Wi-Fi Fingerprint-Based Topological Map Building for Indoor User Tracking

Hyojeong Shin
Department of Computer Science
Yonsei University
Seoul, Korea
hjshin@cs.yonsei.ac.kr

Hojung Cha
Department of Computer Science
Yonsei University
Seoul, Korea
hjcha@cs.yonsei.ac.kr

Abstract— **Estimating the geographical position of mobile device such as Smartphone in an indoor environment is not easy without the use of specific infrastructures. In this article, we introduce an indoor user tracking system. The system constructs a topological map with Wi-Fi signal calibrations, assigns semantically meaningful labels into the map, and estimates the semantic location of the user based on the current Wi-Fi observation. The system does not require a geometric map, or costly radio map building process. We implemented the system with the off-the-shelf Smartphone and experimentally validated the scheme.**

Keywords- Wi-Fi Fingerprint; Topological SLAM; Pedestrian Tracking; Localization.

I. INTRODUCTION

The location information of a user promises to provide attractive services in ubiquitous computing environments. Over the years, diverse user tracking systems have been developed. In an outdoor environment, Global Positioning Systems (GPS) [1] provide precise locations of mobile devices with worldwide coverage. GPS, however, has a shadow problem and is not available in indoor environment. In indoor environments, radio technologies, such as Wi-Fi and cellular signals, are used as observations for location estimates and provide a wide coverage, especially in urban environments. One successful approach for indoor user tracking is a Wi-Fi based fingerprint [2][3]. The technique builds a radio map by measuring the Wi-Fi signals at each reachable calibration point *a priori*, and tracks a mobile device based on run-time observation of the Wi-Fi signals. In these fingerprinting-based approaches, in order to maintain the radio map composed of a calibration vector, which is a set of signal strengths of observable access points (APs), system manager should visit every reachable location and measure the Wi-Fi signals periodically. Interestingly, recent Smartphones are commonly equipped with GPS and Wi-Fi modules, which are adequately used for user tracking system both in outdoor and indoor environments.

Tracking user location is inherently different from the case in robotics. The conventional robot tracking system utilizes highly accurate observation sensors such as a laser rangefinder, multi-dimensional sonar sensor, or image sensor. The trajectory of a mobile robot is estimated simply and accurately with a wheel encoder, for example. Tracking solutions for mobile users, however, should overcome course-grained observation sensors and inaccurate navigation information. Active research has been conducted on indoor pedestrian tracking [4][5]. They equipped a foot-mounted inertial sensor module to encode the steps of the user and used additional sensors such as gyrometers and magnetometers to measure the orientation of the user. Unfortunately, the foot-mounted module is hardly accepted in our daily life. The tracking system using the only sensors embedded in Smartphon is a feasible solution although the inertial sensors equipped in Smartphone has low accuracy.

In contrast to an outdoor map, an indoor map is hardly prepared before the user visits the place. With the lack of *a priori* map data, the tracking system is needed to provide the realtime map building and mapping for the anonymous place. Active research has been conducted on automatic map-building from observations [6]. The work is generalized as Simultaneous Localization and Mapping (SLAM). Full geometric maps of SLAM may consist of thousands of states, and building and dealing with the maps may be computationally expensive. For pedestrian tracking with Smartphone, a topological mapping technique for SLAM is a possible solution. The topological SLAM builds a map composed of places and paths instead of the geometric image of space. The topological SLAM effectively reduces the number of states and the computational demands of mapping. Hence, the topological SLAM is adequate for the indoor localization problem with Smartphone, which removes the offline training phase.

The location of a mobile object is usually represented by the geometric position, composed of longitude, latitude, and altitude. Humans, however, tend to prefer semantic locations to geometric ones. For example, we visit places labeled “my office,” “cafeteria,” “library,” “lecture room,” and so on, and remember the places by name. For navigation purposes, a sketch map, which provides the labeled places and abstract paths, may guide us to the destination. Therefore, the labeled topological map, rather than a geometric one, is suitable for human tracking applications.

In this paper, we describe an indoor user tracking system that automatically builds a labeled topological map and estimates the users’ location. The system consists of three phases; place learning, place naming, and place estimation. Place learning is to build a human-readable map. In this phase, the system uses Wi-Fi signals as an environmental observation, and uses motion sensors to detect the kinetic movement of the user. Based on the sensing data, the system automatically builds a topological map of Wi-Fi calibration vectors, and organizes spaces accordingly. Place naming assigns a label on the place in the topological map. Although users can manually name the places, we devised simple methods to extract semantic information from observations. Place estimation is designed to predict the current location of the mobile user based on current observations. Estimation is achieved by comparing the Wi-Fi signal with the calibrated vectors. Our system is specifically designed for the commercially available Smartphones.

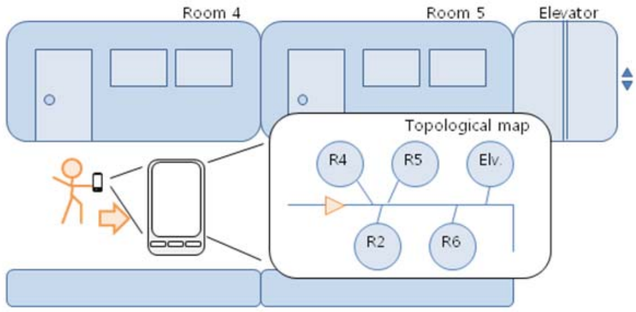
A key challenge in our system is to construct the map effectively. Our scheme employs the SLAM technique with Wi-Fi calibration as observations. While the user is walking around, the signal strength of the observed Wi-Fi signal is automatically measured and used as a landmark to construct the map. Since a Wi-Fi vector is a set of measured values in signal strength, the generated map is a topological map of Wi-Fi vector nodes. To track the trajectory of user, we built a step-counting-based navigation component that estimates the track using motion sensors. Another challenge is effectively extracting and organizing spaces from the radio map. We group the fingerprint vectors in the map into a set of spaces, based on the similarity of signal pattern. We employ a clustering algorithm to organize spaces, and the clustered topological map determines the division of a physical space. The final challenge is to assign a label to the space on the map. Although the user can label the place on the map, we introduce simple automatic methods to extract semantically meaningful place names from the observed data.

