Feature-Based Room-Level Localization of Unmodified Smartphones

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Abstract. Locating smartphone users will enable numerous potential applications such as monitoring customers in shopping malls. However, conventional received signal strength (RSS)-based room-level localization methods are not likely to distinguish neighboring zones accurately due to similar RSS fingerprints. We solve this problem by proposing a system called feature-based room-level localization (FRL). FRL is based on an observation that different rooms vary in internal structures and human activities which can be reflected by RSS fluctuation ranges and user dwell time respectively. These two features combing with RSS can be exploited to improve the localization accuracy. To enable localization of unmodified smartphones, FRL utilizes probe requests, which are periodically broadcast by smartphones to discover nearby access points (APs). Experiments indicate that FRL can reliably locate users in neighboring zones and achieve a 10 % accuracy gain, compared with conventional methods like the histogram method.

Keywords: Room-level localization · RSS · Fingerprinting

1 Introduction

Locating smartphone users in an indoor environment will enable many ubiquitous computing applications, ranging from context-aware applications [1] to location-based services [2,3]. These applications usually require two types of locations, namely geometric locations that are used for mapping and distance-oriented applications; and semantic locations which attempt to represent logical entities and their semantics [4,5]. The concept of semantic location was firstly proposed by HP Labs [6] to address the significant deficiency of geometric locations for providing little context information in mobile web-services. Rooms are typical representation of semantic locations. Getting the room information of users is called room-level localization. Significant as room-level localization is, little attention is paid to this area. Recent research on retail space [7,8] and smart home [9] require room-level localization without modifying users' smartphones, which is both challenging and infusive.

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Due to the proliferation of WiFi APs, wireless indoor localization methods are becoming increasingly popular and attractive as there are no additional infrastructural costs beyond the wireless APs. Currently, the room-level localization methods can be divided into four categories. The first type utilizes channel state information (CSI) of WiFi to discover users' locations and states [7]. The second type uses geometric localization methods. Examples are deterministic and probabilistic fingerprinting methods [10,11]. The third type regards the room-level localization as a classification problem, e.g., WHAM! [12], a rule-based method [13] and the histogram method used in [9]. The last type integrates WiFi data with other smartphone sensor data to improve localization performance, like Ariel [14] and AurroundSense [15].

However, multiple users result in unpredictable changes of channel states, hence CSI is unlikely to work for a large number of people [7]. Fingerprinting [10,11] requires a large amount of training data, which is too labor-extensive to carry out. Methods mentioned in the third type [9,13] solely rely on RSS feature that attenuates in a highly nonlinear and uncertain way in real situations [16], so it is hard to get high accuracy especially in the case where neighboring rooms have similar fingerprints [12]. It is highly possible that the forth type methods [14,15] are inapplicable as those systems need to install some apps in users' smartphones to collect other sensor data.

To solve these problems, we propose a system called Feature-based Room-Level Localization (FRL), which can accurately and reliably derive smartphone users' locations in the indoor environment. FRL is based on the observation that different rooms have various internal structures and diverse human activities. Therefore, from the observation we extract related features (we call them room features) and combine them with the RSS feature to conduct room-level localization. Simple and direct as the main idea of our solution seems to be, there remains some fundamental challenges to be carefully addressed. First of all, how to acquire WiFi data without modifying users' smartphones? Conventional room-level localization methods often assume the data of users' smartphones are available, but it is not possible to directly access users' smartphones and get the required data in some application scenarios such as locating customers in shopping malls. Besides, how to handle the problem raised by a small amount of training data which downgrades the accuracy of localization models? Most of the fingerprinting methods rely on complete training data to build accurate models. Lastly, how to extract features that relate to internal structures and human activities? Extracting new features is non-trivial task and it usually requires solid observations.

We tackle the first challenge by exploiting probe requests which are periodically broadcast by smartphones to collect WiFi data in a non-intrusive way. As for the second challenge, we apply machine learning methods to derive labels from unlabeled data. When it comes to the last challenge, although it is hard to directly measure internal structures and human activities, different structures result in different RSS fluctuation ranges and different human activities lead to different dwell time. Based on this assumption, we measure RSS fluctuation range and user dwell time from a large amount of estimated labeled data. Dedicated experiments demonstrate the feasibility of combining different features and indicate that FRL has better performance in terms of accuracy than state-of-the-art methods.

