PinPlace: Associate Semantic Meanings with Indoor Locations without Active Fingerprinting

Xuan Bao
Samsung Research

Bin Liu
Samsung Research

Bo Tang
Samsung Research

Bing Hu
Samsung Research

Deguang Kong
Samsung Research

Hongxia Jin
Samsung Research

ABSTRACT
Web map services today, such as Google and Bing maps, have digitalized a great portion of the physical world into easily accessible location databases. After the industry invested huge efforts in gathering related information, a user now can search a physical location on the map and know what kind of place it is, known as reverse geo-coding. However, this functionality is mostly limited to public outdoor locations and to building level granularity. We believe that many services can benefit from knowing the semantic meanings of fine-grained locations including indoor places. For example, the phone can mute and delay incoming calls when a user enters a meeting room. Cameras can be disabled in bathrooms to protect users' privacy. In this paper, we present *PinPlace*, an on-device service that can automatically associate semantic meanings with outdoor and indoor locations using the activity, transit, and time related features.

INTRODUCTION
Conventional GPS devices are being replaced by popular web map services such as Google and Bing maps. Apart from navigation, web map services also serve as a portal for other location related semantic information. For example, a search query can inquire a given street address for not only a GPS location but also the corresponding business name and their contact information. This is known as reverse geo-coding. However, like many other services, this functionality is still mostly limited to outdoor places and to building level granularity - the service can tell a building is a company headquarter but has no clue about the rooms inside.

Previous work tackled related problems for indoor localization and location semantics. Radar [2] paper was the first to propose using WiFi fingerprints for indoor localization. PlaceLab [13] utilizes both WiFi and GSM beacons to achieve 20-30 meter median accuracy in the greater Seattle area. The ARIEL [11] significantly helps reduce the manual annotation effort in WiFi localization. The goal of localization is to track a user's physical indoor location. The performance of the technique is measured by the physical distance error between the system provided location and the actual location. On the other hand, several recent

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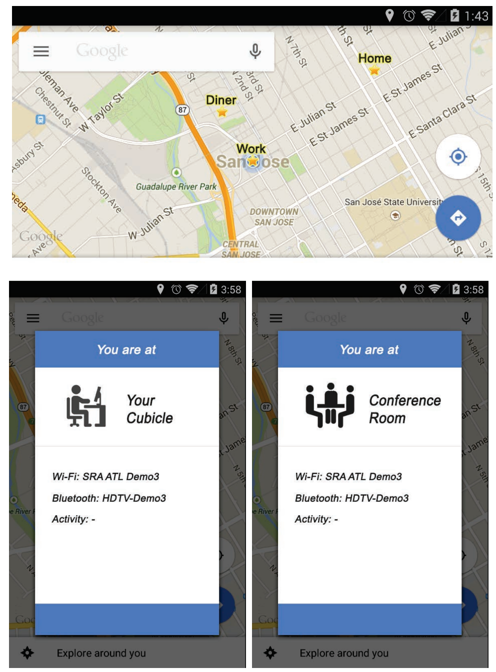

Figure 1. Top: Semantics for building level. Bottom: For indoor places.

work [5, 7, 10, 12, 15, 19] have explored related topics in location semantics. Most notably, the placer paper [12] from MSR, has used supervised learning on labeled datasets for building-level semantics similar to the top figure in 1. These projects are primarily designed for deriving location semantics in a coarse-grained manner and does not necessarily include fine-grained semantics, while in this paper, we explore specialized techniques for effective and efficient inference of fine-grained, room-level location semantics: *we believe such fine-grained inference can be a meaningful addition to existing techniques and can enable intelligent applications beyond the current technology.*

For example, in an office building, room-level tags, such as "conference room", "cafeteria", and "cubicle", can infer the functionality of a place. This information can be used to prevent visitors from entering wrong rooms and interrupting the occupants. The insight can also help understand the real-time context and guide operations in mobile applications. For instance, the phone can mute incoming calls and hide personal apps (e.g., Facebook) when the user enters a meeting room, to address the privacy concerns [4, 17, 18]. Health-related dining suggestions can pop-up upon entering the cafeteria. At the end of the day, the entire trace of visited office places can be analyzed to assess the daily work routine and help estimate stress levels [14].