The contributions of our work are as follows. First, neither map data nor an offline calibration phase is required for the proposed tracking system. We automatically build a topological map, and effectively reduce the maintenance costs of the map. Second, our system does not require high performance observation sensors since the geometric location is not necessary. Third, the proposed scheme is implemented on real Smartphones and experimentally validated.

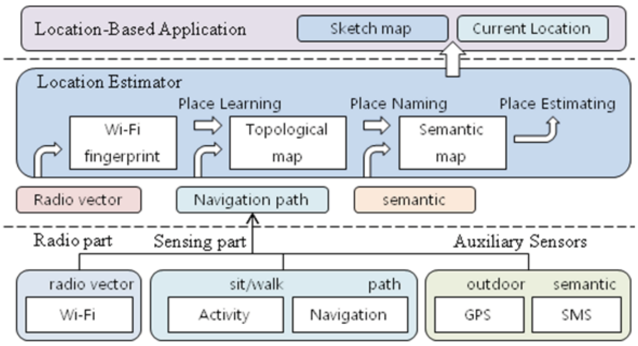
The rest of the paper is organized as follows. In Sections II, we describe the basic concept of the Wi-Fi fingerprinting-based topological SLAM system. Section III, the system is configured by an experimental methodology. Section IV discusses related work. Finally, we conclude the paper in Section V.

II. Wi-Fi Fingerprint-Based Topological SLAM

A pedestrian positioning system estimates the meaningful place name of a mobile user in a certain environment. Figure 1 illustrates the user tracking scenario and the architecture of the system. While the location of Smartphone user is tracked in indoor, the Wi-Fi signals are used as the observation tool for SLAM. The system builds a topological map and tracks the user's location. The hardware layer contains the Wi-Fi device, motion sensors, and an auxiliary observation source.



(a) User tracking scenario



(b) System architecture

Figure 1. User tracking scenario and system architecture

The positioning estimator is implemented in the middle layer, and builds the semantic map through three phases of place learning, place naming, and place estimating. The estimator provides the tracking information of the user. We implemented the system on an off-the-shelf Smartphone, the HTC Hero Android phone, and conducted the experiment in the building where our laboratory is located. On the floor where our laboratory is located, we found eight Wi-Fi access points. More access points on other floors were observed and used for the Wi-Fi calibration.

A. *Topological SLAM Approach*

SLAM is categorized into a metric SLAM and a topological SLAM. The metric framework considers a two-dimensional space in which the objects are placed with precise coordinates. This representation is useful, but sensitive to noise and difficult to precisely calculate the distances. The topological framework only considers places and relations between them [7][8][9]. The map is a graph in which the nodes correspond to places and the edges correspond to the paths. This paper discusses the topological SLAM for indoor user tracking and considers various issues such as mapping, sensing, and location problems required for the system.

Sensing is one of SLAM's major technical problems, since the system builds a map based on sensing data. A typical SLAM uses a highly accurate sensing device, such as image sensors, laser rangefinders, and sonar sensors. Sensing should be accurate enough to differentiate one place from another, and also recognize a place when mobile device returns to where it has previously visited. Our framework employs a Wi-Fi fingerprint as a landmark observation. A Wi-Fi vector is easily identified and distinguished the other vectors from other places.

When using the Wi-Fi fingerprint technique for sensing method for SLAM, locating is simply achieved by searching for the nearest place within a set of pre-learned vectors. Because of the gap between the topological map and physical world, an additional place-learning technique is required, which determines a meaningful place from the topological map. In this paper, this goal is achieved by clustering radio vectors into groups which correspond to places where people reside. The groups are labeled and provided as a result of localization. Finally, the location of a mobile device is served to user as 'what place,' not as Wi-Fi vector.

B. Calibrating Wi-Fi fingerprinting vectors

We used Wi-Fi fingerprinting as the sensing device for SLAM. At a certain point in a building, the mobile device scans the Wi-Fi signals and saves them as a fingerprint vector. The i-th element of the topology map is represented as

$$\left(\mathrm{ID_i}, \left\{\overrightarrow{\mathrm{ss}}_{\mathrm{ij}} \middle| \mathrm{j} \in \mathrm{N_i}\right\}, \mathrm{I_i}\right), \tag{1}$$

where ID_i is the unique identifier of the vector, the vector ss_{ij} is the measured signal strength for the j-th access point, and the k-th element of the vector is denoted by ss^k_{ij}. I_i contains additional information such as inertial sensor data. We collect several signal strength measurements from the j-th access point into vector $\vec{y}_j$. The mean of the measurements is denoted by $\bar{y}_j$, which is the j-th component of vector $\bar{y}$.