The remainder of the paper is structured as follows. We describe the main idea of FRL design in Session 2. Session 3 elaborates on the architecture of FRL and the functionality of different parts. In Session 4, we present a case study in which different methods are applied in a real-world indoor test environment. Session 5 introduces existing and related works. The conclusions are summarized in the last session.

2 System Overview

This paper proposes a system called FRL (Feature-based Room-Level Localization), which combines the RSS feature and room features for room-level localization. FRL utilizes probe requests to periodically collect users' WiFi data as a data sequence. The sequence will be partitioned into snippets based on smoothing and partition rules. Every snippet consists of some data units, for each of which, FRL exploits the histogram method to derive a potential result. After that, FRL uses a voting-based decision fusion strategy for every snippet. If the top two results are neighboring zones and the difference of their votes is under the threshold, then the feature-based localization method will be leveraged to pick up the more possible result.

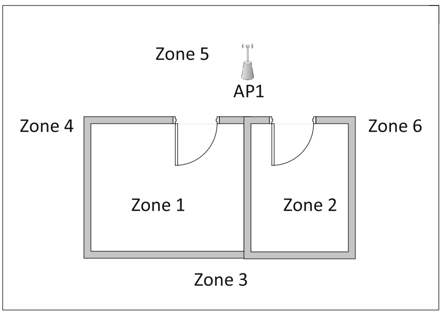

Fig. 1. A example of two rooms

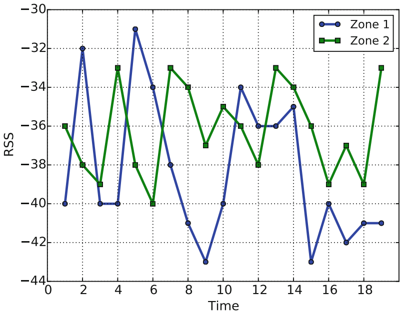

Fig. 2. WiFi data in two rooms

Figure 1 illustrates how FRL works. The floor plan is split into 6 zones with two neighboring rooms (zone 1 is an office and zone 2 is a photocopy room) and two APs. Note that corridors can be represented as more than one zone depending on the need of the application. For each zone, a small amount of (around 10 data units) training data will be collected, i.e., RSS of all APs. Figure 2 is a segment of WiFi data in two rooms. As the RSS feature of two rooms are quite similar and most of them have overlaps, traditional localization methods like [11] or [12] are poor at handling this situation. However, we find that different rooms have diverse internal structure and human activities in those rooms are also different. As the example depicts, zone 1 is large than zone 2, so it is highly possible that the RSS fluctuation ranges of zone 1 are also larger than that of zone 2. Besides, zone 1 is an office where most of the people dwell for hours, while zone 2 is a photocopy room in which people usually only stay for a few minutes. Therefore we conclude that different rooms have different distributions of RSS fluctuation range and user dwell time. Besides, the room features could be used in room-level localization to improve the accuracy. The challenging part is how to extract related features from WiFi data.

3 Design of FRL

FRL consists of two modules (data collection and location inference) and two phases (training phase and testing phase). Figure 3 depicts the overall work flow of FRL. In data collection module, it collects three kinds of data for training and testing. In data processing module, localization models will be built based on the labeled and unlabeled data. The training phase is to extract the binary classifier and smoothing and segmentation rules from labeled data and train feature-based localization method from unlabeled data. The testing phase is to locate users from the collected WiFi data.

Details of data structures are listed below:

- Semantic location set $\mathbb{L}$ (l_i represents i^{th} semantic location):

$$\mathbb{L} = \{l_1, l_2, ..., l_n\},\ |\mathbb{L}| = n$$

- AP set $\mathbb{A}$ (a_j stands j^{th} AP):

$$\mathbb{A} = \{a_1, a_2, ..., a_m\},\ |\mathbb{A}| = m$$

- Labeled data $\mathbb{LD}$ (estimated labeled data has the same structure):

$$\mathbb{LD} = \{(time_i, RSS\_vector_i, l_i)\,|\,0 \le i \le p,\ l_i \in \mathbb{L},\ RSS\_vector_i = (rss_{i1}, ..., rss_{im})\}$$

