Wi-Fi Fingerprint-Based Indoor Positioning: Recent Advances and Comparisons

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***Abstract*—The growing commercial interest in indoor location-based services (ILBS) has spurred recent development of many indoor positioning techniques. Due to the absence of global positioning system (GPS) signal, many other signals have been proposed for indoor usage. Among them, Wi-Fi (802.11) emerges as a promising one due to the pervasive deployment of wireless LANs (WLANs). In particular, Wi-Fi fingerprinting has been attracting much attention recently because it does not require line-of-sight measurement of access points (APs) and achieves high applicability in complex indoor environment. This survey overviews recent advances on two major areas of Wi-Fi fingerprint localization: advanced localization techniques and efficient system deployment. Regarding advanced techniques to localize users, we present how to make use of temporal or spatial signal patterns, user collaboration, and motion sensors. Regarding efficient system deployment, we discuss recent advances on reducing offline labor-intensive survey, adapting to fingerprint changes, calibrating heterogeneous devices for signal collection, and achieving energy efficiency for smartphones. We study and compare the approaches through our deployment experiences, and discuss some future directions.**

***Index Terms*—Indoor localization, Wi-Fi fingerprinting, localization techniques, system deployment, recent progresses and comparisons.**

I. Introduction

INDOOR location-based service (ILBS) has attracted much attention in recent years due to its social and commercial values, with market value predicted to worth US$10 billion by 2020 [1]. Indoor environment is often complex, characterized by non-line-of-sight (NLoS) of reference objects, presence of obstacles, signal fluctuation or noise, environmental changes, etc. Despite such complex environment, high localization accuracy (within meter range) is still expected in order to offer satisfactory ILBS.

As GPS signal cannot penetrate well in indoor environment, various other signals have been investigated for localization purpose. Such signals include Wi-Fi [2], Bluetooth [3], [4], FM radio [5], [6], radio-frequency identification (RFID) [7]–[10], ultrasound or sound [11], [12], light [13], [14], magnetic field [15], [16], etc. Among all these, the use of Wi-Fi signal has attracted continuous attention in both academia [17], [18] and industries [19], [20] because of pervasive penetration of wireless LANs (WLANs) and Wi-Fi enabled mobile devices. The deploymof Wi-Fi positioning systems is hence cost-effective without the need of extra infrastructure investment.

Traditional outdoor localization relies on the trilateration and triangulation [21], [22], which requires line-of-sight (LoS) measurement. Such schemes do not work well indoors with obstacles and room partitions. Without assuming LoS, Wi-Fi fingerprinting, a process of *signal collection and association with indoor locations*, has become a promising approach [18], [23]–[25]. In the scheme, a position is characterized by its detected signal patterns (e.g., a vector of RSSIs [2] from different Wi-Fi APs) [26]. Thus, without knowing exact AP locations, fingerprinting requires neither distance nor angle measurement, leading to its high feasibility in indoor deployment.

Wi-Fi fingerprinting is usually conducted in two phases: an offline phase (survey) followed by an online phase (query) [22]. In Fig. 1(a), we show its basic operation. In the offline phase, a site survey is conducted to collect the vectors of *received signal strength indicator (RSSI)* of all the detected Wi-Fi signals from different access points (APs) at many reference points (RPs) of known locations. Hence, each RP is represented by its fingerprint. All the RSSI vectors form the fingerprints of the site and are stored at a database for online query.

In the online (query) phase, a user (or target) samples or measures an RSSI vector (like the signals in Fig. 1(b)) at his/her position and reports it to the server.[1] Using some similarity metric in the signal space (such as the Euclidean distance [2]), the server compares the received target vector with the stored fingerprints. The target position is estimated based on the most similar "neighbors", the set of RPs whose fingerprints closely match the target's RSSI.

Wireless technology used for indoor positioning has been reviewed in [27]–[34]. While these works are impressive, few have focused on Wi-Fi fingerprint-based positioning system. Furthermore, we have witnessed in recent years significant advances in Wi-Fi localization techniques [18], [20], [35]–[39] and its efficient deployment [40]–[43], which have not yet been properly reviewed. The objective of this survey is to provide a timely and comprehensive overview and comparison on these recent approaches, so that readers may be educated in this fast growing area. Besides discussing the strengths and weaknesses of various state-of-the-art approaches, we also discuss our trials and experience in deploying indoor positioning.

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[1] In this paper, we use "user", "target" and "mobile device" interchangeably.

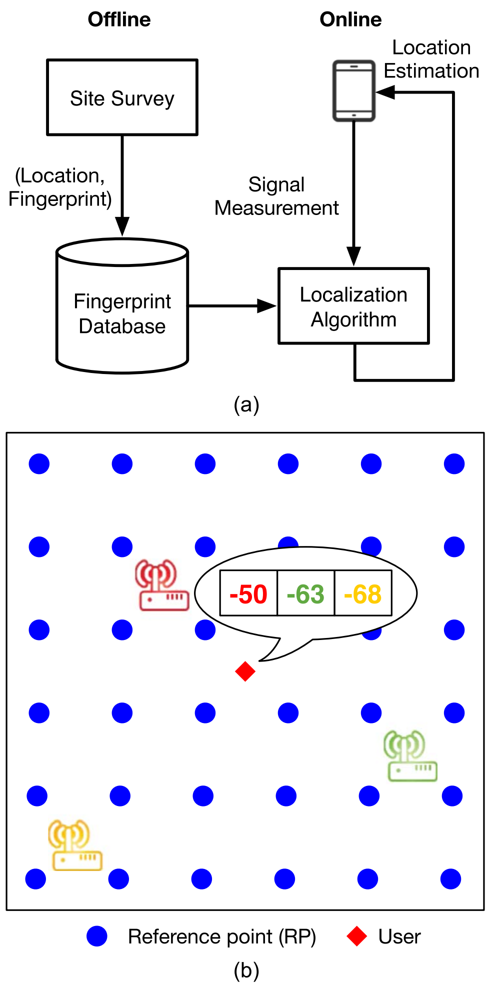

Fig. 1. (a) Basic system flow and (b) site map in a Wi-Fi indoor localization system. ([−50, −63, −68] in (b) represents signal levels in dBm from three detected APs).

We first review advanced localization techniques to achieve higher positioning accuracy. In particular, we discuss novel algorithms and sensor collaboration in the following areas:

- *Use of temporal and spatial signal patterns*: Signal fluctuation leads to location error [23]. In order to mitigate the error, a recent approach is to make use of the correlation between Wi-Fi signals and other observable measure such as walking trajectory, indoor building structures and AP locations. These form temporal and spatial signal patterns to improve the localization accuracy [44], [45].
- *Collaborative localization*: In order to reduce the localization error, we may utilize other sensors in mobile phones such as sound [46] or Bluetooth [3] to obtain the relative locations between neighboring users. This serves as distance constraints in their location estimations [47]. This is so-called collaborative localization, which is shown to substantially improve Wi-Fi localization accuracy [23].
- *Motion-assisted localization*: In contrast to device collaboration, the motion-assisted scheme relies on the inertial sensors in a device and measures the walking trajectory to fuse with Wi-Fi. The works in this area mainly focus on how to improve path estimation using inertial sensors to achieve higher accuracy [24], [38], [48]–[50].

Besides advances in localization techniques, we review recent practical approaches to efficiently deploy Wi-Fi fingerprint-based positing systems. These approaches include the following:

- *Reducing site survey*: Wi-Fi fingerprint collection and maintenance are time-consuming and labor-intensive. As Wi-Fi signals may change due to environmental change (e.g., establishment or tear-down of partitions, introduction or removal of APs, etc.), another costly site survey may be needed to keep the fingerprints in the database up-to-date. We present some recent progresses in reducing site survey and online adaptation to signal/fingerprint change.
- *Calibrating heterogeneous mobile devices*: The mobile devices in the online measurement are likely to be different from those used in offline data collection. Thus, if calibration between devices is not done properly, the localization accuracy would be adversely affected. We present emerging techniques to efficiently calibrate heterogeneous devices.
- *Energy efficiency*: Battery energy is a major concern for mobile localization. While high accuracy and estimation responsiveness may improve with fast Wi-Fi scanning and intensive CPU processing, the energy consumption may correspondingly increase. We review some lightweight localization systems to conserve battery lifetime.

This paper is organized as follows. In Section II, we review the advances in localization algorithms. We present in Section III the schemes for efficient deployment of Wi-Fi fingerprint-based systems. In each section, we compare the approaches qualitatively or quantitatively through our deployment experiments. We conclude by briefly presenting some future directions in Section IV.

II. Advanced Localization Techniques

In this section, we first introduce the basic principles for fingerprint localization (Section II-A). Then we describe recent advances on using spatial and temporal signal patterns (Section II-B), collaborative localization (Section II-C), and motion-assisted localization (Section II-D).

A. Basic Fingerprint Localization (Overview)

Traditional indoor localization algorithms [51] include deterministic [2] and probabilistic methods [52], [53]. *Deterministic algorithms* use a similarity metric to differentiate online signal measurement and fingerprint data. Then the target is located at the closest fingerprint location in signal space [20]. Euclidean distance [54]–[56], cosine similarity [57] and Tanimato similarity [58] have been implemented for signal comparison [31]. The major advantage of the deterministic methods is their ease of implementation. Traditional deterministic methods can be easily implemented based on k nearest neighbors (k-NN) and the computational complexity is often low. Some other more advanced deterministic algorithms such as support vector machine [59] and linear discriminant analysis [60] show better localization accuracy with higher computational cost.

Probabilistic algorithms are based on statistical inference between the target signal measurement and stored fingerprint [61]. Using a training set, these algorithms find the target's location with the maximum likelihood. Horus in [52] estimates the target location using a probabilistic model reflecting the signal distribution in the site. Specifically, given a target signal strength vector $\mathbf{s} = (s_1, \ldots, s_L)$ and L APs, Horus finds the target location $\mathbf{x}$ with the maximum posterior probability, i.e.,

$$\arg\max_{\mathbf{x}} \left[P(\mathbf{x}|\mathbf{s}) \right], \tag{1}$$

where $P(\mathbf{x}|\mathbf{s})$ is the probability of the target at location $\mathbf{x}$ given signals $\mathbf{s}$. It can be further transformed into

$$\arg\max_{\mathbf{x}} \left[P(\mathbf{s}|\mathbf{x}) \right] = \arg\max_{\mathbf{x}} \left[\prod_{l=1}^{L} P(s_l|\mathbf{x}) \right], \tag{2}$$

where $P(s_l|\mathbf{x})$ (probability that signal s_l appear given location $\mathbf{x}$) can be approximated by some parametric distributions including Gaussian distribution.

Other probabilistic algorithms such as Bayesian network [53], [62], expectation-maximization [63], Kullback-Leibler divergence [64], Gaussian process [65] and conditional random field [48] also achieve high accuracy through probabilistic inference.

In probabilistic algorithms, each location estimation can be indicated by a confidence interval [36]. They are also amendable to fuse different sensors such as motion [24], [66] and sound [62]. For example, the location can be estimated by maximizing the joint probability or likelihood with the sensor measurements. However, these algorithms usually require some probabilistic assumptions (such as Gaussian noise or probabilistic independence [24]). Furthermore, training probabilistic models [66] may be complicated, and require more datasets than traditional deterministic algorithms.

Deterministic and probabilistic algorithms are important building blocks for indoor localization. In the following, we describe some advanced systems which are based on these algorithms.

B. Exploiting Spatial and Temporal Signal Patterns

Traditional fingerprinting localization is usually based on the RSS signal vectors [2]. Due to measurement noise (multi-path effects [25]), the target may be mapped to a distant position of similar signal vectors [23], [24], [70]. Higher accuracy can be achieved if the location is estimated by jointly considering temporal or spatial observations:

- *Temporal patterns* are the Wi-Fi signal sequence patterns during walking in the indoor environment. Signal patterns along the trajectory of the route walked can be used to infer the locations. As compared with a single signal vector at a fixed location, the pattern carries temporal information which can be used to constrain and correct the Wi-Fi fingerprint-based localization.
- *Spatial patterns* are related to the geographical distribution of signals beyond simply RSSI vector representation. Temporal Wi-Fi patterns often require knowledge of user motion (walking path or heading direction), which may not be available or accurate in reality. The geographical signal patterns can hence be used to constrain user location. These patterns include RSSI order, signal landmarks (AP locations) and signal coverage.