The topological map is composed of distinguishable fingerprint vectors. Where two distributions of vectors have a large distance in signal space, two vectors are *distinguishable*. The degree of "distinguishability" is defined as the possibility that distributions of the measured signal strengths in two vectors do not overlap. Assuming two vectors have the same deviation, the overlapping probability of vectors is

$$1 - \mathrm{erf}\left(\frac{\mu_1 - \mu_2}{2\sqrt{2}\sigma}\right), \tag{2}$$

where μ_1 and μ_2 are the means of the signal strength sets and erf is the error function. With equation (2), given two vectors 1 and 2, the high overlapping probability means that two vectors are similar and the low probability addresses that two vectors are different each other. The minimum distance between sets of signal strengths is obtained within a given threshold for overlap. For simplicity of implementation, we calibrated the signal as a histogram and empirically determined the non-overlapping distance. The specific parameter is discussed in the preliminary experiment section.

With the measured fingerprint vector, we now build a topological graph. The clustering algorithm groups tightly connected vectors into a place based on the connectivity between vectors. The first step for building the map is to collect signal vectors. At a certain point, the mobile device measures the Wi-Fi signals from various access points. Since each access point has its own MAC address, the mobile device easily collects the fingerprint vector and uniquely names it. At a different position, the mobile device collects another vector when two vectors are distinguishable from each other. Each distinguishable vector is represented as a node in the graph model. The degree of similarity between vectors is represented as an edge. If the newly measured vector is found in the map, the mobile device is assumed to visit the place where it already visited, or a new vector is added to the map. Finally, the topological map is constructed in the form of a graph.

C. The similarity function

The topological map is composed of the distinguishable Wi-Fi vectors, which represent the unique landmarks in a signal space. Since the two vectors calibrated on nearby places have similar signal patterns, the vectors can be clustered based on similarity. With the measured vectors x and $\vec{y}_j$, the similarity function is defined as

$$s_{x,y} = \frac{1}{\|\bar{y} - \bar{x}\|}, \tag{3}$$

where $\bar{x}$ and $\bar{y}$ are the vectors of the means of the signal strength for each access point. In Equation (3), the norm $\|\cdot\|$ is arbitrary. In this article, p-norm is employed by applying the sample means of the signal strength

$$\|x\|_p = \left(\sum_{i=1}^{n} |x_i|^p\right)^{\frac{1}{p}}, \tag{4}$$

where x_i is an element of x. For the similarity function, alternative approaches are also available such as modified p-norm, infinity-norm and Mahalanobis-norm [10][11]. Assigning this similarity value to edges between the vectors, the topological map is built with the clustering algorithm.

The similarity function is the key function that distinguishes exclusive vectors and searches the vectors. Adjusting the physical characteristics of the radio signal, the similarity function can be improved. The signal strength measured nearby an access point (AP) varies widely and the measurement far from the AP is frequently failed. Both measurements are unreliable. Considering the characteristics, we experimentally enhanced the similarity function. The enhancement will be discussed in the experiment section.

D. Clustering

Clustering analysis categorizes a set of observations to subsets so that all observations in one cluster are similar to each other. With the definition of similarity function as in Equation (4), the distance between two Wi-Fi vectors can be calculated and the topological map can be clustered. We use the k-means clustering algorithm [12], which partitions the vectors into exclusive groups of k. The k-means clustering algorithm initially selects k seed vectors on the map and each vector is a single group. And each vector on the map selects the closest centroid which is the mean of the group, and joins the group. Each group updates the centroid of the group and repeats the previous selecting and joining. In steady state, there are k groups and member vectors of them.

The similarity function is applied as an objective function for the k-means algorithm. For our system, the k-means clustering was used to minimize the sum of the similarity within groups:

$$\sum_{i=1}^{k} \sum_{x_j \in G_i} s_{x_j,\mu_i} \;, \qquad (5)$$

where μ_i is the mean of G_i. The seed point k can be tested and selected by recursive simulations. After clustering, the group represents the place which will be labeled in the next section.

E. Naming policy

Labeling the place helps the user recognize the current place. Although the user can manually assign a name to the place after the map is built, our system supports automatic extraction of the semantically meaningful name of the place. In this section, we propose two simple schemes for automatic labeling.

First, we look for the strongest access point from the current location. The access point, which emits a strong radio signal, is simply assumed as being installed in the current location. During the experiments, we recognized that the name of some access points represents their affiliation. We can assign unlabeled places with the name of the nearest access point where the access point has strong signal strength over a threshold, -56 dBm in our experiment. With this method, we extracted meaningful words from our data set: "mobilelab," "hydrolab," "CEL," "CS," and so on. However, we found that many access points were operating in their factory configuration, hence sophisticated filters are required to prevent assigning meaningless names with this approach.

The second scheme is extracting the action of users from billing events, for instance, in our daily life. When people purchase a product with credit cards, the billing system deals with detailed information, such as the customer's private information, shop, and product information. From this, we can extract the meaningful information for the current location. For example, when the user buys a book, the current location is a bookstore. If the item is a cup of coffee, the user is assumed to be in a coffee shop. This system can be provided by mobile carriers and credit card companies. A card company in the author's country sends a text message (SMS) to the user's mobile phone when the user makes a purchase. The text carries billing date, price, and shop's name. The text parser extracts the shop's name and assigns the name on the current location. Although this example is dependent on the services of credit card companies and telecommunication carriers, it shows that the activity of the user observed from the billing event is tightly connected to the semantic meaning of the location.

F. Tracking a location

Because our system constructs a map with a Wi-Fi fingerprint vector, a Wi-Fi fingerprint-based localization algorithm is applied to estimate the position of the mobile node. In general, a Wi-Fi fingerprinting method constructs a radio map during the offline phase and estimates the current location by searching for k largest weighted positions, called the Weighted K-Nearest Neighbor Method (WKNN). The Nearest Neighbor method (NN), where k is 1, is used in our work, since our topological map is a subset of the total set of possible vectors and does not carry geometric information.