- Transferred labeled data $\mathbb{TD}$:

$$\mathbb{TD} = \{prob\_vector_i, label\,|\,0 \le i \le p,\ label \in \{true, false\},\ prob\_vector_i = (p_{i1}, ..., p_{im})\}$$

- Unlabeled data $\mathbb{UD}$:

$$\mathbb{UD} = \{(time_i, mac, RSS\_vector_i)\,|\,0 \le i \le q,\ l_i \in \mathbb{L},\ RSS\_vector_i = (rss_{i1}, ..., rss_{im})\}$$

- Snippet of unlabeled data $\mathbb{SD}_i$:

$$\mathbb{UD} = \mathbb{SD}_1 \cup \mathbb{SD}_2 \cup ... \cup \mathbb{SD}_k$$

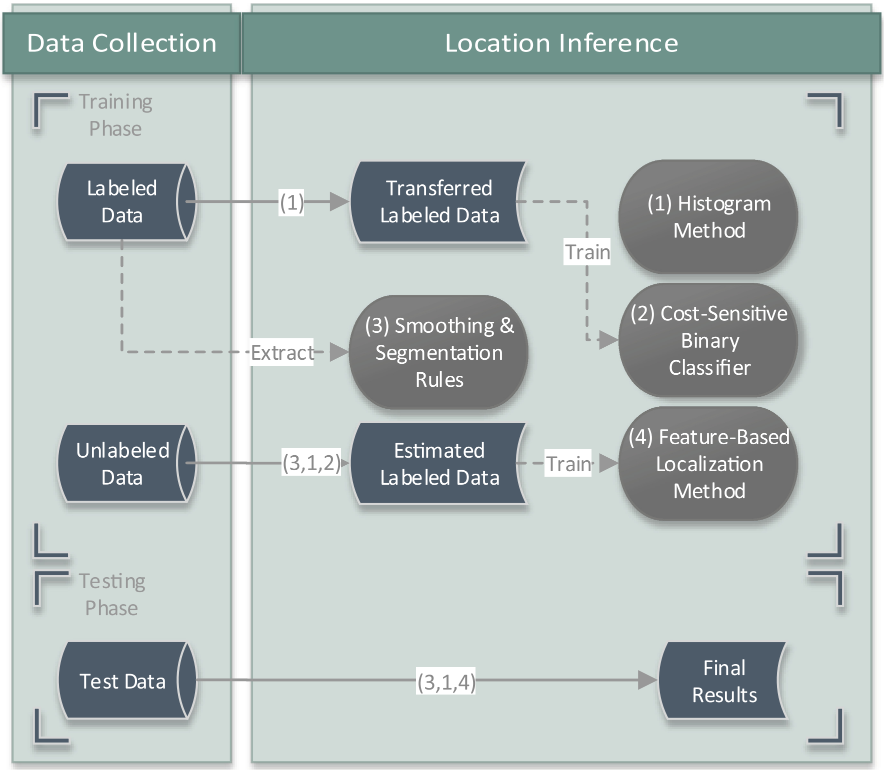

Fig. 3. The architecture of FRL

3.1 Data Collection

As described in Fig. 3, FRL collects labeled data and unlabeled data for training, test data for locating users in real scenarios. To collect the data in a non-intrusive way, FRL exploits probe requests. Probe requests are frames that are broadcast by smart phones to discover nearby APs. Recent research demonstrates great potential of applying this technique in tracking [17,18], crowd density estimation [19,20] and uncovering social relationships [21]. To sniff probe requests, we choose OpenWrt (an embedded operating system based on Linux kernel) as the firmware of the router. After configuration, routers can capture probe requests in the air and store the data on the external storage. Although different smart phones have diverse settings of probe requests [17], generally smartphones will broadcast probe requests every minute. That means in real world, FRL can locate users carrying smartphones every minute, which is adequate for many monitoring applications.