Inspired by previous work in location semantics, our work, *PinPlace*, chooses a different route from conventional indoor localization. Instead of learning where each "location" physically resides, *PinPlace* is only interested in knowing the meaning of significant indoor "places". The app's user interface is shown in Figure 1. Building level as well as room level semantics are presented to the user in real time. The intuition is that each significant indoor place or region may have a distinct pattern of wireless signals - WiFi or Bluetooth. Therefore, these places can be recognized by analyzing the daily traces from users' mobile devices. Then, an analysis of the sequential visit patterns, temporal dwelling features and the associated motion activities can reveal the meaning of each place. For example, a user's own cubicle is often the origination and destination of most walking trips within the office building while the cafeteria usually features relatively fixed visit time and duration. These features can be established and modeled by simply observing the radio traces over time without actively fingerprinting each individual place. Moreover, this method purely relies on readily available radio signals and motion sensors, avoid actively pulling expensive sensors such as cameras and microphones. At current stage, our work focuses on recognizing common indoor places in office buildings and at home. These include places like cubicles, conference rooms, cafeteria, bathrooms, living rooms, etc.

SYSTEM DESIGN

Figure 2 shows an overview of *PinPlace*. It consists of five major modules: data acquisition, macro place classifier, indoor location recognizer, sequential learner, and real-time place detector.

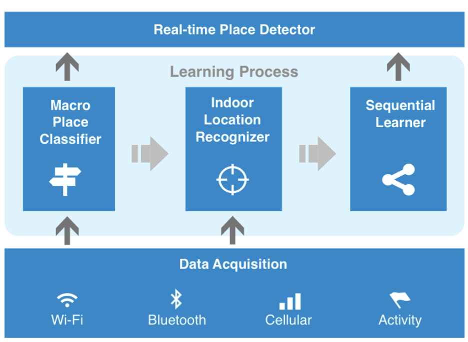

Figure 2. System overview of PinPlace.

Data Acquisition

The data acquisition module collects four types of information: WiFi, Bluetooth, connected cell towers and activities. Then, the MAC addresses of WiFi APs and Bluetooth devices with the highest RSSI, the connected cell tower information, and the activity with the highest inference confidence, are saved to log files on device. These data form the basis for further analysis.

Macro (Building Level) Place Classifier

This module is tasked to categorize a macro place, at the building level, to different classes. The main method is the same as described in paper [3]. *PinPlace* currently supports several categories. Particularly three are used for later processes, including home, work, and others (dining place, entertaining places, etc.).

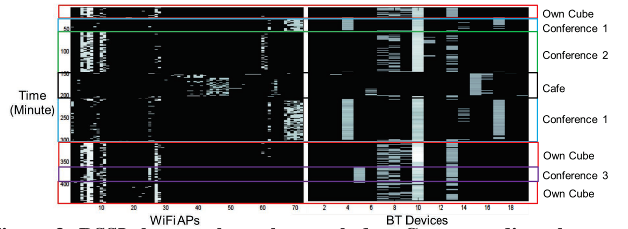

Figure 3. RSSI changes through a work day. Corresponding places are denoted in colors and assigned labels.

Indoor Place Recognizer

With the knowledge about the building, *PinPlace* attempts to further identify the semantic meanings of indoor places. The first step in this process is to understand how many places exist in a building. Moreover, how many of these places are of interest to a certain user. This module is tasked to recognize these places. Similar to existing localization techniques, *PinPlace* differentiates places based on a combination of radio signal patterns from both WiFi and Bluetooth. Both signals are collected with one minute intervals, logging the top five APs/devices with strongest RSSIs to the database.

Figure 3 shows one heatmap of WiFi (left) and Bluetooth signals (right) collected from an office worker through the course of working hours during a day. The X-axis denotes the device IDs for WiFi and Bluetooth and the Y-axis shows the elapsed time in minutes. Thus, each point (square) in the heatmap represents the signal strength of an AP of a given time. Colored blocks surround a series of wireless readings associated with each place the user has visited. These distinct places are also labeled to the right. For example, the first red block corresponds to the user's visit to her own cube and then she moved to conference room 1 afterwards. In total, the user has visited five distinct places this time, including three conference rooms, her own cubicle and the cafeteria.

