FreeNavi: Landmark-based Mapless Indoor Navigation based on WiFi Fingerprints

Yao Guo, Wenjun Wang, Xiangqun Chen
Key Laboratory of High-Confidence Software Technologies (Ministry of Education),
School of Electronics Engineering and Computer Science, Peking University, Beijing, China
{yaoguo, wenjunwang, cherry}@pku.edu.cn

Abstract—**Although many indoor navigation approaches have been proposed, most either require prior knowledge on floor plans, or relying on extra sensors or images, to provide accurate indoor localization and navigation. This paper presents FreeNavi, a landmark-based indoor navigation algorithm that leverages only WiFi signals to direct users in sophisticated indoor environments without prior device deployment or floor plans. FreeNavi takes advantage of human intelligence as an important input to locate and navigate users based on landmarks. With WiFi fingerprints collected at landmarks and walking traces collected in a crowdsourced manner, FreeNavi is able to create a virtual map connecting landmarks with each other. During navigation, FreeNavi produces human understandable directions based on landmarks in the virtual map. Evaluation result shows that FreeNavi can build mostly correct maps and provide efficient directions to users despite relying only on WiFi signals.**

Keywords—indoor localization; WiFi signals; landmarks

I. INTRODUCTION

Although there are mature outdoor navigation systems based on maps and GPS, indoor navigation is still in the research stage. Many localization and navigation techniques have been proposed, but few has been widely deployed and adopted. The main restrictions to indoor localization and navigation are the high deployment cost and extra requirement for devices. For instance, localization techniques using infrared [1], ultrasound [2], and radio-frequency identification (RFID) [3] require both specific devices deployed in the environment and certain hardware components.

Recent attempts [4], [5], [6], [7], [8], [9] have proposed methods to locate or navigate without prior deployment. However, they still require the support from certain locating or navigating devices, such as accelerometer, magnetometer, gyroscopes and even cameras. These requirements may limit the wide application of these navigation systems.

Meanwhile, many smart devices such as smartphones, smart watches and smart bands have the potential to provide indoor navigation services. However, due to different usage scenarios, the hardware components on these smart devices vary a lot. Under such constraints, this paper tries to investigate the following issue: *Can we provide indoor navigation with as few required device components as possible, such that it can be deployed on most smart devices?*

In this paper, we propose *FreeNavi*, a l*andmark-based self-deployable navigation system* that requires only WiFi fingerprints collected on the device. The goal of FreeNavi is to provide navigation to people in a new environment on a typical smartphone equipped with WiFi access capabilities.

FreeNavi takes advantage of human intelligence as an important input during navigation. The key here is that humans are able to identify landmarks easily, which can be used to help simply the navigation process. Landmarks have been used in different navigation systems. There are neural and psychological evidences [10], [11] that landmarks help humans in identifying routes and even shortcuts. Landmark-based navigation has been developed for driving [12], pedestrian guiding [13], [14] and mobile robots navigation [15], [16].

Since human beings identify the environment by landmarks (room numbers, shop names, etc.) instead of coordinates and other virtual descriptors used by existing navigation systems, FreeNavi locates and navigates users based on landmarks. People walk from one landmark to another during navigation. Pathways between landmarks contain little information to users during navigation, so they do not need to be modeled.

Therefore, FreeNavi can build a virtual map by describing only landmarks and their connectivity relations. It locates users at one landmark and guides them to another with a sequence of landmarks. For instance, in an indoor environment, the best landmarks are the room labels in an office building or store names/signs in a shopping center.

FreeNavi builds indoor floor plans based on two kinds of crowdsourced data, i.e. landmark fingerprints at the entrance of each landmark and user traces walking from one landmark to another. Landmark fingerprints represent the location of each landmark by their WiFi fingerprints, while user traces may connect the scattered landmarks to a connected graph, which is used as a virtual map for navigation. Using this virtual map, FreeNavi provides landmark-based navigation for users and guide them with landmark labels.

We implement FreeNavi on Android smartphones and conduct experiments in a shopping center. The results show that FreeNavi can build mostly correct maps and successfully navigate users with human recognizable instructions.

