Indoor Localization Improved by Spatial Context—A Survey

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Indoor localization is essential for healthcare, security, augmented reality gaming, and many other location-based services. There is currently a wealth of relevant literature on indoor localization. This article focuses on recent advances in indoor localization methods that use spatial context to improve the location estimation. Spatial context in the form of maps and spatial models have been used to improve the localization by constraining location estimates in the navigable parts of indoor environments. Landmarks such as doors and corners, which are also one form of spatial context, have proved useful in assisting indoor localization by correcting the localization error. This survey gives a comprehensive review of state-of-the-art indoor localization methods and localization improvement methods using maps, spatial models, and landmarks.

CCS Concepts: • **Human-centered computing → Ubiquitous and mobile computing**;

Additional Key Words and Phrases: Indoor positioning, spatial information, sensory landmarks, landmark detection, wireless localization, hybrid localization, smartphones

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1 INTRODUCTION

Indoor localization has been studied for decades and a number of indoor localization solutions have been proposed [72, 124, 149, 173, 174] that use different localization signals such as WiFi,

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Table 1. Comparison of This Work with Existing Survey Works

Reference	Year	Indoor Localization Methods	Spatial Constraints Used	Landmark
Liu et al. [94]	2007	Proximity, triangulation, fingerprinting	Not covered	Not covered
Gu et al. [51]	2009	Proximity, triangulation, fingerprinting, visual localization	Not covered	Not covered
Harle et al. [52]	2013	Dead-reckoning	Map	Not covered
Yang et al. [188]	2015	Triangulation, fingerprinting, dead-reckoning	Not covered	Context landmarks
Shang et al. [149]	2015	Triangulation, fingerprinting, dead-reckoning, hybrid localization	Map, grid model, graph model	Not covered
Davidson et al. [27]	2016	Triangulation, fingerprinting, dead-reckoning	Map	Not covered
Pei et al. [124]	2016	Fingerprinting, dead-reckoning, hybrid localization	Map	Not covered
Zafari et al. [192]	2017	Triangulation, fingerprinting	Not covered	Not covered
This paper	2019	Triangulation, fingerprinting, dead-reckoning	Map, grid model	Comprehensive

Ultra-wideband (UWB), Zigbee, Bluetooth, Radio-frequency Identification (RFID), Global System for Mobile Communication (GSM), and inertial sensors. However, each of these techniques suffers from limitations in accuracy, coverage, cost, complexity, and applicability. To achieve a higher accuracy with relatively low cost, hybrid methods combining multiple localization signals have been used. Common hybrid methods include multimodal fingerprinting, triangulation-based fusion, and pedestrian dead-reckoning-based fusion. The problem of combining several localization signals is that the required infrastructure (e.g., Bluetooth beacons or WiFi access points) may not be available in many environments or it may be available at a high cost.

Spatial context such as maps and landmarks, which is available in many scenarios, can be used to assist localization without additional hardware. While complex indoor spaces attenuate many localization signals such as WiFi, which makes localization challenging and difficult, they supply spatial constraints that are helpful for calibrating the localization error. Landmarks are one form of spatial context useful for indoor localization, which can be sensed by the sensors built in a smart device. A landmark in linguistics and cognitive science is generally defined as: *everything that stands out of the background* [129]. In the context of indoor localization, a landmark stands for a location point that imposes a certain pattern on the sensor readings [45, 46, 165]. Since these location points exist in indoor environments naturally, one can combine them to bound the localization error at no extra cost.

In this article, we provide a comprehensive survey of state-of-the-art indoor localization methods with particular focus on how spatial context is used to enhance indoor localization. Although several surveys on indoor localization have been conducted, a comprehensive survey focusing on the role of spatial context in various localization methods is currently not available. Table 1 lists existing surveys on indoor localization and demonstrates how the scope of this survey is different from the existing ones.

To summarize, the main contributions of this article are as follows:

- We provide a comprehensive survey on methods for localization improvement using spatial constraints that are in the form of maps, grid models, and graph models.
- We survey state-of-the-art indoor localization methods that use landmarks. Methods for landmark detection are discussed and state-of-the-art indoor localization systems based on

landmarks are introduced. To the best of our information, this survey is the first work on reviewing landmark-based indoor localization systematically.

This survey is structured as follows: Section 2 introduces the taxonomy of indoor localization and gives a systematic review on the state-of-the-art indoor localization methods. Section 3 surveys indoor localization improvement methods, including *map -matching-based* and *spatial -model-based*. Section 4 first gives the definition of landmark in the context of indoor localization, followed by the introduction of different types of landmarks, and then presents the landmark detection as well as the state-of-the-art systems using landmarks. Section 5 concludes this article and gives open research challenges.

2 INDOOR LOCALIZATION METHODS

Indoor localization methods estimate the location of an entity (e.g., a person or object) by using localization signals such as WiFi, UWB, Zigbee, Bluetooth, RFID, Cellular, Infrared (IR), Frequency Modulation (FM), inertial sensors, and camera [27, 43, 51, 94, 100, 123, 157]. According to the localization principles, we categorize indoor localization methods into five types: *Proximity*, *Triangulation*, *Fingerprinting*, *Dead -reckoning*, and *Hybrid Localization*. The performance of each localization method can be improved by making use of spatial context in the form of a map or landmark representation of the environment. The relationship between localization signals, measurements, methods, and spatial context is illustrated in Figure 1. Localization methods use measurements from localization signals to estimate the location of a person or object, which can be further improved by spatial context. Note that this survey focuses on localization for a single individual user or object, and methods for multiple users or objects, such as cooperative localization [26, 175], are out of the scope of this article.

2.1 Proximity

Proximity approaches determine the location of an object by sensing whether the object is close to a known location or an area [56]. Proximity approaches can be categorized as three types. The first one is detecting physical contact, which is usually based on touch sensors, pressure sensors, or capacitive field detectors. A typical system that detects physical contact is the Touch Mouse [58], which can sense the contact from user's hand by using capacitive sensors. The second one is monitoring wireless anchor devices such as WiFi access points (APs) or near-field communication (NFC) readers, which locates a user by checking whether he or she is in range of one or more anchor devices. For example, the Active Badge system [169] determines the location of an individual equipped with an Infrared (IR) badge by detecting at which sensor the badge is observed. The third one is observing automatic identification systems such as public transport card terminals and point-of-sale terminals. These systems usually require to attach a tag, button, or barcode on the object and then locate the object when the attached tag is observed at a terminal or device with known location. In Reference [113], an RFID-based localization system is presented, which consists of tags and readers. By placing a number of readers in known locations, the location of a person or object with a tag can be inferred when a reader receives signals from the tag. The proximity localization approaches are simple and easy to implement, but they can only sense the location within a limited area, and the achieved localization accuracy is low.

2.2 Triangulation

Triangulation localization approaches estimate the location of an object by utilizing triangles' geometry properties [94]. The location is estimated from the measurements between the mobile object and transmitters (e.g., WiFi access points, GSM towers, Bluetooth beacons). These

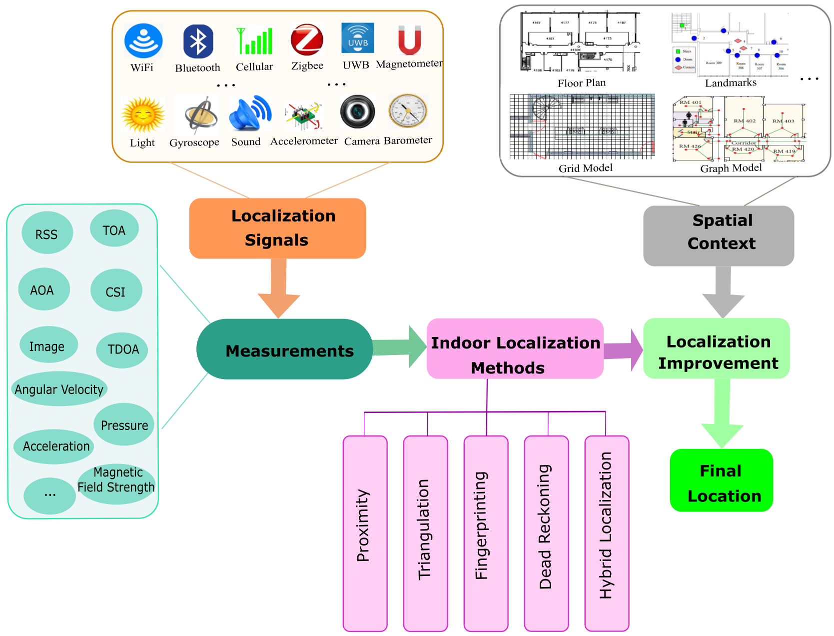
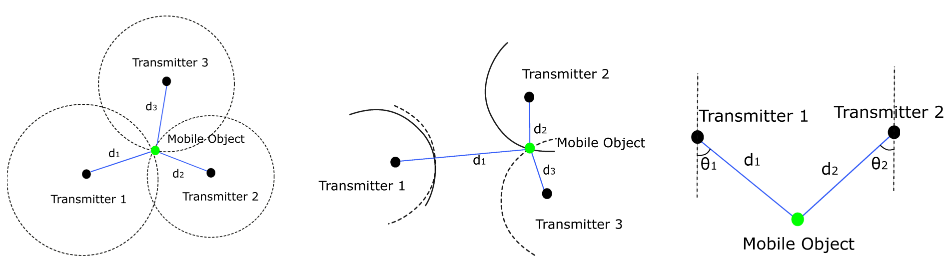


Fig. 1. The relationship between localization signals, measurements, methods, and spatial information.