Table I shows the typical works using different patterns for localization, which are introduced as follows.

Temporal patterns: Peak-based Wi-Fi Fingerprinting (PWF) in [67] considers the *peak* in a sequence of signal values for localization. The peak (with a predefined high signal value) of the signal sequence [67] in the site indicates that a Wi-Fi AP is close to the measurement point. Thus, strong signal measured shows higher confidence than other weaker one to indicate the target position. In order to find the peak, a sequence of Wi-Fi data needs to be collected when the user is walking. The system then detects the peak and also finds the corresponding location in signal map. This algorithm provides accurate correction, especially when the APs are installed in the ceilings of indoor paths. However, the motion information of the user needs to be known during measurement. Besides, if the user is moving too fast, the peak of the measurement may not be correct due to the scan missing of AP signals.

In noisy environment, considering a whole sequence of data is more robust than a single peak value. Walkie-Markie [45] considers a whole *signal sequence* for location classification. Walkie-Markie first records the Wi-Fi RSSI vectors as patterns in different corridors. As shown in Fig. 2, a walking user along the corridor can detect the increase and decrease of signal strength from a nearby AP. The sequence of RSSI data can form the pattern for a given corridor. By matching the user's RSSI sequence during walking, Walkie-Markie knows the location and map information of the target. Inspired by Walkie-Markie, recent works like [71] investigate the temporal patterns for signal and location mapping. Considering a whole signal sequence is more robust to noise than only the peak in the sequence.

However, the signal sequence is more suitable for narrow corridor space rather than the indoor open space like airports or metro station. Besides, the user motion information needs to be considered in order to distinguish the incorrect signal sequences due to random walking user.

Spatial patterns: Wi-Fi APs may be installed at specific indoor positions like corridor corners or offices. Thus, we may measure remarkable signal values limited to a specific area, which can form the *Wi-Fi "landmarks"* and uniquely classify the corresponding regions. Through some simple investigation into the site, these landmarks can be discovered and stored in database for online use. Inspired by such observations, UnLoc [44] and MapCraft [48] use the unique measurement of APs to correct the localization results. As shown in Fig. 3,

TABLE I
DIFFERENT METHODS UTILIZING TEMPORAL AND SPATIAL PATTERNS

Category	Schemes	Signal Patterns	Indoor Site Availability	Additional Information for Location Estimation	Reported Mean Accuracy	Limitations and Robustness
Temporal Patterns	PWF [67]	RSSI peak in a temporal sequence.	Narrow path or corridor; dense AP deployment.	Walking direction.	<2 m in corridors.	If the user is moving quickly, it becomes difficult for accurate peak detection and location determination.
	Walkie-Markie [45]	RSSI sequence.	Narrow path or corridor.	Walking direction.	<1.8 m in corridors.	Work the best if users walk in one direction in corridors for accurate data collection.
Spatial Patterns	UnLoc [44]	Wi-Fi landmark.	Narrow path or corridor; dense AP deployment.	Walking trajectory.	<2 m in corridors.	Size of Wi-Fi landmarks cannot be too large; work the best with dense landmarks.
	HALLWAY [68]	Order of Wi-Fi RSSI values.	Room partitionings.	N/A	$\sim 90\%$ in finding correct rooms.	Granularity of using received signal order may not be very high; the RSSI order in the same room may be the same.
	Wi-Fi Signal Coverage Intersection & Devision [57], [69]	Similar signal values form signal sector; within sector intersection.	Large indoor open space; multiple APs need to be detected.	N/A	<6 m in indoor open space and corridors.	If Wi-Fi AP installations are co-located, the overlapped region can be too large and may not provide tight constraints.

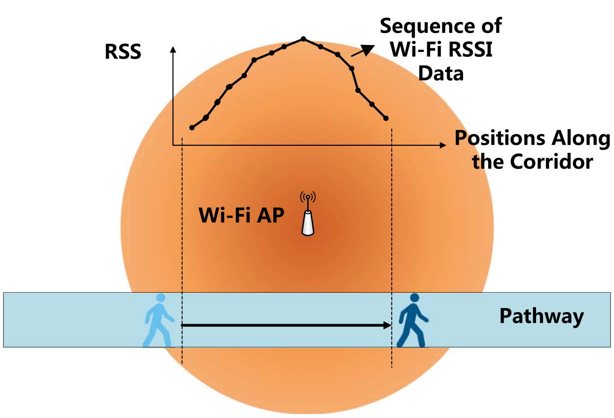

Fig. 2. Illustration of temporal signal patterns in Walkie-Markie system [45].

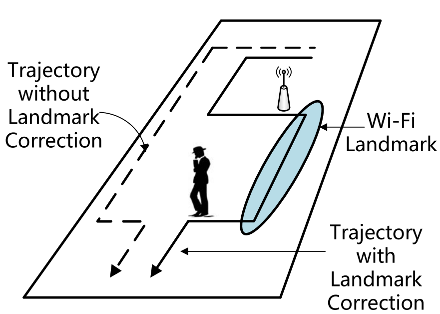

Fig. 3. Illustration of using Wi-Fi as landmarks [44]. The target measures the Wi-Fi landmark (shaded area) and then corrects his/her trajectory from the left to the right one.

given an online measurement of these landmark APs (shaded region on the right), the user's trajectory can be rectified to the correct area on the right. Thus, we can achieve higher accuracy than the left estimation without sufficient landmark correction. Similar to UnLoc, MapCraft leverages the signal landmarks to constrain the location estimation. (Though works like UnLoc and MapCraft contain inertial sensors and motion information, here we focus on their contributions in novel Wi-Fi signal patterns here.) As the Wi-Fi APs are not densely installed in some indoor buildings, landmark corrections may not always be available. Therefore, they also need other signal landmarks like magnetic field for further location correction [72], which increases the complexity of system deployment.

The above approaches consider using APs individually as landmarks, which in deployment may not be robust to measurement errors. If the power of AP is set to be strong, then the coverage of AP may form a large landmark. In such a case, jointly considering multiple APs can be a more reliable choice. HALLWAY in [68] observes that *the order of signal strength* from different APs is location-dependent. For example, denote signal strength for AP 1, 2 and 3 as s_1, s_2 and s_3, respectively. In room A, an order of $s_1 < s_2 < s_3$ is observed while in room B, we may find $s_1 < s_3 < s_2$. HALLWAY utilizes such a difference to classify the rooms. Using RSS orders can reduce the influence of device dependency and small signal fluctuation. Therefore, it can provide relatively reliable indication for a room or office region.

One possible limitation is that in the signal order within a small room may be the same. Therefore, the granularity of the location estimation may be limited to room level. In deployment, the fingerprint needs to be carefully preprocessed to extract their strong difference as the location patterns.

In order to provide tighter constraints, *signal coverage* of different APs needs to be jointly considered. For a given AP, the signal strength at a certain distance from AP is usually similar and forms some geographical constraints over the target. Based

TABLE II
TYPICAL SCHEMES OF COLLABORATIVE LOCALIZATION

Category	Scheme	Collaborative Sensors	Distance Accuracy	Robustness of Distance Measurement	User Mobility	Limitations
Distance based	VC [78]	Wi-Fi Direct; Bluetooth	Medium	Affected by RF multipath.	Static	Not for absolute positioning; distance measurement may not be very accurate.
	PA [23]	Sound	High	High	Static	Require accurate pair-wise distance measurement; rigid network graph may suffer from measurement error; require synchronization.
	Centaur [62]	Sound	High	High	Static	Peer synchronization required; designed for static devices.
Proximity based	ZCL [76]	ZigBee	Low	Affected by RF multipath.	Within a small group (static or moving together)	Users need to be near to each other; cannot accommodate randomly moving users.
	Social-Loc [36]	Wi-Fi Direct; Bluetooth	Low	Affected by RF multipath.	Pedestrian; high mobility.	Thresholds of encounter detection may suffer from noise; encounter and non-encounter information using RSSI may not be accurate.

on such observation, the work in [57] constrains the target estimation using the intersection of signal coverage area from several APs. For each detected AP, it first divides its coverage area according to discrete signal levels. Similarly, using a probabilistic approach, the work in [69] also considers using the signal coverage to reduce the search scope of target location. In online stage, the target is first mapped to the intersection of several sectors. Then within the constraint, the system finds the reference points with the most similar signal patterns as location estimation through deterministic or probabilistic mapping. In this way, the constraints over the target rule out the dispersed nearest neighbors in signal space with high similarity. Similar region intersection or division scheme has also been reported in some sensor network localization systems like [73] and [74].

If the APs are co-located within a small region, the intersection of the APs may become too large and cannot constrain the final estimation sufficiently. Therefore, virtual AP filtering [75] (filtering those MAC addresses generated from the same physical Wi-Fi router) can be conducted before finding the signal coverage and final location decision.

To summarize, temporal and spatial patterns are new to Wi-Fi indoor localization. They help discriminate the locations, and significantly improve the positioning accuracy. However, these signal patterns usually work the best under certain indoor sites, either for narrow corridors [44], [67] or spacious area with good AP coverage [69]. They may not be general enough to apply in different indoor sites. Therefore, according to our deployment experience, a system designer may need to jointly consider the properties of the deployment sites, and select suitable algorithms for practical use. Moreover, a fine-grained site survey and data preprocessing may be needed in order to mine and utilize these patterns. Thus, we also need to balance between efforts in data analysis and improvement in Wi-Fi location estimation.

C. *Collaborative Localization Among Mobiles*

Most of the current works on Wi-Fi fingerprint localization are based on independent estimation, i.e., the system locates each target independently [2] without considering the relative locations of the others. Due to independent estimation errors, two physically close targets may have markedly different estimated locations [23]. Thus, if the information of relative positions can be obtained and utilized, the estimation results can be improved from individual localization.

Recent works have begun to investigate the possibilities of *collaborative localization*. Its emergence basically arises from the following trends in mobile computing:

- ⋆ *Location context of social interaction*: In indoor environment, people may gather together in typical social scenarios [76]. In museums, people often browse through the exhibits with their family and friends. The social interaction among them therefore shows the location pattern. Based on such a context, we can even derive more interesting application with indoor LBS [77].
- ⋆ *Pervasive mobile devices and advanced sensors*: Nowadays smart phones have implemented many sensing techniques. A mobile device can easily discover others in its neighborhood based on various established protocols (such as Bluetooth [3], Wi-Fi direct [78], Wi-Fi Aware [79], Near Field Communication (NFC) [36] and sound wave [23]). Therefore, the emerging smartphones provide the possibilities of sensing the existence of neighboring users.

In Table II, we show several typical works on collaborative localization. Based on the accuracy of mutual distance measurement, we describe the related works in the following two categories: distance-based and proximity-based algorithms:

- *Distance-based*: There have been works focusing on using advanced sensors [46], [80] on smartphones to

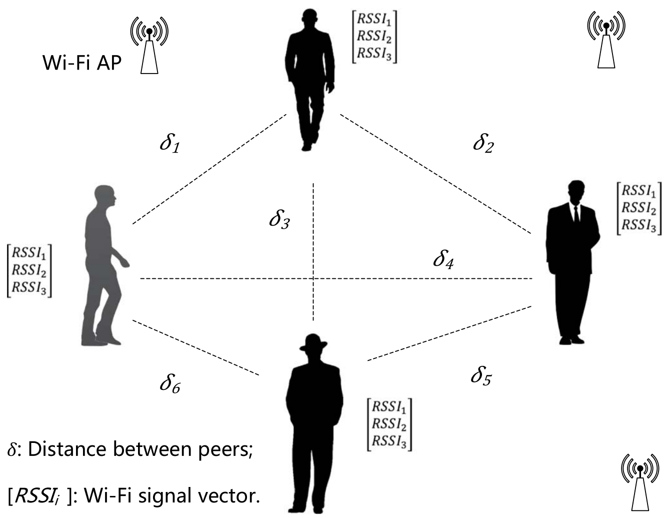

Fig. 4. Illustration of indoor peer-assisted localization [23]. Users simultaneously measure the Wi-Fi signals and their pairwise distances.

measure distances between users. These pairwise distances can be utilized to form the network graph (topology) of different users [23]. Then we can directly constrain the estimation of all the involved users.