II. OVERVIEW

A. Design Challenges

Our first goal is to build a virtual map of the indoor floor plan with only WiFi fingerprints collected at each landmark and from user traces. This task faces some key challenges:

- WiFi-based localization cannot achieve the same accuracy as the ones leveraging various extra sensors, which affects both map construction and navigation;
- Virtual maps constructed with WiFi fingerprints lack the information of heading direction in user traces,

978-1-5090-5932-4/17/$31.00 ©2017 IEEE

because we do not employ any other device or sensors that may help identify heading information;

- We are unable to provide exact walking directions (e.g., turn left or right) during navigation, based solely on WiFi-based localization and the virtual map created.

B. *Basic Idea*

In order to overcome these challenges, our basic idea is to exploit human intelligence, rather than solely depending on navigation systems to provide detailed instructions.

How accurate do users really need for an indoor navigation system? Based on human common sense, as well as neural and psychological evidences [10], [11], landmark-level (i.e., room-level) accuracy is sufficient in most scenarios.

Previous approaches have focused on achieving the best possible accuracy. However, human beings possess strong capability for environment identification. When guiding someone through a building, it is redundant to tell him/her how many steps he/she should take before turning right, and how many additional steps need to be taken until he/she arrives the destination. In contrast, a person might only need this instruction: turn right at room 1234, then walk straight until you see the destination. With this assumption, indoor navigation may be affected in the following ways:

1) Coarse-grained guidance is suffcient to guide users from one landmark to another. Small errors due to localization accuracy can be automatically tolerated by users.

2) We can use landmarks to guide users instead of hard-to-understand steps or distance. In the indoor navigation context, the most common landmarks could be room numbers or shop names that can be easily recognized.

3) We can describe a user's position with landmarks, instead of coordinates or other virtual descriptions. Human can describe their positions using the landmarks around them and specify their destination with the landmark label.

C. *Design Overview*

Since only WiFi signal information can be used, FreeNavi can only be based on indoor localization with WiFi fingerprints. It consists of two phases: (1) constructing maps using crowdsourced landmark fingerprints and user traces, and (2) providing navigation instructions to users.

In the map building phase, we need two types of data collected in a crowdsourced manner: landmark fingerprints for each landmark, which includes WiFi fingerprints at the entrances of landmarks and the landmark label number; and user traces represented by WiFi signal information.

If positions are time sequential in user traces, it indicates that they are adjacent in physical space. Therefore, landmarks can be connected with others based on these traces. The time taken to pass every landmark and the number of users passing every path are calculated simultaneously. However, the resulting virtual map still does not fit the definition of a regular map, as it is only a connected graph without any spatial direction relationships between landmarks.

During navigation, users only need to specify their destinations by their landmark labels. FreeNavi locates their current positions via an indoor localization algorithm and calculates the fastest or most frequently traveled route. Since we lack heading directions from traces, the generated map does not contain spatial direction relationships between landmarks. Furthermore, WiFi fingerprint localization cannot figure out the walking directions. As a result, FreeNavi cannot guide users with heading directions. Therefore, we design FreeNavi to illustrate directions by telling users the next landmarks. Since room labels are always clear enough to serve as landmarks and the rooms are usually named in regular patterns, it is easy for a normal person to follow these instructions.

III. FreeNavi Design

A. *Indoor Localization*

We use an indoor localization algorithm based on relative WiFi signal strengths (LCS in [17]), which is robust against time and different devices in an AP-intensive environment. The LCS algorithm calculates the similarity between two WiFi fingerprints as the length of their common subsequence, when comparing their respective list of access points (BSSID) sorted by the absolute value of their received signal strength (RSS).

According to an experiment in an environment with as many as 300 APs, the algorithm can predict the correct location with errors less than 4 meters during 90% of the time for most devices, even 14 months after the initial sampling date. This level of accuracy is adequate for room-level localization. The resistance to time and device variances also fits the long-term crowdsourcing scenario in FreeNavi.

B. *Map Construction*

Constructing virtual maps is critical for indoor navigation. Although FreeNavi does not require an actual map with complete direction information, it does need to identify how the landmarks are connected.

We design the map construction algorithm based on WiFi signal strength data, including landmark fingerprints and user traces. Each landmark fingerprint is collected at the doorway of every landmark and labeled with the landmark label. User traces are sequences of WiFi signal data that are periodically sampled during each user's walking scenario.

These data provide both physical (spatial) adjacency and temporal adjacency information. On one hand, if the fingerprints of two landmarks are similar, they should be spatially adjacent. Meanwhile, if two landmarks are passed by one after another in a user trace, they should be temporally adjacent (and spatially adjacent as well). We exploit these information to construct the virtual map.

