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A survey on wireless indoor localization from the device perspective

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With the marvelous development of wireless techniques and ubiquitous deployment of wireless systems indoors, myriad indoor location-based services (ILBSs) have permeated into numerous aspects of modern life. The most fundamental functionality is to pinpoint the location of the target via wireless devices. According to how wireless devices interact with the target, wireless indoor localization schemes roughly fall into two categories: device based and device free. In device-based localization, a wireless device (e.g., a smartphone) is attached to the target and computes its location through cooperation with other deployed wireless devices. In device-free localization, the target carries no wireless devices, while the wireless infrastructure deployed in the environment determines the target's location by analyzing its impact on wireless signals.

This article is intended to offer a comprehensive state-of-the-art survey on wireless indoor localization from the device perspective. In this survey, we review the recent advances in both modes by elaborating on the underlying wireless modalities, basic localization principles, and data fusion techniques, with special emphasis on emerging trends in (1) leveraging smartphones to integrate wireless and sensor capabilities and extend to the social context for device-based localization, and (2) extracting specific wireless features to trigger novel human-centric device-free localization. We comprehensively compare each scheme in terms of accuracy, cost, scalability, and energy efficiency. Furthermore, we take a first look at intrinsic technical challenges in both categories and identify several open research issues associated with these new challenges.

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1. INTRODUCTION

Indoor location-based services (ILBSs) have become an essential part of people's activities in living, working, and studying. Examples of such widespread ILBSs can be classified into a couple of groups. To name a few, in places of interests, tourists will need the guiding services or tools to find prestigious yet unfamiliar places; in large shopping arcades, users usually want to look for the shop of a specific brand in a short time

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or restaurants with public praise; in hospitals and medical facilities, there is a need for real-time monitoring the location of wandering patients for timely treatment; in warehouses, staff need assert tracking services that detect the goods and inventory in real time; in art exhibitions, there is a need for viewers to find out the most interesting paintings in a large museum; and so forth. Obviously, these ILBSs have been bounded up with social activities of humans, such that there is a pressing need to accurately and effectively gain the location information. To this end, although outdoor localization has been accurately and successfully completed by GPS technique, indoor localization still leaves an open problem. More specifically, GPS cannot be guaranteed to work well in a complex indoor area due to the blockage of satellite signals. In addition, it requires higher location resolution to pinpoint the position of users in indoor environments than in outdoor. Consequently, it brings new challenges for designing indoor localization systems based on the demands of high accuracy, time-critical constraints, and energy efficiency.

Recent advances in mobile and wireless computing have begun a new era for indoor localization. Nowadays, the adoption of smartphones has driven widespread development of a variety of ILBSs: for example, *Facebook Nearby* to find friends nearby in a fancy party or share current real-world locations, *Yelp* to help customers find nearby recommended restaurants, *Shopkick* to verifies users' present physical location so as to earn check-in rewards of nearby retail, and so forth. These ILBSs associated with social networking help people coordinate interactions, understand social patterns, and meet new friends. More importantly, they trigger the research community to introduce commodity smartphones for indoor localization. In this article, we comprehensively study the corresponding smartphone-based techniques, which are divided into single-modality and multimodality categories. Besides, a review of multiple specific hardware-based technologies, including ultrawideband (UWB), ultrasonic, infrared, RFID, and Zigbee, is also presented. However, all these techniques require special hardware. In contrast, due to its increasing application-driven demand and commodity access, smartphone-based indoor localization is growing with increasing interest in recent research and the marketplace.

Despite that device-based techniques have made considerable progress to improve localization performance, device-free techniques are more favorable when associated with the following important applications. Intrusion detection and tracking identify whether anomaly objects exist and locate them in an area of interest. Border protection prevents terrorists from entering a forbidden area. Safety precaution assists lonely elders or disabled individuals in an emergency like empyrosis, fall, apoplexia, and so forth. In these circumstances, there is an emerging need to seek a cost-effective yet appropriate tool for device-free indoor positioning. First, we need to understand the distinct features of device-free techniques. The key difference from device-based techniques is that no device is attached to the entities in device-free systems, as depicted in Figure 1. Consequently, it brings in new challenges such as anomaly detection and locating the entity. We then investigate existing device-free localization systems that harness UWB radar, ultrasonic, infrared, camera, RFID, Zigbee sensor, and WiFi. Afterward, we provide performance comparisons in multiple aspects.

There are numerous works falling into the category of wireless indoor localization, but in this article, we only focus on some recent advances in this area. We restrict our scope of "wireless" from the low-frequency FM signals to high-frequency (UWB) signals, and also extend it to visible lights due to the increasing ubiquity and importance of built-in cameras on smartphones. The main contributions are:

(1) To the best of our knowledge, this is the first survey on wireless indoor localization from the device perspective, that is, with and without the device attached

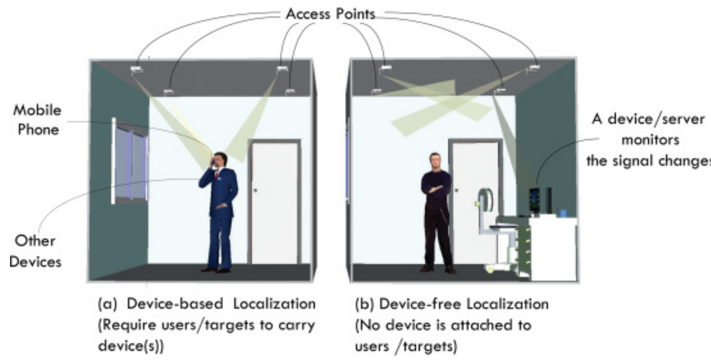


Fig. 1. An illustration of device-based and device-free indoor localization systems.

to the target, in contrast to most other surveys concentrating on techniques and algorithms.

(2) We list the different requirements for both categories and the corresponding challenges, as well as provide a comprehensive comparison for each category.
(3) We also highlight the attraction of using a smartphone for developing device-based indoor location systems because the abundant hardware integrated in it can be leveraged for positioning.
(4) Finally, we discuss the open research issues.

The remainder of this survey is structured as follows. Section 2 introduces the different application scenarios categorized by device based and device free. Section 3 reviews device-based localization for indoor space. In Section 4, we introduce research on device-free indoor positioning. Section 5 discusses open issues and future directions in this vibrant field. Finally, the survey closes in Section 6.

2. APPLICATION SCENARIOS

ILBSs have emerged at incredible speed these years with the tremendous development of wireless technologies. According to different application scenarios, we categorized the existing techniques into two folds: device based and device free. In general, the applications requiring specific devices on the entities to fulfill the localization function belong to the device-based category. Otherwise, the ones whose subjects carry no device pertain to the device-free category. To support adaptive and convenient indoor ILBSs of variety, understanding the distinct requirements is critical for designing a qualified localization system. Figure 2 provides the detailed taxonomy of wireless indoor localization systems from the device perspective. This section introduces the diverse application scenarios together with the corresponding demands ranging from device based to device free. Also, the challenges for each category will be discussed.

2.1. Device Based

To begin with, a device-based indoor localization system needs to meet the following key demands in varying degrees:

—*Accuracy*: High accuracy is the primary concern for a wide range of ILBSs, for example, navigation and way-finding that help users determine their direction from one place to another to find the destination using mobile devices. Another example is assert tracking in which attached tags on products help to identify and locate the missing one. The accurate position information (physical or symbolic) of entities is indispensable in these well-known applications and services. Note that

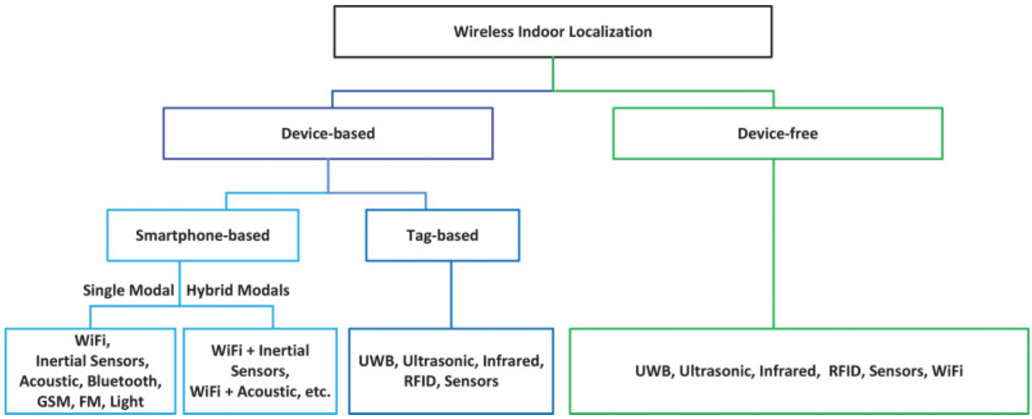


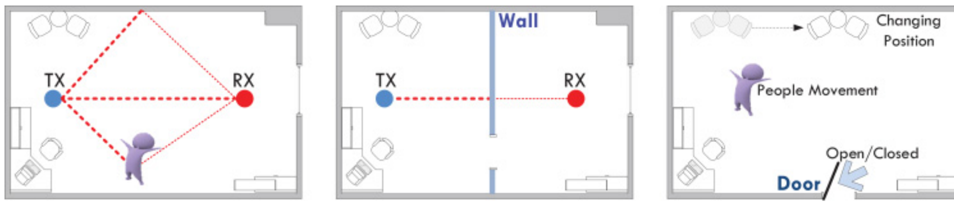
Fig. 2. Taxonomy of wireless indoor localization.

different ILBSs have diverse accuracy needs. For instance, less precision is sufficient for location-based advertisements like restaurant recommendations, as Yelp does, and room-level accuracy is enough to find a specific shop in a large mall.