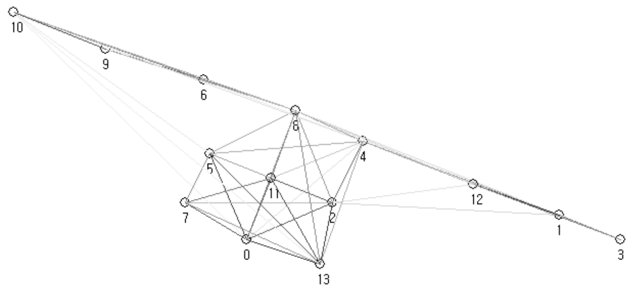


Figure 2. Wi-Fi calibration in office

Comparing a currently observed signal with vectors in the topological map, the current physical location of the user is obtained by searching for the nearest vector.

The clustering method partitions the map into multiple groups; hence, a group containing the selected vector by the NN method reveals the current location of the mobile device. The localization accuracy depends on the size of groups, and accuracy is related to the results of the clustering algorithm.

III. EXPEIMENTAL ANALYSIS

We implemented the proposed system and performed a preliminary experiment on Wi-Fi calibration. We developed our system on an off-the-shelf smart phone and conducted the experiment in a building where our laboratory is located.

A. Testbed setting

In our experiment the location of Smartphone user is tracked in indoor. We used the Wi-Fi as the observation signal for SLAM. The HTC Hero phone is used to implement the system. Hero runs the Android software stack and provides various communication components including Wi-Fi. The application is written in Java. On the third floor where our laboratory is located, we found 8 Wi-Fi access points. However, more access points on the other floors were observed and were used for the Wi-Fi calibration. Note that the Equivalent Isotropically Radiated Power (EIRP) of the Wi-Fi access points used in this experiment were limited to under 20 dBm by the Korean Telecommunication Law.

B. Preliminary experiment

The preliminary experiment was designed to understand the characteristics of the Wi-Fi signals obtained by mobile phones to configure our system. We calibrated the Wi-Fi signals in our office and an adjacent hallway at distances of 3 meters, and built the topological map with the calibration points. The number of samples was 100, and the sampling frequency was one sample every 0.8 seconds. The map and the experimental results are shown in Figure 2, where nodes represent calibration points and edges represent similarities. The result successfully reflects the structure of our environment. The standard deviation of the total observation was an average of 2.4 dBm, and varied from 0.9 to 4.9. Additionally, 90 percent of the sets of signals had a standard deviation under 3.7 dBm. One sample vector is shown in Table 1. The distributions are accurate enough to label a landmark in signal space. Figure 3 shows the overlapping probability of two separate signal sets, where both sets have the same deviation. Covering 90 percent of the vectors, two vectors are overlapped under 20 percent where two signal sets have 10 dBm distances.

TABLE 1. A SAMPLE VECTOR

SSID	Cnt.	Avr.	Min.	Max.	Std.	OR 10%	OR 20%
HotGuys	100	-60.5	-67	-58	2.14	7.06	5.50
dd-wrt	100	-71.9	-79	-67	2.54	8.38	6.53
iptime	100	-72.2	-76	-69	1.43	4.70	3.66
33333	84	-88.3	-93	-84	1.59	5.25	4.09
COMSYS3	100	-80.3	-89	-74	3.44	11.33	8.82
myLGNet	43	-88.2	-92	-82	2.48	8.17	6.36
COMSYS2	95	-86.7	-93	-81	2.49	8.22	6.40
myLGNet	100	-83.2	-90	-77	2.33	7.69	5.99

C. *Optimizing the similarity function*

The experiment outlined in this section configured the similarity function to build the topological map on the signal strength domain. The similarity function assigns the weight into the edge between Wi-Fi vectors based the observed signal patterns. We arranged the observed vectors on geometric plane to represent the adaptability of the map. The map, however, does not carry the geometric information.

In the experiment, we widened the space and calibrated 5 samples for each 1.5 meters. The first map is shown in Figure 4(a), where calibration points are denoted by nodes and the similarity by lines. The dark line means that two nodes are similar. Since there were neighboring offices and hallways, the topological map is a little complicated. The similarity is measured by Equation 2, with common sets of observable access points. The Euclidean distance is used where p is 2.

Although nodes A and B were located far from each other and had different sets of signals, they have a small similarity value. Concerning the set of visible access points, we assume that the invisible signal had the weakest signal strength (in this case, -99 dBm). This approach makes it

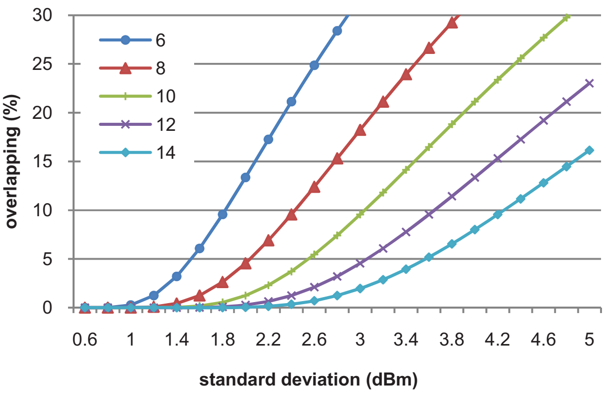
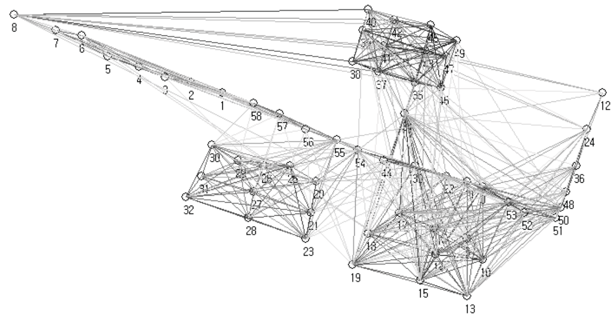
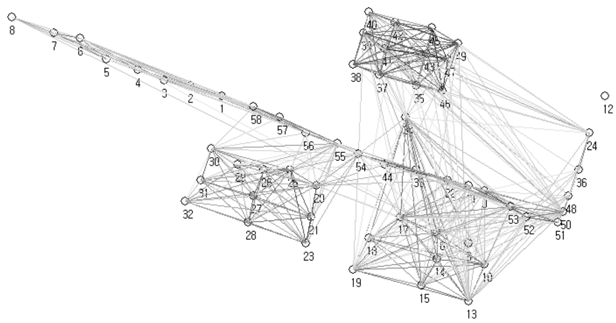