1) Map Construction based on Landmark Fingerprints: First of all, the similarity of the collected landmark fingerprints can be used as an indication of their distance in physical space to a certain degree. For each pair of landmarks, the more similar their fingerprints, the closer they are. Therefore, FreeNavi calculates the similarities of these WiFi fingerprints for all landmark pairs. The similarity formula is defined using the same way as in the localization algorithm, based on the longest common subsequence of their BSSIDs ordered by received signal strength [17].

We first connect the pairs of vertices whose similarities exceed a pre-determined threshold. We then order the remaining pairs by their similarities and add edges between the pairs if one of their corresponding vertices has fewer than two edges. Using only landmark fingerprints, we can connect most of the dots: most edges are correct, but we are still unable to connect all landmarks because some of them are adjacent physically but not close enough in their WiFi fingerprints.

The detailed steps in this procedure are shown in Algorithm 1, which takes the fingerprints collected for each landmark, and generate a virtual map based on the similarity between them.

Algorithm 1 Map construction based on landmark fingerprints

Input : The *fingerprints* collected from all landmarks
Output: $G\_SIMILARITY(V, E)$

for *pairs* ∈ *landmarks* : **do**
  similarity ← *the LCS between the pairs*
  if *similarity* > *threshold* **then**
    Connect the vertices belong to the pairs
  end if
end for
Order the remaining pairs by their similarity
for *pair* ∈ *remaining pairs* **do**
  if One of its vertices has fewer than two edges **then**
    Connect the vertices of it
  end if
end for
return $G\_SIMILARITY(V, E)$

2) Extract Landmark Relationships from User Traces. We can extract further information on landmark relationships based on collected user traces. As we can infer how each user walks from one landmark to another, the time sequential points on the trace indicate that they are adjacent in physical space. Thus we can infer that these corresponding landmarks are neighbours.

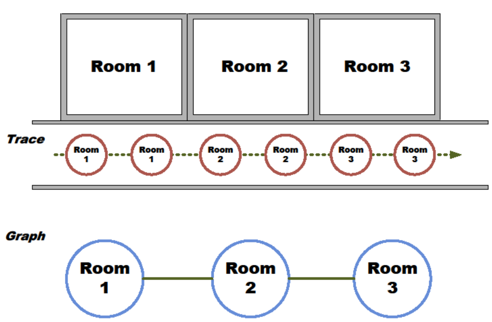


Fig. 1 Every individual point on the trace is identified as a landmark label. As a result, the corresponding landmarks are connected into a graph based on the traces.

As illustrated in Fig. 1, the periodically sampled individual points on a user trace are identified as one of the rooms, i.e., Room 1, 2 and 3. Since Room 1 and Room 2, Room 2 and Room 3 are adjacent in the time sequence, they are determined as neighbors in space. Thus, vertices of Room 1 and Room 2 are connected, so are the vertices of Room 2 and Room 3.

After processing all traces, we build a connected graph where the vertices are landmarks and the edges indicate that users can walk from one landmark to the other without passing any other landmarks. We then combine the results with the graph we constructed earlier using proper weights.

C. Navigation

FreeNavi implements two route planning algorithms: the fastest route and the most frequently travelled route.

The algorithm of calculating these two types of routes are based on the well-known Floyd algorithm for shortest paths. This algorithm calculates the shortest paths between all pairs of vertices in a weighted graph. Since it can be implemented with dynamic programming, the time complexity is reduced to $O(N^3)$, where N stands for the number of vertices.

The only difference between these two algorithms is the method of setting edge weights. Since the method of building the graph from traces can only obtain the time users spent passing every landmark instead of the time they use to walk from one landmark to another, FreeNavi records time on vertices. Translating weights from vertices to edges, the weight of the edge from *vertex A* to *vertex B* is the passing time of *vertex A*. In reverse, the weight of the edge from *vertex B* to *vertex A* is the passing time of *vertex B*. Hence, the undirected graph is translated into a directed graph. The algorithm for the most frequently travelled route is still an undirected graph, with its weight on an edge defined as *1/passing_time*.

As the result of the navigation algorithm, the user will receive a direction with a list of landmark labels after he/she enters a landmark label as the destination. Fig. 2 shows a simple navigation interface, where the user is given a list of room numbers to follow in order to reach his/her destination. Note that some room numbers are clustered in previous steps because they are very close to each other.