—*Real time*: To quickley estimate the location of lost or injured people is of the highest priority for a certain time-critical ILBS. Emergency response is at one end of the spectrum, and the user is nearly always motivated to disclose location information as accurately and quickly as possible. In this way, ambulance staff can move quickly to approach the victim location to conduct the search-and-rescue work. Real-time action is also required in healthcare assistance for preventing medical negligence by locating the patient promptly.

—*Cost*: To realize an indoor localization system, cost is one of the most important factors for commercial success. Four major ingredients exist: (1) *Hardware cost*: This includes terminals like tags and smartphones carried by users or objects to be localized. (2) *Infrastructure cost*: Some localization systems can work with standalone devices, but most systems need the support of extra infrastructure to construct a network. For example, for a WLAN-based localization system, the device is required to transmit or receive signals with AP to obtain the measurements for position estimation. (3) *Installation cost*: Most of the localization systems require installation and configuration before usage. For network-based systems, equipment should be installed, powered, and connected to form a network, and related software may also need to be installed on this equipment for management and data collection. Moreover, for fingerprint-based systems, offline calibration is a prerequisite of localization, which is known to be a tedious process. (4) *Maintenance cost*: For a positioning system using a large set of devices (such as Zigbee sensors, active RFID tags), the long-term maintenance process (e.g., battery replacement) can be complicated and costly. All these costs need to be taken into consideration such that it will not be too exorbitant to develop an indoor positioning system.

—*Energy efficiency*: Alleviating energy concerns is of high importance for the design of localization methods. For vast ILBSs (e.g., social networking, advertising, and promotion) enabled by context-aware smartphones, power consumption is a limiting factor. This is because the capacity of the smartphone battery restricts proper functioning of these ILBSs. Nevertheless, power-limited wireless sensor networks encounter the same problem. The numerous deployed sensor nodes need to be powered with a dry cell for communication so as to fulfill the positioning duty. Since replenishment of power resources might be impossible in some circumstances, an energy-efficient strategy will be indispensable for these device-based approaches.



(a) Signal Reflection (b) Signal Blocking (c) Environment Dynamic

Fig. 3. Challenges for device-based indoor localization.

—*Scalability*: Scalability is a key element for an indoor location system, especially for enterprise usage. The localization system can be overloaded with the increase of user density, which results in inadequate latency in tracking. For some localization systems that involve information exchange between the devices and the server, the devices have to compete with each other for the transmission opportunity due to limited number of wireless channels. The delay will increase as the competition intensifies. In addition, since the transmission range of wireless signals using a specific technique is limited, the wider the area of interest is, the more infrastructure is needed. Therefore, the system should be scalable to cope with additional devices and be able to cover a large area of interest without degrading the service.
—*Privacy*: Device-based indoor localization raises many privacy concerns if entities are tracked by their positions or by analyzing their route history. Although such history analysis may help many applications to get a perfect customer model, it can disclose the location information of users, and the location information is closely related to a user and reflects the user's everyday life. To maintain privacy, the user should be informed prior to collecting their information and be able to decide whether to provide this information to the business communities or to hide their real identifications.

In order to meet the aforementioned requirements, several challenges exist:

—*Signal reflection*: The foremost source that brings difficulty for indoor localization is the multipath effect. The complex indoor areas surrounded by equipment (i.e., furniture) and human beings are the causes of the multipath effect in radio propagation (Figure 3a). Thus, coordinating the location estimation of an entity is susceptible to the presence of obstacles and humans due to multipath effect. The phenomenon becomes even worse when multiple entities exist between the transmitter and receiver in radio-based techniques. It also serves as the major concern for Time of Arrival (TOA) as a distance metric.
—*Signal blocking*: Most indoor localization techniques also suffer from Non-Line-of-Sight (NLOS) propagation, which is known as radio based. These radio-based approaches depend on the Line-of-Sight (LOS) radio signal propagation path between the transmitters and receivers. However, the ambient obstacles in indoor venues commonly lead to NLOS that constrains the radio transmissions and results in erroneous location estimation (Figure 3b). In particular, the performance of the Angle-of-Arrival (AOA)-based positioning system degrades greatly if the LOS signal is blocked by obstructions.
—*Environment dynamic*: The indoor environment is more dynamic than outdoor for localization. Human movement is one of the main reasons for the variance of the measurements. Opening and closing the door and changing the position of large furniture can also cause significant influence on the performance of indoor localization, especially for fingerprint-based systems (Figure 3c). As a result, we need to update the map, the position information of the infrastructure, or the fingerprint database periodically.

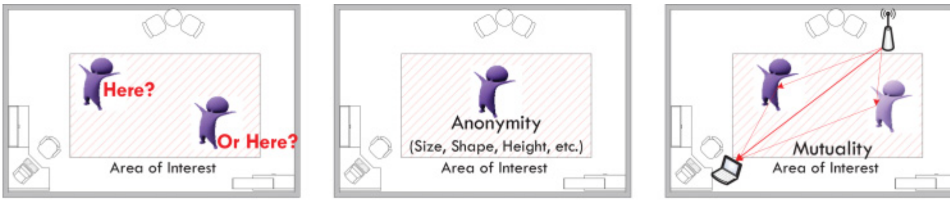
2.2. Device Free

As mentioned previously, device-free indoor positioning systems will take over the role of device-based ones in some important application scenarios like intrusion detection and burglary prevention. This is because device-based mechanisms will no longer be suitable since there aren't any trackable devices attached to entities. Hereby, we summarize the requirements for the device-free category as follows:

—*Accuracy*: Similar to the device-based localization context, to accurately locate the device-free object is important. It should be noted that here the accuracy includes not only the localization accuracy but also the detection accuracy. Unlike device-based techniques that naturally obtain the status of the subject, the foremost step of device-free ones is to accomplish the detection function. The result of detecting the appearance or movement of an entity will directly influence the localization performance.
—*Reliability*: In a device-free location system, the prerequisites of localization include detecting the motions and counting the coexisting entities. False alarm and miss detection are two of the most commonly used metrics to evaluate the reliability of the system, which, however, involve tradeoff and compromise. On the one hand, false alarm will introduce unnecessary location computations and also has the potential to divert responders away from legitimate emergencies. On the other hand, miss detection will greatly degrade the localization accuracy and may also lead to property or even life loss due to ignored emergencies.
—*Real time*: Real-time positioning and tracking have been recognized as of great importance for many device-free ILBSs, for example, to monitor the status of an alone elder person or to perceive the activity of an immature child at home. Timely response will help to prevent certain dangerous situations like falls, cardiopathy, or epilepsy.
—*Robustness*: For application scenarios like intrusion detection and border protection, the targets are definitely noncooperative. Hence, to avoid intentional circumvention of intruders, there should be as few dead spots as possible within the area of interest. Moreover, the localization system should be robust enough to provide relatively consistent performance in different conditions like weather, temperature, humidity, light, and so on.

The interesting challenges in device-free indoor localization arise mainly as follows:

—*Burstiness*: Since the target is not able or willing to exchange information with the location system, it is impossible to predict the appearance and disappearance of any target. As the trigger of localization, the system needs to continuously monitor the area of interest to detect the abnormal variance. Unfortunately, a larger scan interval leads to a higher miss detection ratio, while a shorter scan interval is less energy efficient and also results in a higher false alarm possibility.
—*Anonymity*: We can easily distinguish different targets in device-based location systems according to the identifications of the devices. Unfortunately, in the device-free scenario, it is difficult to obtain the identification of the entities, even their size or shape, and to discriminate each individual entity, which is essential for tracking, because the measurement results are the combination from multiple entities (Figure 4b).
—*Mutuality*: Unlike localizing multiple targets with devices, whose procedures are nearly independent, the localization of one entity may be affected by the coexistence of another if in device-free localization. This mutuality brings in difficulty to properly locate multiple targets simultaneously. Take the fingerprint-based system as an example: in a device-based scenario, all users can share the same fingerprints with no



(a) Burstiness (b) Anonymity (c) Mutuality

Fig. 4. Challenges for device-free indoor localization.

Fig. 5. Candidate sensing modalities on smartphones for indoor localization.

significant error. However, a fingerprint for each possible coexisting case is required to localize multiple device-free entities accurately (Figure 4c).

3. DEVICE-BASED INDOOR LOCALIZATION

Device-based approaches are widely applied for localization to support numerous ILBSs. With the proliferation of smartphones that are used for social communication these days, smartphone-based indoor localization has become a popular method for providing a variety of ILBSs. Smartphones are known to be of easy programmability, large storage capacity, and low price. Moreover, there are all kinds of modalities as shown in Figure 5 (e.g., WiFi, cellular, FM radio, Bluetooth, microphone, inertial sensors, etc.) embedded in smartphones today that can be used separately or integrally for localization purposes. It should reinforce the point that leveraging the smartphone's built-in modalities can eliminate the need for additional hardware. In this circumstance, numerous smartphone-based approaches are springing up to address the indoor localization problem. Meanwhile, several candidates exist to achieve the same goal that require specific hardware, including infrared, ultrasonic, RFID, and Zigbee, and we categorize them as tag based. In this section, we review a large body of proposals and systems in recent years, mainly in two folds: smartphone based and specific tag based. Note that, although some works are not evaluated on a smartphone, we still classify them as smartphone based if we can find the corresponding modules on a smartphone that hold the potential to meet the technique requirements.

3.1. Smartphone Based

In this subsection, we introduce smartphone-based solutions according to different modalities, including visible lights, WiFi, inertial sensors, acoustic, FM, Bluetooth, cellular, and the combination of different modalities.

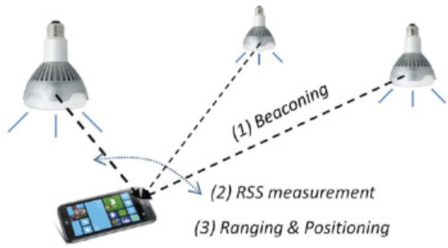


Fig. 6. Light based: Epsilon [Li et al. 2014a].

