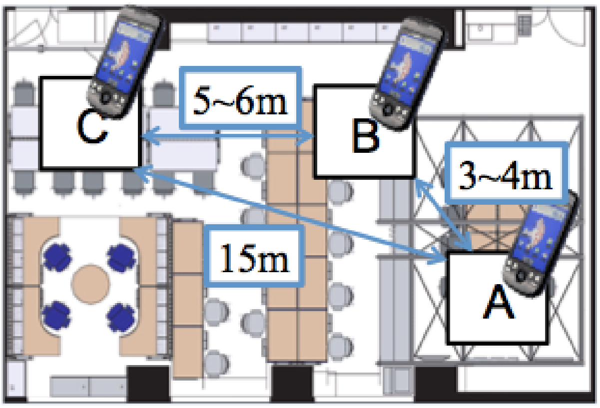


Fig. 6 Fixed observation points

Precision indicates what is correct for the system. "Update threshold" is used for positioning. The distance between Wi-Fi radio signal statistics a user is currently observing and samples is calculated. A sample is selected if the distance is the smallest. The sample is selected as an output if the distance is smaller than "Update threshold." Correct behaviors for the system are that outputting a valid sample if a user visits a place where the sample is created, and not selecting a valid sample if a user does not visit places where samples are created. The Recall indicates the degree of completeness for positioning. Correct behaviors for positioning are to output a valid sample if a user visits a place where the sample is created.

First, we describe the evaluation of PatternAC. **Fig. 7** indicates the Precision and the Recall for each day. Wi-Fi samples are created at A, B, and C. Two samples created at A and C are selected as valid samples. 80% of the positioning is performed at places where selected valid samples are created. On the other hand, 20% of the positioning is performed at places where samples not selected as valid are created. The Precision of the system is about 80% on the 9th day because the system outputs that the sample is created at A though a user actually visits B. The Recall of the system is about 80% because the Recall decreases when a user visits B.

Second, the evaluation with PatternB is described. Wi-Fi samples are created at A, B, and C. A sample created at B is selected as a valid sample. 60% of the positioning is performed at places where selected valid samples are created. Whereas, 40% of positioning is performed at places where samples not selected as valid are created. The Precision of the system is about 80% on the 5th day because the system outputs a sample, which is created at B though a user visits A. The Precision of the system is almost the same in the whole period. The Recall of the system is about 60% because the Recall decreases when a user visits A and C. These results of PatternAC and PatternB showed that the Precision is about 90% because the Wi-Fi samples are updated and the Recall is maintained. Therefore, localization can be performed with high accuracy for a long period.

Finally, we explain the evaluation with PatternACtoB. In this pattern, we evaluated to adapt samples to a rapid environmental change. The systems to be compared are the same as before. A user frequently visits A and C at first, though, the user frequently visits B after a fixed interval. The pattern change is performed on the 7th day. The system can adapt samples to the rapid environmental change because samples important to a user are selected according to the pattern changes. This result shows that the system can select valid samples according to Wi-Fi environmental changes like user's movement.

Table 2 Cluster prrecision of site

Label	Cluster Precision
Class Room	0.875
Hall	1.0
Lab	0.92
Store	1.0
Home	1.0
Cafeteria	0.86
Room	1.0
Restaurant1	1.0
Restaurant2	1.0
Restaurant3	1.0
Restaurant4	1.0
Restaurant5	1.0
Average	0.971

7.2.1 Site Evaluation

The data from accelerometer and Wi-Fi signal information is collected in two weeks. A user records the name of stay point at each stay point. 113 Wi-Fi samples and 10 sites are created.

First, the precision of site is evaluated with Cluster Precision[6]. If Cluster Precision is 1, it means that the site is precisely classified. **Table 2** indicates that sites are precisely classified.