- *Proximity-based*: Due to the diversity of dynamic human behaviors and social interaction, accurate pairwise distance between users may not be always available. In order to relax the user mobility requirement and address the noisy distance measurement, some recent works focus on leveraging the proximity [76] and encounter between users [36]. As proximity information may not be very accurate, probabilistic inference are often implemented for robust estimation.

Distance-based Scheme: Virtual Compass (VC) [78] proposes a novel algorithm to locate neighborhood users. VC aims at relatively locating the friends nearby based on Wi-Fi direct and Bluetooth. VC is based on Vivaldi algorithm [81] to find the coordinates such that all the linked users' locations satisfy their pairwise distance. In particular, all the users form a network, and Vivaldi algorithm constructs the network topology given pairwise measured distances. To mitigate the error in radio-based distance measurement, VC fuses Bluetooth and Wi-Fi direct together. By modeling the confidence interval of both sensors, VC achieves better distance accuracy than using a single sensor. However, using RF signals for distance measurement is still vulnerable to the signal noises. VC has not yet been specifically built for absolute target positioning. It provides the potential of further adaptation based on Wi-Fi localization or GPS fixes to estimate user absolute locations.

Instead of using radio signals, sound-based scheme [46], [80] provides new opportunities in accurate distance measurement between smartphones. Two typical works using sound are the peer-assisted (PA) localization [23] and Centaur [62].

PA utilizes the technique in Beep [46] for distance measurement between smartphones. As shown in Fig. 4, PA requires peer users to collect mutual distances as well as Wi-Fi RSSIs. Wi-Fi signals of all users are first fed in traditional fingerprint localization for initial location estimations. Then pairwise distance information helps transform the above positions into a network graph. By rotating and translating the network graph, PA finds the locations of all users which minimizes the overall Euclidean distances from stored Wi-Fi signal map. More specifically, suppose M users are involved in PA localization. Let $\mathbf{r}_n = (r_1, r_2, \ldots, r_L)$ be the Wi-Fi fingerprint at reference point n $(1 \le n \le N)$ from L APs. The objective of rotation and translation of PA is to jointly find the reference point set $\{n\}$ such that the overall Euclidean distance between target signals and fingerprints is minimized, i.e.,

$$\arg\min_{\{n\}} \left[\sum_{m=1}^{M} (\mathbf{r}_n - \mathbf{s}_m)(\mathbf{r}_n - \mathbf{s}_m)^T \right]. \tag{3}$$

The highly accurate distance measurement ensures the high accuracy in PA localization. However, as the graph shape is rigid, if there are distance measurement errors, the location estimation will be significantly influenced. Moreover, pairwise measurements are needed in building a complete graph. Therefore, the synchronization in PA becomes complicated and may be vulnerable to measurement errors.

Different from PA, Centaur [62] implements Bayesian network for collaborative localization. Centaur does not rely on a rigid graph, which is vulnerable to large distance measurement error. Instead, Centaur finds the locations with the maximum likelihood for all involved devices, and shows more robustness under noisy environment compared with PA. However, the prototype of Centaur focuses on static device localization while the dynamic positioning of peer users has not been explored. For PA and Centaur, sound estimation based on commercial smartphones is novel and achieves high accuracy for distance measurement. Despite the advances, in indoor environment such sound may be audible for some users and may become a kind of noise [82]. In the future development, such a scheme using the smartphone sound module may need to consider improving its applicability under crowded indoor environment.

Proximity-based scheme: Some recent works [83], [84] have utilized the users' temporary stop to measure the accurate distance between each other. To improve the robustness in practical deployment, we still need to consider the movement of the users and imperfection in mutual distance measurement in real application. Proximity, rather than accurate distance values, can be utilized for dynamic measurement.

Proximity information can be obtained from Wi-Fi AP list (or MAC addresses) [85] and Bluetooth [3] to infer the proximity between users or targets [86]. A more fine-grained system in [76] proposes ZigBee-based collaborative localization (ZCL) for absolute location estimation under scenarios like museum environment. ZCL first implements ZigBee radio as the neighbor-detection sensor. Then it computes a confidence score for each target within the neighborhood, which is according to the combination of motion model and Wi-Fi location estimation. Based on the difference between the confidence scores, the system jointly corrects the neighboring estimations through a proposed distributed algorithm. This scheme works like the attraction (pairwise distance constraint) between magnetic interaction, filtering the candidate locations with low confidence.

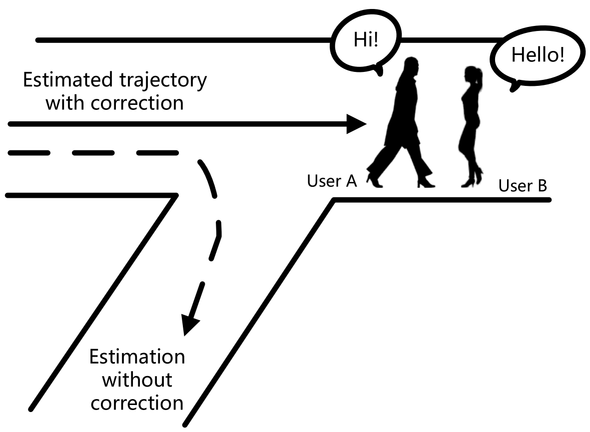

Fig. 5. Illustration of indoor encounter-based localization. The encounter of user A and B corrects their previous location estimations.

Although ZCL provides interesting application scenarios in museums and exhibits, ZigBee used in the system may still suffer from multipath and therefore the proximity information may be incorrect. To address this issue, multiple samples and averaging filter may be applied in ZCL with cost of longer waiting time. Besides, ZCL works the best when the users are within a group in a relatively small region (static or moving in the same direction), which may not accommodate more dynamic user behaviors.

If the users are walking around in the buildings, the useful proximity information between users is often temporary. Leveraging the above interaction, Social-Loc [36] proposes utilizing users' "meeting" or "missing" for localization. A user may come across another user, which is defined as "encounter". If he does not meet another specific user during the localization process, such an event is defined as "non-encounter". Social-Loc utilizes these encounter and non-encounter events to cooperatively correct the localization errors.

The user locations are first initialized through traditional Wi-Fi fingerprint-based localization [52]. Each user estimation has multiple candidates (reference points), with different prior probability. In Fig. 5, if two users encounter each other, their estimated locations should have overlapping. Thus, the candidate location which does not satisfy encounter information of two users would be filtered out. The location estimation will be constrained to the place where user A and B just meet. Similarly, if the user A and B have not encountered each other in a candidate position, the confidence for that position in final Wi-Fi estimation will decrease. Given the above posterior probability, the final Wi-Fi location estimations can be updated for all involved users in Social-Loc. In real deployment, the thresholds for encounter and non-encounter detection may suffer from signal noise. If misclassification of neighboring users happens, the localization performance probably degrades.

To summarize, collaborative localization emerging in the above works has shown large improvement in localization accuracy. However, in practical deployment, several issues need to be considered. Computational complexity is high for collaborative localization due to the pairwise communication [87] and synchronization [23]. User mobility also makes the user collaboration challenging, as the relative positions of peer

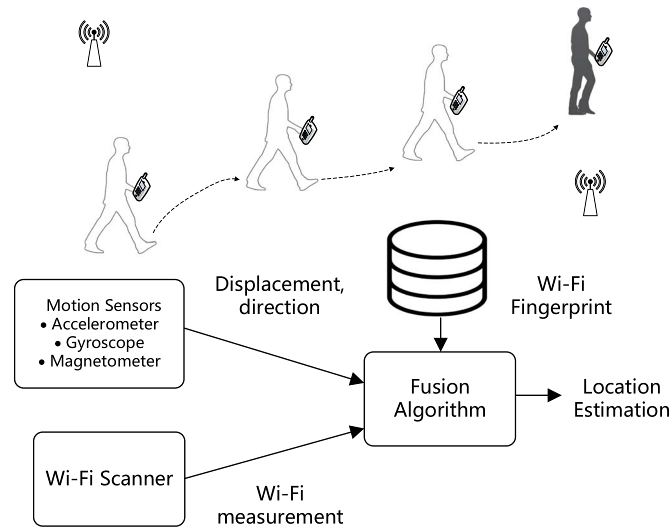

Fig. 6. Illustration of fusing Wi-Fi and motion sensors for indoor localization.

users change frequently, especially in the airport or train station [88]. During the social interaction, sensor collaboration may also release the information of the device owners. Therefore, to address the privacy issues, collaborative localization in the future work requires designing a specific secured protocol for location share [78], [89], [90].

D. Motion-Assisted Localization

Motion-assisted Wi-Fi localization is a classical hybrid technique for indoor localization. It has advanced quickly in the recent years due to the pervasive application of motion sensors on mobile devices. In this survey, we focus on the following recent advances in motion-assisted localization:

- *Advances in motion measurement*: Precisely monitoring the pedestrian's walking behaviors is important for accurate motion-assisted localization. The major challenge in obtaining motion information is that the inertial sensors in commercial smartphones often suffer from imperfect calibration and noisy measurement. Step counting is currently a major approach to capture the movement and walking path of pedestrians [91]. Therefore, recent works aim at improving walk detection, step counting and step length measurement. Besides, how to adapt to different users' personal motion profiles is also challenging.
- *Advanced and efficient fusion models*: How to fuse the motion and Wi-Fi is essential to the localization accuracy. The model used in fusion needs to capture the correlation (either temporal or spatial) between the measured signals. Besides, if the model is highly complicated, the high computation expenses also affect the quality of location estimation. Therefore, finding an accurate and efficient fusion algorithm or model is recently an important trend for motion-assisted Wi-Fi localization [24], [48].

Fig. 6 shows a typical system of motion-assisted localization. Motion sensors measure the user walking distance (between two sequential Wi-Fi measurements) and heading direction.

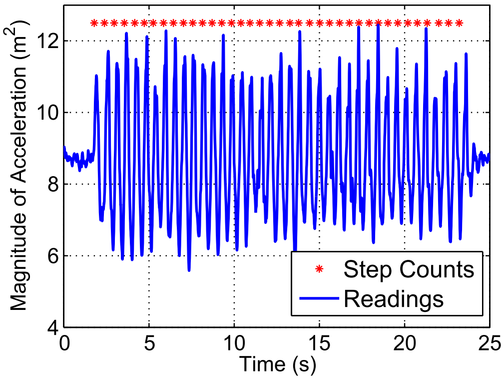

Fig. 7. Readings from the smartphone accelerometer (HTC One X). Each red dot corresponds to one step.

Combining the above information and Wi-Fi signal measurement, a certain fusion algorithm in the system returns the user with the location estimation.

Advances in motion measurement: With the accelerometers, gyroscopes and magnetometers, the recent smartphones can capture the walking direction, distance and gesture information. These sensors are usually called microelectromechanical systems (MEMS). Accelerometers measure the 3D linear acceleration (m/s^2) or g-force (gravity or g) of the device. Gyroscopes give the angular velocity (rad/s) and measure the orientation in principle of angular momentum. Magnetometers provide the strength and direction of magnetic fields [92]. With gyroscopes and magnetometers, we can know the heading direction of the user. Based on the sensors and signal filtering techniques, more advanced motion detection can be conducted, such as device rotation, step counting and gesture recognition.

To measure the walking distance of the user, *pedometer* (step counter) is a suitable scheme for the pedestrian localization [93]. In terms of getting the position offset, pedometer has better performance than direct integration of acceleration since the signal drift leads to large errors after double integration. As shown in Fig. 7, we show the readings from accelerometers on an HTC One X smartphone, where the signal patterns during walking can be used for step inference. In recent works utilizing the pedometer [93], researchers have focused on the following three components:

— *Walk detection*: Walk detection first classifies the current motion state of the target (such as using thresholds in accelerometer readings or advanced learning algorithms [93]). If a user is identified as "moving", the step counting starts to work.
— *Step counting*: Simple step detection can be based on peak detection or zero crossing of acceleration readings [94]. However, it may suffer from noisy sensor readings or imperfect calibration. More advanced schemes like [93], [95]–[97] focus on finding repetitive step patterns from sensors. It can be based on autocorrelation of step patterns [96] or extracting the step frequency pattern through Fast Fourier Transformation (FFT) [97].
— *Stride length measurement*: Through walk detection and step counting, the mobile device can measure the walking distance by multiplying the stride length with the step counts. The stride length depends on the step frequency, user height and other factors [98]. Some works utilize Gaussian distribution to model the noise in step length [99]. More advanced works implements some linear step model [98], [100] to calibrate the relationship between stride length and step frequency. Some other work [101] models the relationship between step length and height change of user waist during walking.