3.1.1. Camera. Cameras are one of the most important smartphone sensors and offer to leverage computer vision for indoor localization. With photos as input, visual features are extracted as spatial references, forming a 3D map. Werner et al. [2011] introduce a camera-based positioning system by combining image recognition with a flexible distance estimation. OPS [Manweiler et al. 2012] enables object localization by constructing a 3D model of the object and mapping it to ground locations. Conversely, Sextant [Tian et al. 2014] combines built-in inertial sensors to obtain relative position measurements from visual reference points and computer-vision-based image matching to triangulate user locations. Computer-vision-based approaches often achieve high accuracy but are vulnerable to light conditions, require LOS propagations, and are relatively computational extensive.

The increasingly widely used Light-emitting Diode (LED) lights have been proposed for accurate localization. Based on the existing lighting infrastructure, any devices with light-sensing capability (e.g., a smartphone) can be located in a highly accurate, low-cost, and easy-to-use fashion. Li et al. [2014a] use LED lamps as anchors. Each bulb acts as a landmark and broadcasts location beacons carrying information, such as the position of the bulb. The receiver uses the light sensor to retrieve the beacon information and measures the distances from these beacon lamps based on optical channel models. It then determines its location via triangulation (Figure 6). Luxapose [Kuo et al. 2014] further improves Visible Light Positioning (VLP) to support high light density without coordination and to provide orientation with improved localization accuracy. Yang et al. [2015b] enable VLP on smart glasses.

3.1.2. WiFi. Due to its wide availability and prevalent infrastructure, WiFi-based indoor positioning has become an attractive approach of supreme importance. The discovery of the position can be realized utilizing various measurements including TOA, AOA, RSS, and CSI. Figure 7 illustrates the settings of WiFi-based localization systems.

TOA is a popular location estimation method commonly applied for ultrasonic-based indoor localization. The feasibility of performing TOA on WiFi-based networks (i.e., 802.11b) has been studied in Yamasaki et al. [2005] with a positioning accuracy of 2.4m at the 67th percentile with 10 APs and three-branch diversity. Giustiniano and Mangold [2011] develop the CAESAR system with commodity hardware using a combination of time-of-flight (TOF) and signal-to-noise (SNR) measurements. However, the performance of a TOA-based system will degrade significantly under NLOS conditions. Besides, due to the high speed of the RF signal, it requires highly accurate time synchronization. Sen et al. [2015] proposed CUPID2.0, a TOF-based localization system achieving a mean localization error of 1.8 meters using commodity WiFi devices. It combines the Energy of the Direct Path (EDP) and the Time-of-Flight of the Direct Path (TFDP) to enable accurate ranging to deal with hardware noises and client diversity for TOF-based ranging schemes. ToneTrack [Xiong et al. 2015] combines measurements from multiple channels to derive a high-resolution channel impulse response and TOAs,

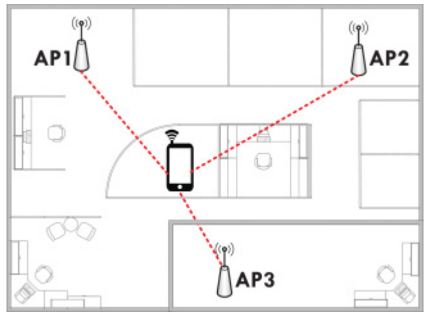


Fig. 7. An overview of WiFi-based indoor localization systems. A WiFi-enabled device measures WiFi signal features (e.g., TOA, AOA, RSS, CSI) from multiple access points to pinpoint its location.

and proposes a spectrum identification scheme to eliminate the impact of NLOS paths. The system achieves a median accuracy of 90cm by combining three 20MHz channels.

AOA provides another way for indoor localization with submeter accuracy. To determine the object's position, AOA estimates the angle of the arrived signal from the object with measurements of at least two APs. Xiong and Jamieson [2012] leverage the MIMO techniques with multiple antennas in APs to enable fine-grained AOA-based indoor localization. In ArrayTrack [Xiong and Jamieson 2013], there are two novel heuristics: intra-AP triangulation for distinguishing LOS from the NLOS path and pseudospectrum matching that eliminates multipath reflections. Based on the WARP platform, ArrayTrack achieves a median accuracy of 23cm. However, such AOA-based ArrayTrack prototypes are far from practice because neither the tailoring hardware (i.e., 16 antennas for each AP with complicated arrangements) nor nontrivial collaborative measurements by multiple APs are available. SpotFi [Kotaru et al. 2015] adopts superresolution AOA estimation algorithms and proposes a set of filtering and estimation techniques to derive the LOS AOA using commercial WiFi infrastructure. The system achieves a median accuracy of 40cm and is robust to multipath propagation.

Received Signal Strength (RSS) is the most commonly used signal feature for WiFi-based indoor localization [Bahl and Padmanabhan 2000; Youssef and Agrawala 2005; Chintalapudi et al. 2010; Park et al. 2010; Goswami et al. 2011]. Theocratically, RSS decreases monotonically with distance in free space [Rappaport 2002], so that the distance of the target can be calculated from RSS. Unfortunately, in indoor spaces with severe multipath effects, the propagation model can fail and these RSS-based distance measurements can be inaccurate. In this manner, an RSS-based fingerprinting approach is proposed. It consists of two phases: (1) *offline training phase* RSS fingerprint (radio map) generation (site survey) and (2) *online positioning phase* localization by matching the test point to a radio map. Although RSS-based fingerprinting has shown to be comparatively accurate, it is still far from practical for the following reasons:

—It is *labor intensive* and *time consuming* to construct an RSS-based radio map.
—It is difficult to *maintain* and *update* this fingerprint database for a specific indoor area since the environmental dynamics are inevitable.

Many researchers endeavor to reduce the overhead of fingerprinting. Chintalapudi et al. [2010] ease the calibration task via a genetic algorithm that models the physical constraints. The key finding is that WiFi-enabled devices like smartphones can obtain the location fix of the edge of the indoor area, which provides the environment characteristics. Park et al. [2010] design an Organic Indoor Location (OIL) system to release the radio map construction efforts. The initial OIL fingerprints database is empty and developed by user-provided information. To improve convergence rates, a Voronoi-based

Table I. CSI Versus RSS

Metric	Measurement Band	Layering	Granularity	Temporal Stability	Frequency Diversity
CSI	Base Band	PHY	Fine grained (per symbol)	High	Yes
RSS	RF Band	MAC	Coarse (per packet)	Low	No

user promoting algorithm is applied in OIL. Goswami et al. [2011] bypass the laborious fingerprint construction phase by proposing an unsupervised learning-based WiGEM system. WiGEM can adapt to real time changes in environments by learning the parameters from the Gaussian Mixture Model (GMM). Therefore, the predeployment burden of RSS-based fingerprinting can be relieved. On the other hand, fingerprinting-based localization schemes may perform better at some locations than others. It is simply difficult to expect consistent localization performances using an evenly sampled fingerprint database. Some researchers proposed an algorithm to optimally approximate the actual fingerprint database using both model-based virtual fingerprints and actual fingerprints [Li et al. 2014b]. Therefore, scenario-catered calibration (e.g., fingerprint database building) seems indispensable if the localization system were to be deployed at scale.

Recently, an alternative to RSS has been suggested for indoor localization using the ubiquitous WLAN infrastructure, known as *Channel State Information (CSI)* [Wu et al. 2012a, 2013]. CSI is used today (e.g., in IEEE 802.11a/g/n, WiMax, and LTE) and is available on commercial products. It represents the channel conditions over individual OFDM subcarriers across the physical (PHY) layer. Specifically, CSI ($\hat{H} = \{h_i\}_{i=1}^{n}$) represents the wireless channel at the granularity of subcarriers. For each subcarrier i, h_i represents its complex channel gain:

$$h_i = |h_i| e^{j \cdot arg(h_i)}, \tag{1}$$

where $|h_i|$ and $arg(h_i)$ denote its amplitude and phase, respectively.

Instead of only one RSS per packet, CSI values over multiple subcarriers can be obtained at one time. The main differences between CSI and RSS are displayed in Table I, which reveals the superiority of CSI compared to RSS.

The superiority of CSI was first proved in Halperin et al. [2010], and Halperin et al. apply CSI for throughput improvement by adaptively adjusting the transmission rate. Inspired by this work, FILA [Wu et al. 2012a] initiates the use of CSI for locating the target in complicated indoor environments by extracting the LOS path for ranging. As such, FILA is the first attempt at leveraging CSI for modeling-based indoor localization. Even with a simple trilateration calculation for location coordinates, FILA can achieve good performance. In Xiao et al. [2012a], a fine-grained CSI-based fingerprinting scheme is proposed for indoor localization. It explores frequency diversity of CSI to uniquely identify a location based on the fact that CSIs over multiple subcarriers have different amplitudes and phases at multiple propagation paths. After building up the radio map, FIFS applies a coherence bandwidth-enhanced probability algorithm for matching the target object to the radio map. Likewise, Sen et al. [2012] develop a spot indoor fingerprinting system, PinLoc, using CSI and achieve an accuracy of 89% for 100 spots.

3.1.3. Inertial Sensors. With rapid technological developments, contemporary commercial smartphones offer up a whole slew of embedded sensors, including accelerometers, gyroscopes, proximity sensors, and ambient light sensors. Here, we will introduce the indoor positioning solutions that rely on these low-power-consumption, low-cost smartphone-based sensors only.

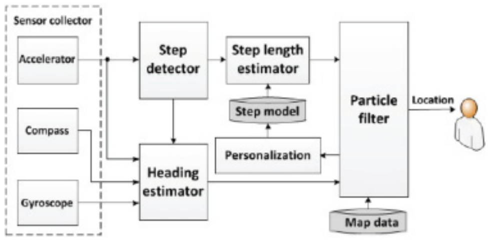


Fig. 8. Dead-reckoning based: IndoorNav [Li et al. 2012] overview.