(a) RSS/TOA/RTOF (b) TDOA (c) AOA

Fig. 2. The principle of localization by triangulation, where the green dot indicates the location of a mobile object or person, and the black dot represents the location of a transmitter or base station. d is the distance between the object and the transmitter, and θ is the angle. (a) The location is estimated by the intersection point of three circles. (b) The location is estimated by the intersection point of two hyperbolas. (c) The location is estimated by the intersection point of directional lines. The figures are adapted from Reference [94].

measurements can be the received signal strength (RSS) [125], time-of-arrival (TOA) [127], time-difference-of-arrival (TDOA) [186], round-trip time-of-flight (RTOF) [73], angle of arrival (AOA) [162], and camera pose [143, 163]. These measurements can be obtained from different localization signals such as WiFi, cellular, FM, IR, Bluetooth, UWB, sound, light, and camera. Figure 2 shows the triangulation localization principle of using different measurements.

RSS-based triangulation relies on an accurate signal propagation model, which converts the RSS into the distance, from which the location of an object is computed using the geometry of circles [116]. RSS-based methods are simple, low-cost, and easy-to-implement; however, building an accurate signal propagation model is challenging in indoor environments because of multipath interference and shadowing [27]. Besides, RSS is vulnerable to mobility of the phone or reflectors (e.g., people walking in the environment), device orientation, device type and model, and so on. The accuracy of RSS-based methods is usually low due to the inaccuracy of converting RSS measurements to corresponding distances.

TOA-based triangulation estimates the locations of an object by measuring the time-of-arrival between the object (equipped with a receiver) and transmitters [42]. To achieve 2D localization, at least three TOA measurements from different transmitters are required. Since the speed of wireless signal is constant, the distance to different transmitters can be calculated once the TOA measurement is obtained. Then the object's location can be computed by using least-squares algorithm, closest neighbor, or residual weighting [67]. Compared to the RSS-based methods, the TOA-based methods can achieve a high localization accuracy. The main problem of TOA-based methods is the requirement of precise synchronization between all transmitters and receivers, resulting in a relatively high cost.

Similar to TOA-based triangulation, RTOF-based triangulation locates an object by measuring the round-trip time of flight (RTOF) of the signal propagating from the mobile receiver to the transmitters and back [140]. However, the RTOF-based approach has no need for clock synchronization between the mobile receiver and transmitters [105]. A challenge of the RTOF-based approach is to obtain the exact delay/processing time caused by the mobile receiver, which cannot be ignored when the distance between the receiver and transmitters is short.

TDOA-based triangulation has been proposed to relieve the need of TOA-based methods for precise synchronization, which measures the time difference of receiving the signal at multiple transmitters. A 2D object's location can be calculated with two or more TDOA measurements via nonlinear regression methods such as a linear iterative algorithm [160]. TDOA-based methods can achieve a relatively high accuracy and have no requirement for strict clock synchronization between transmitters and mobile object. However, it is still required to synchronize the clock between transmitters.

AOA-based triangulation determines the location of an object by measuring the AOA from multiple transmitters [162], which can be done with an array of antennas or directional antennas. The advantages of AOA-based approaches are that the 2D location estimation can be made only with two transmitters and that it has no requirement for clock synchronization. Its drawbacks include the need for special and expensive hardware (e.g., directional antennas) and the degradation of location estimates as the distance between the mobile object and the transmitters increases [94, 123]. ArrayTrack [184] and SpotFi [75] use the channel status information (CSI) from existing WiFi APs to derive AOA and/or TOF information, which achieve a decimeter-level accuracy.

The triangulation principle for localization has been widely used in visual localization by one or more cameras, which is usually called camera-pose-estimation-based method. It estimates the location by calculating the pose of the camera carried by a user. Visual features in the images such as point descriptors and image edges have been used for estimating the camera pose [143, 163] by modeling the transformation between the image coordinate system and the world coordinate system (e.g., perspective n-point problem) [144]. Visual odometry [114], visual simultaneous localization and mapping (SLAM) [28], and model-based visual tracking [83] fall under this category. Pose-estimation-based methods are able to achieve a centimeter-level accuracy when there are sufficient distinctive visual landmarks or features in the environment. However, these methods are likely to fail in environments with poorly textured surfaces. Also, visual odometry and visual SLAM methods suffer from the drift of the estimated trajectory due to the accumulation of local motion estimation errors, whereas model-based visual tracking does not have this problem, because the errors are continuously corrected by using the known world coordinates of the landmarks.

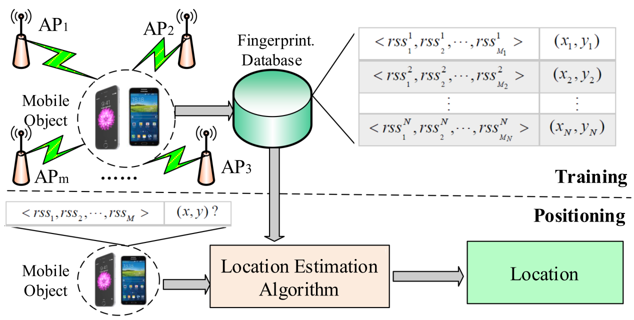


Fig. 3. The principle of WiFi fingerprinting.

2.3 Fingerprinting

Fingerprinting is a popular method for estimating an object's location, the key idea behind which is computing the location of the object by matching a set of measurements called a fingerprint with a set of fingerprints that are collected and stored in a pre-built database [27, 60, 153]. A fingerprint is the measurements from a localization signal at a certain location. For example, WiFi fingerprints are the RSS measurements from visible APs. Fingerprinting consists of two phases: training and localization. In the training phase, a fingerprint database within the area of interest is established at a certain level of granularity. Finer granularity usually means better accuracy, but requires more effort in terms of time and labor for the collection of fingerprints. In the localization phase, the location of the object is computed by matching the collected fingerprint with the fingerprints in the database using deterministic algorithms or probabilistic algorithms [29]. Depending on the used localization signals, fingerprinting can be categorized as *wireless fingerprinting*, *magnetic fingerprinting*, and *visual fingerprinting*.

Wireless fingerprinting uses wireless signals including WiFi, cellular, FM, Zigbee, RFID, Bluetooth, and so on to locate an object. Among them, WiFi fingerprinting is the most popular one because of its ubiquity in public areas. Figure 3 shows the rationale of WiFi fingerprinting using RSS measurements. Apart from RSS measurements, CSI measurements can also be used for localization. The difference is that RSS-based fingerprinting uses the total received power [53], while CSI-based fingerprinting utilizes the amplitude and/or phase of each subcarrier of the channel [167, 189]. Compared with RSS-based fingerprinting, CSI-based fingerprinting is more robust and has higher accuracy [145]. However, the WiFi cards on modern smartphones and other smart devices (except some laptops) do not support the extraction of CSI, which constrains the applicability of CSI fingerprinting. The main challenge of wireless fingerprinting is that the construction of a fingerprint database is troublesome and time-consuming. Many efforts have been made to relieve the site survey task, mainly including WiFi SLAM [36, 38] and crowdsourcing [101, 121, 187]. However, the heavy computational load of these WiFi SLAM systems prevents them from being implemented on the resource-limited mobile devices. Compared with WiFi SLAM methods, crowdsourcing methods consume less computational cost, but they suffer from the requirement for active user participation, low accuracy, and limited applicability.

Magnetic fingerprinting is similar to wireless fingeprinting. A magnetic field map, composed of tuples of magnetic readings and location coordinates, is constructed in the training phase. Each tuple is called a fingerprint. Unlike WiFi fingerprints, which can be collected by the user standing at known points, magnetic fingerprints are usually extracted from temporal traces, since a single magnetic fingerprint is not useful for localization. There are usually three forms of magnetic measurements: raw 3D magnetometer readings [24], magnitude [155], and horizontal and vertical

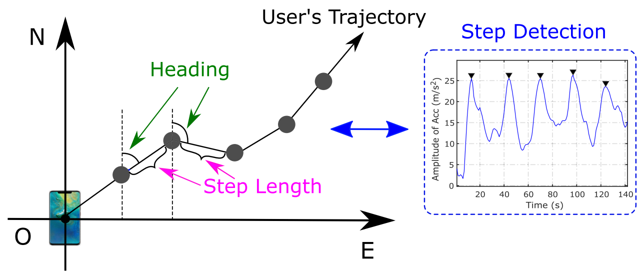


Fig. 4. The principle of pedestrian dead-reckoning.

components [85, 183]. Magnetic fingerprinting based on raw readings is easy to implement and has high location discernibility, but it is sensitive to noise. Magnitude-based fingerprinting is relatively robust to noise, but it has low location discernibility. Methods using horizontal and vertical components of magnetic fields perform moderately in terms of robustness to noise and location discernibility. Similar to the construction of a wireless radio map, the cost of constructing a magnetic field map can be very high if it is conducted manually. To reduce the time and effort required to build the magnetic field map, one can either deploy other localization systems such as vision-based systems [194] or use crowdsourcing [121]. In the localization phase, the newly measured magnetic field trace is matched with magnetic fingerprints from the magnetic field map to infer the location through spatial-temporal sequence-based methods [54]. Spatial-temporal sequence-based methods model the magnetic localization problem as a sequence/string matching problem, which can then be done via dynamic time warping [152] or probabilistic approaches such as hidden Markov model [146] and conditional random fields [181].