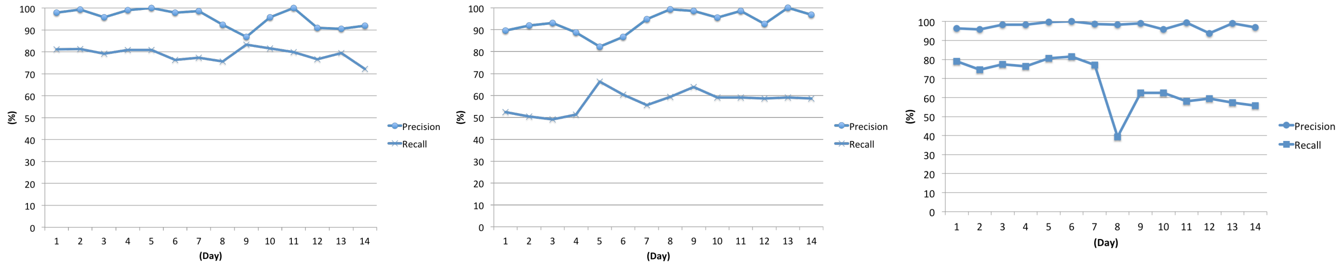
Next, the precision of localization is evaluated for the site creation. Evaluation is conducted at Lab, Home, and Room. The numbers of observed access points are 60 in Lab, 30 in Home, and 40 in Room. **Table 3** shows that the precision of localization increases when sites are created. The numbers of Wi-Fi samples are 4 in Lab, 7 in Home, and 5 in Room when sites are created The numbers are 5 in Lab, 8 in Home, and 6 in Room when sites are not created. The precision of localization increases because the creation of Wi-Fi samples at the same position is limited by applying the site mechanism.

Table 3 The precision of localization

	Lab	Home	Room
non_site	91.1%	90%	68.8%
site	93.3%	94%	81.3%

7.3 Moving Period Evaluation

Experimentation is performed to evaluate path matching. **Fig. 8** shows the experimentation environment. Wi-Fi signal information is collected every 3 seconds while a user is moving along each path. The matchRate is calculated while the user is moving along one path. The numbers of scan Wi-Fi samples are 30 for routeA, 31 for routeB,



(a) PatternAC (b) PatternB (c) PatternACtoB

Fig. 7 Precision and recall

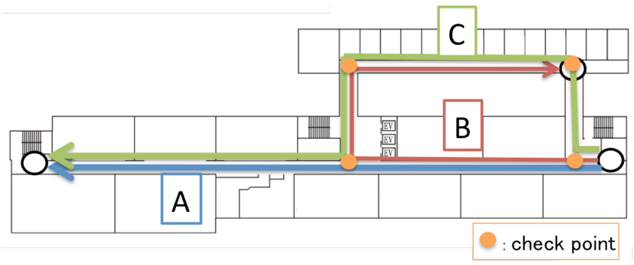


Fig. 8 Experimentation environment

and 41 for routeC when the scan Wi-Fi sample is not limited. Whereas the number of scan Wi-Fi samples are 12 for routeA, 15 for routeB, and 22 for routeC when the scan Wi-Fi sample is limited. **Fig. 9** shows that the matchRate of all route(Unique) is over 90. The match Rate rapidly decreases when the scan Wi-Fi sample is limited. In addition, **Fig. 10** indicates that the scan Wi-Fi sample ID value monotonically increases according the user's movement along the path and the user's route can be roughly identified based on the information.

8. Related Work

Low-cost indoor positioning methods have been proposed to date. Chai[2] proposed a method to reduce the effort of collecting Wi-Fi signal information. Krishna[3] and Wang[11] proposed methods which do not collect Wi-Fi signal information preparatory with GPS or some landmarks. However, these researches mainly consider the collection of Wi-Fi information and do not take the updating of Wi-Fi signal information into account.

Regarding the updating of Wi-Fi signal information, Bolliger[1] proposed a method that Wi-Fi signal information is updated automatically with some users' efforts. Pan[8] proposed a method that Wi-Fi signal information is updated automatically with Manifold co-Regularization. Yin[14] and [10] proposed a method that Wi-Fi signal information is updated automatically with some devices located indoor and observing new Wi-Fi signal information. However, these researches take much cost because they need to combine Wi-Fi signal information with latitude and longitude.

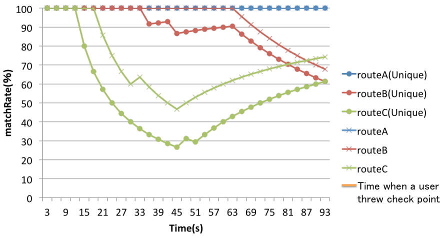
To cope with these costs, Froehlich[4] and Hightower[5] proposed methods that automatically create samples with the signal of Wi-Fi or Cellular phone base stations by focusing on the places a user visited. Hyojeong[9] proposed a method for automatically creating Wi-Fi samples by K-means clustering. However, these researches do not consider the updating of Wi-Fi samples.