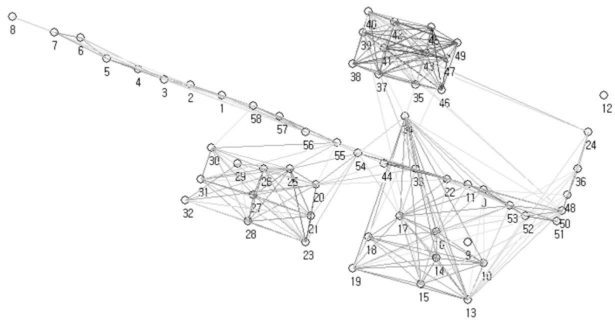
Figure 3. Overlapping probability between two vectors: the legend represents the difference of means (dBm)



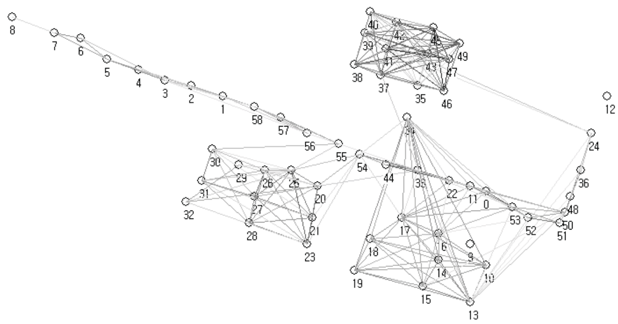
(a) Euclidean distance: comparing common sets of APs



(b) Comparing total sets of APs



(c) p-norm (p=4)



(d) p-norm (p = 6)

Figure 4. The optimization for the similarity function

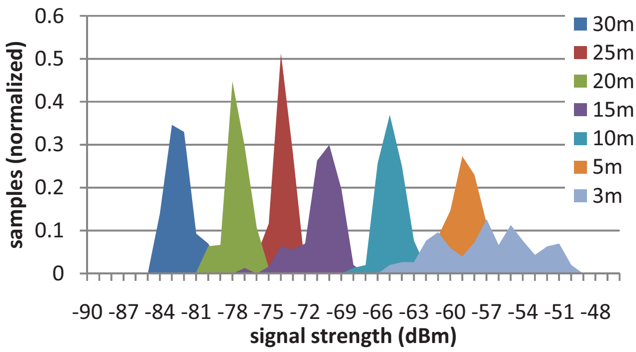


Figure 5. Distance and measured vector

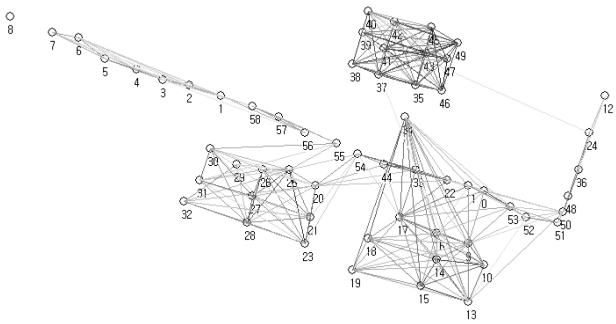
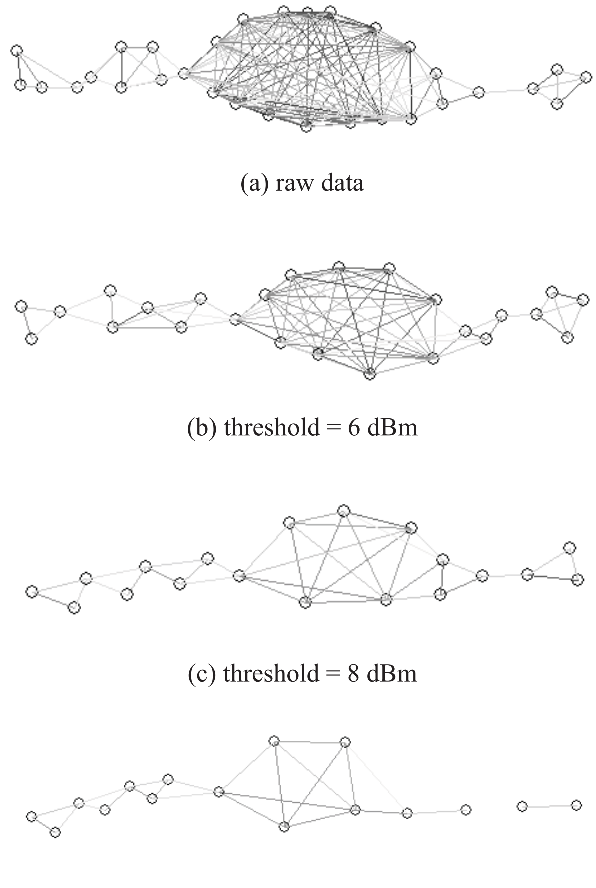


Figure 6. The final topological map



(a) raw data

(b) threshold = 6 dBm

(c) threshold = 8 dBm

(d) threshold = 10 dBm

Figure 7. The topological map with various resolutions; the vectors in the figure are manually arranged.

possible to compare the distance in signal space between two vectors with different sets of signals. The result is shown in Figure 4(b). Here, node A and B lose their connection.