The principle of fingerprinting can be applied to visual localization as well. In fact, image retrieval and pose regression methods can be categorized as visual fingerprinting methods [132]. In nonparametric image retrieval approaches, the location of a query image is inferred by searching for the images from a large geo-tagged reference image database that are best matched with the query image [108]. Parametric approaches train a model (a classifier or regressor) using geo-tagged images and predict the corresponding location of the query image using the trained model [68, 171]. Images can be represented by different types of features, including local features (e.g., point features, geometric features, point features with geometric relations), global features (e.g., GIST-descriptor-based, CNN-based), hybrid features (e.g., patch features, combined features), and semantic features (e.g., skyline features, point ray) [128]. The main challenges of visual fingerprinting include construction of an accurate reference image database, image annotation, and robustness improvement against different conditions.

2.4 Dead Reckoning

Dead Reckoning (DR) uses inertial sensors to estimate relative location and requires little or no infrastructure to be deployed [15, 52]. The basic idea is inferring the current location from the moving direction, velocity, and sampling interval, given an initial position. The ubiquity of sensor-rich smart devices has made DR a popular indoor localization method [25, 95, 147]. In this study, we focus on reviewing dead-reckoning for pedestrians called pedestrian dead-reckoning (PDR). As shown in Figure 4, PDR is composed of three components: step detection (or counting), step length estimation, and heading estimation.

Step detection can be done by using camera [119], accelerometer [15], commercial pedometers [106], and so on. This article reviews mainly the step detection methods using smartphone accelerometers, including peak detection [47], threshold setting [151], auto-correlation analysis

[133], and spectral analysis [52]. Peak-detection-based methods are based on the observation that the number of steps corresponds to the number of acceleration peaks [193]. Therefore, by detecting these peaks, one can count how many steps a user takes. The threshold-based methods detect steps by comparing the accelerometer readings with a certain threshold [93, 117]. The auto-correlation analysis methods utilize the auto-correlation of the acceleration signal to detect steps. The spectral analysis methods work by first transforming accelerometer data into frequency domain and then identifying the dominant frequency corresponding to a step [52]. The main challenges of step detection are variations in phone poses and walking modes, which may lead to a large detection error if not properly considered.

After detecting steps, different models can be used to compute the step length. Because of the inherent smartphone sensor noise, double integration of the acceleration measurements results in inaccurate estimates of step length. Weinberg [170] proposed a step length estimation approach based on the maximum vertical displacement of the hip. Kim et al. [74] also introduced a similar model that uses the acceleration samples to estimate the step length. The disadvantage of these acceleration-based models is that they do not consider different phone poses and varying walking speeds, which have an important effect on the accuracy of step length estimation. A linear model that considers walking speeds was used in Reference [139], but it requires users' height information, which may limit its applicability, since some users may not be comfortable providing their individual information. An adaptive step model is proposed in Reference [86], which uses a personalization algorithm to learn a personal model from a generic step model. However, this personalization process is based on spatial constraints from a floor plan, which may not always be available. In Reference [23], a neural-network-based method is introduced, which considers walking frequency, variance of the accelerometer signals, and the ground inclination. However, it is based on the shoe-mounted accelerometer and hence is unsuitable for smartphone-based applications. In addition, the step length can be estimated by combining step counting with spatial information such as landmarks or floor plans [147, 165]. Although these methods eliminate the requirement of users' height information and are independent of phone poses, they assume that the user walks at a consistent speed, which may not always be a valid assumption. A deep-learning-based step length estimation method is presented in Reference [50], which considers different phone poses, varying walking speeds, and different users.

Another important component of PDR is heading estimation, which is usually based on the compass [95] or the gyroscope [165]. The compass measures the angle with respect to the Earth's magnetic north, while the gyroscope reports the angular velocity. However, the compass is vulnerable to ferromagnetic materials (e.g., metals) and the gyroscope readings drift over time. To tackle these problems, some researchers have suggested combining with different sensors or spatial information. A combination of the compass readings and gyroscope readings by using the Kalman filter is presented in Reference [147]. WalkCompass fuses the gyroscope readings with the compass readings and the accelerometer readings [141]. WiDir uses WiFi signals to estimate a human's walking direction [177]. Zee infers the heading by using a particle filter to fuse the compass readings with a floor plan [133]. In UnLoc [165], the drift problem of gyroscope readings is addressed with landmarks. A landmark graph is used to assist in achieving accurate heading estimation in Reference [45].

Overall, PDR is a self-localization technique that has become one of the mainstream indoor localization methods. The advantages of PDR are that it needs no extra infrastructure and has no coverage limitation. This makes it especially applicable to locate and navigate in the WiFi-deprived areas. However, it suffers from the accumulated error problem, leading to the degradation of accuracy over time. Thus, it needs to be corrected periodically, which can be done by using other localization methods or using spatial information such as maps and landmarks.

2.5 Hybrid Localization

Different localization techniques have various advantages and limitations in terms of accuracy, coverage, requirement for infrastructure, and cost of deployment, and no single localization method can meet the demands of all applications. The key to implementing a practical localization system is fusing different localization signals such that they can complement each other [149]. The method integrating multiple localization signals is called hybrid localization. The most common hybrid localization methods include *multimodal fingerprinting* [152], *triangulation-based fusion* [17], and *PDR-based fusion* [18].

Multimodal fingerprinting is similar to WiFi fingerprinting, but it uses signals from multiple sources. The commonly used multimodal fingerprinting combines WiFi fingerprints and magnetic fingerprints [7]. Generally, WiFi fingerprinting is able to provide a global location accuracy, but its accuracy is relatively low. On the contrary, magnetic fingerprinting can achieve a higher accuracy, yet it works only locally. The combination of WiFi fingerprints and magnetic fingerprints can compensate the drawbacks of the two methods, achieving a high accuracy. Another popular implementation of multimodal fingerprinting is integrating WiFi with other opportunistic signals such as FM, GSM, and DTV, which exist in the environment but are not specially created for localization purposes [124]. Apart from the above combinations, ambient features such as color, light, and sound can also be regarded as fingerprints. The advantage of multimodal fingerprinting is that it can achieve a higher localization accuracy than using single fingerprinting without needing extra infrastructure. Nevertheless, the construction of the fingerprint database is labor-intensive and time-consuming. Although many efforts have been made to accelerate the site survey process of fingerprinting, most of them rely heavily on fine-grained maps or active user participation.

Triangulation-based fusion improves the localization accuracy by integrating multiple types of measurements, such as RSS, TOA, TDOA, and AOA. In complex indoor environments, using one single type of measurement is insufficient to obtain a satisfactory accuracy due to the non-line-of-sight propagation of signals, but fusing multiple kinds of measurements can overcome this issue to some extent. Typical fusion methods are least squares (LS) [164], Bayes filters [168], maximum likelihood [17], and Taylor series [79]. The main drawback of triangulation-based fusion is its requirement for two or more types of hardware, which increases the cost of deployment and maintenance.

PDR-based fusion combines PDR with wireless localization methods, which is widely used in the literature. PDR is a self-localization technique that provides continuous relative location estimation, but it suffers from the drift problem, resulting in unsuitability for long-term localization. By contrast, wireless localization gives absolute location but fails to achieve continuous location estimation when there are not enough access points or beacons in the environment. Fusing PDR with wireless localization addresses both the drift problem of PDR and the failure of wireless localization methods for continuous localization (tracking). This fusion is usually implemented using Bayes techniques such as Kalman filter [21] or extended Kalman filter [30], particle filter [64], and hidden Markov model [95]. The main challenge of PDR-based fusion is the accurate heading estimation of the user, which is especially difficult when the user carries their device in an arbitrary pose.

Fusion of visual observations taken from a single or multiple cameras with inertial measurements can also be categorized as PDR-based localization [69, 135]. Since localization only by visual observations can be compromised in low-textured environments due to insufficient geometric features, inertial measurements such as the outputs of accelerometers and gyroscopes can complement visual observations, resulting in a seamless localization. The integration of visual observations with inertial measurements is known as visual-inertial odometry (VIO) [89]. State-of-the-art

VIOs exploit different types of cameras such as perspective, which have a limited field-of-view (FoV) and follow the standard perspective projection model in mono mode [84, 89, 136] or stereo mode [136, 158]; rolling-shutter [88, 90], in which images are stored row by row, typically with a constant delay; and omnidirectional cameras [137, 138], which have a FoV wider than 180° utilizing the maximum potential of surrounding visual observations. From an estimation point of view, VIO techniques mostly use either non-linear optimization [84], which minimizes a least-squares error function iteratively [76], or a recursive algorithm, which estimates motion parameters recursively in a filter as visual and inertial measurements become available. Although localization by using visual observations decreases the drift over time to a considerable extent and provides fully seamless localization, the VIO approach still suffers from drift over long trajectories.

2.6 Summary and Discussion

Table 2 gives a summary of popular indoor localization systems and solutions. It presents the used localization signal, reference, measurement, method, accuracy, cost, complexity, and test area. Note that the test area is provided to avoid prejudice on the performance of different technologies that are affected by the test environments.

Overall, proximity methods are very simple and easy to deploy, but their localization accuracy of proximity methods depends on the number of anchor devices (e.g., POS terminals, RFID readers) that sense the tags. The coverage and applicability of proximity approaches are poor, since these anchor devices are usually installed at certain areas, making it difficult to scale up proximity-based systems.