Detailed information of collected data is listed in Table 1. Collecting labeled data requires plenty of manpower, while collecting unlabeled data barely consumes any human resources. Therefore, FRL firstly collects a small amount of

Table 1. Details of collected data

Data type	Structure	Purpose	Required Amount	Manpower	Sampling Rate
Labelled Data	Time, RSS Vector of APs, Label	Training	Small	Needs	4 seconds
Unlabeled Data	Time, MAC, RSS Vector of Aps	Training	Large	No Need	N/A
Test Data		Testing	No Requirement	No Need	N/A

labeled data and a large amount of unlabeled data. Then FRL adopts traditional localization method to estimate labels for unlabeled data and utilizes a classifier to filters out snippets whose accuracy is above the threshold. As for test data, the quantity mainly depends on specific applications.

3.2 Location Inference

FRL inferences locations via traditional localization method and feature-base localization methods. It consists of three steps to train necessary rules and methods for localization. Firstly, it trains a classifier to filter out snippets from unlabeled data. Secondly, smoothing and segmentation rules will be extracted to partition unlabeled and test data into snippets. Lastly, we extract room features from unlabeled data with the help of the rules, conventional localization methods and the classifier.

FRL choose the histogram method, for the reason that using a histogram of signal strength for fingerprints in a zone may offer a good compromise between a single average and storing large number of fingerprints needed for improved accuracy [9]. The method requires a fixed set of bins, i.e., a set of non-overlapping intervals that cover the whole range of the variable from the minimum to the maximum RSS value. The width of the bins, denoted as w, is an adjustable parameter, which affects the performance. The outputs the method is a vector $prob\_vector_i$ indicating the possibilities of all zones.

Then FRL exploits the histogram method to labeled data and Cost-Sensitive Binary Classifier is to identify snippets from unlabeled data over the threshold. FRL gets transferred labeled data after applying the histogram method to labeled data. Based on transferred labeled data, FRL identifies true positive cases, which means real labels and estimated labels are both true. In order to transfer unlabeled data to labeled data with high accuracy, FRL adopts cost-sensitive learning, which makes optimal decision based on a misclassification costs [22].

Smoothing and Segmentation Rules is to remove outliers, smooth data sequence, and partition unlabeled data and test data into snippets. We follow the practice proposed in [12], which declares that a sharp change in signal data indicates that the user is likely to move from one zone to another. In addition, FRL merges small neighboring snippets because localization based on small snippets is not reliable. Figure 4 is an example showing how smoothing and segmentation works. The four cut-off points are chosen according to the accumulative changes

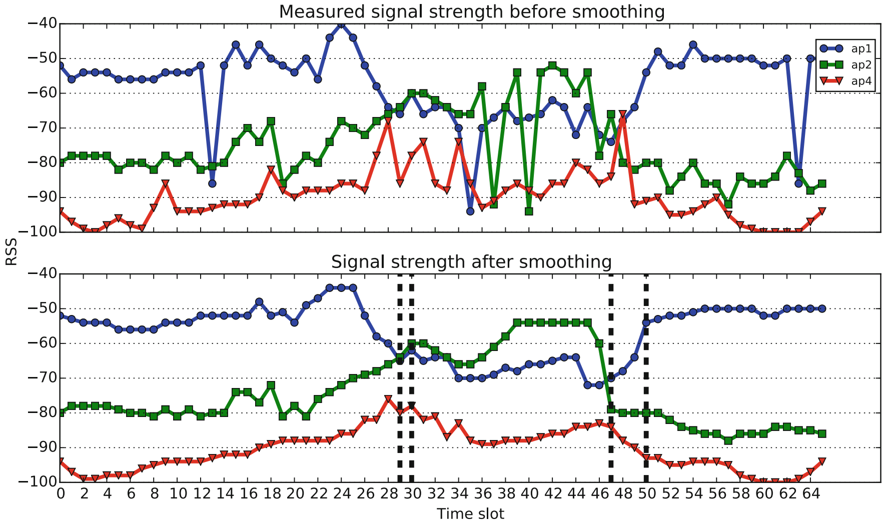

Fig. 4. Example of smoothing and segmentation

of $ap1$, $ap2$, $ap1$ and $ap2$ sequentially in a time window, as their accumulative changes all exceed the predefined threshold.

Feature-Based Localization Method provides another way for room-level localization. Feature-based localization method consists of two features, RSS fluctuation range and user dwell time. Both of the two features adopt the histogram method like RSS feature. Basically, FRL uses the result of the histogram method as the final result. If the top two zones of the histogram method are neighboring zones and the difference of their probabilities is below a threshold, then feature-based localization method will be applied to give the final result.