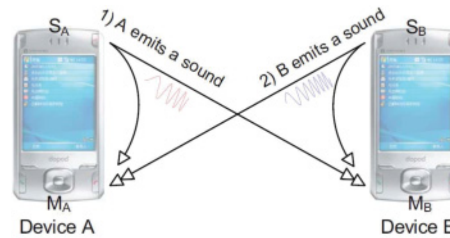


Fig. 9. Acoustic ranging: Peng et al. [2007].

CompAcc [Constandache et al. 2010] is an indoor localization system using an accelerometer and digital compass. It fetches a local map (i.e., Google Map) over the surrounding area of a user's location by GPS. Then, the walking patterns, speed, and orientation of this user will be recorded with the accelerometer and compass accordingly. By mapping the walking patterns of user to the local map, the location of the smartphone user can be approximately estimated without war-driving efforts. The IndoorNav [Li et al. 2012] system collects sensor data as input for step detector and heading estimator modules by using an accelerometer, compass, and gyroscope. In common sense, each individual may have different body shapes like height and weight that influence the step length estimation. IndoorNav proposes a reliable step model for step detection and a personalization algorithm to adapt users' stride length. By combining these modules with an indoor floor map, IndoorNav can achieve meter-level accuracy without infrastructure, that is, a mean accuracy of $1.5m$ in a testbed of $31m \times 5m$. Figure 8 provides the work flow of Indoor Nav. We refer interested readers to Harle [2013] for a comprehensive survey on inertial-based indoor localization using the dead-reckoning principle.

3.1.4. Acoustic. The acoustic ranging technique is newly adopted for indoor positioning. With the innate speaker and microphone in a commodity mobile phone, high-accuracy acoustic ranging becomes achievable. Here we will review the research on acoustic-based indoor localization.

BeepBeep [Peng et al. 2007] is a pioneer acoustic ranging system with high accuracy. In BeepBeep, one smartphone A and its peer device B will perform "two-way sensing." Both devices will in turn send a "*Beep*" signal and record successive second-scale sound signals from the microphone. Then, each device will count the elapsed time between two TOA events. Noted that this sensing scheme can be extended to multiple devices. In this way, the differential of elapsed times can be computed to realize TDOA for localization (Figure 9). The Whistle [Xu et al. 2011] system introduces a synchronization-free TODA framework for estimating the location of an object, which is a big breakthrough for the previous TDOA-based approaches. In Whistle, two-signal (source signal and successive signal) sensing is done in the first recording step. The second step comes to sample the counting operation, which is done by the receiver. In the third step, AP will finish TDOA calculation by receiving the counting results from the receiver. The experimental results show that Whistle can achieve accuracy in the centimeter level, that is, 10–$20cm$ in a 3-dimensional $9 \times 9 \times 4m^3$ area. Qiu et al. [2011] extend acoustic-based TOA ranging for real-time phone-to-phone localization to 3-dimensional spaces. Liu et al. [2013] propose an accurate acoustic smartphone-based indoor localization system. The acoustic communication between anchor nodes is realized by the standard speakers and microphones on a mobile phone. EchoTag [Tung and Shin 2015] adopts an acoustic-based fingerprinting approach to enable location tagging, achieving a resolution of 1cm with 98% accuracy.

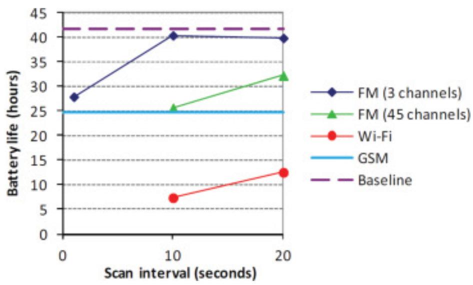


Fig. 10. Battery life of different modes [Popleteev et al. 2012].

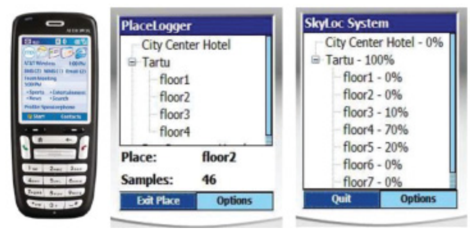


Fig. 11. GSM: SkyLoc [Varshavsky et al. 2007].

3.1.5. FM. FM radio (88–108MHz) has been long integrated on smartphones for entertainment like listening to music or news. The features of FM radio signals are investigated in Popleteev et al. [2012]. The advantages of FM for indoor localization are as follows: (1) FM radio consumes less energy than WiFi, which is energy efficient for positioning on a smartphone, as shown in Figure 10; (2) FM signals can penetrate walls more easily than WiFi or GSM; and (3) FM radio is more robust to short-wavelength obstacles than WiFi and GSM due to the long wavelength. Matic et al. [2010] first propose the feasibility of using FM radio for smartphone-based indoor localization. In their system, they introduce the spontaneous recalibration concept to automatically update the fingerprint database. Besides, WiFi is synergetically integrated with FM radio to enhance the performance of the positioning system.

An FM-based indoor fingerprinting system [Moghtadaiee et al. 2011] is also devised to bypass the timing problem of FM signals and serious multipath effects. In Moghtadaiee et al. [2011], RSS values of FM radio are measured by USRP2 (Universal Software Radio Peripheral 2) and locations are decided by deterministic nearest-neighbor (NN, KNN, KWNN) algorithms. The results show that applying the KWNN algorithm will lead to a minimum mean distance error of $2.96m$ in an $11m \times 23m$ indoor area.

Recently, Chen et al. [2012] proposed adding physical layer information to FM RSS for generating richer location fingerprints, and the accuracy can be improved by 5%. The experimental results suggest that FM signals are more robust to temporal variations compared to WiFi signals. Specially, human presence, multipath, and fading have less influence on FM signals. Moreover, combining these two signals as a location fingerprint can improve the localization accuracy.

The main disadvantage, however, is that FM radios are less popular than WiFi in indoor environments. Smartphone users tend to turn on WiFi or cellular to get online wherever possible, while fewer users would turn on an FM radio broadcast. This makes FM-based solutions complementary and less mainstream.

3.1.6. Bluetooth. Bluetooth (IEEE 802.15.1), pervasively available on a smartphone, is designated for short-range (i.e., $10m$) wireless communication in the $2.4GHz$ range. It can also be an attractive modality for locating and tracking people and assets indoors. Dietrich et al. [2004] deploy a moving Bluetooth-enabled mobile device as the transmitter, along with a dedicated correlation IC and microcontroller as two receivers. The position is calculated by TDOA measurement to achieve meter-level accuracy. Chen et al. [2010] present an inquiry-based locating approach using Bluetooth RSS measurements. There also exist several commercial Bluetooth-based indoor positioning systems, such as ZONITH [Teldio 2006], which is used to assist people who work in hazardous environments. The Bluetooth chipsets exist in many products like mobile phones, tablets, and portable computers with low cost. However, a short-range feature makes it suffer from dense deployment for ubiquitous positioning. This results in relatively high capital investment for infrastructure support.

3.1.7. Cellular. Cellular networks are ideal for ubiquitous and seamless indoor and outdoor localization, and are complementary to WiFi-based solutions. Various generations of cellular signals have been explored, including Global System for Mobile (GSM), Code Division Multiple Access (CDMA), and Long-Term Evolution (LTE). Otsason et al. [2005] propose the first accurate GSM-based indoor fingerprinting system achieving a within-floor median accuracy in 2.48m to 5.44m. Figure 11 shows the interfaces of SkyLoc, a GSM-based indoor localization system. Aside from GSM, CDMA proves to be a reliable cellular positioning modality [ur Rehman et al. 2008]. Unlike GSM-based approaches that rely on RSS, CDMA leverages signal delay as location fingerprints, which stays robust in frequent cell resizing. The experiments exhibit high accuracy (i.e., 4.5m and 6.7m) in two indoor scenarios. To improve the localization capability of cellular networks, the current LTE standard [3GPP 2010] has already specified a localization scheme based on the Observed Time Difference of Arrival (OTDOA). Medbo et al. [2009] evaluated the performance of LTE OTDOA-based positioning in urban scenarios using channel sounders. In del Peral-Rosado et al. [2014a], researchers present a joint time-delay and channel estimator to assess the achievable localization performance of LTE signals in the presence of multipath. Two software-defined radio (SDR)-based LTE positioning receivers are implemented in del Peral-Rosado et al. [2014b] to assess the localization performance in commercial LTE deployment. Experimental results show the potential of accurate indoor localization using commercial LTE networks. The synchronization problem when adopting LTE OTDOA is also addressed in del Peral-Rosado et al. [2015] using time-delay and frequency-tracking loops and a priori known receiver position. With the development of small cell and femtocell, which are specially designed for home or small business regions, the cellular system will cover a wide range of indoor environments and become a competitive indoor localization tool in the coming years.

3.1.8. Hybrid. Hybrid schemes have been developed by compromising the merits of various modalities on smartphones to ponder the indoor localization problem. The aim of these multimodality proposals is to enhance the overall positioning performance. Here, we mainly introduce two mainstreams: (1) the integration of WiFi and inertial sensors and (2) the integration of WiFi and acoustic.