Triangulation methods have a much larger coverage and usually achieve a higher localization accuracy than proximity methods. For example, triangulation using UWB or light signals can generally achieve centimeter-level accuracy. However, triangulation methods using wireless signals also suffer from varying limitations, such as multipath interference and shadowing, time synchronization, and requirement for specific hardware. Triangulation using vision does not have the above limitations and can achieve a high accuracy by making use of visual features from the environment. However, it is affected by light conditions, resolution of camera, and richness of texture in the environment. Also, camera-based methods are intrusive towards people's privacy, which may prohibit their application in some scenarios.

Fingerprinting is one of the commonly used indoor localization methods because of its ability to make use of existing infrastructure (e.g., WiFi APs) or indoor signatures (e.g., magnetism, visual features of objects). The main challenge is the construction of a fingerprint database, which can be cost-prohibitive for large-scale environments if it is done manually. Many efforts have been made to reduce the time and effort of constructing the fingerprint database, such as SLAM methods and crowdsourcing methods. Nevertheless, these methods of fast fingerprint database construction are usually computationally expensive or cannot obtain accurate results.

DR is a self-localization method that can provide continuous location estimates given an initial localization. However, it cannot be used for long-term localization and tracking tasks because of its accumulated error problem. Specifically, DR is affected by different user motion states, device poses, device heterogeneity, and ferromagnetic disturbance (affecting the heading estimation using the compass). To overcome these challenges, DR is often combined with other localization methods or spatial information.

Hybrid localization combines multiple localization signals to improve localization accuracy or expand localization coverage. It can somehow overcome the limitations of single individual localization signal. However, multiple localization signals may not exit in the environment of interest. Also, it is challenging to decide which localization signal should be used in different areas or to fuse these localization signals in an efficient way.

Table 2. Popular Indoor Localization Systems and Solutions

Localization Signal	System/Solution	Measurement	Method	Accuracy	Cost	Complexity	Test Area
WiFi	RADAR [8]	RSS fingerprint	Fingerprinting	~5.9m within 90%	Low	Moderate	43.5m×22.5m
	Horus [190]	RSS fingerprint	Fingerprinting	~2.1m within 90%	Low	Moderate	68.2m×25.9m
	Ekahau [34]	RSS fingerprint	Fingerprinting	~2m within 50%	Low	Moderate	Not specified
	SpotFi [75]	AOA and TOF from CSI	Triangulation	~0.4m within 50%	Low	Moderate	16m×10m
	ArrayTrack [184]	AOA from CSI	Triangulation	~0.2m within 50%	Low	Moderate	Not specified
	DeepFi [167]	CSI amplitude	Fingerprinting	~1m within 60% ~1.7m within 60%	High	High	4m×7m 6m×9m
	PhaseFi [166]	CSI phase	Fingerprinting	~1m within 60% ~1.7m within 60%	High	High	4m×7m 6m×9m
Bluetooth	System in [10]	inquiry response rate fingerprint	Fingerprinting	room-level	Low	Moderate	4m×6m
	Bluepass [32]	RSS	Triangulation	~8.39m within 50%	Low	Low	13m×15m
	System in [37]	RSS fingerprint	Fingerprinting	~2.6m within 95%	Low	Moderate	50m×15m
	DABIL [179]	RSS fingerprint	Fingerprinting	~2m within 92.5%	Low	High	17.5m×9.6m
RFID	LANDMARC [112]	RSS	Proximity	~1m within 50%	Low	Medium	5m×10m
	WhereNet [123]	UHF TDOA	Triangulation	~3m within 50%	Low	Moderate	20m×20m
	System in [97]	RSS	Proximity	Depending on the coverage of RFID tag	Medium	Low	10m×10m
Zigbee	Sysetm in [13]	RSS	Triangulation	~2.6m within 50%	Medium	Medium	43m×43m (simulated)
	System in [66]	RSS	Triangulation	~1.4m within 80%	Medium	Medium	8.4m×5.6m
UWB	Ubisense [142]	TDOA + AOA	Triangulation	~2.4m within 90%	High	Low	24m×14m
	BeSpoon [142]	TDOA	Triangulation	~1.2m within 90%	Relatively High	Low	24m×14m
	DecaWave [142]	TWR TOF or TDOA	Triangulation	~1.1m within 90%	Relatively High	Low	24m×14m
	Quantitec Intranav [62, 100]	TDOA	Triangulation	an average error of 0.17m	Relatively High	Low	N/A
GSM	System in [118]	RSS fingerprint	Fingerprinting	~10m within 80%	Medium	Medium	88m×113m
	CellSense [61]	RSS fingerprint	Fingerprinting	a median error of ~27.8m	Medium	Moderate	5.45 s. km

(Continued)

Table 2. Continued

Localization Signal	System/Solution	Measurement	Method	Accuracy	Cost	Complexity	Test Area
FM	System in [20]	RSS fingerprint	Fingerprinting	room-level accuracy	Medium	Moderate	Not specified
	System in [109]	RSS fingerprint	Fingerprinting	a median error of ~2.9m	Medium	Medium	11m×23m
IR	Active Badge [169]	Proximity	Proximity	room-level accuracy	Medium	Low	Not specified
	IRIS-LPS [5]	AOA	Triangulation	a RMS error of ~0.16m	Medium	Moderate	15.1m×9m
Magnetism	Work in [85]	Magnetic horizontal and vertical components	Fingerprinting	~1m within more than 90%	Low	Medium	Not specified
	Solution in [24]	Magnetic raw measurements	Fingerprinting	~1.6m within 90%	Medium	Medium	13.8m×9.9
	IndoorAtlas [98]	Magnetic fingerprint	Fingerprinting	1-2m	Low	Medium	Not specified
Light	Luxapose [78]	AOA	Triangulation	~10cm	Moderate	High	0.711m×0.737m
	Epsilon [87]	AOA	Triangulation	~1m within 90%	Medium	Moderate	5m×8m
	LIPS [182]	RSS	Triangulation	an average error of ~0.4m	Medium	Medium	Not specified
Vision	2DTriPnP [144]	Images	Triangulation	a median error of ~3.3m	Moderate	Moderate	Not specified
	Ocrapose [143]	Images of landmarks (e.g., text/number)	Triangulation	a median error of ~1.5m	Medium	Medium	7m×1m
	System in [159]	Images	Triangulation	a standard deviation of ~16cm	Relatively high	High	N/A
	System in [16]	Images	Triangulation	a mean error of 1.56m	Moderate	Moderate	N/A
Acoustic	Beep [104]	TOF of audible sound	Triangulation	~0.6m within 97%	Moderate	Medium	9.8m×5.5m
	BeepBeep [126]	TDOA of sound	Triangulation	~0.05m within 95%	Medium	Medium	5m×11m
	EchoTag [161]	Acoustic signature	Fingerprinting	~0.01m within 98%	Moderate	Moderate	an office and a two-floor house
	Guoguo [96]	TOA of sound	Triangulation	~0.25m within 90%	Moderate	Low	a classroom and an office
Hybrid	Magicol [152]	Inertial measurements, magnetic field strength, WiFi RSS fingerprint	Hybrid	~3.5m within 90%	Medium	Moderate	~9750 sq.m
	MaLoc [183]	Inertial measurements, magnetic field strength		an average error of ~1-2.8m	Medium	Medium	72m×64m
	Travi-Navi [194]	Inertial measurements, images, WiFi RSS fingerprint		~3m	Moderate	Moderate	~5900 sq.m
	Visual-inertial odometry [136]	Inertial measurements, images		~0.5m	Medium	Moderate	15m×30m

3 LOCALIZATION IMPROVEMENT BY SPATIAL CONSTRAINTS

While hybrid localization methods are successful in improving localization accuracy, they usually require additional hardware or infrastructure such as WiFi APs and Bluetooth beacons. However, spatial context, which is available or easy to obtain in many situations, can be used to improve the localization accuracy to alleviate the need for extra hardware or infrastructure. Dey [31] defined context as *any information that can be used to characterize the situation of an entity (e.g., a person or object).* In this study, we consider spatial context as spatial information that imposes constraints on the entity's location or characterizes a certain area. Three types of context are taken into account in this article, namely maps, spatial models, and landmarks. Maps and spatial models impose spatial constraints on the entity's reachability, which can be utilized to refine coarse location estimates. Landmarks represent a unique area in spatial space, which can be used to correct the localization error. In this section, we introduce the localization improvement methods provided by spatial constraints, including *map matching* and *spatial-model-based methods*.

3.1 Map Matching

In the context of indoor localization, map matching can be categorized into three types: *point-to-point matching*, *trajectory matching*, and *probabilistic graphical model*. A map describes the layout and elements of an indoor environment. It is often in the form of a floor plan. Point-to-point method matches location points with the places of indoor spaces according to floor plans. Point-to-point matching is advantageous for its simplicity and high computational efficiency, but it is sensitive to the way in which the path network is digitized [172].