In real application, users may show heterogeneity in their motion patterns, including their stride length, walking gesture, step frequency and other information which affect the sensor readings. Therefore, the motion sensors may still require specific calibration for different users in real deployment [93]. However, they either require offline calibration [38], [44] or external infrastructures for distance estimation [102]. Some recent works propose online calibration on step counter [96], which measures the step length when the user is walking in indoor corridors. With indoor map constraints, the system may estimate the walking distance more accurately and learn the stride length. More advanced works like [103], [104] calibrates the step length through particle filter learning or expectation maximization.

Most of the works above usually assume the mobile phone is at a static position relative to the user body throughout the movement. However, in reality, the *relative position of the smartphone* changes and hence may influence the step counter and heading direction accuracy. Therefore, some compensation on rotation angle is needed to correct the drift, which is introduced by relative change of device position from the user body [105]. Another approach is to use wearable devices, which can be attached to human body, and capture more accurate motion information for localization [101], [106], [107].

Fusion problems, algorithms and model simplification: Given motion measurement, how to conduct fusion is a challenging and interesting question. In Table III, we summarize the corresponding approaches used in this section, which will be further elaborated as follows.

Traditional fusion often focuses on problems of finding the target location [38] and reduces the errors in wireless localization [24]. Motion information in fusion filters the incorrect positions returned from Wi-Fi localization, especially under signal fluctuation or fingerprint ambiguity. Map information is often available and may contribute to location filtering [99].

A more complicated problem, Wi-Fi-based *Simultaneous Localization and Mapping* (SLAM) [108], focuses on simultaneously localizing the target and constructing the indoor maps. To approach this, Wi-Fi-based SLAM [109] utilizes fusion of Wi-Fi and motion measurement to jointly minimize the location difference with the indoor structure and infer the map. It has also been widely applied in robot localization application scenarios without explicit map information [110].

Robot localization [111] has leveraged the motion information to improve wireless localization. Some early approaches like signal-strength-based SLAM [109] utilizes the Gaussian process [65] to estimate the position of robots. However, robots are different from human in motion patterns. It is more difficult

TABLE III
RECENT APPROACHES FOR MOTION-ASSISTED WI-FI LOCALIZATION

Scheme	Localization Algorithm	Motion Information	Online Complexity	Robustness	Reported Mean Accuracy	Limitations
Zee [99]	Particle Filter	Step counts (autocorrelation -based); heading direction.	High	Utilize map information to filter incorrect particles; robust under narrow corridors.	< 2 m	Crowdsourced signal data may carry noise.
XINS [120]	Particle Filter	Step counts (peak detection); heading direction.	High	Utilize particle filter to fuse different signals; a generic framework to accommodate different environment with different signals.	N/A	Work the best when different signals (cell, GPS and Wi-Fi) are available for location fixing.
Graph -Fusion [38]	Particle filter and graph discretization of indoor map	Step counts (peak detection); heading direction; online stride length estimation.	Medium	Simplify the indoor map model; high accuracy for narrow corridors.	< 2 m	Large indoor open space is hard to be discretized.
HMM Fusion [66]	Hidden Markov Model	Step counts; heading direction.	Low	Require independence assumption between Wi-Fi signals and motion; influenced by signal noise.	< 6 m	Training HMM requires large training data set; expensive training process.
Moloc [24]	Maximum likelihood of fingerprint and motion	Step counts (autocorrelation -based); crowdsourced motion profile; heading direction.	Low	Require independence assumption between Wi-Fi signals and motion; influenced by signal noise.	< 1 m	Need to collect user motion profile for later localization.
MapCraft [48]	Conditional random field	Step counts; heading direction.	Low	Joint consideration of motion and Wi-Fi signals; no dependence assumption needed; high robustness.	< 2 m	Rely on large training sets; complicated training.

to associate the sensor data with the human motion information due to the higher randomness in pedestrian motion. Based on the idea of SLAM [112], some recent works like Wi-Fi GraphSLAM [113] and WiSLAM [114] propose fusing Wi-Fi and user motion for pedestrian indoor localization. Wi-Fi GraphSLAM [113] formulates an optimization problem to find the mapping of target position to the indoor map. In order to facilitate the SLAM convergence, WiSLAM [114] instead uses Bayesian inference in target localization.

Approaching SLAM problems includes algorithms of finding the best graph matching and solving optimization problems [113], which can be computationally expensive. To approach traditional localization or SLAM problems, the fusion algorithms in some more recent works of pedestrian or smartphone localization include

— *Kalman filter*: Kalman filter is a typical formulation to describe the discrete time system. Fusing Wi-Fi fingerprints and inertial sensors based on Kalman filter has been studied extensively in works like [20], [87], [115]–[118]. Compared with other techniques like least square estimation schemes [113], Kalman filter achieves better results under linear Gaussian environment [87]. Assuming the knowledge of walking motion model with additive Gaussian noise, conventional Kalman filter can effectively solve the localization fusion problem, especially for the linear motion model. Some further extensions, including extended Kalman filter and unscented Kalman filter, have been proposed to approach some nonlinear problems.

— *Particle filter*: Compared with traditional Kalman filter, particle filter is often more general and suitable for more sophisticated tracking problems based on the nonlinear motion model. Particle filter [119] first spreads particles in the potential indoor area. Then those particles inconsistent with walking distance, estimated location fixes and map constraints will be filtered. Therefore, the particles approximate the confidence of potential trajectories and the location with the more particles surviving gets the higher weight in final estimation. In practical deployment, however, engineers may not choose particle filter if the conventional Kalman filter-based schemes can already produce satisfactory results with much lower computational cost.

— *Using more advanced and efficient fusion models*: Recent works like [24], [38], [48] propose using some advanced and efficient models between wireless signals and motion to locate the target by:

1) *Reducing number of particles*, which considers simplifying indoor map structures [38] to reduce the need of many generated particles.
2) *Using efficient or simplified probabilistic models*, which implements Hidden Markov Model (HMM) [66] or conditional random field (CRF) [48] to simplify the localization computation while achieving satisfactory estimations.

Kalman filter has been implemented for fusion with wireless signals in robot and later pedestrian localization. In order to support more challenging pedestrian localization, some work proposes using Extended Kalman filter (EKF) to achieve more adaptivity in motion modeling [121]. Fingerprint Kalman filter (FKF) in [116] utilizes the best linear unbiased estimator, combining all the current and past signal measurements. Kalman filter achieves high computation efficiency, as the knowledge of system models and Gaussian noise may provide an simple closed form formulation. However, in practice, sensor noise may not be Gaussian and the motion model is rather complicated, which may degrade the performance of traditional Kalman filter. Furthermore, Kalman filter may not be suitable for some scenarios with only map information and user motion information [122]. To improve Kalman filter performance, dense input of wireless localization fixes and knowledge (or some heuristics) of noise covariance may be often required in implementation [122].

In the traditional localization system for pedestrian, the map information is often available and therefore accurate localization is more important. In more recent works, Sequential Monte Carlo method (SMC) [119] has been implemented for fusing Wi-Fi and motion sensing. Particle filter is a well-known application of SMC method. In particle filter, the estimations of Wi-Fi and motion sensing are merged based on weighted particles. With the map constraints and weight resampling, the particles with incorrect locations are filtered and the location estimation converges to a more accurate position.

Zee [99] and XINS [120] are two typical works using particle filter. Zee utilizes the map constraints to filter the particles and narrows the search region of target localization. Therefore, the incorrect heading directions and trajectories will be filtered. XINS also leverages other signals like GPS or GSM to increase the chance of location fixes. Based on motion sensors and particle filter, some recent works make a further step to recognize the user activity and embed this information in LBS system. The activity information, when the user is in elevators [105], [123] or passes through the indoor corners [124], shows location-dependent patterns, which can be leveraged to narrow the search scope.

Particle filter achieves promising localization accuracy while requiring large quantities of particles. Therefore, many recent works have focused on addressing the issues of computational complexity.

Reducing particle number: A 2-D map representation of the large open space needs many particles. If we discretize the map and represent the corridor path with the 1-D line segment, the number of particles can be reduced.

Based on the above idea, Graph-Fusion [38] proposes a system which simplifies the computation of particle filter. To reduce online localization complexity, during offline map preprocessing, Graph-Fusion discretizes the indoor map into simplified connected graph by removing the unimportant degrees of freedom. Therefore, fewer particles are needed to traverse along the narrow edges of the graph. By measuring the walking frequency and walking distance, the system also considers fitting different users in location estimation. Despite the expensive work load in graph preprocessing over the indoor maps, this work provides a practical and efficient motion-assisted localization algorithm. Nevertheless, for large indoor open space like the airport, the sharp reduction in particles may lead to large estimation errors. It is because the randomness of pedestrians in the airport is higher than in narrow corridors. A large number of particles are still needed in such sites.

As using many particles significantly increases the complexity [66], some other works focus on using more efficient fusion models to replace particle filter.

Simplified probabilistic models: HMM Fusion [66] proposes using *Hidden Markov Model* (HMM) to fuse the sensor and simplify the fusion process. As in the HMM formulation the motion state only depends on the previous state, the computational complexity is low. However, HMM requires large training sequence of data and the offline training process is still computationally heavy [24].

Beyond HMM model, MoLoc [24] models the probabilistic transition between different locations in the site based on the user's walking length and direction. Meanwhile, it considers the probability of different locations returned from Wi-Fi estimation. By independently considering the joint probability of Wi-Fi and motion, the system simplifies the calculation and localizes the target. Through the motion matching, the ambiguous Wi-Fi fingerprints at distant locations can also be filtered. In particular, let d and o be the walking displacement and heading direction, respectively. Denote $P(\mathbf{x}|\mathbf{s})$ as the conditional probability of target at location $\mathbf{x}$ given Wi-Fi measurement $\mathbf{s}$, and $P(\mathbf{x}|d, o)$ as conditional probability of target at location $\mathbf{x}$ given motion measurement d and o. Based on the independence assumption, MoLoc finds the location with the maximum likelihood, i.e.,

$$\arg\max_{\mathbf{x}} P(\mathbf{x}|\mathbf{s}, d, o) \propto \arg\max_{\mathbf{x}} P(\mathbf{x}|\mathbf{s})P(\mathbf{x}|d, o), \tag{4}$$

which therefore simplifies the localization model and increases computation efficiency. In reality, however, fingerprint and position transition may be well correlated [48], [122]. Assuming independence between fingerprints and motion matching may leave out some useful observations for better performance. If they are jointly considered, higher accuracy and robustness can be achieved.

In order to increase location accuracy and computational efficiency, some recent works focus on *jointly* considering the correlation between Wi-Fi measurement and motion. MapCraft [48], [122] proposes a system based on *conditional random field* (CRF). CRF [125] is previously implemented in natural language processing in order to classify the sequence of words. By modeling the indoor sensor measurement (Wi-Fi, magnetic field, walking distance and direction) as data sequences, MapCraft utilizes CRF to map them onto the indoor map and locates the target. Without spreading many particles, CRF in MapCraft jointly considers the wireless signal observations and motion measurement. Therefore, it achieves higher robustness towards signal noise compared with other works. The online localization complexity using CRF is small once the conditional probability model is trained.

TABLE IV
DIFFERENT ALGORITHMS FOR OFFLINE SURVEY REDUCTION

Scheme	Explicit User Participation	Extra Site Survey	Erroneous Data Filtering	Training Complexity	Limitations
OIL [130]	Yes	No	Yes	Low	Prompt users for signal update; may bring inconvenience in deployment.
WILL [18]	No	No	Yes	High	Rely on step counter accuracy; survey data may come from limited areas.
EZ [131]	No	No	Yes	Low	Rely on relative RSSI signals mapping and location fix of other devices; RSSI carries noise and affects mapping.
WiGEM [35]	No	No	Yes	High	Rely on explicit knowledge of AP locations; computationally expensive.
HIWL [132]	Yes	Yes	Yes	High	K-means clustering of signals requires specific setting of cluster number; the training of Hidden Markov model (HMM) is computationally expensive.
UMLI [133]	Yes	Yes	No	High	Designed for room localization; hierarchal localization leads to higher computation and risk of large error.
Co-Embedding [134]	Yes	Yes	No	High	Work best with similar floor plans in a given building; unlabeled data contains error, which requires filtering.