Jiang[13] proposed a method that Wi-Fi samples are automatically created and updated by focusing on user stay points. However, the scope of localization is too large to use some applications, such as reminding service, behavior recognition and so on, because this method focuses on the room localization. In addition, this method cannot recognize the moving period. Many services cannot be conducted on path if the recognition of movement cannot be performed. Jiang[12] proposed a method that recognized the moving path with room Wi-Fi samples. However, this method cannot recognize paths without room Wi-Fi samples. In addition, it cannot detect the progress of movement on the path.

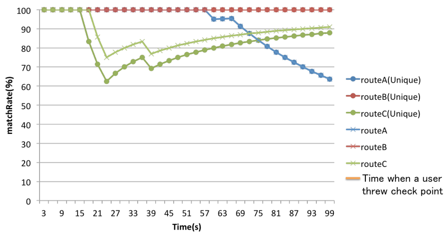
9. Conclusion

We proposed an automated Wi-Fi sample management method depending on the user's behavioral characteristics for low cost localization. The distance between distinguished Wi-Fi samples created at stay points was calculated, and it was possible to recognize the stay points if the distance is over 4 m. In addition, in the staying period, Wi-Fi samples created at the user's stay points were classified with about 97% accuracy according to the similarity of Wi-Fi environment. Positioning accuracy increased 12.5% by removing wasteful samples. The accuracy of similarity calculation for positioning increased about 11.9% by removing ill-behaved access points where there are many ill-behaved access points. It indicates that it is possible to increase positioning accuracy. In the moving period, the distance between distinguished Wi-Fi samples created on a path was calculated, and it was possible to recognize paths if the path length is over 14.4 m. The path was identified with 95% accuracy, and it was possible to localize the user's position approximately.

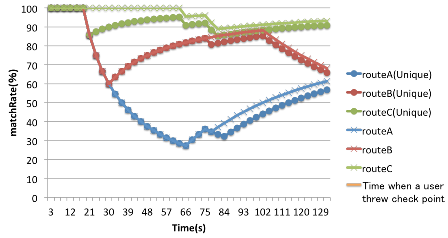
In the future, scan Wi-Fi samples need to be updated automatically to follow Wi-Fi radio environmental changes. Ill-behaved access points need to be detected automatically in advance because currently it is detected with accumulated data. In addition, the route recognition needs to be considered with a user's walking pace because the user's walking pace is unstable. Finally, we plan to apply the route recognition we proposed to the hall context recognition.



(a) routeA

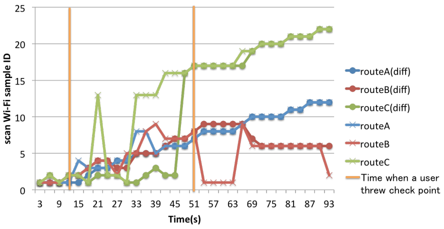


(b) routeB

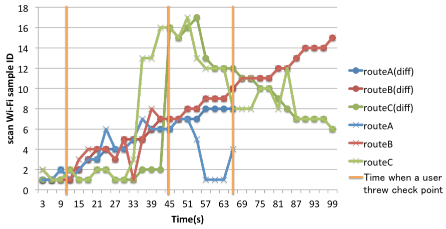


(c) routeC

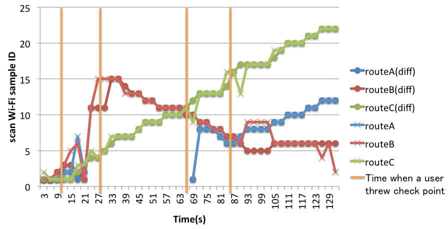
Fig. 9 matchRate



(a) routeA



(b) routeB



(c) routeC

Fig. 10 ID of scan Wi-Fi sample

References

[1] Philipp Bolliger. 2008. Redpin - Adaptive, Zero-configuration Indoor Localization Through User Collaboration. In *Proc. ACM International Workshop on Mobile Entity Localization and Tracking in GPS-less Environments (MELT '08)*. ACM, 55–60. DOI:http://dx.doi.org/10.1145/1410012.1410025

[2] Xiaoyong Chai and Qiang Yang. 2007. Reducing the Calibration Effort for Probabilistic Indoor Location Estimation. *IEEE Transactions on Mobile Computing* 6, 6 (2007), 649–662. DOI:http://dx.doi.org/10.1109/TMC.2007.1025