Trajectory matching utilizes the geometry and topology information of indoor structures (e.g., corners, corridors, and rooms) to match the obtained trajectory. A geometric-similarity-based trajectory matching method is applied to correct the drift error of the gyroscope in Reference [81], which is implemented by comparing the user's trajectory and the floor plan. Park et al. [122] proposed a method to compare the sequence of user motion states (standing still, walking straight, turning right, etc.) with a prior map, which can calculate the location of the user at an average accuracy of 5m. Ma et al. [102] developed a trajectory matching algorithm to automatically determine the absolute locations of a trajectory estimated by PDR methods. Specifically, they match the PDR trajectory with most-possible trajectories derived from a floor plan by using image processing methods. These most-possible trajectories are derived based on the movement patterns of pedestrians in the environment. Instead of matching users' trajectories with trajectories derived from floor plans, Abdelbar et al. [1] presented a method to improve the cellular positioning techniques by matching the low-accuracy motion trajectory computed from them to one of high-accuracy anonymous building-tracked trajectories. Compared to point-to-point matching, trajectory matching is more robust and has smaller matching error, but it is more complex and has poor real-time capability.

Localization methods based on probabilistic graphical models determine the location by associating each location with a probability and then updating the probability using spatial constraints. The most widely used probabilistic graphical models in localization are conditional random fields (CRF) [11, 180] and Bayesian techniques, such as particle filters [176, 191] and hidden Markov models (HMMs) [103, 178]. Bayesian techniques represent the conditional dependence structure between observation and state variables using directed graphical models, while CRF models the problem using undirected graphical models. Take the particle filter as an example to illustrate the rationale behind Bayesian approaches. Particle filters use a set of particles to approximate the distribution. In each round, particles propagate according to the transition model (e.g., PDR), and their weight would be updated based on observations and spatial constraints. For instance, if a

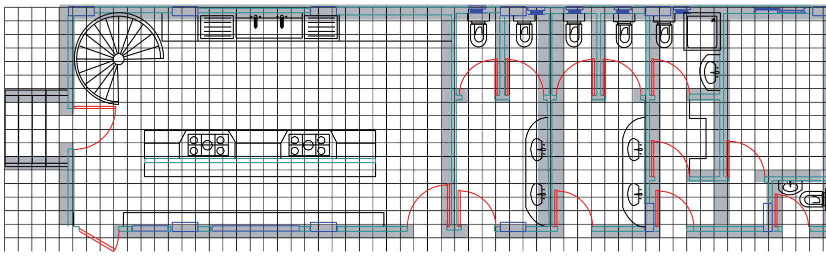


Fig. 5. The grid model of an indoor environment [3].

particle crosses a wall or lies in non-navigable areas, then the weight of this particle would be set to 0. The final step is to resample these particles according to their weight and those whose weight value is below a threshold are removed. Over time, the particles typically converge to the most likely position of the user. Bayesian approaches can achieve higher accuracy than point-to-point matching and trajectory matching, but the computational burden is also heavy. To overcome this issue, Xiao et al. [180] proposed a lightweight algorithm based on CRFs, fusing multiple observations (e.g., dead-reckoning and radio frequency) and constraints (e.g., floor plans, fingerprints, and landmarks). Experiments by Xiao et al. have showed that CRFs have higher computational efficiency than the Bayesian techniques.

3.2 Spatial Model-based Methods

Spatial models are another type of spatial information that can be used to improve localization accuracy. Compared with floor plans, which usually include information about basic structures (e.g., rooms, doors, and furniture), spatial models contain richer information (e.g., sensors, people). This extra information that is not described in the floor plans is also useful in improving localization accuracy [4]. In this section, we introduce spatial-model-based used in indoor localization, including *grid models* [91, 148] and *graph models* [80].

The grid model divides indoor spaces into a grid where each cell contains a value that represents the probability of an object to be tracked within this cell. It is obvious that for all cells occupied by static objects (e.g, walls, furniture), the corresponding probabilities are 0. A typical grid model is shown in Figure 5, in which the space is decomposed into regular cells with the exact same shape and size. Fox et al. [39] used a grid-model-based Markov algorithm to localize robots in indoor spaces. The probability for each cell is updated as the robot receives new sensor data. Bhattacharya et al. [12] employed the grid model of a grocery store to refine location results from WiFi fingerprinting. Recently, Shang et al. [148] proposed a GridiLoc system that uses a backtracking grid filter to combine grid model and smartphone-based PDR techniques. The backtracking process is used to recover the estimated trajectory from dead ends.

Different from grid models, which decompose space into grids, graph models represent indoor environments by using nodes and edges. The graph models can be categorized into five different kinds [4]: *place graphs*, *visibility graphs*, *generalized Voronoi graph (GVG)*, *fine-grained graphs*, and *sensor-based graphs*. Each node indicates a certain location with semantic information, such as a room node or a door node. The edges are used to connect nodes, which can be associated with extra information such as distance or traveling time. Figure 6 shows a typical graph model of an indoor space. Jensen et al. [63] proposed a graph-model-based method for indoor positioning and tracking. They constructed a base graph that represents the connectivity and accessibility of the indoor space. Based on the base graph, an RFID deployment graph is built considering users' maximum speed, which can improve the traditional RFID localization results. Krumm et al. [77]

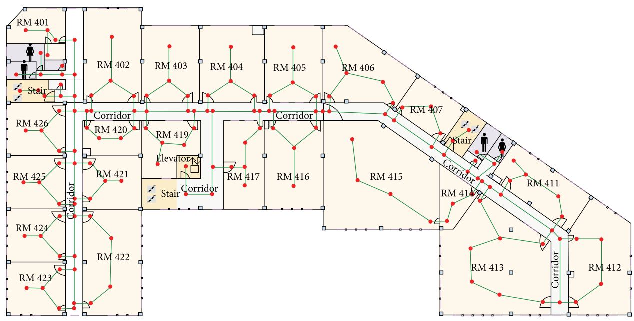


Fig. 6. The graph model of an indoor environment [149].

utilized a graph to enforce constraints on the movements between nodes and obtain location estimates using an HMM. The location error they achieved was much lower than the simple nearest neighbor algorithm. Qian et al. [130] applied a vector-graph-based particle weighting method to correct the deviation in step length and heading estimation. Chen et al. [19] proposed a novel WiFi-based subarea localization method with zero-configuration. To construct subarea fingerprints, the method uses crowdsourced RSS traces to build a logical floor graph that is then mapped to a physical floor graph. In the online localization phase, a Bayesian-based approach is utilized to estimate the unknown subarea.

3.3 Summary and Discussion

Table 3 summarizes popular localization improvement methods using spatial information, which are compared in terms of the type of spatial information used, granularity (grid size or node interval for spatial models), localization method/signal, fusion method, accuracy, and cost of creating a model or running the algorithm.

Map matching is a commonly used localization improvement method that utilizes spatial constraints. The main advantage is that it does not require extra hardware to improve localization accuracy. However, the achieved localization accuracy is determined by the accuracy of maps, and some maps might not be very precise. Besides, the matching process is computationally expensive, especially for those using probabilistic methods.

Spatial models, which contain richer information than maps, are used to improve the localization accuracy by dividing space into a grid of cells or representing space by nodes and edges. Compared to map-matching methods, spatial-model-based methods can usually achieve better accuracy. The main challenge is the construction of indoor spatial models. While manual methods are slow and labor-intensive, automated methods are still in their infancy and not yet applicable in general practical scenarios [33, 59].

4 LOCALIZATION IMPROVEMENT BY LANDMARKS

4.1 Definition of Landmarks

Researchers in linguistics and cognitive science consider landmarks as decision points or reference points in the space, which serve as either an organizing concept or a navigational aid in wayfinding [129, 154]. The concept of landmarks has also been used for the purpose of indoor localization in recent years [9, 147, 165, 195]. In Reference [9], the authors consider geometric beacons (e.g., planes, corners, cylinders, and obstacles) as landmarks, by which a robot is able to construct an indoor map and localize itself within a SLAM framework. Landmarks in SLAM are described by a shape model with an embedded coordinate frame representing the landmark origin. Wang et al.

Table 3. Indoor Localization Improvement Methods Utilizing Spatial Information

Reference	Spatial Information	Granularity	Localization Method	Fusion Method	Accuracy	Cost
Rai et al. [133]	Map	N/A	DR	Particle filer	~1.2m (50%)	Low
Jung and Myung [65]	Map	N/A	Triangulation	Particle filter	~1.3m (50%)	Moderate
Rajagopal et al. [134]	Map	N/A	Triangulation	N/A	1m (80%)	Medium
Shang et al. [147]	Floor plan	N/A	DR, fingerprinting	Particle filter	~2m (80%)	Low
Woodman and Harle [176]	Floor plan	N/A	DR, fingerprinting	Particle filter	~0.5m (70%)	Low
Qian et al. [130]	Vector graph	N/A	DR	Particle filter	sub-meter level	Low
Xiao et al. [180]	Graphical model	0.8m	DR, fingerprinting	Conditional random fields	~2m (80%)	Low
Shang et al. [148]	Grid model	0.7m	DR	Backtracking grid filter	~2.5m (95%)	High
Fox et al. [39]	Grid model	0.1-0.4m	Triangulation	Markov model	a mean error of ~10 cm	Medium
Bhattacharya et al. [12]	Grid model	Three cells for an aisle	Fingerprinting	N/A	~3.2m (90%)	Medium
Bataineh et al. [11]	Grid model	0.8m	DR	Conditional random field	~1m (50%)	Medium
Bohn and Vogt [14]	Grid model	Vary with scenes	Fingerprinting	Probabilistic algorithm	N/A	Moderate
Liao et al. [92]	Voronoi graph	Room level	Proximity	Particle filter	a mean error of ~2.3m	Low
Krumm et al. [77]	Voronoi graph	Room level	Proximity	Viterbi algorithm	a mean error of ~3m	Low
Hilsenbeck et al. [57]	Generalized Voronoi graph	0.7m	Fingerprinting, DR	Particle filter	~2.2m (50%)	Medium
Nurminen et al. [115]	Voronoi graph	Room level	Fingerprinting	Particle filter	a mean error of ~4m	Low
Chen et al. [19]	Voronoi graph	Room level	Fingerprinting	Bayesian inference	Sub-area localization (88.2%)	Low

∗N/A indicates not applicable.