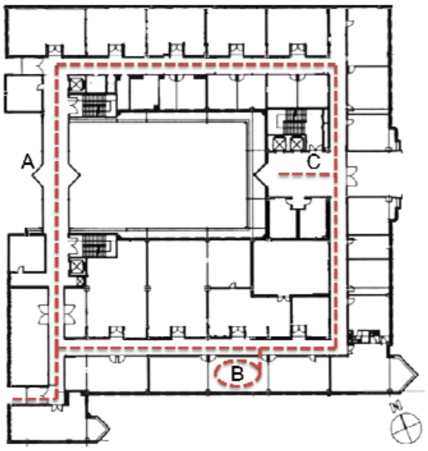
There was another false link between node A and C which had a common set of similar signals. Although two signals with large differences existed, the common set of signals dominated the similarity function. To remove this effect, we increased the p factor in the norm equation. Figure 4(c) and Figure 4(d) show the similarity between node A and C with the difference in p values. The larger p factor increases weight on the signal in the big difference. In our work, we used the six-norm. As a result, many links in the topology were weakened as the p factor increased.

To improve the similarity function, we observed the spectrum of the Wi-Fi signals. The Wi-Fi signal was calibrated in 100 samples at various distances from a single access point, and the result is shown in Figure 5. At the closest position, the signal shows a large variation and the partial calibration may generate enormous errors. Two calibrations at the distances of 3 and 5 meters show a big difference in signal space. This error was simply removed by limiting the maximum average signal strength. Meanwhile, scan failures existed within the weak part in the spectrum. To reflect this effect, each signal distance was weighted by the successful scan rate for each access point. Figure 6 shows that this adjustment slightly enhances the result because the reliable and stable information has high weights. Although the link between node D and E, which were calibrated in the same office, was weak in the previous result, it became strong in the current result.

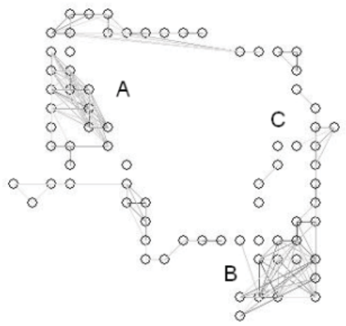
D. *Walking calibration*

The Wi-Fi calibration was performed while the user was walking. We measured five samples on each calibration point. Note that the HTC Android phone is able to measure five samples in three seconds. This sampling frequency has the coverage of five strides, and good enough to obtain room-level accuracy and find a meaningful place. We built a topological map while walking through the hallway and entered the office (see the scenario in Figure 2). The result shows that the topological map successfully found the office. The hallway was built as a linear path and the office was built in the form of a mesh. The calibration points on the map were arranged manually.

The system has generated calibration points for every five samples; hence, the map has plenty of nodes. Duplicated calibrations, which have similar signal patterns, were dropped. After the filtering phase, the map was composed of nodes that exclusively covered the signal space. The filtered map with various thresholds is shown in Figure 7. In the case of the 6-dBm threshold, duplicated nodes were successfully filtered out. The larger threshold removed more nodes, since each node had a larger coverage. In the case of the 10-dBm



(a) a building layout & moving path



(b) the topological map

Figure 8. The topological map measured by moving device

threshold, a room was built with about six nodes, while the previous case was built with 12 nodes. Since the number of nodes in a space is related to the resolution of the map and the threshold is related to the accuracy of matching signal patterns, the accuracy of map-building and the accuracy of localization are tradeoffs.

To enhance the visual representation of the map, we utilized the trajectory of the user. We tracked a rough trajectory of the mobile device based on observations from motion sensors, such as magnetometer and accelerometer, with which recent Smartphones are equipped. The magnetometer tracks the heading direction and accelerometer counts the user steps. The orientation from the magnetometer has a distortion due to nearby steel gates and machines. The effect of distortion is minimal since the system does not use the absolute location estimation. The accelerometer observes the wave of inertial force from the human walking pattern and estimates the step count. The trip distance is obtained by multiplying the average stride and step counts. The trajectory tracking roughly arranges Wi-Fi calibration vectors in the topological map. We repeated the experiment with various walking scenarios, and the results are shown in Figure 8. Here, a dotted line denotes a calibration path. In the constructed map, hallways, an open space (denoted as A), a room (denoted as B), and a lobby (denoted as C) were found. Spaces and hallways were linked, based on their similarities.

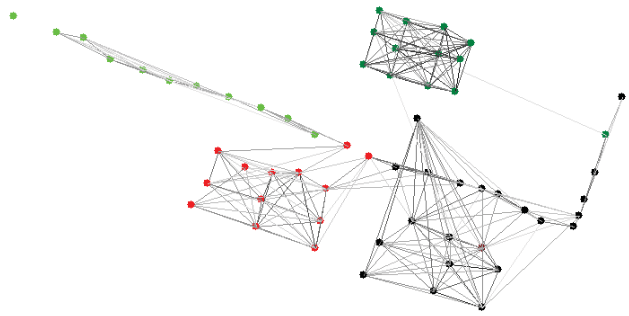


Figure 9. Clustering the topological map of Figure 3

E. *Clustering*

In the previous section, our scheme provided the 'clusterable' topological map. Clustering algorithm is employed to determine the place from the topological map. The k-means clustering algorithm is useful to partition the topological nodes into groups. The clustering results are shown in Figure 9.