[3] Krishna Chintalapudi, Anand Padmanabha Iyer, and Venkata N. Padmanabhan. 2010. Indoor Localization Without the Pain. In *Proc. Annual International Conference on Mobile Computing and Networking (MobiCom '10)*. Association for Computing Machinery, Inc., 173–184. DOI: http://dx.doi.org/10.1145/1859995.1860016

[4] Jon Froehlich, Mike Y. Chen, Ian E. Smith, and Fred Potter. 2006. Voting with Your Feet: An Investigative Study of the Relationship Between Place Visit Behavior and Preference *(Proc. of UbiComp'06)*. Springer-Verlag, 333–350. DOI: http://dx.doi.org/10.1007/11853565$_2$0

[5] Jeffrey Hightower, Sunny Consolvo, Anthony LaMarca, Ian Smith, and Jeff Hughes. 2005. Learning and Recognizing the Places We Go. In *Proc. International Conference on Ubiquitous Computing (UbiComp'05)*. Springer-Verlag, 159–176. DOI:http://dx.doi.org/10.1007/11551201$_1$0

[6] Tâm Huynh and Bernt Schiele. 2005. Analyzing Features for Activity Recognition *(Proc. of sOc-EUSAI '05)*. ACM, 159–163. http://doi.acm.org/10.1145/1107548.1107591

[7] Nishio Nobuhiko, Fukuzaki Yuuki, and Azumi Takuya. 2013. Detecting Wi-fi Base Station Behavior Inappropriate for Positioning Method in Participatory Sensing Logs *(Proc. of UbiComp '13 Adjunct)*. ACM, 665–672. DOI: http://dx.doi.org/10.1145/2494091.2495987

[8] Sinno Jialin Pan, James T. Kwok, Qiang Yang, and Jeffrey Junfeng Pan. 2007. Adaptive Localization in a Dynamic WiFi Environment Through Multi-view Learning. In *Proc. National Conference on Artificial Intelligence - Volume 2 (AAAI'07)*. AAAI Press, 1108–1113.

[9] Hyojeong Shin and Hojung Cha. 2010. Wi-Fi Fingerprint-Based Topological Map Building for Indoor User Tracking *(Proc. of RTCSA '10)*. IEEE Computer Society, 105–113. DOI:http://dx.doi.org/10.1109/RTCSA.2010.23

[10] Daisuke Taniuchi and Takuya Maekawa. 2015. Automatic Update of Indoor Location Fingerprints with Pedestrian Dead Reckoning. *ACM Trans. Embed. Comput. Syst.* 14, 2, Article 27 (Feb. 2015), 23 pages. DOI: http://dx.doi.org/10.1145/2667226

[11] He Wang, Souvik Sen, Ahmed Elgohary, Moustafa Farid, Moustafa Youssef, and Romit Roy Choudhury. 2012. No Need to War-drive: Unsupervised Indoor Localization. In *Proc. International Conference on Mobile Systems, Applications, and Services (MobiSys '12)*. ACM, 197–210. DOI: http://dx.doi.org/10.1145/2307636.2307655

[12] Jiang Yifei, Yun Xiang, Pan Xin, Li Kun, Lv Qin, Dick Robert P., Shang Li, and Hannigan Michael. 2013. Hallway Based Automatic Indoor Floorplan Construction Using Room Fingerprints *(Proc. of UbiComp '13)*. ACM, 315–324. DOI:http://dx.doi.org/10.1145/2493432.2493470

[13] Jiang Yifei, Pan Xin, Li Kun, Lv Qin, Dick Robert P., Hannigan Michael, and Shang Li. 2012. ARIEL: Automatic Wi-fi Based Room Fingerprinting for Indoor Localization *(Proc. of UbiComp '12)*. ACM, 441–450. DOI: http://dx.doi.org/10.1145/2370216.2370282

[14] Jie Yin, Qiang Yang, and Lionel Ni. 2005. Adaptive Temporal Radio Maps for Indoor Location Estimation. In *Proc. IEEE International Conference on Pervasive Computing and Communications (PERCOM '05)*. IEEE Computer Society, 85–94. DOI: http://dx.doi.org/10.1109/PERCOM.2005.7

[15] Shun Yoshimi, Kohei Kanagu, Masahiro Mochizuki, Kazuya Murao, and Nobuhiko Nishio. 2015. PDR Trajectory Estimation Using Pedestrian-space Constraints: Real World Evaluations *(Proc. of UbiComp/ISWC'15 Adjunct)*. ACM, 1499–1508.