The patterns visualized by Figure 3 are promising as signals do vary in response to place changes. But it also illustrates several key challenges. First, nearby places tend to share similar RSSI patterns. In this case, the user's cubicle is close to conference 2 and conference 3, so these three places share similar signal patterns. Note that, there are actually a distinct AP (28) and BT device (4) that can differentiate conference 3 and the user's cubicle. This could be captured by supervised learning with fingerprinting as the model will proportionally assign higher weights to these distinctive features. However, a naively applied unsupervised classifier will not even know the two places are different in the first place and will not look for these devices as distinguishing features. For example, a clustering algorithm looking at conference 3 and users' cube may think the difference of AP 28 is nothing special since there are so many other APs showing similar patterns. Therefore, it will incorrectly cluster those two places as one place.

Lack of knowledge regarding weights, our experiments show that a K-means algorithm, even with the knowledge of K, mixes distinct places into the same cluster. Then, this vague cluster center becomes an average signal pattern over several nearby places and, unfortunately, can not be used to correctly distinguish any of them. Moreover, the signal properties of the same place may change due to random fluctuations [8, 9], interference, user's mobility, device orientation, etc. The major challenge, therefore, is to correctly identify unique places from this continuous stream of observations, without fingerprinting. This means that the system needs to distinguish between signal fluctuations, probably due to interference, and changes caused by actual users' movements and location changes.

Incorporate Motion States

The key intuition to address this challenge is to incorporate motion sensing into the system. Physical indoor place changes are coupled with walking, so motion sensing helps the system to distinguish between signal fluctuations and actual place changes. *PinPlace* aggregates continuous walking segments into walking sessions - walking periods for more than 15 seconds. However, the walking algorithm may produce errors, making some periods mis-classified as either unknown or staying. As a temporary solution, within a continuous walking session, we allow up to 1 minute period of interruption. This means that if there is a break less than 1 minute, our algorithm still treats the two split walking periods as continuous. This treatment implicitly also limits our algorithm for places that users have stayed for more than 1 minute. Notice that, the walking sessions are essentially the movement periods when the user walks from one place to another. For each walking session, the system records its origination and destination by logging the WiFi and Bluetooth signals associated with them. Note that, this means two fingerprints are logged for each session and ideally, if all walking sessions are captured, the previous destination should be the origination of the successive session.

Figure 4 shows the originations and destinations logged for an anonymous user. In total, 18 places are captured as the result of 9 walking sessions. Most of the time, the previous destination matches the next origination, showing the walking sessions are correctly captured. Also, note that, in this treatment, the two fingerprints captured for each place is upon the user's first arrival and leaving, thus they are maximally separated in time. In this way, *PinPlace* will be able to observe, to some extent, the signal fluctuation range at each place. To this end, only 18 points corresponding to the originations/destinations are left for further analysis. Compared with more than 400 sample points in the raw data, our algorithm reduces the data volume significantly.

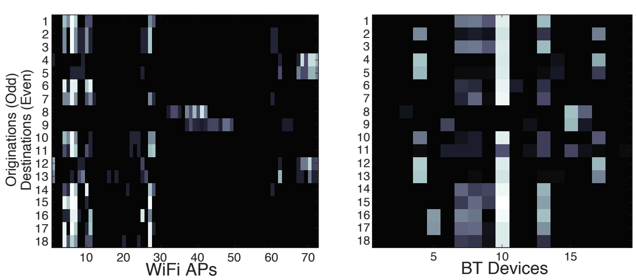

Figure 4. originations (odd numbers) and destinations (even numbers) of each walk session.

Hierarchical Clustering

Note that, among these 18 places, duplicates exist. A user may visit her own cubicle multiple times or attend multiple meetings in the same room. In larger rooms with open space, a user may also randomly walk around, making the origination and destination of that walking session being the same place. *PinPlace* employs a hierarchical clustering algorithm to decide how many distinct places there are and rules out duplicates.