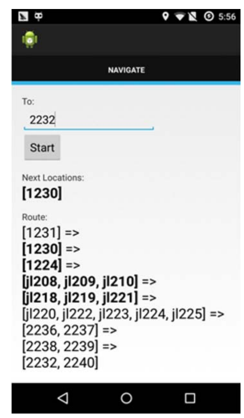


Fig. 2 The screenshot of a simple navigation interface. The users will be given directions based on room labels, where crossroads are highlighted to reminder users. Note that some room labels are clustered because they are very close to each other.

As in walking directions in real life, the user only needs to pay attention to crossroads or junctions, thus the landmark labels at crossroads are highlighted to remind the users. The user needs to find the correct direction at junctions, which are given by landmark labels instead of turning directions (left or right). If there are more than one choices at the junction, the user needs to take a guess and check whether it is the correct direction. As the landmarks are easily recognizable in most cases, the user only needs to take a few wrong steps before find the correct direction at a junction.

IV. EVALUATION

A. Experimental Environments

We evaluate FreeNavi in the first floor of a shopping center in downtown Beijing. Fig. 3 shows the map of the shopping center. There are about two dozens of shops in the setup, where they are connected by two vertical and three horizontal hallways.

In preparation, we have collected the fingerprints for 23 landmarks (as specified in Fig. 3) from the shopping center and recorded 9 traces with a Nexus S phone, during a period of one week. Every room has been covered multiple times and the total length of the traces are about 1,200 meters.

These preparation steps can be collected in a crowdsourced manner by people working in the shopping center. For example, store owners are more than willing to help provide the WiFi fingerprint at the entrance of their store, as well as walking traces to their stores from other landmarks in the shopping center. As it takes time to collect all required data from crowdsourcing, we use volunteers to complete this step instead. Nonetheless, the process do not have any influence on the navigation accuracy of our approach.

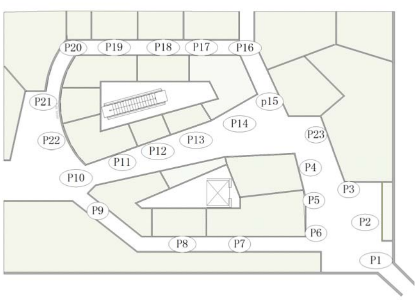


Fig. 3 The floor plan used in Case Study, a single floor in a shopping center.

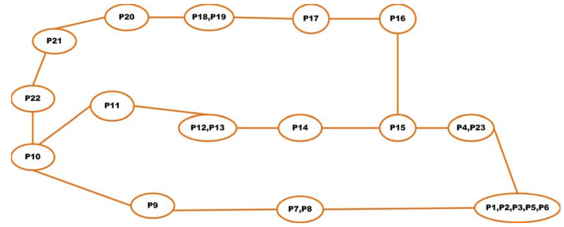
B. Map Construction

We first evaluate the virtual maps constructed. Fig. 4 compares the original map (Fig 4(a)), the virtual map generated based on fingerprint similarity (Fig. 4(b)), and the final virtual map generated with user traces and optimization (Fig. 4(c)).

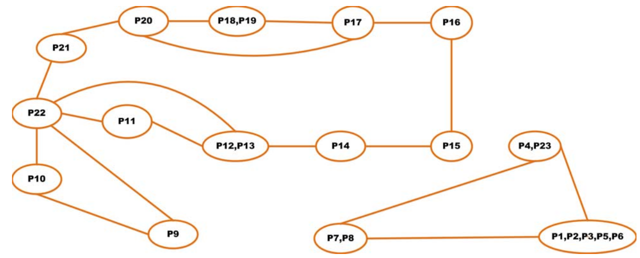
Note that the original map shown in Fig. 4(a) is used as the ground truth of virtual map construction, which is different from the actual floor plan shown in Fig. 3. The key difference is that during virtual optimization, we cluster many landmarks into groups because they are very close to each other, such that it is difficult to distinguish them in a virtual map. As a result, the ground truth we used in this case only contains 15 vertices, instead of 23 landmarks in the actual setup.

In the virtual map generation process, the virtual map generated solely based on fingerprint similarity (Fig. 4(b)) reflects mostly correct relations between landmarks. However, it missed some important connections such as from P9 to [P7, P8]. The reason is: although they are adjacent in reality, their distance is not so close, which causes that the similarity of their fingerprints are not high enough to connect them.