WiFi + inertial sensors: Recently, the idea of combining WiFi and inertial sensors on a smartphone for positioning has received considerable attention. Based on different purposes, the incorporation can be collapsed into two categories:

—*To ease the calibration efforts:* Zee [Rai et al. 2012] is a “zero-effort” indoor localization system via crowdsourcing. With the assistance of a floor plan, Zee can obtain site-specific information like the pathways and barriers. Without any user participation, Zee utilizes crowdsourced sensor data (accelerometer, compass, and gyroscope) to automatically infer locations. These sensor data are combined with WiFi and processed by an augmented particle filter. Unloc [Wang et al. 2012] is another hybrid indoor positioning system that eases the burden of site survey. The key observation is that some locations can be identified as “landmarks” using inertial data, such as elevator and corridor corner. To extract these landmarks, Unloc employs unsupervised learning to enable dead-reckoning. Unloc can automatically update the landmarks by increasing users without a floor plan. WILL [Wu et al. 2012b] proposed a “logical map” to bypass site survey. In the training phase, the floor plan is constructed logically instead of physically leveraging user trace. This logical map can reveal the relative location relationship between virtual rooms and then be associated with physical rooms. In the serving phase, the user query (WiFi readings and accelerometer data) will be sent to the WILL server. And the server will give back the location information and update the database using newly added data. LiFS [Yang et al. 2012] further reduces the manual cost of site survey by exploring the connection of user motions and previous RSS fingerprints. It reforms a high-dimensional logical floor plan and maps it to real locations by spatial similarity. In a $1600m^2$ academic building, LiFS achieves an average location accuracy of $5.8m$.

—*To increase the positioning accuracy by data fusion:* Azizyan et al. [2009] develop an ambient fingerprinting SurroundSense system by combining the WiFi information and sensing modalities (light, sound, color, and accelerometer). In SurroundSense, these five-part fingerprints compose an ambience fingerprint to be accumulated into a fingerprinting factory. By matching the test fingerprint to candidate ones in this factory, the target logical location can be finally obtained. In Kemppi et al. [2010], a hybrid angle-based indoor positioning system is associated with pedestrian dead reckoning (PDR) and particle filter. Particularly, using a fusion filter, PDR movements and angle-based location estimates are combined with a building vector map. Evaluation of the system in different indoor environments shows that seamless positioning coverage and acceptable accuracy can be achieved. Kim et al. [2012] observe that the location with maximum RSS is preserved regardless of the severe RSS variance. Thus, they develop a smartphone-based pedestrian tracking system by using Peak-based WiFi Fingerprinting (PWF). In addition, digital compass and accelerometer are combined with PWF for improving the accuracy.

WiFi + acoustic: Tarzia et al. [2011] present the idea of using an acoustic background spectrum for room-level indoor localization. They design an ABS system that first records the background sounds using commercial smartphones. After that, ABS extracts the noise-robust fingerprints by filtering out the transient noise and storing it in a database. Finally, it guesses the current unlabeled location by finding the closest fingerprint in this database. The ABS system is implemented as a free application called "Batphone" on iPhones. Users can use Batphone to distinguish a pair of adjacent rooms with 92% accuracy. However, the noise rejection problem remains unsolved. It cannot cope with the noise introduced by tens of speaking occupants (the chatter state). Liu et al. [2012] develop a WiFi-enabled smartphone indoor localization system. The key observation is that there are abundant peer phones in public indoor places, which bring in physical peer constraints. They thus apply the acoustic ranging technique to reduce the WiFi similar signature error. Finally, peer-assisted localization can be achieved by jointly using a WiFi signature map and acoustic ranging. The prototype results show that it can reduce the maximum and 80% errors to as small as $2m$ and $1m$. Argus [Xu et al. 2015] proposed another assistant-based WiFi localization framework leveraging geometric constraints extracted from photos.

Other systems target fast response time or energy efficiency. For instance, CLIPS [Noh et al. 2013] considers that the region is infrastructure free but each user has a received signal strength map for the area in reference by ray-tracing. Specifically, CLIPS incorporates WiFi beacon messages with dead reckoning to drastically reduce the convergence time. EnLoc [Constandache et al. 2009] proposes an energy-efficient positioning system by integrating GPS, GSM, and WiFi. They quantify the tradeoff between energy and accuracy that underlies a range of emerging services, and characterize the optimal localization accuracy for a given energy budget. Gao et al. [2013] exploit cross-technology interference signatures for indoor positioning. They design a ZiFind system that records WiFi interference signals by low-power ZigBee devices. By applying digital signal processing techniques, unique fingerprints can be extracted from these interference signatures. Compared to previous WiFi-based fingerprinting systems, ZiFind is more energy efficient.

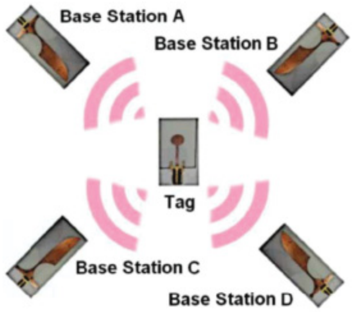


Fig. 12. UWB.

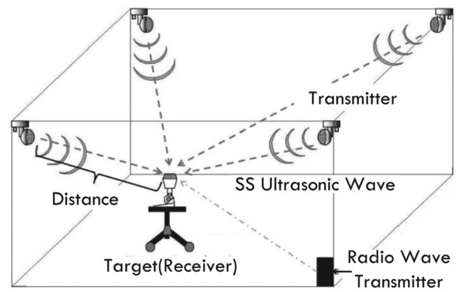


Fig. 13. Ultrasonic [Itagaki et al. 2012].

3.2. Tag Based

In the previous section, we delineated various localization modalities embedded on smartphones. This subsection presents means of localization using UWB, ultrasonic, infrared, RFID, and wireless sensors. All these approaches require specific hardware to fulfill the positioning functionality and are summarized as "tag based."

3.2.1. UWB. UWB is a radio technology originally used for wireless communication and later applied for in-building 2D or 3D localization systems [Li et al. 2007, 2009]. UWB has been issued as the radio wave whose fractional bandwidth is greater than 20% or at least $500MHz$ based on the Federal Communication Commission (FCC) in 2002. This ultrashort (i.e., nanoseconds) impulse UWB with very large bandwidth can suppress rich multipath effects and also result in a high time resolution, which greatly improves positioning accuracy. In addition, UWB signals can penetrate through obstacles easily with low power consumption. These favorable characteristics of UWB account for high positioning accuracy in centimeter scale. Figure 12 depicts the common setting for UWB-based localization system. In general, TOA or TDOA measurement of the UWB signal is applied to obtain the location of the target [Fischer et al. 2010; Zhang et al. 2006]. While NLOS is a challenge for UWB indoor positioning, a novel probabilistic TDOA model is proposed to accommodate this NLOS in Prorok et al. [2011]. In a nutshell, for positioning systems employing UWB devices, time-based schemes provide very good accuracy due to the high time resolution (large bandwidth) of UWB signals. Moreover, they are less costly than the AOA-based schemes, the latter of which are less effective for typical UWB signals experiencing strong scattering. With the new IEEE 802.15.4a standards, the cost of UWB chips is now reduced to around only $ 20 USD [decaWave 2015], making UWB competitive with WiFi-based indoor localization. The increasing popularity of indoor robots and quadrotors has also attracted renewed interest in employing UWB for highly accurate ranging and localization [Kempke et al. 2015]. However, metallic and liquid materials are sources of interference to the UWB signal and the short communication range (less than $10m$) limits its applications except in exceptionally dense networks.

3.2.2. Ultrasonic. Ultrasonic [Fischer et al. 2008] is a well-known ideal candidate for indoor positioning that relies on the TOA scheme. The key idea is to use an ultrasonic transceiver to emit and detect ultrasonic signals. While recording the signal traveling time between a pair of transmitter and receiver, it is possible to compute their separating distance given the medium traveling speed. In general, ultrasonic wave emission is usually directional, which introduces difficulties in orienting the transceiver precisely. The early Cricket system [Priyantha et al. 2000] utilizes the difference in propagation speeds and estimates the distance via coupled RF and ultrasonic signals. Although Cricket exhibits high accuracy (i.e., 6*cm*) as well as privacy protection, it suffers from the inherent narrowband disadvantage. Instead, Hazas and Hopper [2006] explore the usage of broadband ultrasonic that has superior characteristics over the narrowband counterpart. Such a broadband ultrasonic system is deployed using Dolphin units and the ranging performance is *2cm*. Itagaki et al. [2012] develop a moving object tracking method based on spread spectrum ultrasonic (Figure 13). To handle the Doppler effect brought by moving targets, a tracking method by limiting correlation calculation in a defined range is proposed. Fercu et al. [2009] present an ultrasonic-based living assistance system for people (i.e., elders or handicapped) who may accidentally fall in residences.

Unfortunately, the presence of obstacles in the surrounding area may block the ultrasonic wave due to its coverage limitations, leading to a decrease in the wave traveling time measurement accuracy, along with high power consumption.

3.2.3. RFID. Radio-Frequency Identification (RFID)-based positioning has become more and more popular, for example, in hospitals for locating patients [Cangialosi et al. 2007]. LANDMARC [Ni et al. 2004] is the first attempt to apply active RFID tags for localization. It uses reference tags with known locations to adapt to environmental dynamics to enhance the accuracy of location estimation. Seco et al. [2010] present the usage of Gaussian processes to model the RSS distribution of RFID tags. In Seco et al. [2010], 71 tags are distributed in an area of $1600m^2$ to achieve median accuracy of 1.5*m*. Wang et al. [2007] propose an RFID-based 3D positioning approach to locate the mobile user equipped with an RFID reader or tag. It applies the RSS proximity and optimization to enhance the performance (i.e., $0.3–3\,ft$).