However, the offline training of CRF is more computationally expensive [125] than that of HMM [126]. To ensure high localization accuracy, large data set of pedestrian information is usually needed, which makes CRF training difficult. All the sequences have to be labeled beforehand in order to maintain the training accuracy [127].

To summarize, improving Wi-Fi fingerprinting localization with inertial sensor measurements is an interesting direction for indoor LBS system deployment. Compared with collaborative localization in Section II-C, the motion-assisted scheme does not rely on neighboring users, and therefore achieves higher adaptability and scalability. Although many emerging smartphones and sensors, including devices in Google Project Tango [128], have laid a hardware foundation for motion-assisted scheme, how to accurately capture the user motion without expensive calibration in practice is still challenging and worth further exploration. Besides, energy efficiency for sensor measurement and location computation is also important for future studies.

III. EFFICIENT SYSTEM DEPLOYMENT

In this section, we will present some recent approaches on efficient system deployment. We will first focus on survey reduction in Section III-A and III-B. As the site survey for Wi-Fi localization consists of offline fingerprint database construction and online database update (maintenance). Therefore, we will investigate the recent progresses in reducing labor-intensive site survey (Section III-A) and adapting to online measurement variation (Section III-B) respectively. Then we will describe the recent development in addressing device heterogeneity (Section III-C). Finally, we present the recent works on reducing energy consumption of Wi-Fi fingerprint localization (Section III-D).

A. *Reducing Offline Site Survey*

Traditional fingerprinting algorithms are often labor-intensive. Take the Hong Kong International Airport as an example. Given a survey site of 8,000 m^2, if we choose 5 m as the site survey grid size, there are still many reference points for survey. Therefore, reducing the density of site survey or cutting down direct large-scale survey is currently an important issue for fingerprinting localization [34], [129]. The tradeoff between cost and accuracy is also an interesting question.

Based on user incentive in Wi-Fi data collection and degree of user participation, we discuss the following directions in the offline survey reduction:

- *Explicit crowdsourcing-based data collection*: Different from the implicit fingerprinting, users can be also prompted to participate in data collection. If more people have incentive to join the site survey in a crowdsourcing manner, we can also reduce the costly site survey from the professional surveyors. The major advantage is that crowdsourcing splits the tedious survey into reasonably small portion of work for each involved user.
- *Implicit data collection*: Reducing site survey does not mean no Wi-Fi fingerprint signal collection. Offline survey reduction can be achieved by conducting data collection *implicitly* or transparently, i.e., the data collectors do not need to have incentive to participate in signal collection. Therefore, signal collection is *transparent* to the users merging with their daily life, and the survey cost can be reduced significantly.
- *Partially-labeled fingerprints*: Some Wi-Fi measurement data may be already labeled with indoor locations. In reality, the users may also collect unlabeled signal data without corresponding location information. If these unassociated RSSI signals can be labeled according to a

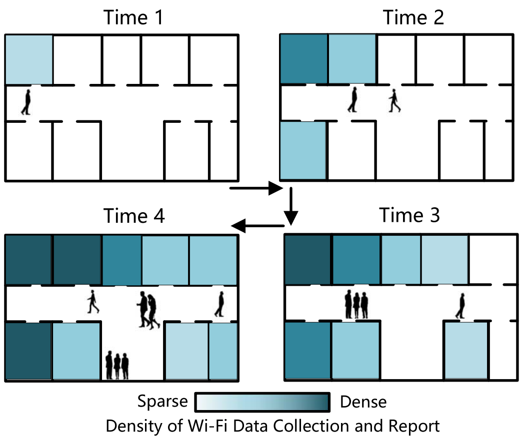

Fig. 8. Illustration of building fingerprint database through crowdsourcing. Depth of the color indicates the density of survey data. As more users provide feedbacks, the fingerprint database at the rooms grows with more Wi-Fi data collection (the room color becomes darker).

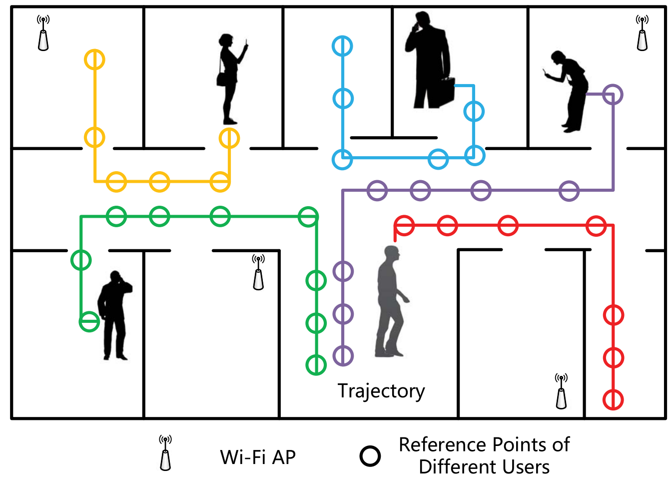

Fig. 9. Illustration of implicit site survey through user trajectory. The paths where users walk along indicate the locations of fingerprints.

certain association rule, the workload of professional site survey can be also reduced. Such a method is particularly suitable for scaling up existing Wi-Fi based systems equipped with fingerprint database with low cost.

In Table IV, we show the corresponding recent approaches which fully or partially remove site survey, which are presented as follows.

Explicit crowdsourcing-based data collection: In many recent works, crowdsourcing-based approaches [130], [135] have been proposed to replace the professional site survey with explicit and unprofessional user participation. We show in Fig. 8 a typical crowdsourcing-based localization system [130]. The system prompts the volunteer users to report their current locations and corresponding Wi-Fi fingerprints. We can observe that as more users are walking around and uploading signals at different locations, the colors of these areas become darker, which means that the fingerprint database organically "evolves" with data input. The concept of "organic indoor localization" (OIL) is derived from such steady user update of fingerprint database.

To reduce the influence of feedback error or noise in OIL, a clustering-based method has been proposed to filter the wrong user input. Different signal data will be fed into the clustering process. The correct signal data will be clustered together while outliers correspond to incorrect data. Thus, the influence from erroneous input can be reduced.

However, in reality, prompting users for instant feedbacks brings inconvenience for user experience. The quality of the feedback remains to be further improved, since crowdsourced fingerprints are vulnerable to imperfect fingerprint data. In our deployment experience, feedback data usually carries much noise in the first several trials, since the involved users need to get accustomed to the feedback systems. To maintain the online LBS experience and fingerprint quality, the volunteers may need some trainings before they start site survey.

Implicit user participation: To reduce user burden, some recent work, including WILL [18], is proposed to map collected RSSI vectors onto the indoor map during users' daily walk. Users do not need to intensively conduct data collection and the specialized site survey is not needed. By measuring walking path and direction, the users' locations can be leveraged to label the position of each Wi-Fi fingerprint.

As shown in Fig. 9, when the user is walking during the training phase, RSSI vectors and the relative distance between them is recorded by the inertial motion sensors [18]. Based on these relative distances and RSSI vectors, the system maps the corresponding RSSI vectors to the floor plan, and builds up the signal map. The novelty is that even when the user is working with routine business and walking in the office, the site survey can be conducted transparently. Hence, there is no need to conduct dense fingerprinting by professional surveyors. As the mapping results may contain errors, WILL proposes a floor plan correction scheme to mitigate the influence of noise. A recent work PiLoc [136] also proposes a similar approach for indoor signal collection through motion sensors. PiLoc improves from WILL by providing more insights into the indoor map construction.

One limitation of the works like WILL is that the quality of fingerprint collection largely relies on the step counter and displacement measurement. Given noisy measurement and users' biased input (the collected data may gather around certain area), the quality of survey data would be affected. In real deployment, some landmark points (such as RFID tag or Wi-Fi signal landmark) for motion-sensor calibration can be deployed in the indoor site. Then the error of step counting can be further reduced.

Signal measurements may come from unknown locations, making it difficult to construct fingerprint database. However, spatial distribution of signal measurements is constrained by the physics of wireless propagation. If mapping relationship between RSSIs and locations can be obtained, with some occasional location report or fix from GPS of some devices, the other users can be located based on the RSS mapping [131] scheme. Inspired by such an observation, EZ [131] models these geometric constraints based on Wi-Fi signal data, and finds the location mapping based on the relative signal measurement. The constraint is modeled using traditional path loss model. In other words, the received signal strength s at a location $\mathbf{x}$ given distance d_l is given by

$$s = s^0 - 10\gamma \log_{10} \frac{d_l}{d_0}, \quad d_l = \sqrt{(\mathbf{x} - \mathbf{c}_l)^T(\mathbf{x} - \mathbf{c}_l)}, \tag{5}$$

where s^0 and γ are hyperparameters, d_0 is the reference distance, and $\mathbf{c}_l$ is the estimated location of AP l. Then a genetic algorithm locates the target position efficiently. Therefore, the prior knowledge of the RF environment is not required and the survey cost is significantly reduced.

However, EZ needs occasional GPS signal in order to get location fix. In real deployment, the external fix may not always be available or accurate. Besides, the dynamics of Wi-Fi environment may also affect the geometric constraints, leading to measurement errors in distance. Therefore, more advanced works like EZPerfect [62] have used labeled fingerprints to derive the distance constraints and improve localization accuracy.

Advanced machine learning schemes have been implemented for survey reduction. To reduce the survey cost, a potential approach is to model the signal propagation for signal prediction at different indoor locations. WiGEM [35] utilizes Gaussian mixture model (GMM) and expectation maximization to estimate target location, and learns the signal propagation parameters. Then, the signal strength at different locations can be predicted correspondingly. Therefore, the survey process is greatly reduced given implicit user signal data. However, it relies on explicit knowledge of AP locations. Moreover, the computation in parameter training is rather heavy and should be conducted on a server.

Using partially labeled fingerprints: For explicit and implicit data collection, labeling locations for fingerprints is often tedious, especially in spacious area. HIWL [132] proposes using Hidden Markov Model (HMM) to classify the unlabeled signal data to the locations. It requires limited topology information of indoor environments in the HMM training phase. Through HMM training, the system learns the mapping relationship in geographical and signal distribution. Therefore, HiWL can match the unlabeled fingerprints to the corresponding physical locations based on the mapping model. However, training HMM increases the computational complexity of the system [137] and requires large training data set to ensure the learning accuracy. Meanwhile, HIWL implements k-mean clustering to partition the signal data, which requires user to specify the number of clusters.

To reduce computation, UMLI [133] proposes using clustering methods to classify the unlabeled signal data. Through clustering analysis, it has been observed that neighboring reference points show similar signal patterns and tend to cluster together. By utilizing the clustering method, unlabeled signal data can be classified into locations storing similar signals, achieving less site survey and labeling work. Using a hierarchal structure, UMLI first classifies the unlabeled fingerprints to the corresponding rooms. Then based on the coarse location result, it conducts further fine-grained localization. The results show that UMLI is more suitable to classify the room locations. Hierarchal localization in UMLI increases the localization complexity. If the coarse stage of estimation is incorrect, the deviation of final results will increase.

Utilizing the correlation within labeled Wi-Fi fingerprints can also help in labeling new data at different floors in a given building. Inspired by this observation, Co-Embedding [134] proposes a new algorithm aiming at reducing multi-floor survey cost. The idea of this work is based on the similar floor plans at different floors in a building. Therefore, the wireless signals at different floors are correlated. This algorithm first analyzes the embedded relationship between the fingerprints at different floors based on labeled reference points. By learning their spatial correlation and signal similarity, the system finds the locations of the unlabeled reference points at other floors. Similarly, the transfer learning based algorithm [41] has been implemented to map the unlabeled signal data with the corresponding indoor locations. The mapping is also based on the correlated signal patterns in indoor environment. However, such an assumption may not be valid for buildings with significantly different floor plans. Moreover, Co-Embedding does not provide error analysis and filtering for the unlabeled signal data. The computational complexity for correlation analysis is also high.

The major concern about offline survey reduction is how to balance between localization accuracy and survey cost. Some research shows that due to uncertainty in signal collection localization accuracy under survey reduction is relatively lower than that based on traditional fingerprinting [138]. In order to filter the noise or errors, post-processing after sampling becomes important here, and may increase the system complexity and deployment cost. Thus, professional survey may be still needed in scenarios with high accuracy demand.