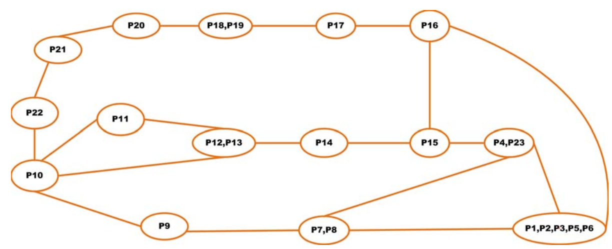
In the next step, when user traces are taken into consideration, we will figure out that they are adjacent because they are passed by sequentially in user traces. The resulting virtual map (Fig. 4(c)) is improved and the missing connections are included. Although there are still some minor



(a) Original map after merging close landmarks.



(b) The virtual map constructed with location similarity only.



(c)The virtual map after optimization with user trace information.

Fig. 4 The virtual maps constructed by FreeNavi (and comparison to the original map) for the experiments in a shopping center.

differences from the actual connections (Fig. 4(a)), the map is good enough for FreeNavi to provided navigating directions to human users.

1) Map Construction Accuracy. We evaluate the map construction accuracy by comparing the graph similarity between the virtual maps generated and the original map (after merging close landmarks). Because the maps for each case contain the same list of vertices, we compare their similarity by the correct inclusion of the respective edges.

The comparison results are shown in Table I. We can see that both accuracy and recall are improved after the optimization steps based on user traces. The final virtual maps have an accuracy of 84% and 91%, while their recall reaches 100% and 93%, respectively.

TABLE I. VIRTUAL MAP CONSTRUCTION ACCURACY.

Virtual Maps	Original Edges	Total Edges	Correct	Accuracy	Recall
After Step 1	16	19	14	0.73	0.88
Final graph	16	19	16	0.84	1

C. Navigation

We ask our volunteers to walk towards a given destination following the fastest routes given by FreeNavi. We tested a total of seven routes and all volunteers successfully arrived at their destination. The detailed information of the routes taken and evaluation results are shown in Table II.

TABLE II. NAVIGATION RESULTS.

Route	Start Point	End Point	Total Steps	Wrong Steps
#1	P1	P13	106	14
#2	P6	P22	93	13
#3	P10	P5	91	0
#4	P21	P7	81	0
#5	P22	P23	128	25
#6	P19	P16	46	0
#7	P1	P10	136	28

In the seven routes taken during navigation, the volunteer made no wrong steps in three of these routes. In the other four routes, as many as 28 wrong steps are taken in a single navigation route. In summary, a total of 80 wrong steps are taken out of the total of 673 steps, which indicates a 11.9% error step rate. Most of the wrong steps are unavoidable since the users will have to guess which way they should take at each junction. Nonetheless, the results show that FreeNavi is pretty accurate as a lightweight indoor navigation tool using only WiFi fingerprints, with no maps needed.

V. RELATED WORK

Indoor navigation. With the help of indoor localization, several self-deployable navigation systems has been proposed recently. Travi-Navi [5] uses WiFi and magnetic field fingerprints to merge PDR traces and filter PDR tracking during navigation, and utilized images taken from camera to help guidance. It requires many hardware components in the navigating devices, such as magnetometer, accelerometer, gyroscope, WiFi adaptor and even camera. In contrast, FreeNavi requires only WiFi capabilities on a smart device.

Several navigation systems depend on other positioning techniques. SugarTrail [18] uses radio and magnetic signals to merge PDR traces. Riehle *et al.* [19] navigate blind users with traces and magnetic field signals. Constandache *et al.* [4] solve the problem of navigating to a moving person by following the traces which are combined by audio signals from the other people who met him/her before.

Landmark-based navigation. Landmark-based navigation techniques have been studied previously in different scenarios, including driving [12], pedestrian guiding [13], [14] and even mobile robots navigation [15], [16]. Ramirez *et al.* proposed human-centered indoor navigation techniques to support firefighters in creating and finding their own paths in critical situations [20]. To the best of our knowledge, FreeNavi is the first to introduce landmark-based techniques in indoor navigation for human beings, relying on only WiFi signal strength information on mobile devices.

VI. CONCLUSION

This paper proposes a mapless indoor navigation mechanism FreeNavi, which depends solely on WiFi signal information. While recognizing human knowledge as an important input, FreeNavi is able to provide landmark-based indoor navigation with minimal hardware requirements. We demonstrate the effectiveness of FreeNavi with experiments in a shopping center.