Another interesting application based on RFID is to localize and track the demanded library books. Choi et al. [2006] introduce an RFID-based Library Information Management (R-LIM) system to determine the location of a book in search. R-LIM system records the IDs (i.e., books and shelves) associated with location using RFID tags into a database. Thus, the tagged book position can be effectively retrieved by the RFID reader. Phase-based RFID ranging allows coherent signal processing and achieves better performance than RSS-based schemes [Zhang et al. 2010]. However, simple phase measurements have to deal with phase wrapping. It is thus necessary to perform multiple measurements and use phase difference [Povalac and Sebesta 2011]. Nikitin et al. [2010] proposed three-phase difference-based positioning techniques in the time, frequency, and spatial domains with modeling and simulations. Hekimian-Williams et al. [2010] adopted a maximum likelihood method for accurate phase difference-based localization and prototyped an SDR-based positioning system. BackPos [Liu et al. 2014] proposed a phase-based hyperbolic positioning technique and achieved a mean accuracy of 12.8cm. MIMO techniques further pushed RFID-based localization to centimeter-level accuracy using Synthetic Aperture Radar (SAR) [Wang and Katabi 2013], Inverse Synthetic Aperture Radar (ISAR) [Scherhaufl et al. 2014], and hologram [Yang et al. 2014].

3.2.4. Sensors. Low-cost, low-power-consumption, multifunctional sensor nodes, which consist of sensing, data processing, and communicating components, are widely used tools for localization in wireless sensor networks (WSNs). In Kusy et al. [2007] and Chang et al. [2008], the Doppler shift effect is leveraged to estimate the direction of moving sensors. When a transmit sensor is moving toward a stationary received one, the relative velocity between them determines the Doppler shift in the frequency domain. By using the knowledge of the transmitted frequency and the received frequency at the known position, the translational velocity of mobile nodes can be calculated to estimate the location. However, the limitation of the scheme is that it can only locate moving objects.

Table II. Judging Criteria in Terms of Accuracy, Cost, Scalability, and Energy

	0 (Worst)	1	2	3	4	5	6 (Best)
Accuracy	$>100m$	$51m$–$100m$	$16m$–$50m$	$7m$–$15m$	$2m$–$6m$	$0.5m$–$2m$	$<20cm$
Cost (US$)	$>300k$	$101k$–$300k$	$31k$–$100k$	$10k$–$30k$	$6k$–$10k$	$1k$–$5k$	$<1k$
Scalability	$<10m^2$	$11m^2$–$50m^2$	$51m^2$–$100m^2$	$101m^2$–$500m^2$	$501m^2$–$1000m^2$	$1001m^2$–$0.1km^2$	$>0.1km^2$
Energy	$>100w$	$20w$–$100w$	$5w$–$20w$	$1w$–$5w$	$0.1w$–$1w$	$1mw$–$0.1w$	$< 1mw$

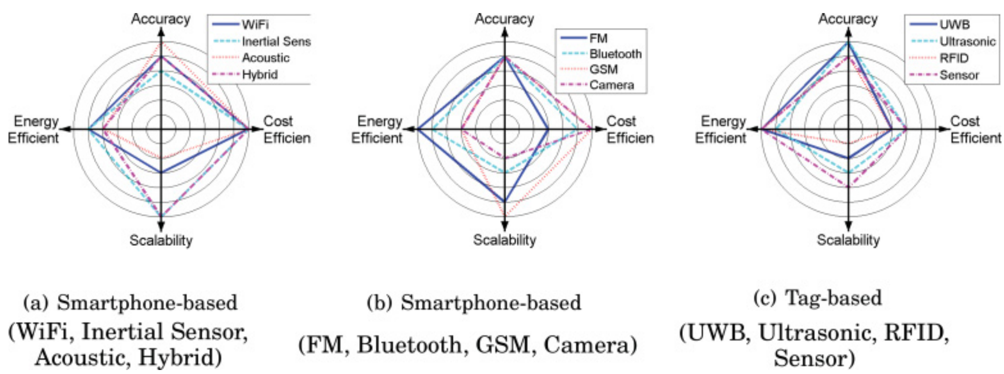


Fig. 14. Performance comparison of all recent device-based approaches.

Chung et al. [2011] propose to use magnetic field distortion as location fingerprints to develop an indoor geo-magnetism navigation system. Such a system can achieve high accuracy of 90% within $1.64m$. Pirkl and Lukowicz [2012] employ resonant magnetic coupling for designing a 3D indoor positioning system. In this oscillating magnetic field system, the accuracy resolution is within $1m^2$.

3.3. Performance Comparison

In summary, while the aforementioned technologies share some common traits, there exist certain differences with respect to technological aspects such as *accuracy*, as well as implementation details (*cost*, *scalability*, and *energy consumption*). The corresponding judging criteria are first given in Table II, divided into seven levels. As shown in Figure 14, the star chart consists of four directional axes representing the four-category criteria. And for each criterion, there are seven different circular layers (i.e., corresponding to Table II Level 1–6). The innermost layer gives the lowest value of 0 and the outermost layer gives the highest value of 6. The higher the value is, the better performance can be achieved. Thereby, a larger area indicates the overall performance is better.

Accuracy is the key factor to describe how close the estimation from a positioning technique is to match the actual position of users/devices. It is usually determined by the mean distance error. The positioning systems have been developed over a few decades and improved a lot. The measuring units of the positioning accuracy changed from kilometers to meters. The most recent and finest positioning systems can even have few centimeters of error. For this reason, the worst positioning accuracy is set to larger than $100m$ and the best is set to smaller than $20cm$.

Cost efficiency is evaluated under four mentioned expending costs like hardware, infrastructure, installation, and maintenance costs. The figures can vary from less than US$$1k$ to greater than US$$300k$.

Scalability determines how large of a positioning system can be scaled up. We analyze the possible coverage area of different positioning techniques. Due to the limitation of signals or infrastructure, the measuring units could be largely deviated from less than

$10m^2$ to larger than $0.1km^2$. For instance, if a positioning technique makes use of a Bluetooth signal, it can be only practical under a few square meters.

Energy efficiency is measured by how much energy of a positioning technique is spent in an hour in watts (w). We estimate each positioning technique depending on the usual operating power usage of its hardware. A green positioning system may have less than $5w$ power, for instance, usages of low-power inertial sensors. This criterion can vary from less than $1mw$ to larger than $100w$.

For those infrastructure-based indoor localization approaches, infrastructure is the main concern when evaluating cost, while device is the concern when evaluating energy, because only the devices are battery limited. Take GSM for example: the power for the base station is $20w$, which is much higher than that of the smartphone backend, that is, $2w$. Unlike the GSM-based location system that can make use of an existing base station, the FM-based system needs extra radio towers, which requires an additional licensing fee for spectrum access. Note that for those modalities that work in the ISM band such as WiFi, sensor, and RFID, this expense is exempted.

Due to the highly controlled and ad hoc evaluations of indoor localization systems, Microsoft launched the Microsoft Indoor Localization Competition [Microsoft 2014] to provide a relatively unified and practical venue for researchers from both academia and industry to compare different indoor localization solutions. In Lymberopoulos et al. [2015], the organizers summarized the main evaluation results during the 2014 Microsoft Indoor Localization Competition with 22 different solutions. They concluded that while $1.6m$ accuracy is achievable with merely commercial WiFi access points, the indoor localization problem is still not solved. The main hurdle is the deployment cost. Out of the 22 solutions, the average setting and calibration time is 5 hours for two rooms covering 300 square meters. This may be unrealistic and intrusive when deploying these localization systems in large deployment sites like shopping malls.

4. DEVICE-FREE INDOOR LOCALIZATION

Device-based indoor localization systems are capable of providing location information of the target who wears a specific smartphone-based or tag-based device. However, this basic requirement does not hold in myriad scenarios. The potential applications are many: in residence communities, emergency situations of elder people (i.e., falls, stuns) can be timely detected for safety precautions; in hospitals, doctors can monitor the status of patients to rescue them whenever they are in a paroxysm of disease; in large warehouses and stores, security action is needed for surveillance of an anomalous intrusion. Toward this end, device-free indoor positioning is certainly a better fit for the previous ILBS that can mitigate the necessity of carrying it on devices. It serves as an indispensable complement in the context of wireless indoor localization.

4.1. Existing Systems

In a similar fashion to Section 3, we will introduce the state-of-the-art device-free systems categorized by the frequency in the following.

4.1.1. Camera. Cameras are common for device-free motion detection or localization in a specific site. Shieh and Huang [2009] describe a video-surveillance system by leveraging multiple cameras for time-efficient elder fall detection. The idea is to identify accidental fall events with a human-shape retrieving algorithm and pattern recognition approach. To reduce the complexity of multi-video-stream processing, pipeline and multithreading methods are introduced. Experiments with four web cameras show that the false detection rate is as low as 1% to 3%. In the EasyLiving Project, Krumm et al. [2000] designed a visual person-tracking system using images from two sets of color Triclops stereo cameras in a typical living room environment. A Stereo Module records the images, which works along a Person Tracker program to produce the result

Fig. 15. Camera DfP [Xu et al. 2012].

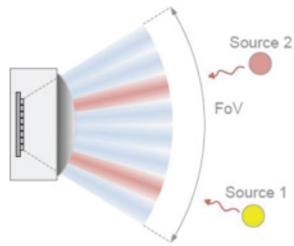


Fig. 16. Infrared DfP [Kemper and Hauschildt 2010].

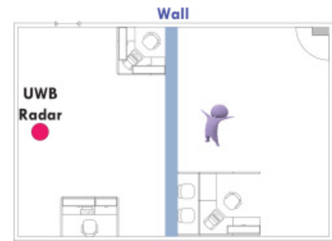


Fig. 17. UWB radar.

of location estimation and identity maintenance. However, the system is constrained in coherent tracking of more than three people due to poor clustering through occlusion. To handle this occlusion problem, Yang et al. [2007] implement a real-time indoor surveillance and tracking system with 18AXIS210 network cameras in an office building. A sensor camera SenCam [Xu et al. 2012] system was presented recently for reducing privacy concerns over solely camera-based device-free indoor positioning. Besides, camera-assisted recalibration in SenCam helps to lessen the time-consuming RSS measurements. Figure 15 shows the deployment of SenCam.