4 Implementation and Experiment Results

FRL is mainly implemented in Python with some C code and shell scripts. The system is tested in our department, in a area of 8 m by 20 m, with 11 zones separated and 3 APs installed, the layout and AP installation are shown as Fig. 5. Basically, $|\mathbb{L}| = 11$, $|\mathbb{A}| = 3$. For labeled data, $|\mathbb{LD}| = 110$, i.e., each zone has 10 training data units. We collect unlabeled data for one week, $|\mathbb{UD}| = 693,231$, including $2,162$ different devices and most of their data sequences are too short to use. For test data, we get four volunteers with smartphones in the test environment for one day and ask them to record their activities (start time, end time, locations). Finally we get 105 snippets and $|\mathbb{TD}| = 1,408$. We compare the performance of FRL with KNN, the histogram method, and the random selection method.

First of all, we leverage test data to evaluate the performance of smoothing and segmentation rules. After applying the segmentation rules, we get 121

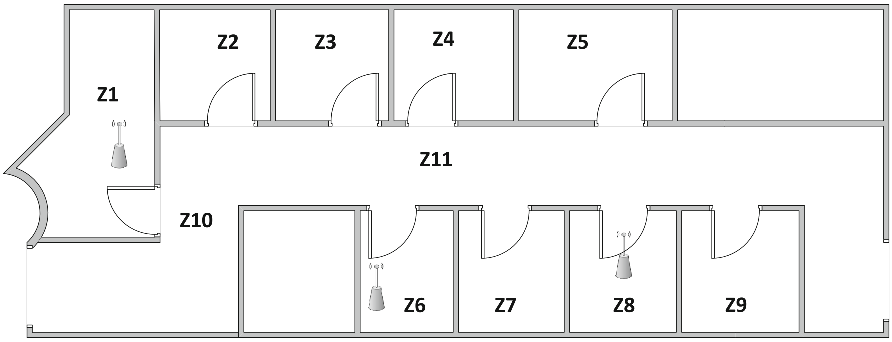

Fig. 5. Floor plan of the test bed

snippets. We define the correctness of snippets by two measurements, offset and length. Offset means the difference between start points of real snippets and derived snippets. Length represents the size of the snippets. Experiment results indicate the rules can identify 85 % the snippets whose errors of offset and length are below 5 %.

Table 2. Comparison of different classifiers

	Cost-sensitive with Random forest	Random forest	Naïve Bayes	Logistic
True positive cases	428	184	132	52
Accuracy	58.24%	71.31%	63.92%	69.03%
Precision	95.54%	41.07%	29.46%	11.61%

Then we use test data to evaluate the performance of the cost-sensitive binary classifier. Among all 1, 408 test data units, there are 428 true positive cases, 20 false positive cases, 392 true negative cases, and 568 false negative cases. Table 2 shows detailed information of four classifiers, and the cost-sensitive classifier with random forest outperforms other classifiers in terms of precision and true positive cases. The cost-sensitive classifier improve the precision by increasing the number of true positive cases while reducing the number of false positive cases.

The performance of the system is evaluated by the 1^{st} ranked zone. Due to space limitation, here we only show the final results of those methods. Figure 6 shows the overall accuracy of different methods. It is obvious that among all localization methods, FRL achieves the highest accuracy. FRL targets at the cases where the top two results are neighboring zones and have similar votes. Then it leverages the features of RSS fluctuation range and user dwell time to give the final result. Through the experiments we find that FRL is effective in handling neighboring zone problem and improves the accuracy of such cases by 50 %.

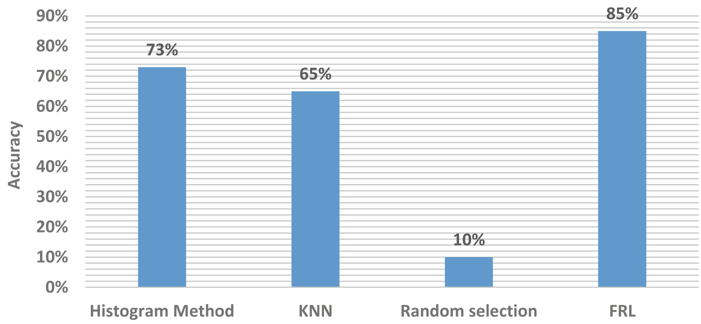

Fig. 6. Results of the experiment

5 Related Works

Currently, room-level localization methods can be divided into four categories. The first type methods rely on channel state information (CSI) of WiFi to discover users' locations and states [7]. These methods even do not require users to carry smartphones, they exploit the information of how a signal propagates from the transmitter to the receiver to locate users. The problem is that multiple people will result in unpredictable changes of channel states, hence it cannot be used to detect large number of users.