The k-means algorithm successfully determined rooms, paths, and also some open places that have large variations in signal strength such as a lobby. However, each trial had different results since the k-means algorithm is sensitive to the initial randomly-selected cluster centers. Therefore, the clustering should be performed multiple times and the best result should be selected. The k-means algorithm recursively updates membership, as the result the clustering algorithm became stable in 10 rounds in every case of the experiment. An important factor on the k-means algorithm is that the results depended on the k value which is known *a priori*. Furthermore, the clustering algorithm is not suited for pathways, since paths have large coverage on the radio spectrum. Since k-means algorithm has limitations, a sophisticated clustering algorithm to meet our goal, will be studied in future work.

IV. RELATED WORK

Although RSSI fingerprinting is an attractive indoor localization [2][3], the fingerprinting requires a radio map construction and a heavy off-line phase for a specific site of interest. Active research explored the methods to reduce the off-line cost. Place Lab [13] automatically collects the radio signals via vehicles in outdoor environments. Redpin [14] achieved the off-line training by allowing users to collect radio signals explicitly. Nattapong et al. [15] reduced the size of the fingerprint map by clustering the radio signals with similar signal patterns. These approaches, however, still rely on off-line training, and the map-maintenance phase is the major cost of the system.

The SLAM approach is interesting for indoor localization, since the scheme automatically builds a map. Active work has been conducted to construct the geometric map based on environmental observations [6]. These approaches require highly accurate sensors to estimate the landmark and trajectory of a mobile object. Meanwhile, the topological SLAM builds an environmental representation, which is composed of the connectivity of spaces, rather than constructing a geometrically accurate map [9]. The topological SLAM is adaptable to ubiquitous computing, since the trajectory for human mobility is considered as conceptual movement between places. Since the topological map is hardly accepted by users, work has been done to enhance the topological map with geometric information to build a well-accepted means of guidance [16][17]. Our scheme also constructs the topological map and transforms it to a user-acceptable map by cluster algorithm.

Place learning algorithms which indentify densely clustered regions from the geometric coordinates, such as GPS and RF-based coordinate inferring systems, were introduced [18][19]. Research investigates the relationship between the explicit place ratings and the implicit aspects of travel, such as visit frequency. The fingerprint-based place learning algorithms use the observed signal pattern [20][21]. The algorithms calibrate signals from Wi-Fi access points or cell towers to represent the place. Since the Wi-Fi connectivity is usually unstable and the mobile user moves around from place to place continuously, the accuracy of place detection is limited and often fails. For the place-labeling problem, previous work explored the end-user labeling of locations [14][18][20]. These approaches allow end-users to label the places they frequently visit.

V. Conclusion

Previous research on mobile object tracking has focused on enhancing the accuracy of the system. In a ubiquitous computing environment, trajectory tracking is not trivial since the precision and accuracy of handheld device are limited. Additionally, the precise geometric location represented by x and y coordinates is hardly understood by users. The semantic information, which is represented as a topological map in our work, is enough to represent user location, such as the building name, floor number, and room number.

In this article, we proposed a lightweight user tacking system that uses a topological map based on Wi-Fi observations. During daily life, mobile users would scan the Wi-Fi channels and build the topological map automatically. The proposed system investigates the map and determines interesting places. Simultaneously, the system estimates the current place of a mobile user based on current observations. To the best of our knowledge, our work is the first Wi-Fi fingerprinting-based SLAM implementation for indoor pedestrian localization that is implemented with off-the-shelf Smartphones.

Our approach has attractive features for tracking mobile devices. First, Wi-Fi is an acceptable technique for ubiquitous computing. Wi-Fi fingerprinting shows highly accurate results at matching signal patterns. Technically, the Wi-Fi fingerprint technique can be extended to other kinds of radio, such as GSM, and Bluetooth. Since Smartphones are generally equipped with GSM, or Bluetooth devices, fingerprint observations from these devices are also treated as landmarks for topological SLAM. Second, a topological map guides users to their destination with navigation components: places and paths. The direction and name of places from the topological map is more acceptable to people over the x-y coordinates in the geometric map. Finally, SLAM has no offline calibration phase due to its automatic map-building scheme. The map can be shared in the network, since the mobile device is often connected to broadband networks.

Our system makes contributions over the many emerging mobile applications and research area on pedestrian tracking. The system outputs a clustered topological map and it tracks the position of the user. The map and position tracking of our system can be employed by third-party Location-Based System (LBS) applications. An interesting application that uses our system is automatic Smartphone configuration. In this application, Smartphone is automatically configured according to its position in the building: vibration mode in a conference room, bell mode in a lobby and Wi-Fi-available mode in an office room. Moreover, the place tracking can be utilized to schedule data collection or data delivery in Delay Tolerant Network (DTN).

Since this is our first proposal for indoor pedestrian tracking, we will enhance the system. We will design a sophisticated clustering algorithm for our system. A priori k value is one of the major weaknesses of the k-means algorithm, and the result is sensitive to k value. The algorithm has different result in each trial. By intuition, a room is composed of tightly connected multiple calibration points with variation, and a path is composed of series of calibration points. So, a clustering algorithm can utilize physical constraints. And we will enhance the visibility of the topological map. Employing sensors in mobile device, the topological map can be arranged as its geometric layout. In contrast to highly accurate sensors in traditional SLAM, sensors from mobile device give us hints on rough outline of the map. In addition to the map assignment, an automatic place labeling also enhance the readability of the map.