ACKNOWLEDGMENT

This work was partially supported by National Key Research and Development Program Grant No. 2016YFB1000105 and National Natural Science Foundation of China Grant No. 61421091.

REFERENCES

[1] S. Lee, K. N. Ha, and K.-C. Lee. “A pyroelectric infrared sensor-based indoor location-aware system for the smart home,” Consumer Electronics, IEEE Trans on, vol. 52, no. 4, pp. 1311-1317, Nov 2006.

[2] M. Hazas and A. Hopper, “Broadband ultrasonic location systems for improved indoor positioning,” Mobile Computing, IEEE Trans on, vol. 5, no. 5, pp. 536?47, May 2006.

[3] S. Willis and S. Helal, “RFID information grid for blind navigation and wayfinding,” in Wearable Computers, 2005. Proceedings. Ninth IEEE International Symposium on, Oct 2005, pp. 34-37.

[4] I. Constandache, X. Bao, et al., “Did you see Bob?: Human localization using mobile phones,” in MobiCom’10, 2010, pp. 149-160.

[5] Y. Zheng, G. Shen, et al., “Travi-Navi: Self-deployable indoor navigation system,” in MobiCom’14, 2014, pp. 471-482.

[6] G. Shen, Z. Chen, P. Zhang, T. Moscibroda, and Y. Zhang, “Walkie-Markie: Indoor pathway mapping made easy,” in NSDI 2013, pp. 85-88.

[7] H. Wang, S. Sen, et al., “No need to war-drive: Unsupervised indoor localization,” in MobiSys 2012, pp. 197-210.

[8] A. Rai, K. K. Chintalapudi, et al., “Zee: Zero-effort crowdsourcing for indoor localization,” in Mobicom’12, 2012, pp. 293-304.

[9] C. Wu, Z. Yang, Y. Liu, and W. Xi, “Will: Wireless indoor localization without site survey,” in INFOCOM, 2012 Proceedings IEEE, March 2012, pp. 64-72.

[10] K. M. Gothard, W. E. Skaggs, K. M. Moore, and B. L. McNaughton, “Binding of hippocampal ca1 neural activity to multiple reference frames in a landmark-based navigation task.” The Journal of neuroscience, 1996.

[11] P. Foo, W. H. Warren, A. Duchon, and M. J. Tarr, “Do humans integrate routes into a cognitive map? map-versus landmark-based navigation of novel shortcuts.” Journal of Experimental Psychology: Learning, Memory, and Cognition, vol. 31, no. 2, p. 195, 2005.

[12] S. Bhattacharya, R. Murrieta-Cid et al., “Optimal paths for landmark-based navigation by differential-drive vehicles with field-of-view constraints,” IEEE Trans on Robotics, vol. 23, no. 1, pp. 47-59, 2007.

[13] A. Millonig and K. Schechtner, “Developing landmark-based pedestriannavigation systems,” Intelligent Transportation Systems, IEEE Trans on, vol. 8, no. 1, pp. 43-49, 2007.

[14] H. Hile, R. Grzeszczuk, A. Liu, R. Vedantham, J. Kosecka, and G. Borriello, “Landmark-based pedestrian navigation with enhanced spatial reasoning,” in Pervasive Computing. Springer, 2009, pp. 59-66.

[15] H. Hu and D. Gu, “Landmark-based navigation of industrial mobile robots,” Industrial Robot: An International Journal, vol. 27, no. 6, pp.458-467, 2000.

[16] A. J. Briggs, C. Detweiler, D. Scharstein, and A. Vandenberg-Rodes, “Expected shortest paths for landmark-based robot navigation,” Intl J of Robotics Research, vol. 23, no. 7-8, pp. 717-728, 2004.

[17] X. Chen, J. Kong, Y. Guo, and X. Chen, “An empirical study of indoor localization algorithms with densely deployed APs,” in GLOBECOM, Dec 2014, pp. 517-522.

[18] A. Purohit, Z. Sun, S. Pan, and P. Zhang, “Sugartrail: Indoor navigation in retail environments without surveys and maps,” in SECON, 2013.

[19] T. Riehle, S. Anderson, et al., “Indoor magnetic navigation for the blind,” in EMBC 2012, pp. 1972-1975.

[20] L. Ramirez, S. Denef, and T. Dyrks, “Towards human-centered support for indoor navigation,” in CHI 2009, pp. 1279-1282.