4.1.2. Infrared. Passive infrared (PIR) techniques are widely adopted for device-free indoor motion detection and localization. The basis relies on detecting changes of the infrared spectrum in the monitoring region caused by human movements. Specifically, there's an obvious distinction between body temperature of a person and ambient temperature. Such a difference makes it possible to develop a device-free infrared-based positioning system based on the thermal radiation caused by people. Figure 16 shows a representative setting of Infrared based DfP localization system. Several systems [Hauschildt and Kirchhof 2010; Kemper and Hauschildt 2010] are proposed to localize entities. In Hauschildt and Kirchhof [2010], thermal radiation is measured by thermopile arrays to determine the position of the object using the AoA scheme. Experiments in a $4.9m$ to $5.2m$ area show that the system can achieve centimeter accuracy. Kemper and Hauschildt [2010] suggest a probability hypothesis density filter to resolve the problems for multitarget counting and data association. Even in noisy situations, the mean position error of system is less than $30cm$ for discriminating and localizing three people. The OPTEX company [OPTEX Passive Infrared Sensor] provides a large amount of PIR products for detecting anomaly events. However, PIR sensors are limited to LOS vision and thus the cost of covering a large area will be prohibitive. Moreover, the additional radiation from the dynamic environment also brings in challenges for PIR technology.

4.1.3. UWB Radar. UWB radar serves as a means for device-free LBAs such as indoor through-wall detection and surveillance (Figure 17). Yang and Fathy [2005] propose a UWB radar system operating at $10GHz$. The system composes of a UWB double-ridge horn antenna as the transmitter and a 16-element Vivaldi antenna as the receiver. Since the short-pulse UWB has strong penetration ability and high power efficiency, through-wall image reconstruction can be performed with high resolution. However, the high sampling rate is challenging for the system of Yang and Fathy [2005] and also is a crucial requirement for data acquisition. Yang and Fathy [2009] further developed a real-time see-through wall system with customized FPGA firmware. This firmware successfully deals with the challenging UWB signal acquisition problem that maintains high equivalent-time sampling resolution (i.e., $100Msamples/s$). In addition, the system enables motion tracking by integrating a set of analog-to-digital converters,

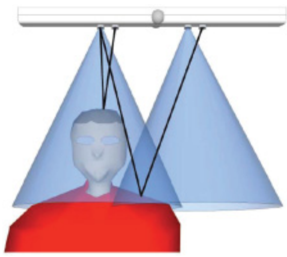
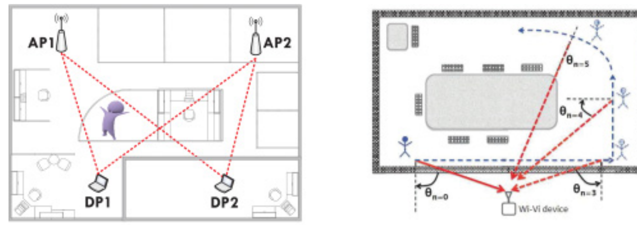


Fig. 18. Ultrasonic DfP.



(a) Pilot overview. (b) WiVi overview.

Fig. 19. WiFi DfP.

memory, microcontroller, timing, and auxiliary circuit. To further reduce the complexity of large-scale antennas, a three-dimensional imaging algorithm is presented by Sakamoto et al. [2011] to estimate the moving target with five antennas. In their work, a spheroidal model is constructed to approximate the shape of a target to determine the translational motion. Lei and Ouyang alternatively apply the finite-difference time-domain (FDTD) method to design a UWB-based surveillance system [Lei and Ouyang 2007]. The position of the target can be determined by measuring the round-trip time of a UWB wave including the time traveling through the concrete wall.

4.1.4. Ultrasonic. Ultrasonic is well suited for supporting device-free ILBSs like pilferage prevention and fall detection inside residences for security and safety purposes (Figure 18). One typical example is indoor human presence detection [Caicedo and Pandharipande 2012]. In Caicedo and Pandharipande [2012], consecutive ultrasonic signals are periodically transmitted and the echoes caused by user movement will be recorded by the receiver. Thus, the occurrence of human movement can be monitored by a tracking algorithm with high detection probability. Another example is the Doorjamb [Hnat et al. 2012] system, which aims at room-level tracking in dwelling places. Ultrasonic range finders are used in each doorway to estimate the user's height and direction, as well as to record the passing sequence. Doorjamb achieves an average tracking accuracy of 90%. However, to deploy ultrasonic in large indoor surroundings will be very expensive.

4.1.5. WiFi. Although the previous approaches have contributed to device-free indoor localization, they may not work well in terms of scalability due to either high specialized infrastructure cost like video cameras and RFID tags or maintainable costs (i.e., sensors). WiFi-based approaches [Youssef et al. 2007], on the other hand, leverage the available infrastructure for device-free indoor localization.

To enable device-free indoor localization, a process of determining abnormal events—*anomaly detection* or *motion detection*—is a prerequisite. Youssef et al. [2007] discuss the challenges that lie in designing a reliable device-free passive (DfP) localization system. In addition, two feature extraction algorithms are proposed for motion detection, namely, moving average (MA) and moving variance (MV). These two algorithms exhibit very high detection performance (i.e., 100% recall and precision) but are constrained in a controlled environment. Moussa and Youssef [2009] instead apply the Maximum Likelihood Estimator algorithm to enhance the performance of the DfP system in real environments. Recently, the RSS-based RASID system [Kosba et al. 2012] further improved the detection accuracy by analyzing the RSS features and adopting a nonparametric technique for adapting to environment changes. In Xiao et al. [2012b], the fine-grained metric CSI from the PHY layer is introduced for motion detection, which proved to be sensitive to environment changes and resistant to temporal variance. Other CSI-based human detection schemes harness multipath propagation to extend the detection range of a single link [Zhou et al. 2013, 2015]. DeMan [Wu et al. 2015] further proposed a unified framework to detect both moving and static humans via breath detection. In all, these works mainly focus on detecting or predicting the movements of entities in a given area of interest.

After the anomaly event of an entity is detected comes the critical yet more challenging part: to ascertain the corresponding position of entities. Recently, Seifeldin et al. [2013] developed a WiFi RSS-based Nuzzer system in a large-scale indoor space. In Xiao et al. [2013], a fine-grained CSI-based device-free indoor localization system, Pilot, is proposed (Figure 19a). CSI can be resistant to temporal variance and sensitive to environment changes by exploiting the frequency diversity. In other words, CSI can detect anomalies caused by environmental changes in the area of interest. Another beneficial characteristic of CSI—frequency diversity—can reflect the varying multipath reflections due to entities' existence. Thus, Pilot processes CSI to generate "passive" fingerprints for single-entity localization. Note that Pilot is the first work to apply CSI from the PHY layer to improve localization performance.

In Wi-Vi [Adib and Katabi 2013], WiFi enables us to see moving objects through walls and behind closed doors. By using MIMO interference nulling, the reflection from static objects is eliminated, and moving targets can be detected. Using inverse synthetic aperture radar (ISAR), Wi-Vi can track multiple moving objects simultaneously and identify their directions with high probability (Figure 19b).

4.1.6. Wireless Sensors. Zhang et al. [2007] the synonym "transceiver-free" in WSNs. A pioneer Zigbee-based transceiver-free tracking system is built up in Zhang et al. [2007], relying on detecting the small-scale fading caused by human movement. Three algorithms are applied to track the moving entities, including midpoint, intersection, and best-cover algorithms. Evaluations in a $9m \times 12m$ empty room indicate that the best-cover algorithm has the best tracking performance (i.e., average error $0.99m$) in a 4×4 grid setting using MICAZ2 sensors. This work is subsequently improved by a distributed dynamic clustering approach [Zhang and Ni 2009] that ensures high accuracy even in multiple-target scenarios. Other than signal dynamics, the distance between sensor nodes along with the transmission power are taken account in Zhang and Ni [2009]. Meanwhile, the proposed probabilistic cover algorithm can reduce the tracking latency to about $2 seconds$. Yang et al. [2010] develop a grid-based clustering over K-neighborhood (GREEK) algorithm to diagnose the presence of intrusion. Integrated with a multiple transmitter-receiver pair collaboration strategy, passive intrusion can be accurately detected. Later, Zhang et al. [2011] make further improvement by designing a real-time RASS system (Figure 20). Based on a Support Vector Regression model, RASS enables comparative performance (i.e., tracking accuracy $4m$) using a much smaller set of sensor nodes (i.e., 10 TelosB nodes in two adjacent hexagon cells).

In Wilson and Patwari [2010], a radio tomographic imaging (RTI) technique is presented for imaging the passive moving entities by applying a linear model. Wilson and Patwari [2011] make an improvement by leveraging motion-induced variance of RSS measurements. Zhao and Patwari [2011] propose a subspace variance-based radio tomography (SubVRT) algorithm for noise reduction. SCPL [Xu et al. 2013] adopts a successive cancelation scheme to enable simultaneous counting and localization of multiple static users.

4.1.7. RFID. The RFID technique is widely used in large shopping malls or warehouses for preventing pilferage. Kuksa et al. [2010] propose a device-free geometric system for estimating the location of human beings who move around a monitoring area. In their work, a lines-intersecting-tiles strategy is used for detecting the motion event between a set of RFID-based transmitted readers and received tags. Specifically, with a low-density deployment (one for every $500 ft$), this system demonstrates mobility

Fig. 20. RASS [Zhang et al. 2011] overview.

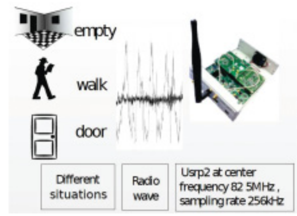


Fig. 21. FM DfP [Shi et al. 2012b].