[165] consider landmarks as certain location points with identifiable signatures, which exist in indoor environments naturally and can be sensed by one or more types of sensors. Zhou et al. [195] define a number of activity-related locations as activity landmarks. Each activity landmark has two properties: activity type and WiFi fingerprints collected at the activity. Gu et al. [46] give a systematic definition of landmark for the purpose of indoor localization, which is called a sensory landmark. In Reference [46], a sensory landmark is defined as: *a location point where at least one type of sensor presents a distinctive, stable, and identifiable pattern in the readings.* Accordingly, a sensory landmark must have three features: distinctiveness, identifiability, and stability.

4.2 Types of Landmarks

According to the sensor pattern used to detect a landmark and its physical location, landmarks can be categorized as: seed landmarks and organic landmarks [2, 165], as shown in Figure 7. Seed landmarks are the landmarks whose sensor pattern and physical location are known *a priori,* while organic landmarks are those without *a priori* knowledge about their sensor pattern and physical location. Seed landmarks correspond to certain structures in a building, such as stairs, elevators, doors, and escalators. The locations of seed landmarks can be obtained from the floor plan of the environment. On the contrary, organic landmarks cannot be obtained from a floor plan and require to be learned dynamically. Organic landmarks can be further divided into three types: WiFi landmarks, magnetic landmarks, and inertial sensor landmarks [2, 165]. Such taxonomy of landmarks is adopted in many research works [21, 147].

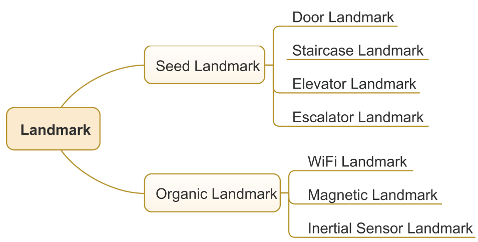


Fig. 7. Taxonomy of landmarks in UnLoc [165] and SemanticSLAM [2].

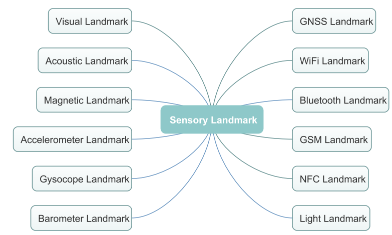


Fig. 8. Taxonomy of sensory landmarks.

Nowadays, smart devices have integrated a variety of sensors that can be used to detect a landmark. For example, there are 12 types of sensors available in most modern smartphones. According to the type of the used sensor, sensory landmarks are categorized into 12 types, as shown in Figure 8, namely GNSS landmark, WiFi landmark, NFC (short for near-field communication) landmark, visual landmark, Bluetooth landmark, acoustic landmark, magnetic landmark, accelerometer landmark, gyroscope landmark, and barometer landmark [46]. In this article, we extend the taxonomy of sensory landmarks in Reference [46] by adding three types of landmarks, namely GSM landmark, Bluetooth landmark, and light landmark. With the development of smart devices, it is foreseeable that more sensors will be integrated into a smart device and hence more sensory landmarks can be defined and used for assisting localization and navigation. Compared with the taxonomy of seed landmarks and organic landmarks, the taxonomy of sensory landmarks eliminates the requirement for *a priori* knowledge of a landmark's physical location. All the sensory landmarks can be learned through crowdsourcing. Also, the number of sensory landmarks is much larger than the number of seed landmarks and organic landmarks, since sensory landmarks involve more sensors available in a smart device. In fact, seed landmarks and organic landmarks are a subset of sensory landmarks. Therefore, in the following, we focus on sensory landmarks.

4.3 Landmark Detection

In the following, we introduce different sensory landmarks and their common physical location and detection methods.

GNSS landmark: The number of visible GNSS satellites changes of a user entering or exiting a building or approaching a window. As shown in Figure 9, the GNSS module built in a smart device can receive the signal from more satellites when the user is in an open outdoor area and fewer satellites when the user approaches a building entrance or window. In indoor environments, there are usually no GNSS satellites visible, since GNSS signals cannot penetrate walls or other obstacles. The user might only receive the signal from a few satellites when approaching a building entrance or window. Therefore, the entrance or the window of a building can be regarded as a GNSS landmark if it possesses the three features of being a sensory landmark. In Reference [22], the authors proposed an indoor localization system called EZ, which uses location fixes occasionally obtained from a GPS lock at the entrance or near a window to solve the equations of the propagation model of WiFi signals (e.g., the log-distance path loss). GPS location fixes are also used as landmarks to correct the location estimates of PDR in Reference [107]. In the CrowdInside system [6], the loss of the GPS signal is used to detect the location of the nearest building entrance/window to improve the trace accuracy.

GSM landmark: GSM landmarks are defined as location points where the cellular RSS witnesses a significant sudden change. It is observed that a significant variation occurs in the cellular RSS when the user moves from outdoor environments to indoor spaces and vice versa. Figure 10

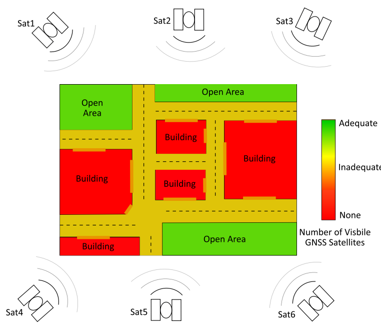


Fig. 9. An example of GNSS landmarks.

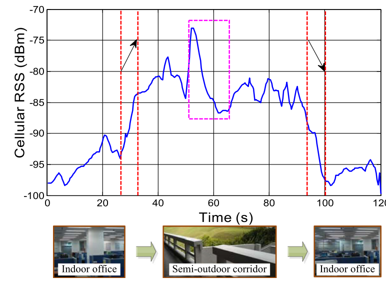


Fig. 10. An example of GSM landmarks [196].

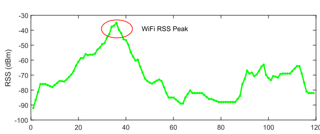


Fig. 11. An example of WiFi landmark that receives the strongest RSS.

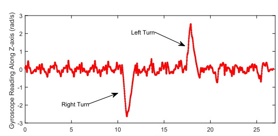


Fig. 12. The change in the gyroscope readings on the Z-axis when a user takes a turn.

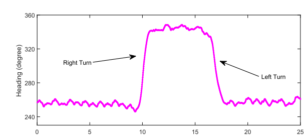


Fig. 13. The change in the compass reading (azimuth) when a user takes a turn.

gives an example of GSM landmarks where the cellular RSS value from the connected cell tower changes as the user walks out to the balcony and returns back to the office. The physical locations of GSM landmarks are usually entrances and stairs. In the IODetector system [196], GSM landmarks are used to distinguish whether the user is in indoor, outdoor, or semi-outdoor environments.

WiFi landmark: WiFi landmarks are defined as location points or small areas that receive the strongest RSS from an AP or experience a sudden change in the RSS. The WiFi RSS changes with the distance between the smartphone and the AP. When a user walks around in a building, their phone receives the strongest RSS from a specific AP only when they are in the vicinity of this AP. This vicinity can be considered as a WiFi landmark, since the strong RSS is usually stable, distinctive, and identifiable. Figure 11 illustrates the change of the RSS from an AP while the user is walking in a corridor. The location point corresponding to the 36th second is a WiFi landmark, since it receives the strongest RSS from the corresponding AP. Another type of WiFi landmark are location points that correspond to a sudden change in the RSS. This sudden change may appear when the user enters an elevator or passes a corner or other obstacles that can lead to an abrupt attenuation of RSS. This type of WiFi landmark can be detected based on the RSS similarity [165]. In both UnLoc [165] and SemanticSLAM [2] systems, the RSS similarity is used to detect WiFi landmarks.

Bluetooth landmark: Bluetooth landmarks are similar to WiFi landmarks. The main difference is that WiFi landmarks are identified by detecting the WiFi RSS from WiFi APs, while Bluetooth landmarks are recognized by checking the inquiry or the Bluetooth RSS from Bluetooth beacons. The new generation of Bluetooth low-energy technology, which consumes much less power than WiFi technology, is promising to be widely used for localization and navigation [37, 197]. In the BlueDetect system [198], Bluetooth low-energy beacons placed at specific locations are used as Bluetooth landmarks to detect the entrances/exits of buildings and the boundary of corridors.

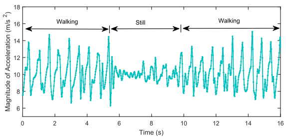


Fig. 14. The change of acceleration when a user passes through a door.

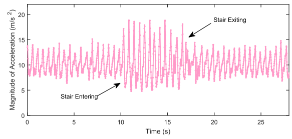


Fig. 15. The change of acceleration when a user enters and exits stairs.

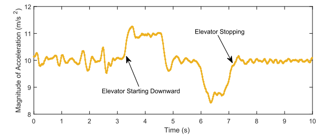


Fig. 16. The change of acceleration when a user takes an elevator down.