A more reasonable consideration is to conduct site survey in a flexible and cost-effective manner. Specifically, for sites with dense visitors and high accuracy demand, the traditional site survey plays a major role in localization system setup. For sites with low user access, different survey reduction algorithms above can be applied to reduce overall deployment cost.

B. Adapting to Fingerprint Changes

Given site survey data, it is also imperative to maintain fingerprint database for the dynamically changing environment. The online signal strength in the survey site may vary significantly overtime due to various factors. Firstly, crowds of people and humidity change can influence the signal strength [139]. Secondly, dynamic power control in WLAN may also change the transmission power [36]. What is more, Wi-Fi APs may be added, replaced or removed due to the renovation of the building [43]. Therefore, the signal database may become outdated and large estimation error happens. Conducting another site survey is not cost-effective. To address this, there have been a lot of works focusing on adapting to online signal variation. These approaches include:

- *Infrastructure-based schemes*: Recent works [140]–[142] propose deploying external infrastructures to monitor the signal variation in the survey site. Two key components for infrastructure monitoring are Wi-Fi monitors

TABLE V
ADAPTING TO FINGERPRINT CHANGES

Scheme	Update Algorithm	Extra Infrastructure	Deployment Cost	Robustness of Update	Update Frequency	Limitations
Wi-Fi Sniffer [142]	Gaussian process; signal map regression.	Wi-Fi monitor (sniffer)	High	High	Fast	Sparse sniffer deployment may degrade the performance; AP locations need to be known.
Hybrid Monitor [139]	Monitor environmental factors; change the signal map based on environmental contexts.	RFID; Bluetooth sensor	High	High	Fast	Contexts of environment may change from the training stage; stored signal map may be outdated.
Transfer Learning [143]	Dimension reduction; signal space correlation.	N/A	Low	N/A	N/A	High computation expense for online localization; suitable for environment with small signal variation.
Crowdsourcing [144]	Explicit user feedback; upload of location and signal vectors.	N/A	Medium	Low	Slow	User feedback contains noise; need more error filtering.
Crowdsourcing Fusing with Motion Sensor [43]	Localization and fingerprint maintenance; implicit data update; erroneous data filtering.	N/A	Low	High	Slow	Rely on accurate motion sensors for trajectory mapping.

(sniffers) and signal map reconstruction [140]. By detecting the environmental change, the system can update the fingerprint database with the measured signals, using regression or other machine learning algorithms.

- *Non-infrastructure-based schemes*: Non-infrastructure-based schemes are based on algorithmic adaptation to fingerprint signal noise. These works consider using the spatial and temporal correlation between the locations and signal measurement to reconstruct the Wi-Fi fingerprints. Recent works often leverage the signal correlation [143], user feedback [144] and crowdsourcing [43].

In Table V, we show the corresponding algorithms adapting to the Wi-Fi fingerprint changes, which are presented as follows.

Infrastructure-based: The signal map reconstruction [142] reveals the overall change in signal spatial distribution and provides information of the dynamics at the RPs (distribution model). As shown in Fig. 10, deployed Wi-Fi sniffers can detect the temporal change of the APs and environment. Then the system reconstructs the signal map in the site based on:

— *Regression-based algorithms* [141] are based on the signal propagation model (like path loss model). These algorithms perform well in indoor large open space and the complexity of signal map reconstruction is relatively low [141], [142]. However, with wall partitioning and signal fluctuation, the regression may not produce satisfactory results.

— *Advanced machine-learning algorithms*:For complex indoor environment with wall partitioning, other machine learning algorithms are more suitable since they consider the inherent signals and spatial correlations without assuming LoS measurement [142], [145], [146].

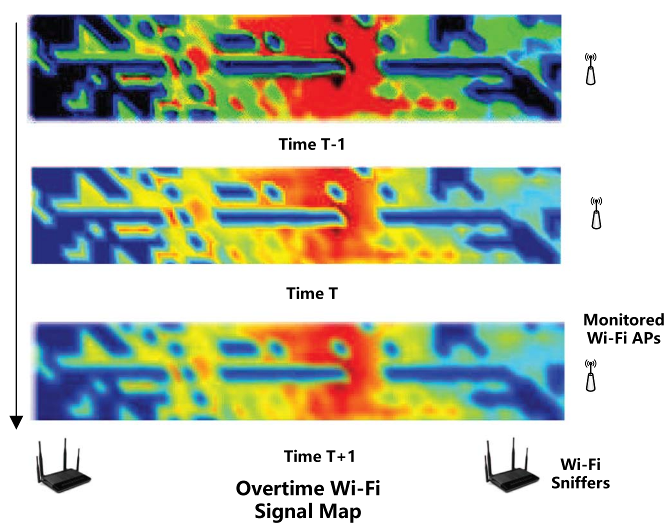

Fig. 10. Illustration of dynamic signal map adaptation using Wi-Fi sniffers. Color map indicates different RSSI distribution (warm colors mean strong RSSI while cool colors mean weak RSSI). Deep blue colors mean that no RSSI is collected due to building structure partition.

Given some labeled reference points and online signal measurement, these algorithms achieve higher signal reconstruction accuracy [142]. Typical algorithms include Gaussian process [142] and decision tree [145], [146], which are based on existing statistical learning techniques [147], [148].

Gaussian process (GP) [142] is utilized to reconstruct the signal spatial distribution based on Wi-Fi sniffer measurements. GP models the relationship between signal fluctuation and distance between the reference points. The work in [142] proposes two schemes based on Bayesian inference and the signal propagation model respectively.

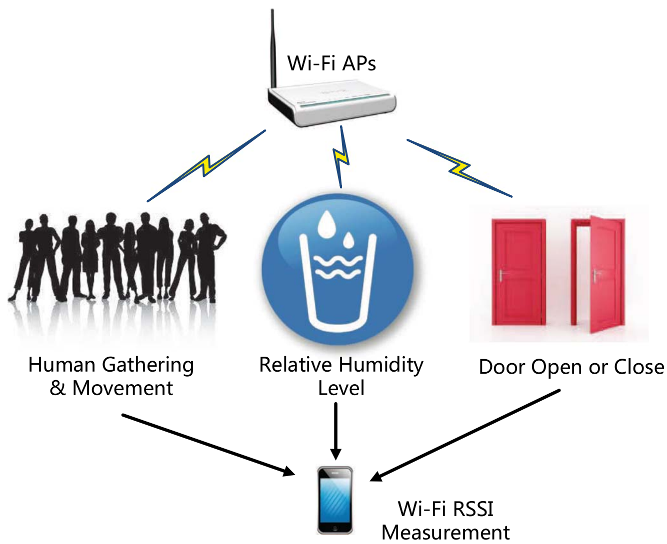

Fig. 11. Illustration of different potential environmental factors that affect the Wi-Fi signal online measurement [139].

To be more specific, let $s_{\mathbf{x}}$ be the signal strength at a location $\mathbf{x}$, which can be further expressed as

$$s_{\mathbf{x}} = f(\mathbf{x}) + \epsilon, \tag{6}$$

where ϵ is an additive zero-mean Gaussian noise. Given N training locations $\mathbf{X}$ and fingerprints $\mathbf{S}$, let N-by-N matrix $\mathbf{K}$ be the covariance matrix between these samples. An element $k(\mathbf{x}_i, \mathbf{x}_j)$ in $\mathbf{K}$ is usually given by an exponential kernel. Based on Gaussian process [142], the predicted RSSI for unknown location $\mathbf{x}^\star$ is given by

$$\mu_{\mathbf{x}^\star} = m(\mathbf{x}^\star) + k(\mathbf{x}^\star, \mathbf{X}) \left(\mathbf{K} + \sigma_n^2 \mathbf{I}\right)^{-1} (\mathbf{S} - m(\mathbf{X})), \tag{7}$$

where σ_n are the hyper-parameters of GP. The mean function, $m(\mathbf{x}^\star)$, is given by either kernel regression (using Bayesian inference) or propagation model regression.

Experimental studies show the latter signal model achieves higher reconstruction accuracy given locations of Wi-Fi APs. One strength of GP is that statistical inference can be integrated with existing probabilistic localization algorithms and sensor fusion [149]. However, training of these machine learning algorithms is usually computationally expensive.

If the dynamic environmental factors can be monitored, the change in the signal map can then be predicted and updated accordingly. If we can prepare a signal map for each context of Wi-Fi measurement, we can also adapt the system to the environmental changes. As shown in Fig. 11, the relative humidity level, people's movement, and open/closed doors are assumed to be the important factors which influence the Wi-Fi fingerprints [139]. In [139], [150], different sensors are deployed to monitor these changes. Based on these sensor readings, the system learns the environmental changes as well as signal maps for corresponding environment contexts. In other words, different environments correspond to different signal maps and settings. Therefore, given the online sensor readings, the system adapts the current signal map for better online localization.

The signal measurement using sniffers and sensors is accurate if the infrastructures are densely deployed. Besides, sniffers can immediately capture the signal change and therefore achieves rapid update. However, infrastructure-based monitoring brings the extra deployment cost, which may not be suitable for large survey site.

Non-infrastructure-based: The transfer learning based algorithm [151] has been proposed to adapt to the signal change [143]. It is based on the observation that nearby positions have more similar RSS values than those far away. Given the training fingerprint set, the system learns the correlation between fingerprints and the locations. The target RSSI vector can be then projected to a physically near location. However, the offline training and online localization complexity is relatively high. Besides, such a scheme relies on the stored fingerprints and aims at approaching small signal variation. If many APs are changed in transmission power, removed or added in the environment, this algorithm cannot adapt to such large change.

Therefore, a more adaptive scheme is to update the signal map. It can be achieved through user feedback or "crowdsourcing" [144]. Based on the online user feedback, the system can get the RSSI vectors and the corresponding locations. Then the signal map can be updated according to the signal interpolation. Besides, if the AP transmission power is changed [152], the system can also detect and update the fingerprints [43], [144], [153].

Crowdsourcing can provide sufficient fingerprint updates for indoor LBS. However, in some cases it may be inconvenient to prompt users to upload their collected signal data. Explicit fingerprint and position uploading brings inconvenience and privacy issue for signal map update. Another concern is the correctness of database updates. Feedbacks from the users are likely to carry noise. Therefore, error filtering are still needed before the updates of the database.

The work in [43] proposes crowdsourcing-based update automation (CUA) for fingerprint update. CUA conducts implicit fingerprint collection while the user is using LBS for location estimation. Through motion sensors, the trajectory of the user along with the collected fingerprints can be jointly mapped to the indoor map. By comparing similarity between the signal sequences with the stored signal map, CUA filters the incorrect trajectory mapped. Meanwhile, mislabeled fingerprints can be filtered by a clustering algorithm of all fingerprints. Compared with [18] in Section III-A, CUA utilizes previously collected fingerprint map to reduce trajectory mapping errors. Similar works like [154]–[156] also implement motion sensors to improve fingerprint update.

One limitation of CUA is that the accuracy of motion sensor may still suffer from measurement noise. Therefore, a robust sensor-fusion-based location estimation needs to be considered in deploying CUA for future development.

For above crowdsourcing-based algorithms, a common challenge lies in the frequency of user updates. Moving users may not have stable Internet connection and the data upload is likely to be delayed. Thus, the later uploaded data may be already outdated and the fingerprint update performance may degrade correspondingly.

TABLE VI
SOME RECENT SMARTPHONES AND THEIR DIFFERENCE IN WI-FI CHIPSETS

Host Smartphone	Chipset	Wi-Fi Channels	Antenna Positon [159]	Year
HTC One X	Broadcomm BCM4335	802.11 a/b/g/n	Middle Left	2012
LG Nexus 4	Qualcomm WCN3360	802.11 a/b/g/n	Upper Right	2012
LG Nexus 5	Broadcomm BCM4339	802.11 a/b/g/n/ac	Upper Right	2013
Samsung Galaxy Note 3	Broadcomm BCM4339	802.11 a/b/g/n/ac	Upper Right	2013
Samsung Galaxy S5	Qualcomm QCA6174	802.11 a/b/g/n/ac	Top of the Phone	2014

To summarize, the well-designed combination of different fingerprint update schemes, infrastructure-based and non-infrastructure-based, can be a potentially feasible approach in real deployment. Infrastructures can be deployed in a large open area with high visitors flow in order to maintain localization accuracy. User feedbacks can be leveraged at other areas to reduce the deployment cost.