Acknowledgment

This work was supported by the National Research Foundation of Korea(NRF) grant funded by the Korea government(MEST) (No.2010-0000405).

References

[1] S. Pace, G. Frost, I. Lachow, D. Frelinger, D. Fossum, D. K. Wassem, and M. Pinto, “The global positioning system, chapter GPS history, chronology and budgets,” RAND Corporation 237–270, 1995.

[2] P. Bahl, and V. N. Padmanabhan, “RADAR: an in-building RF-based user location and tracking system.” In *Pro. of IEEE Infocom 2000*, Tel-Aviv, Israel March 2000.

[3] V. Honkavirta, T. Perälä, S. Ali-Löytty, and R. Piché, “A Comparative Survey of WLAN Location Fingerprinting Methods,” In *Proc. of Workshop on Positioning, Navigation and Communication* (WPNC 09), Hannover, Germany, March 2009.

[4] B. Krach and P. Roberston, "Cascaded Estimation Architecture for Integration of Foot-Mounted Inertial Sensors," in *Proc. of IEEE/ION Position Location and*

Navigation Symposium (IEEE/ION PLANS 2008), California, USA, May 2008.

[5] P. Robertson, M. Angermann, B. Krach, "Simultaneous Localization and Mapping for Pedestrians using only Foot-Mounted Inertial Sensors," in *Proc. of 11th International Conference on Ubiquitous Computing* (UbiComp 09), Flordia, USA, September 2009.

[6] J. Leonard and H. F. Durrant-Whyte. "Simultaneous map building and localization for an autonomous mobile robot." In *Proc. of IEEE International Workshop on Intelligent Robots and Systems*, Osaka, Japan, December 1991.

[7] A. Eliazar and R. Parr. Dp-slam: Fast, robust simultaneous localization and mapping without predetermined landmarks. In *Proc. 18th Int. Joint Conf. on Artificial Intelligence (IJCAI-03)*, pages 1135–1142, 2003.

[8] C. Stachniss, D. Haehnel, W. Burgard, and G. Grisetti. On actively closing loops in grid-based fastslam. *The International Journal of the Robotics Society of Japan* (RSJ), 19(10):1059–1080, 2005.

[9] F. Ferreira, I. Amorim, R. Rocha and J. Dias, "T-SLAM: Registering Topological and Geometric Maps for Robot Localization in Large Environments" In *Proc. of IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems* (MFI 2008), Seoul, Korea, August 2008.

[10] P. Prasithsangaree, P. Krishnamurthy, and P. Chrysanthis, "On indoor position location with wireless LANs," Telecommunications Program, University of Pittsburgh PA 15260, Tech. Rep., 2002.

[11] W. M. Yeung, J. Zhou, and J. K. Ng, "Enhanced Fingerprint-Based Location Estimation System in Wireless LAN Environment," *Emerging Directions in Embedded and Ubiquitous Computing.* Springer, pp. 273–284. 2007.

[12] J. B. MacQueen, "Some Methods for classification and Analysis of Multivariate Observations." In *Proc. of Berkeley Symposium on Mathematical Statistics and Probability.* Vol. 1, pp. 281–297. 1967.

[13] A. LaMarca, Y. Chawathe, S. Consolvo, J. Hightower, I. Smith, J. Scott, T. Sohn, J. Howard, J. Hughes, F. Potter, J. Tabert, P. Powledge, G. Borriello, and B. Schilit, "Place Lab: Device Positioning Using Radio Beacons in the Wild," In *IEEE Pervasive Computing*, pp. 116-133, 2005.

[14] B. Philipp, "Redpin - adaptive, zero-configuration indoor localization through user collaboration," in *Proc. of the first ACM international workshop on Mobile entity localization and tracking in GPS-less environments* (MELT 08), California, USA, September 2008.

[15] S. Nattapong and V. K. Prashant, "On clustering RSS fingerprints for improving scalability of performance prediction of indoor positioning systems," in *Proc. of the first ACM international workshop on Mobile entity localization and tracking in GPS-less environments* (MELT 08), California, USA, September 2008.

[16] B. Kuipers, J. Modayil, P. Beeson, M. MacMahon, and F. Savelli. "Local Metrical and Global Topological Maps in the Hybrid Spatial Semantic Hierarchy." In *IEEE International Conference on Robotics and Automation (ICRA 2004)*, New Orleans, LA, USA, April 2004.

[17] H. Choset and K. Nagatani. "Topological simultaneous localization and mapping (SLAM): toward exact localization without explicit localization." *IEEE Trans. on Robotics and Automation*, 17(2):125–137, 2001.

[18] J. H. Kang, W. Welbourne, B. Stewart, and G. Borriello. "Extracting places from traces of locations." In *Proc. of ACM Workshop on Wireless Mobile Applications and Services on WLAN Hotspots (WMASH '04)*, pages 110–118, New York, NY, USA, October 2004.

[19] D. Ashbrook and T. Starner. "Using GPS to learn significant locations and predict movement across multiple users." *Personal and Ubiquitous Computing*, 7(5): pp. 275-286, 2003.

[20] J. Froehlich, M. Chen, I. Smith, and F. Potter. "Voting with your feet: An investigative study of the relationship between place visit behavior and preference." In *Proc. of Conference on Ubiquitous Computing (Ubicomp 2006),* Orange County, USA, September 2006.

[21] J. Hightower, S. Consolvo, A. LaMarca, I. E. Smith, and J. Hughes. "Learning and recognizing the places we go." In *Proc. of Conference on Ubiquitous Computing (Ubicomp '05)*, Tokyo, Japan, September 2005.