The second type focuses on geometric localization approaches, such as deterministic and probabilistic fingerprinting [10,11], that are also applicable for room-level localization determination. This kind of methods work quite well in static environment as it automatically take into account obstacles such as walls and furnitures [9]. On the contrary, dynamic factor cannot be reflected such as the change of layout, the number of people. RADAR [11] is a classic fingerprinting approach. Although it is not intended for room-level localization, the idea is also applicable here. RADAR consists of training phase and testing phase. During the training phase, a fingerprint database will be constructed. In the testing phase, one or more reference points in the fingerprint database will be chosen to estimate the real location. Simple and effective as this approach is, it is barely applied in practice, as constructing fingerprint database is too labor-extensive and boring to be done.

The third type is designed for room-level localization but most of them have troubles in handling neighboring zone with similar fingerprints. Correa et al. [9] utilize k-nearest-neighbor (KNN) with Euclidean distance measurement for indoor localization. According to their experiments, they conclude that only room-level granularity accuracy can be consistently achieved in wireless fingerprinting method. But the accuracy is influenced by the number of people moving around. WHAM! [12] is a nice work utilizing connectivity of semantic locations to resolve localization ambiguities. The system records users' historic location information, when current estimated location(s) are not unique, the system will make a choice based on the relation with previous locations. For example, the last location of a user is A, current estimated locations are B and C, but according to the floor plan, B is reachable while C is unreachable from A, then the system will return B as the estimated location. To some extent, this approach is effective, but most of the time, estimated locations are close to each other and all connect to the previous location. Besides, the experiments of WHAM! indicate it requires carefully tuned parameters to handle the situation where two rooms are separated by a thin wall. Another work is a rule-based WiFi localization method [13]. The authors find that the relative relation of RSS from different APs is more stable then absolute RSS. Based on this observation, they formulate the problem as a Hidden Markov Model (HMM) problem with the semantic locations as hidden states. But in some scenarios, such as shopping malls, with lots of customers moving around, the relative relation is changing frequently over time, thus this method could also be ineffective in real situations.

The forth type methods exploit other smartphones sensor data along with WiFi data to locate users. Ariel [14] utilizes gyroscope to collect WiFi data when users are in still. AurroundSense [15] exploits multiple sensors including the sound sensor, the accelerometer and the camera to construct ambience fingerprints. As it is not possible to get other sensor data without modifying users' smartphones, so these methods are inapplicable.

6 Conclusion

In this paper, we present a system called feature-based room-level localization (FRL). To addresses the deficiency caused by similar fingerprints of neighboring zones, FRL combines RSS feature and room features. In addition, FRL leverages probe requests to locate users without modifying their smartphones. The system is tested in a real scenario of 8 m by 20 m with 9 rooms and 3 APs. Experiments indicate that FRL can achieve a 10 % overall accuracy gain and 50 % accuracy gain in neighboring-zone situations, compared with conventional methods like the histogram method.

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References

1. Liao, L., Patterson, D.J., Fox, D., Kautz, H.: Learning and inferring transportation routines. Artif. Intell. **171**(5), 311–331 (2007)
2. Zheng, Y., Xie, X.: Learning travel recommendations from user-generated GPS traces. ACM Trans. Intell. Syst. Technol. (TIST) **2**(1), 2 (2011)
3. Farrahi, K., Gatica-Perez, D.: Discovering routines from large-scale human locations using probabilistic topic models. ACM Trans. Intell. Syst. Technol. (TIST) **2**(1), 3 (2011)
4. Hu, H., Lee, D.-L.: Semantic location modeling for location navigation in mobile environment. In: Proceedings of IEEE International Conference on Mobile Data Management, pp. 52–61. IEEE (2004)