C. Calibrating Heterogeneous Devices

The rapid evolution of mobile computing has spawned a very heterogeneous spectrum of mobile devices in indoor LBS. Various devices are implemented in offline and online signal measurement. Such device heterogeneity will affect the performance of indoor localization [157].

We first briefly describe the device dependency and the related factors [40], which may provide some intuition in calibrating heterogeneous devices. Specifically, denote the received signal strength (RSS) from a given AP at distance d as $P(d)$ (dBm). P_{AP} represents the transmission power of AP. G_{AP} and G_{MN} represent the antenna gain at the AP and the mobile phone, respectively. Let d_0 be the reference distance. The received signal strength at distance d is given by [40]

$$P(d) = 10\log_{10}\left(\frac{P_{AP}G_{AP}G_{MN}\lambda_{AP}^2}{16\pi^2 d_0^2 L_1}\right) - 10\beta\log_{10}\left(\frac{d}{d_0}\right) + X(0,\sigma^2). \quad (8)$$

Due to different Wi-Fi network interface controllers (NICs) embedded in smartphones, the antenna gain (G_{AP} and G_{MN}) may be different across different devices.

In Table VI, we show some differences in Wi-Fi chipsets, channels supported, and antenna positions relative to the phone body [158] of different Android smartphones. To summarize, the device heterogeneity mainly comes from the following aspects:

- ⋆ *Wi-Fi chipset sensitivity*: The Wi-Fi chipsets on different smartphones may be sensitive to different Wi-Fi APs and channels. The antenna gain and detected AP channels in signal strength measurements are different. Therefore, we can observe the differences in the signal values and length of signal vectors [40].
- ⋆ *Antenna installation position*: As the antennas may be installed at different positions on the phones [67], the signals received when the users are facing different directions are likely to differ.

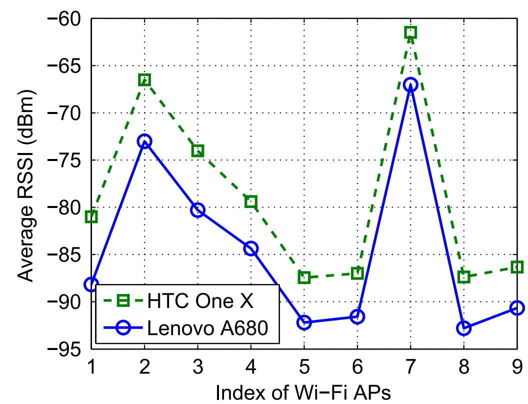

Fig. 12. Wi-Fi RSSI measured by HTC One X and Lenovo A680.

- ⋆ *Operating systems (OS) of smartphones*: The OS of smartphones may support different Wi-Fi APs. The detection rate and number of APs can be different [159]. Therefore, even the same device may still have heterogeneity given different operating systems.

To further illustrate the device dependency, we conduct an experiment to show the RSSI heterogeneity measured by two different smartphones at the same location. We use a Lenovo A680 and HTC One X to collect RSS from nine different APs at a fixed location in an HKUST office, respectively. Then we plot the mean RSSI values in Fig. 12 for each detected AP. From this figure, we can observe the noticeable difference in the signal measurement.

From Table VI and Fig. 12, we obtain a basic understanding of device dependency. Given above, we will go through the recent works addressing the device heterogeneity issues as follows:

- *Offline calibration*: These schemes consider adapting the target RSSI via offline calibration. In the offline stage, the system collects large quantities of signal data from different smartphones and finds the corresponding signal mapping models given different user smartphones.
- *Online signal calibration and adaptation*: In contrast to offline methods, online calibration and adaptation schemes focus on utilizing only target Wi-Fi data (online measurement) for self-calibrating and adapting to the heterogeneous devices instantly. Therefore, the manual efforts can be largely reduced compared with offline training.

Offline calibration: The works in [160], [161] observe that RSSIs at different devices follow a linear model for the same signals. Given signals from two devices, they conduct regression and derive the linear calibration model. Clearly, it requires offline training before an accurate mapping relationship can be learned. However, manual data collection and calibration bring inconvenience for the deployment. To reduce such labor-intensive work, some crowdsourcing-based algorithms [162] can be implemented to provide sufficient signal data for calibration.

However, signal variation may affect the linear mapping relationship between values. The work in [163] observes that the major characteristics of signal strength diversity lie not only in the linear signal difference between devices, but also in the signal deviation and shape of individual RSSI distributions. Therefore, it utilizes the kernel function for location estimation by mapping between signal distributions of different devices instead of only linear transformation. In order to accommodate different devices, the system adjusts the shape of the kernel density functions so that the signal distribution can be matched.

Online calibration and adaptation: In order to calibrate a given device, some works consider the common patterns between the device measurements which are irrelevant of the heterogeneity factors. Based on the signals and antenna gain model, signal strength difference (SSD) [40] proposes a simple algorithm which picks out one AP measurement and each of other RSSIs is deducted by its signal values. Therefore, the constant factor of antenna gain is deducted. Another similar idea is using the RSSI ratio [164]. The work in [164] selects one of the AP measurements and each of other AP signals is divided by this constant value. These methods are easy to implement for online calibration of signal vectors.

Expectation Maximization (EM) [165] is proposed for joint localization and signal calibration. By adding the constant value into Euclidean distance [2] between signal vectors, the system measures the offset between the signals of two devices. Then it learns the signal difference by iteratively minimizing the offsets in Euclidean distance between fingerprints. The joint calibration and localization can reduce the effect of signal noise. However, the process of applying EM algorithm is more computationally expensive than SSD or RSSI ratio above, and the calibration quality may be affected by signal noise.

Combining the advantages of signal ratio and linear dependency, the work in [166] proposes an algorithm which jointly finds the reference points matching both AP signal order and linear relationship. Pearson product moment correlation coefficient [147], which gets rid of device constant difference, is implemented to compare the linear relationship between two signal vectors.

The major concern for online calibration is that large signal noise can influence the signal values under limited RSSI sampling. The process of signal deduction and ratio is vulnerable to measurement noise, which may further lead to localization errors. Therefore, the average of multiple RSSI samples may be implemented to filter the noise.

Besides calibration, *online adaptation* is another recent approach to tolerate the device dependency in location estimation. The works in [67] and [167] leverage the signal order of multiple APs and the peak of an RSSI sequence respectively to address the device dependency issue. These patterns can reduce the calculation efforts in the online calibration schemes.

TABLE VII
DIFFERENT APPROACHES OF CALIBRATING HETEROGENEOUS DEVICES

Category	**Calibration Scheme**	**Robustness of Calibration**
Offline Calibration	Linear calibration [160], [161], [168]	Require large data set for regression or fitting.
	Kernel-based calibration [163]	Require training of kernel width; need large data set.
	Crowdsourcing [162]	Contains signal noise; need erroneous data filtering.
Online Calibration and Adaptation	Signal strength difference [40]	Suffer from signal noise fluctuation.
	Signal strength ratio [169]	Suffer from signal noise fluctuation.
	Expectation maximization [165]	Adding constant to signal values during fingerprint comparison; influenced by noise.
	Homogeneous patterns [166]	Joint consideration of signal strength ratio and linear dependency.
	Received signal strength order [167]	Granularity of location estimation is relatively low.
	Peak of the signal sequence [67]	Peak detection is sensitive to signal noise.

Besides, patterns like signal strength order are less vulnerable to small RSSI fluctuation than the above online value calibration, which tailors for concrete signal values.

However, the RSSI order may be the same in a room and lead to low granularity of localization. How to select the subsets of all APs for order comparison is also challenging. For the signal peak, the online signal fluctuation may also influence the accurate measurement of signal peak. Therefore, these patterns work the best for narrow indoor space (corridors and small rooms [67]), where signal order and peak can be more distinguishable. For more general cases in different indoor sites, the online calibration of signal values is a reasonable choice.

To summarize, we have shown the different schemes and the robustness of their calibration performance in Table VII. Offline scheme is usually based on large data samples and regression calculation. To reduce the efforts in offline stage, crowdsourcing may be a possible solution as it may provide large data samples [162]. For crowdsourced data, error filtering may become important to mitigate influence of outliers. In practical deployment, however, online calibration is more convenient and adaptive given unknown devices, but the inherent signal noise can invalidate the calibration assumption. Multiple samples are needed in order to filter the inherent uncertainty. Besides, online calibration increases the computational complexity compared with the traditional algorithm. In online schemes, an extra stage is added before the final location estimation can be conducted.

Note that traditional Wi-Fi fingerprint systems usually use certain signal comparison metrics for location estimation. If the

TABLE VIII
RECENT SCHEMES TO ACHIEVE ENERGY EFFICIENCY

Category	Scheme	Energy Reduction	Deployment Cost	Computational Complexity	Deployment Limitations
Reducing Scanning Frequency	User mobility suppression [171]	Low	Low	Low	Rely on accurate motion sensor readings and motion classification.
	Wi-Fi scanning optimization [170]	Medium	Low	High	Useful for the long-term energy scheduling; computationally expensive.
Reducing APs Used	Wi-Fi selective scanning [159]	Medium	Medium	N/A	Require modification on smartphones beforehand; need to conduct AP filtering or selection.
	Dimension reduction [175], [176]	Medium	Low	Low	Selected APs based on offline training may be different from those needed in online measurement.
Replacing Wi-Fi Scanning	Scanning Wi-Fi with ZigBee [42]	High	High	N/A	Require specialized OS supports and modifications on existing smartphones.

signal comparison metric implemented is device independent, the traditional system can adapt to different devices without significant design modification. This is also a practical direction in improving existing Wi-Fi fingerprint systems.

D. Achieving Energy Efficiency for Mobiles

Green computing is a recently hot topic in mobile computing. For LBS system, how to achieve energy efficiency has also recently attracted much attention. The battery capacity in smartphones is usually small. For outdoor location-based service, it is well-known that the intensive use of GPS often leads to high energy consumption [170], which can cause complete drain of battery in short time. Similar to GPS, Wi-Fi scanning and data transmission are also energy-consuming for indoor LBS systems [171].

For server-based indoor LBS systems [172], the computation of localization is conducted on the server. Thus, Wi-Fi scanning as well as the data communication between the client and the server causes the major energy concern for the mobiles. For client-based localization systems [173], the computation of location decision is conducted locally on smartphones. Therefore, the client does not have to intensively communicate with the server through Wi-Fi or cellular network. However, high computational complexity leads to high energy consumption, since the local fingerprint database often contains thousands of reference points and introduces large signal comparison calculation. Frequent Wi-Fi scanning also consumes the battery power quickly. Therefore, we can observe the Wi-Fi scanning, data transmission and computation are the major energy issues for indoor LBS [174].

Based on their influence and modification over Wi-Fi scanning, we mainly discuss the following directions:

- *Frequency of Wi-Fi scanning*: Traditional Wi-Fi fingerprinting requires intensive use of Wi-Fi for real-time navigation. However, frequency of Wi-Fi scanning for localization purpose can be reduced when the user is static or the localization accuracy is relaxed. Typical schemes include using motion or other sensors to control the Wi-Fi scanning.
- *Number of APs scanned*: Traditional scanning in smartphones goes through all the channels in order to maintain quality of communication. A smartphone in an indoor site may detect at a single position tens of Wi-Fi APs, among which only some are important for accurate localization [159] (i.e., differentiating the reference points in site for further classification). If the number of APs can be reduced, we can reduce the energy used for scanning and localization computation.
- *Replacing Wi-Fi with other RF signals*: Some recent works have proposed cross-interface technology using ZigBee to scan Wi-Fi signals. Such RF signals can improve the energy efficiency of existing Wi-Fi localization system. Coexistence of these heterogeneous signals may be possible and may introduce some further interesting applications [177].

In Table VIII, we show the recent works to achieve energy efficiency for Wi-Fi fingerprint-based indoor localization. In the following, we introduce some emerging schemes accompanied by their strengths and weaknesses for real deployment.

Reducing scanning frequency: A simple method for energy consumption reduction is to control the scanning frequency of Wi-Fi. *Mobility suppression* [170], [178]–[180] utilizes motion sensors to monitor the motion state of the target and controls the scanning frequency. If the motion sensors like accelerometers detect the user is static, the mobile device suppresses Wi-Fi scanning until the user begins to move. However, motion sensors often carry noise and lead to decision error in user motion state. The state recognition may not be very accurate. Therefore, in real deployment, such a simple method cannot fully address the high energy consumption problem.