Hierarchical clustering is essentially a way to group data together by creating a clustering tree. Data points that are closest under the defined distance metric (Euclidean distance in

Table 1. Current supported semantic places by *PinPlace*

Building Level	Room Level
Home	Bedroom, Living Room
Office	Own Cubicle, Others' Cubicles, Bathroom, Cafeteria, Conference Room
Other (Diner, Commute, Entertaining Places)	

PinPlace) are joined as clusters at the bottom level and then closest clusters are joined as bigger clusters at higher levels. Our algorithm keeps increasing the inconsistency threshold till the drop in cluster numbers becomes stable, yielding both reasonable cluster numbers and appropriate cluster separation.

Figure 5 shows the dendrogram (the clustering tree) produced by hierarchical clustering. The numbers at the leaf nodes correspond to the same origination/destination IDs as in Figure 4. As the dendrogram visualizes, most of the time, originations and previous destinations are clustered together right from the lower levels of the tree, showing the algorithm is performing correctly. Ideally, an algorithm with multiple thresholds may perform better to accommodate variation in room sizes and even incorporate user feedbacks for further refinement.

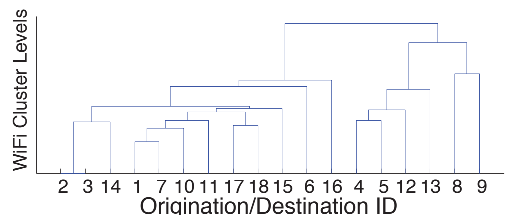

Figure 5. Dendrograms for hierarchical clustering. Originations (odd) are mostly clustered with previous destinations (even).

Sequential Learner

At this point, *PinPlace* knows what type of place the building is and has already identified unique places inside that the user has visited. The next step is to associate semantic meanings with each indoor place. The intuition is to rely on analyzing sequential and visit features associated with each indoor place. The used features for semantic place classification in room-level include: (1) sum of transition probability from other indoor places (the sequential feature), (2) average duration of stay, (3) maximum duration of stay, (4) frequency of visits and (5) start time of the visit. To this end, a decision tree algorithm is used for this final classification. We believe other algorithms may also work but rather choose decision tree for its simplicity and for execution on the mobile device.

To verify our assumption, we have conducted a small-scale study (10 users) that contains 7 room-level semantic places (Table 1). We ask users to note down the rooms they have visited and the time of visits. The summary of the study does reveal some interesting common points. For example, most of walking sessions include the user's own cubicle as the origination or destination, while conference rooms usually feature less frequent visit but longer staying duration. Bathrooms feature much shorter and periodical visits. And cafeteria is typically visited during lunch hours and rarely afterwards.

EVALUATION

The data used in *PinPlace* come from two sources. We used part of the DataAnalyzer dataset from Cambridge [16] mainly to verify our macro place classifier. Due to computational limitations, we randomly chose 300 users with data volume between $30 - 300MB$ for our evaluation. We also have experts to label the building level places based on visualization of statistical features about each place. Using methods similar to paper [3], we are able to achieve a recognition accuracy of 88% for home, work and others, comparable with [12].

At the same time, we conducted a field study with 10 company employees including engineers and interns. The devices in use are Samsung Note3 and Galaxy 5 phones. Each employee's company phone is installed with *PinPlace* for more than three days and we are primarily interested in places for home and offices. The employee also uploads their daily schedule for meetings and are encouraged to note down as much details as possible about their daily visits. Moreover, inside the company building, we know the associated radio fingerprint for some of the frequently visited places. By comparing the logged signals with these known patterns, we are able to add back some of the missing labels too.

Place Recognition Performance

For indoor place recognition, we verify our results with the ground truth and compare our algorithm with K-means algorithm. Figure 6 shows the indoor places being detected over time (black solid line) along with the ground truth when there is a mismatch (red thick line). Most of the time and most of the places are correctly recognized by *PinPlace*.