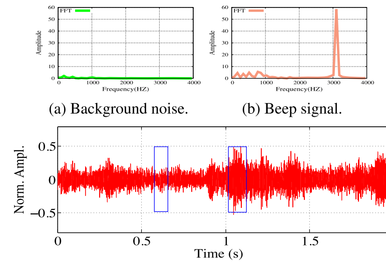
Gyroscope landmark: The gyroscope measures the angular velocity without being influenced by ferromagnetic materials. Figure 12 depicts the change pattern of a user taking a turn with the phone in hand. Gyroscope landmarks usually correspond to the locations of turns, corners, and some doors where the user has to change her direction when passing through. It should be noted that the gyroscope may not be able to detect some turns with small bending coefficient [165], which represents the notion of path curvature. This is because the change in the gyroscope readings is insignificant when taking a gentle turn, resulting in difficulty to distinguish it from noise. Gyroscope landmarks have been used in several works to enhance the accuracy of PDR [2, 21, 147, 165, 195].

Compass Landmark: Similar to the gyroscope readings, the compass readings can be used to detect turns, corners, and so on. Figure 13 shows the change in the azimuth readings of the compass when the user takes a turn with the phone in hand. It should be noted that there is no physical compass sensor in the smartphone; the compass readings are derived from the magnetometer readings and accelerometer readings. Consequently, the compass readings are susceptible to ferromagnetic materials or equipment, which do not affect the gyroscope readings. However, the advantage of the compass over the gyroscope is that the compass is able to capture turns with small bending coefficient [165]. Compass landmarks have been applied to correct the accumulated error of PDR in Reference [147].

Accelerometer landmark: Accelerometer landmarks refer to location points where the motion state of the user presents a certain change pattern, which can be identified from the accelerometer readings [44, 48, 49]. For example, the change pattern of "Walking–Still–Walking" will appear when a user opens a door, as shown in Figure 14; the change pattern of "Walking–Stairs–Walking" will arise as the user goes downstairs/upstairs, as shown in Figure 15. The location of a door and the entry and exit points of stairs can be regarded as accelerometer landmarks if the corresponding change pattern can be detected every time the user passes through the door or stairs. Similarly, there is a distinctive pattern in the accelerometer readings when the user takes an elevator downward or upward. Figure 16 demonstrates that a pair of symmetric bumps appear in opposite directions as the user takes an elevator down. Thus, the location of the elevator can also be considered as an accelerometer landmark, since it is distinctive, stable, and identifiable. Accelerometer landmarks have been widely used to improve the accuracy of indoor localization and mapping [6, 35, 55, 147, 165] and label the semantics of indoor environments [2].

NFC landmark: NFC technique is one type of RFID technology that has been built in many modern smart devices. NFC readers, which are usually fixedly installed, can be considered as landmarks. The location of an NFC tag can be inferred when it touches on an NFC reader. NFC technique has wide applications, such as electronic payment and check-in. Since NFC readers are normally installed at certain locations, their locations can be regarded as NFC landmarks, as shown in Figure 17. In the research works [40, 120], NFC tags deployed at specific locations were used as NFC landmarks for indoor navigation.

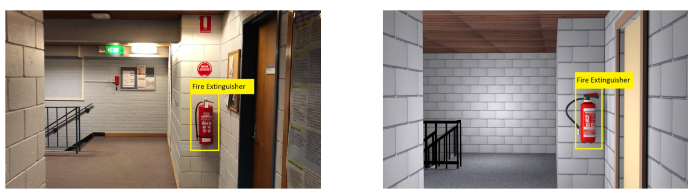
Fig. 17. An example of an NFC landmark [46].



(a) Background noise. (b) Beep signal.

(c) The original audio signal in time domain

Fig. 18. The sound pattern of using a ticket vending machine [35].



(a) (b)

Fig. 19. (a) A real image captured from a camera where the fire extinguisher is detected and can be used as a visual landmark. (b) The corresponding location of the fire extinguisher in a 3D model.

Acoustic landmark: The microphone can capture the sound of its surroundings. Certain locations may be associated with unique sounds, and there might be some unique sounds that can be considered as landmarks as long as the sound patterns are stable and identifiable. For instance, an automatic door, which may not be sensed by the accelerometer readings or other sensor readings due to the lack of corresponding patterns, may be recognizable by the sound it makes when a user passes through; a ticket/drink vending machine may emit a unique beep sound when used. To recognize such patterns, the sound signal is typically preprocessed by using a high-pass filter and a low-pass filter to remove background noise. Then, the preprocessed sound data are segmented. After this, acoustic detection algorithms can be used to extract useful features such as Mel frequency cepstral coefficients (MFCC) [111] and dominant components of fast Fourier transform (FFT) [35], which makes it possible to recognize the unique pattern of a potential acoustic landmark. Figure 18 shows that the original sound pattern of using a ticket vending machine in Figure 18(c), from which the unique beep signal, shown in Figure 18(b), can be extracted from the background noise, shown in Figure 18(a), and used to detect this acoustic landmark.

Visual landmark: Visual landmarks are generally defined as objects that have salient features and can be recognized from images. The definition of visual landmark in the context of indoor localization is similar to its definition in the field of linguistics and cognitive science. However, visual landmarks for indoor localization are usually small objects such as doorplates, lights, posters, and signs of fire extinguishers or first-aid kits that can be recognized by certain visual features [143, 156]. To detect a visual landmark, different features can be extracted from the image, including edge segments, geometric features, SIFT features, CNN features, and so on. Figure 19 shows an indoor visual landmark and its corresponding location in a 3D model.

Barometer landmark: The barometer measures the air pressure, which changes with altitude. As such, the barometer readings can be used to detect vertical movements such as taking stairs or elevator up or down. Although the barometric pressure is influenced by other factors such as

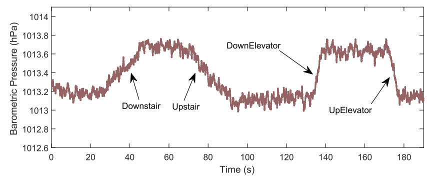


Fig. 20. The change in the barometer readings when going down/up stairs and taking an elevator downward/upward.

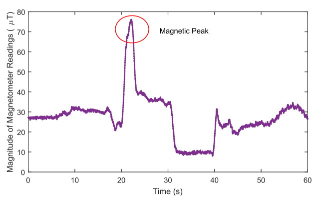


Fig. 21. The change of the magnitude of magnetometer readings when entering an elevator.

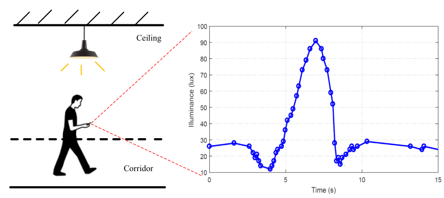


Fig. 22. The change of luminance when a user walks under a ceiling lamp.

temperature, the short-term variations caused by temperature are often negligible. Figure 20 shows the barometric pattern of different motion states. The entrance and exit points of stairs and elevators can be considered as barometer landmarks, since the changes in barometer readings are identifiable, distinctive, and stable. The entrance point can be detected by observing the change pattern "horizontal movement–vertical movement." Similarly, the exit is detected by using the pattern "vertical movement–horizontal movement." Both change patterns are recognized by utilizing the barometer readings. The barometer landmarks are used to assist indoor localization in References [21, 147].

Magnetic landmark: The magnetometer measures Earth's magnetic field as well as magnetic anomalies, and is often used in metal detectors. In most indoor environments, there are ferrous objects, structures, and equipment, around which the magnetometer readings will present a salient change. For instance, Figure 21 shows the magnetic pattern of a user entering an elevator. Since the change pattern of magnetometer readings is stable, distinctive, and identifiable at such locations (e.g, refrigerator, elevator, metal door), these can be considered as magnetometer landmarks. Magnetic landmarks have been widely used to enhance indoor localization and mapping [2, 147, 165], to detect indoor/outdoor environments [196], and to label the semantics of indoor environments [35].

Light landmark: The light sensor built in a smartphone is capable of measuring the light intensity of the environment. It can be used to detect various light sources such as a lamp installed on the ceiling, which can be regarded as a landmark. As shown in Figure 22, the light sensor in the smartphone presents a peak of illuminance when the user passes below a ceiling lamp. Apart from detecting lamps in indoor environments, the light sensor can also detect the entrance of a building and the vicinity of windows, since the illuminance of indoor spaces is different from that of outdoor spaces. In Reference [185], the authors proposed a system called IDyLL that uses light landmarks to correct the accumulated error of PDR.