Some advanced algorithms consider *optimizing the Wi-Fi scanning* according to the need of location accuracy and application scenarios [171], [181]. This scheme finds the optimized allocation of Wi-Fi scanning and sensor utilization. In the energy optimization, we can relax the localization accuracy based on algorithm complexity and sensor implementation. Through some simple algorithms or low-energy sensors, we may satisfy the positioning accuracy while the energy consumption in CPU calculation and sensing can be reduced. It is especially

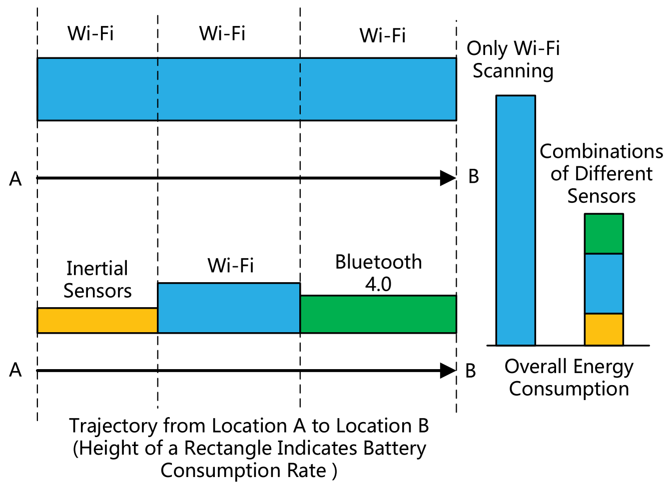

Fig. 13. Illustration of optimizing Wi-Fi energy consumption based on hybrid sensor scheduling.

important given limited battery budget. Combinatorial use of motion sensors [174], [182] and other low-energy sensing techniques (like Bluetooth 4.0) can decrease the need of frequent Wi-Fi scanning [181].

Fig. 13 shows the basic idea of optimizing energy consumption scheduling for Wi-Fi indoor localization. The traditional approach conducts Wi-Fi scanning all the way from location A to B. Instead of only using Wi-Fi, different sensors (inertial sensors [183] or Bluetooth 4.0 [4], [184]) can be scheduled for certain parts of the walking path while the overall accuracy does not degrade significantly [185]. As the walking path (or indoor context) and energy consumption of sensors are jointly considered, optimal sensor scheduling extends the overall battery life. Compared with simple mobility suppression, such an optimized scheme can achieve better energy saving [183]. However, the complexity of the optimization algorithm is often high. Therefore, it is usually suitable for scheduling long pathway at the server side while simplified or heuristic algorithms are implemented for mobiles.

Reducing APs scanned: Selective scanning in [159] modifies the Wi-Fi scanning in order to reduce the number of APs to be scanned. By focusing on the useful channels of APs for localization [186], the overall scanning time and energy consumption can be reduced. Though it is a novel approach to save energy from physical layer modification, configuring the Wi-Fi scanning requires OS support, which may not be applicable for all the smartphones. Priority of communication quality is usually higher than localization purpose, and some smartphone vendors may not allow such modification. Besides, it is also important to know how to select the subset of APs in advance. The selected APs should contribute to localization estimation the most so that we can ensure the estimation error will not increase significantly.

Some other algorithms focus on utilizing subsets of given AP lists to reduce online computation, which is usually defined as *dimension reduction* in machine learning. As each AP in a signal vector can be considered as a dimension or feature [176], reducing the dimensions can decrease the online computation time. CaDet in [173] computes the entropy of each AP and selects those with high information gain for localization. In CaDet setting, the survey site is discretized into different reference grids G_n ($1 \le n \le N$). In analysis of AP l, let $H(G) = -\sum_{n=1}^{N} P(G_n) \log P(G_n)$ be the entropy of the grids when AP l's value is not known. Here the user is assumed to be distributed in the survey site and therefore $P(G_n)$ follows uniform distribution. The conditional entropy of grid G given AP l is defined as

$$H(G|l) = -\sum_{v} \sum_{n=1}^{N} P(G_n|s_l = v) \log P(G_n|s_l = v), \quad (9)$$

where $P(G_n|s_l = v)$ is the conditional probability that the location is at G_n given a signal measurement value $s_l = v$ (v is within the potential RSSI range). Then the information gain of AP l is

$$\text{InfoGain}(l) = H(G) - H(G|l). \quad (10)$$

The top several APs with highest InfoGain(l) are selected. After the filtering in CaDet, the computation can be significantly reduced without large accuracy loss.

Principal Component Analysis (PCA) in [175] has also been proposed to reduce the dimensions used in location computation. By finding the principal components [151] through the correlation of APs, PCA replaces the APs with some components which differentiate the signal measurements the most.

The AP-grouping scheme proposed in [176] divides the AP sets into groups and evaluates the contribution of each group over positioning. This group-based scheme considers the correlation between APs in improving localization, assuming APs can have joint effect in location estimation. If they are not kept together for localization, large estimation errors may happen. Therefore, this work considers differentiating the groups and finding the important ones for localization.

A major concern with dimension reduction for Wi-Fi fingerprint localization is that the AP reduction principles and models derived from offline training samples may be different from APs needed in online measurement. It is because the environment dynamically changes and the importance of APs in online localization will also change. If the training samples are too small or outdated, the performance of training for dimension reduction is likely to degrade.

Replacing Wi-Fi with energy-efficient collectors: ZiLoc [42] and ZiFind [172] are typical works using ZigBee (802.15.4) to collect the Wi-Fi signals. The key observation is that ZigBee and Wi-Fi share similar frequency channels in 2.4 GHz band. The network interface of ZigBee can be programmed to capture the packages in the adjacent frequency bands with Wi-Fi. By adding such an extra interface to the smartphones and laptops, these mobile devices can conduct Wi-Fi fingerprinting and online measurement through ZigBee interface. Therefore, the energy consumption in Wi-Fi scanning can be significantly reduced. Other more recent works like HoWiES [187] investigate using ZigBee to replace Wi-Fi for more general communication purposes. However, in real deployment adding external chipsets on smartphones increases the deployment cost, and brings inconvenience for users. Besides, how to cope with device dependency in signal measurement is also a practical problem.

TABLE IX
SOME COMMERCIAL INDOOR LOCALIZATION ENGINES IN THE MARKETS (UNTIL MAR. 2015)

Engine	**Localization Technology**				**Service Features**					**Other Features**	**Reported Mean Accuracy**	**Years of Establish-ment**
	Wi-Fi	BLE[i]	AGPS /GPS	INS	Map Search	Social Network & Sharing	Geo-fencing[ii]	Location -based Advertise -ment	Indoor /Outdoor Switch			
Insiteo [189]	√	√		√	√	√	√	√		Visualize the user behaviors for analysis.	2 m	2009
Wifarer [190]	√	√	√		√		√	√	√	Combined with various wearable devices.	$\leq$ 3 m	2010
Indoo.rs [191]	√	√		√	√		√	√	√	Optimizing battery life; building transition.	$\leq$2 m	2010
Pole Star [191]	√	√	√	√	√		√	√	√	Map data fusion for better user experience.	2 m	2002
Infsoft [192]	√	√	√	√	√		√	√	√	Extra infrastructures for user analytics.	$\approx$ 1 m	2006
Navizon [193]	√		√		√	√	√	√		Provide Wi-Fi tags for asset tracking.	$\leq$ 1 m	2005
Skyhook [194]	√		√		√		√	√		Hybrid and cross -platform approach for precise localization.	3 $\sim$5 m	2003

[i] BLE = Bluetooth Low Energy [ii] Geo-fencing defines geographical boundaries using RF signals and forms a virtual barrier.

In summary, Wi-Fi scanning and algorithmic facilitation should be based on the accuracy demand, user experience and battery budgets [188]. It is possible that the overall accuracy may diminish due to energy saving. However, if the degradation in localization accuracy is ignorable or there is no substantial influence over user experience, the scheme of achieving energy efficiency is acceptable and worth large-scale deployment.

IV. CONCLUSION AND FUTURE DIRECTIONS

Due to ease of deployment beyond existing network and adaptivity to indoor environment, Wi-Fi fingerprint-based localization has attracted much attention in recent research and industrial trials. Therefore, we conduct this survey to review the popular and important techniques in the recent works.

We briefly go through the recent development of Wi-Fi fingerprinting positioning techniques. The demand for accurate and cost-effective localization has triggered two major directions in Wi-Fi based fingerprint positioning: advanced localization techniques and efficient system deployment. For each direction, we introduce several recently popular issues and the related works.

In advanced localization techniques, we describe the new signal patterns, collaborative localization and motion-assisted schemes. Then in efficient system deployment, we introduce the emerging schemes in survey reduction, device calibration and energy saving. By reviewing several typical works in each selected direction, we sum up their basic principles and also qualitatively compare their overall performance for practical deployment. Through the timely and comprehensive overview of the recent works, this survey may further encourage new research efforts into this promising field.

We briefly go through some future research directions as follows. Some other emerging fields of Wi-Fi fingerprint-based localization may include:

Channel state information (CSI) is an emerging technique to replace RSSI information [195]–[197]. CSI describes how a signal propagates from the transmitter to the receiver. Such information represents the combined effect of, for example, scattering, fading, and power decay with distance. It achieves higher robustness than traditional RSSI information and therefore can be used for fingerprinting. Currently, Wi-Fi interfaces on smartphones do not support the data collection of CSI. Therefore, specialized infrastructures are still needed in current prototype systems [198]. Other signal patterns, including channel impulse response [199] and signal eigenvector [200], [201], are also emerging for better indoor localization.

Consistent localization experience has become important for indoor LBS. The traditional localization system under different environment may show different localization accuracy (localizability) for the target, including the open indoor hall space [37] and narrow office environment [202]. Switching between indoor and outdoor also leads to different localization performance [203], [204]. If we have a generic approach which caters for different scenarios with suitable signals and devices, we can achieve seamless switching and optimal combinatorial localization accuracy [165].

Combining vision with Wi-Fi fingerprinting localization is also an interesting research direction. Some recent works [13], [205]–[208] have proposed using vision for indoor or outdoor localization. Through digital cameras and the inertial sensors, fusion with vision provides more location information to assist wireless signal localization. Integrating vision within existing

Wi-Fi fingerprint localization will also provide more abundant applications.

Accessibility of localization system for physically disabled people has become important for indoor LBS. Through motion sensing, sound detection [209], special user interface design (including augmented reality) [210], many indoor LBS systems have improved their accessibility for visually disabled people [211].

Floor recognition of targets [212]–[215] is an important issue for indoor localization, especially for sites with different floors [216], [217]. Users may need to be located on a certain floor first through existence of signals [217], fusion of sensors [214] or crowdsourcing [215]. Then the traditional 2-D localization is conducted on the corresponding floor map. Higher dimension for indoor localization will be *3-D localization*, and may target at higher accuracy with information of human body and gesture recognition [196], [218].

Optimizing deployment for accuracy improvement or cost reduction has recently attracted research attentions in Wi-Fi fingerprinting localization, including placement of APs [219], [220], reference points [221], accuracy assessment [222] and signal reporting strategy [223]. These works investigate the possibility of achieving high localization performance under low deployment cost or system modification. Further investigation into some optimality of deployment may provide theoretical guidance or inspiration for engineers.

With the increasingly pervasive deployment of indoor localization, large-scale *location-based data mining* [224] becomes possible and more lucrative. For example, people may tend to cluster at some region or share a certain location through social network. Leveraging such location information, more interesting applications such as indoor landmark discovery [225], geofencing and queue detection [82], [226] significantly increase the business and social values of indoor LBS.

Building a practical Wi-Fi-based indoor positioning system has become more and more challenging. Table IX has listed several existing indoor location engines, accompanied by their similarity and difference. Some of these features have more or less reflected the recent advances that we have reviewed. We can observe that despite accuracy and deployment cost, diversity in applications and services is also increasingly important to attract various LBS customers. Boosting more novel and distinguished features under diversified application demands also makes the indoor LBS market increasingly interesting and competitive.

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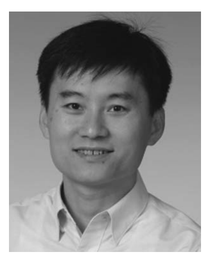

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