5. Kelley, K.J.: Wi-Fi location determination for semantic locations. Hilltop Rev. **7**(1), 9 (2015)
6. Pradhan, S.: Semantic location. Pers. Technol. **4**(4), 213–216 (2000)
7. Zeng, Y., Pathak, P.H., Mohapatra, P., Xu, C., Pande, A., Das, A., Miyamoto, S., Seto, E., Henricson, E., Han, J., et al.: Analyzing shopper's behavior through WiFi signals. In: Proceedings of the 2nd Workshop on Workshop on Physical Analytics, pp. 13–18. ACM (2015)
8. Spink, A., Locke, B., Van der Aa, N., Noldus, L.: Tracklab: an innovative system for location sensing, customer flow analysis and persuasive information presentation. In: Proceedings of the ACM Conference on Pervasive and Ubiquitous Computing Adjunct Publication, pp. 985–990. ACM (2013)
9. Correa, J., Katz, E., Collins, P., Griss, M.: Room-level Wi-Fi location tracking (2008)
10. Roos, T., Myllymäki, P., Tirri, H., Misikangas, P., Sievänen, J.: A probabilistic approach to WLAN user location estimation. Int. J. Wirel. Inf. Netw. **9**(3), 155–164 (2002)
11. Bahl, P., Padmanabhan, V.N.: Radar: an in-building RF-based user location and tracking system. In: INFOCOM, Proceedings of Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies, vol. 2, pp. 775–784. IEEE (2000)
12. Lee, D.L., Chen, Q.: A model-based Wifi localization method. In: Proceedings of the 2nd International Conference on Scalable Information Systems, p. 40. ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering) (2007)
13. Chen, Q., Lee, D.-L., Lee, W.-C.: Rule-based WiFi localization methods. In: IEEE/IFIP International Conference on Embedded and Ubiquitous Computing, EUC 2008, vol. 1, pp. 252–258. IEEE (2008)
14. Jiang, Y., Pan, X., Li, K., Lv, Q., Dick, R.P., Hannigan, M., Shang, L.: Ariel: automatic Wi-Fi based room fingerprinting for indoor localization. In: Proceedings of the ACM Conference on Ubiquitous Computing, pp. 441–450. ACM (2012)
15. Azizyan, M., Constandache, I., Roy Choudhury, R.: Surroundsense: mobile phone localization via ambience fingerprinting. In: Proceedings of the 15th Annual International Conference on Mobile Computing and Networking, pp. 261–272. ACM (2009)
16. Pan, J.J., Pan, S.J., Yin, J., Ni, L.M., Yang, Q.: Tracking mobile users in wireless networks via semi-supervised colocalization. IEEE Trans. Pattern Anal. Mach. Intell. **34**(3), 587–600 (2012)
17. Musa, A. Eriksson, J.: Tracking unmodified smartphones using Wi-Fi monitors. In: Proceedings of the 10th ACM Conference on Embedded Network Sensor Systems, pp. 281–294. ACM (2012)
18. Cunche, M.: I know your MAC address: targeted tracking of individual using Wi-Fi. J. Comput. Virol. Hacking Tech. **10**(4), 219–227 (2014)
19. Handte, M., Iqbal, M.U., Wagner, S., Apolinarski, W., Marrón, P.J., Navarro, E.M.M., Martinez, S., Barthelemy, S.I., Fernández, M.G.: Crowd density estimation for public transport vehicles. In: EDBT/ICDT Workshops, pp. 315–322 (2014)
20. Schauer, L., Werner, M., Marcus, P.: Estimating crowd densities andpedestrian flows using Wi-Fi and Bluetooth. In: Proceedings of the 11th International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services, pp. 171–177. ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering) (2014)

21. Barbera, M.V., Epasto, A., Mei, A., Perta, V.C., Stefa, J.: Signals from the crowd: uncovering social relationships through smartphone probes. In: Proceedings of the Conference on Internet Measurement Conference, pp. 265–276. ACM (2013)
22. Ling, C.X., Sheng, V.S.: Cost-sensitive learning. In: Sammut, C., Webb, G.I. (eds.) Encyclopedia of Machine Learning, pp. 231–235. Springer, USA (2010)