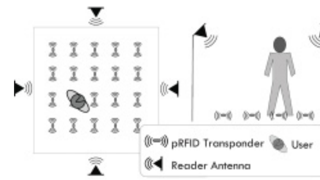


Fig. 22. pRFID [Shi et al. 2012b].

localization accuracy of 20 ft. To ease the system maintenance, Shi et al. [2012b] replace the active RFIDs with passive ones and a few active RFID reader antennas, and propose a tomographic imaging algorithm that provides both low computational complexity and highly accurate position estimates. The benefits of using passive RFIDs are twofold: they are not only low cost but also easily deployed. Although they can achieve 30cm mean accuracy, the authors place 36 transponders in a square with the length of 2.7m in their experiment, and thus the scalability is much lower compared with that of using active RFIDs. Tadar [Yang et al. 2015a] enables device-free object tracking by deploying a group of RFID tags behind walls as an antenna array and tracking the reflections of objects using a hidden Markov model. The system achieves a median tracking error of below 20cm.

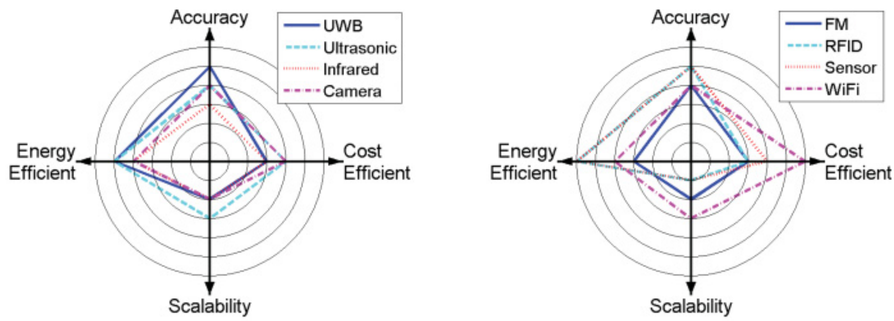
4.1.8. FM. Recently, FM radio [Shi et al. 2012a, 2012b] has proved to be an adequate counterpart for a device-free application, specified as situation awareness. Shi et al. [2012b] introduce the noncooperative FM radio for distinguishing various activities in ambient environments, including empty room, opened door, people standing, and people walking (Figure 21). They implement the prototype using a USRP3 device working at 82.5MHz to extract the FM features, consisting of average amplitude, average magnitude squared (AMS), and root of amplitude mean squared (RAMS). The subsequent classification task is fulfilled by three well-known algorithms, which results in accuracy as high as 90%. However, those activities are conducted only in a small restricted $1\times2m$ rectangle, which inflicts hardly predictable near-field effects at the receiver's antenna, thus making the system less practical.

4.2. Performance Comparison

In this section, a comparison summary of the aforementioned device-free systems is given. Figure 22 gives you a quick view of the performance of each positioning modality. The criteria we apply remain the same as the ones for device-based comparison, in terms of accuracy, cost, scalability, and energy efficiency. Note that some systems only provide results such as room-level or location distinction accuracy; we convert these results to our criteria approximately.

In summary, every design of device-free indoor localization techniques possesses its own propose and scope. To pick out a positioning scheme for a specified application scenario, we can refer to this comparison diagram and choose the most suitable one. In the next section, we will discuss the open research issues for both device-free and device-based techniques.

As with device-based localization systems, it is hard to quantify the effectiveness of a device-free localization system. Factors such as deployment cost, energy efficiency, and scalability should also be taken into account when selecting the proper device-free localization scheme. In addition, as device-free localization systems rely on the human impact on wireless signals to detect and localize humans, they are more vulnerable



(a) UWB, Ultrasonic, Infrared, SenCam (b) FM, RFID, Sensor, WiFi

Fig. 23. Performance comparison of all recent device-free approaches.

to environmental interferences and dynamics. Few studies have explored issues such as the RF interference from other existing wireless networks. Environmental changes (e.g., furniture changes) may also require tedious recalibration for device-free localization systems to retain satisfactory performance.

5. OPEN RESEARCH ISSUES OF THE FUTURE

The criticality of indoor localization has been admitted intimately and received a lot of attention and research. Even so, many open issues still exist in the foreseeable future to meet all kinds of applications' requirements. In this section, we aim at presenting these unfathomed issues faced when designing and implementing an indoor positioning system. Specifically, we identify the corresponding ones in two categories: device based and device free.

5.1. Device Based

Despite the considerable works that have been concerned about device-based indoor localization, including both commercial products and research-oriented solutions, important issues need to be further studied and addressed to keep pace with the requirements of different applications.

—*Modality selection:* Many devices like smartphones support multiple technologies that can be leveraged for localization. Utilizing them all with data fusion is not a bad choice for high localization accuracy, but this is not necessary when energy efficient is preferred over accuracy. Moreover, from the implementation perspective, the cost of the devices and infrastructure is also a concern in system design. Therefore, efforts should be made to provide adequate selection of a localization modality based on application preference and requirements in order to balance the target among accuracy, energy, cost, and scalability.

—*Integration with device-free systems:* Since users may not carry devices everywhere in indoor environments, this can greatly improve user experience and provide convenience for object tracking, for example, in supply chain management, if device-based and device-free localization systems are seamlessly integrated. In fact, some projects, for example, the SELECT project [SELECT 2007], have explored designing a smart indoor wireless network where the detection, identification, and tracking of objects are integrated leveraging RFID, UWB, radar, and various data fusion techniques. This will facilitate future automatic identification, real-time localization and tracking, and user-friendly navigation and ambient intelligence on a unified platform.

—*Infrastructure placement:* While techniques like WiFi and FM utilize signals of opportunities from already-deployed infrastructure, the placement of the infrastructure may not primarily be planned for localization purposes. Consequently, the positions of the infrastructure can affect the system performance, and optimization of the infrastructure placement or additional assistant infrastructure deployment may be required to boost localization accuracy while retaining the networking or communication performance of WiFi or FM devices.
—*"Green" localization:* Device-based approaches are dependent on hardware including smartphones, RFID tags, Zigbee sensors, and so forth. While these devices have limited energy, frequent measurement will inevitably induce high power consumption. In fact, much previous work concentrates on accurate localization while neglecting the energy issue, or even achieves high accuracy by sacrificing power. However, such a sacrifice is not affordable for systems that are not easy to recharge like wireless sensor networks, or acceptable for devices that function otherwise like a smartphone. Energy saving has recently drawn increasing attention driven by the trend of green computing.
—*Map construction:* To localize and navigate a target in the real world, indoor maps are required, which describe the topology and size of rooms, corridors, elevators, and so on. Currently, most of this map construction job is done manually. However, since the environment will change eventually, we have to continuously update the map, which is time consuming and labor intensive. Crowdsourcing has proved to be a success in outdoor map construction by Waze, and also has the potential to be used in indoor scenarios. Currently, some works have been done by leveraging crowdsourcing to generate the indoor radio map [Rai et al. 2012]. More efforts are still needed to ease the process of physical map construction and updating.

5.2. Device Free

From the previous review, we can see that many advances have been made in various research aspects on device-free indoor localization, including the well-studied wireless radar system. However, there are still many open research issues that need to be solved before the current technologies can be of practical use in not only military or industrial scenarios but also daily life.

—*Anomaly detection*: While entities' appearance or movement is usually not available for device-free techniques in advance as for the device-based ones, anomaly detection is a primary step for the subsequent localization. Plenty of works have been done to address this problem, yet new approaches are still needed to better trade off between false alarm and miss detection.
—*Entity identification*: It is challenging to figure out the type or identity of the entity being detected, like the height, shape, and so forth. However, to track a specific target, the system should be able to differentiate one target from all others. In computer vision, pattern recognition is commonly used to distinguish different objects. If we can connect each entity with a unique pattern extracted from the measurements, we will be able to discriminate them.
—*Multiple entities counting:* The estimation problem of the number of entities arises in many real-world applications, especially when no assistant device is installed on the entities, for example, when conducting population statistics in retail and shopping malls for strategic advertisement arrangement, monitoring crowds in museums or residence communities for safety precaution or rescue operations, and performing flow control in high-density vocal concerts for security enforcement. Some recent works explored counting moving humans using the Percentage of nonzero Elements

(PEM) metric in the CSI matrix [Xi et al. 2014], yet it is still an open issue to count both static and moving targets using off-the-shelf wireless network infrastructures.

—*Multiple-entities localization*: It is of great demand for many indoor ILBSs to locate multiple objects at the same time. However, this is known to be much more challenging than single-object localization. In the multiobject case, more changes will be perceived in the indoor surroundings occupied by several objects. Consequently, the severe multipath impression will give rise to many problems when applying device-free approaches. Existing approaches for multiperson localization [Xu et al. 2013; Adib et al. 2015] mainly adopt a successive cancelation scheme to separate the impact of each person, yet require either a network of multiple links [Xu et al. 2013] or customized hardware [Adib et al. 2015].

—*Equipment deployment*: The deployment of the device-free localization equipment in a specific indoor setting directly influences the positioning performance. For instance, moving the sensing node from ceiling to floor will result in different detection and localization accuracy. Therefore, the positions of the equipment should be optimized to cover as large an area with as fewer dead spots as possible.

—*Extending location contexts*: While device-free localization systems are primarily designed to localize humans without requiring the targets to carry any devices, such a device-free sensing modality has extended from detecting locations to richer contexts such as keystrokes [Ali et al. 2015], location-aware activities [Wang et al. 2014], and daily activities [Wang et al. 2015]. However, it is still difficult to sense location-independent activities without per-person training using commercial wireless networks in a device-free manner.

6. CONCLUSION

In wireless communications, increased attention and efforts foster improvement in a wide range of indoor ILBSs. Indoor localization, which is one of the most essential modules of ILBS, has become an open problem without a universally appropriate solution. In this article, we present the first in-depth analysis of the existing state-of-the-art research, divided into device based and device free, from the device perspective. In the device-based category, we mainly discuss different approaches that can be applied on a commercial smartphone. In a similar fashion, various systems for device-free indoor localization are reviewed. Correspondingly, a comprehensive comparison for each category has been shown.

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