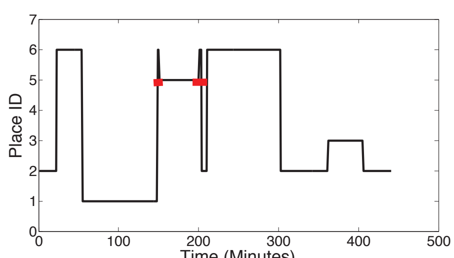

Figure 6. Recognized places compared with ground truth. Mismatch is highlighted with red line.

The mismatches are also interesting. The short, temporary mistakes (red lines) are caused by the user passing by a conference room and the same mistake happens again when she comes back. This "passing-by" effect happens especially if the user briefly stopped during walking.

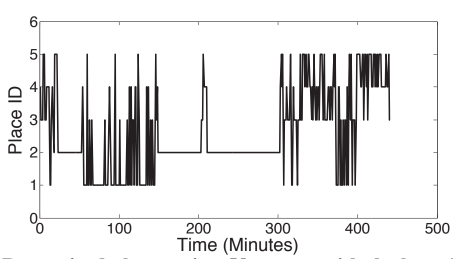

Figure 7. Recognized places using K-means, with the knowledge of K.

Figure 7 shows the detection results for the same period using the clusters produced by K-means algorithm knowing the correct number of K. Unfortunately, the results show unstable place detection almost all the time. This is because K-means produces ambiguous cluster centers that mix several places together. As a result, one place can be assigned to different clusters with similar probabilities, causing flipping in the detection results. Therefore, our method outperforms K-means even when K-means has the knowledge of K.

Performance for Indoor Places

Figure 8 shows the precision and recall for identifying each indoor place category. Currently, *PinPlace* supports 7 categories of indoor semantic locations mainly for office and home environment (Table 1). One challenge for home environment is that the wireless signal properties are less diverse across rooms especially for smaller apartments.

At this stage, *PinPlace* achieves on average 74.7% precision and 66.9% recall across all semantic places. For home, the dominant error is that some bedrooms close to living rooms may be mislabeled as living rooms. Note that, collecting ground truth for two categories (bathroom, short stays at others' cubicles) is extremely hard since users may not be able to correctly label all of these short-events.

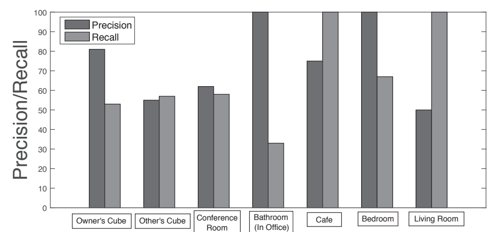

Figure 8. Precision/recall for recognizing indoor places.

System Performance

Table 2 lists the statistics regarding system overhead measurement based on implementation running on Samsung Galaxy S5. The implementation of the learning module uses open-source libraries - EJML [1] and Weka [6].

Table 2. Overhead Measurement

Component	Avg. Power	Exec. Time	Memory
Data (Macro)	5.62mw	N/A	33MB
Data (all)	15.47mw	N/A	38MB
Learning	1931mw	5.9S	107MB
Detection	1475mw	0.037S	35MB

LIMITATION AND FUTURE WORK

Mobile and wearable devices today are transforming from conventional communication handsets to converged sensing platforms. *PinPlace* attempts to leverage this opportunity to enhance conventional location based services with fine-grained location semantics.

At this stage, *PinPlace* is definitely a prototype with many limitations. The vocabulary of building level and indoor places can be further expanded to incorporate more interesting places. We have not yet expanded our experiments to many public places beyond homes and offices. The irregular mobility patterns may bring additional challenges for charting the locations. In the future, human users can be brought into the loop to help refine models and improve performance. Demographic information such as users profession and age may also be used as prior knowledge. Energy cost can be optimized by adjusting duty cycling. Even more previous research work such as ARIEL [11] can be used as modules in the *PinPlace* system.

With these limitations, we still believe there is value in building a service that provides semantics to fine-grained locations, especially in a world where location services becomes essential to all types of businesses, advertisement and recommendation systems. *PinPlace* is an early attempt towards a working system, with many potential applications.

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