It should be noted that some locations may be associated with multiple landmarks. For example, a door may be considered as an accelerometer landmark, a gyroscope landmark, a compass landmark, and so on, because these sensor readings may present corresponding landmark patterns when a user passes through the door. In this case, the features extracted from different sensors

Table 4. Summary of Sensory Landmark Detection

Landmark	Sensor	Typical Physical Location	Common Detection Feature
GNSS landmark	GNSS	Entrance, exit, window vicinity	Number of visible satellites
WiFi landmark	WiFi	Vicinity of WiFi access point, some region with special WiFi features	Change of WiFi RSS
Bluetooth landmark	Bluetooth	Vicinity of Bluetooth beacon	Bluetooth RSS
NFC landmark	NFC	Vicinity of NFC reader	NFC RSS
Light landmark	Light sensor	Entrance, exit, window vicinity, beneath lamp	Change of illuminance
Visual landmark	Camera	Objects with special color, background, shape e.g., doorplates, fire extinguisher signs	Salient Color, shape, edge
Acoustic landmark	Microphone	Places or locations with distinctive sound	Acoustic features, e.g., FFT, MFCC
Magnetic landmark	Magnetometer	Locations of ferromagnetic equipment	Change of magnetometer readings
Accelerometer landmark	Accelerometer	Door, stair, elevator, escalator	Change of walking pattern
Gyroscope landmark	Gyroscope	Turn, corner	Change of the reading along vertical component
Compass landmark	Compass	Turn, corner	Change of the azimuth reading
Barometer landmark	Barometer	Stair, elevator, escalator	Change of pressure

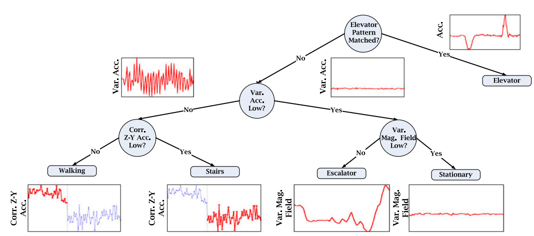


Fig. 23. Landmark detection using a decision tree [165].

can be merged together, which will increase the uniqueness of this hybrid landmark that presents different sensory patterns simultaneously.

Table 4 summarizes the sensors used to detect various sensory landmarks, as well as their typical physical locations and common detection features. Some sensory landmarks, such as light landmarks and GNSS landmarks, can be detected simply by applying an appropriate threshold on certain features (e.g., those given in Table 4); others, such as accelerometer landmarks, require use of more complex methods. In Reference [165], a decision tree is used to detect seed landmarks (which correspond to accelerometer landmarks and barometer landmarks). As shown in Figure 23, the decision tree first distinguishes the elevator based on its distinct acceleration pattern. Then, it separates stairs and walking from escalator and stationary state according to the variance of the acceleration. After that, the variance of magnetic field is used to separate the escalator from the stationary state. The correlation between the Y and Z acceleration components is used to recognize the stairs from walking state. Similar landmarks have also been detected by using least-squares support vector machines [147].

4.4 Summary and Discussion

Landmark-based indoor localization is a relatively new and promising field of research because of the increasing ubiquity of sensor-rich smart devices. Compared to methods using other spatial contexts (e.g., those based on maps and spatial models), landmark-based methods have a much lower computational cost while achieving a high localization accuracy. Table 5 gives the

Table 5. Indoor Localization Systems Enhanced by Landmarks

System	Landmark	Sensor	Feature	Localization Method	Fusion Method	Accuracy	Computational Cost
EZ [22]	GNSS landmarks	GPS	Location fix from a GPS lock	WiFi RSS	Genetic algorithm	a median error of 2-7m	Low
UnLoc [165]	Stairs, elevators, escalators	Accelerometer, magnetometer	Acceleration pattern, variance of acceleration, correlation of acceleration, magnetic variance	PDR	N/A	a median error of 1.69m	Low
	WiFi landmarks	WiFi	WiFi RSS similarity				
	Magnetic landmarks	Magnetometer	Magnetic anomaly				
	Turns	Gyroscope	Bending coefficient				
SemanticSLAM [2]	Stairs, elevators, escalators	Accelerometer, magnetometer	Acceleration pattern, variance of acceleration magnitude, correlation of acceleration, magnetic variance	PDR	SLAM	a median error of 0.53m	Medium
	WiFi landmarks	WiFi	WiFi RSS similarity				
	Magnetic landmarks	Magnetometer	Magnetic anomaly				
	Turns	Gyroscope	Bending coefficient				
APFiLoc [147]	Stairs, elevators, doors	Accelerometer, barometer	Mean and variance of acceleration magnitude, mean of vertical acceleration, barometric change	PDR	Particle filter	2m (80%)	Moderate
	Magnetic landmarks	Magnetometer	Magnetic anomaly				
	Directional landmarks	Compass, Gyroscope	Salient change in orientation and gyroscope readings				
System in [21]	Stairs	Barometer	Barometric change	PDR, WiFi fingerprinting	Kalman filter	an average error of 1m	Medium
	Elevators	Accelerometer	Vertical acceleration pattern				
	Escalators	Accelerometer, magnetometer	Vertical acceleration pattern, magnetic variance				
	Doors	WiFi	WiFi RSS change				
	Turns	Gyroscope	Angular change				
ALIMC [195]	Stairs, elevators	Accelerometer, barometer	Acceleration pattern, barometric change	PDR, WiFi	Clustering	0.8-1.5m (80%)	Medium
	Turns, corners	Gyroscope	Angular change				
Walkie-Markie [150]	WiFi landmarks	WiFi	Trend of RSS changes	PDR, WiFi	N/A	~3m	Low
AMID [82]	Magnetic landmarks	Magnetometer	Local minima/maxima of magnetic intensity	Magnetic sequence pattern	Convolutional neural network	a mean error of 2.3m	High

(Continued)

Table 5. Continued

System	Landmark	Sensor	Feature	Localization Method	Fusion Method	Accuracy	Computational Cost
Pallas [99]	WiFi landmarks	WiFi	RSS peaks	WiFi fingerprinting	N/A	an average error of 5.21m	Medium
IDyLL [185]	Light landmarks	Light sensor	Light peak	PDR	Particle filter	an average error of 0.5m	Moderate
Luxapose [78]	Light landmarks	Camera	Images of LED luminaries	Optical AOA	N/A	decimeter-level	Moderate
Knitter [41]	Geometric landmarks	Camera, WiFi	Local scale-invariant features, WiFi RSS similarity	Visual localization	Particle filter	3-4m	High
OCRAPOSE [143]	Visual landmarks	Camera	SIFT features	Visual localization	N/A	a median error of 0.5m	Moderate
IODetector [196]	GSM landmarks	GSM	GSM RSS variation	N/A	N/A	N/A	Low
	Light landmarks	Light sensor	Light intensity				
	Magnetic landmarks	Magnetometer	Magnetic intensity				
PERCEPT-II [40]	NFC landmarks	NFC	Proximity	N/A	N/A	N/A	Low
CrowdInside [6]	Stairs, elevators, escalators	Accelerometer, magnetometer	Acceleration pattern, variance of acceleration, correlation of acceleration, magnetic variance	PDR	N/A	~5m (80%)	Low
	GPS landmark	GPS	Loss of the GPS fix				
SenseWit [55]	Turns	Gyroscope	Direction change	PDR	N/A	N/A	Low
	Water dispensers	Accelerometer, gyroscope	Direction change, stationary duration				
	Doors	Accelerometer, gyroscope	Motion state change, direction change				
Transitlabel [35]	Stairs, elevators, escalators	Accelerometer, magnetometer	Acceleration pattern, variance of acceleration, correlation of acceleration, magnetic variance	N/A	N/A	N/A	Low
	Entrance gates	Accelerometer, magnetometer	Change of motion states, magnetic field change				
	Coin operated machines	Microphone	FFT				
	Waiting areas	Accelerometer, gyroscope	Change of motion states, direction change				
	Restrooms	Speaker, microphone	Acoustic characteristics				
SignalSLAM [107]	GNSS landmarks	GPS	Location fix from a GPS lock	PDR	SLAM	a median error of 5m	Low
	Visual landmarks	Camera	Text string encoded in QR codes				
	NFC landmarks	NFC	Proximity				
BlueDetect [198]	Bluetooth landmarks	Bluetooth	Bluetooth RSS	N/A	N/A	N/A	Low

*N/A indicates not applicable.

state-of-the-art indoor localization systems that utilize landmarks. It can be seen that the most commonly used landmarks are those corresponding to stationary building structures (e.g., stairs, elevators, escalators, doors). Magnetic landmarks and WiFi landmarks are also popular because of the pervasiveness of geomagnetism and the prevalence of WiFi infrastructure. Light landmarks are becoming increasingly popular, since modern smart devices have integrated the light sensor that can capture the light intensity. Although different types of landmarks have been applied in indoor localization, there is still room to investigate the feasibility of other types of landmarks mentioned above.

Landmark-based methods improve the localization accuracy by recognizing the encountered landmark and matching it with those that are collected and stored in a database. A major challenge in using landmarks for assisting localization is the matching, also known as the data association issue [110]. In other words, when there are multiple landmarks nearby, it is difficult to determine which one matches with the encountered landmark. This problem is caused by the fact that sensory landmarks do not have to be unique in the whole environment. Instead, often landmarks are unique in a local area (e.g., a room). The reason for this is to obtain a sufficient number of landmarks in the environment.

A simple solution to this problem is to increase the uniqueness of a landmark by adding other sensor data. WiFi fingerprints are often integrated into the property of accelerometer and gyroscope landmarks [2, 165]. When the sensor pattern of a potential landmark is detected, its corresponding WiFi fingerprint is first matched with the WiFi fingerprints of the landmarks in the database, and the landmarks with similar WiFi fingerprints are chosen. Out of these candidates, one landmark is finally selected by matching the detected sensor pattern with those of the candidates. The main limitation of this solution is its reliance on WiFi fingerprints, which means that it will not work when the user is out of WiFi coverage range. In addition to WiFi fingerprints, walking orientation is useful in solving the data association problem. For example, when the user's location is near two doors on two sides of a corridor, the two doors can be distinguished by observing the walking orientation of the user as they pass through one of the doors.

Another solution to data association is to use the history of detected landmarks. One single landmark may not be distinguished from other landmarks in the environment, but a trajectory of several encountered landmarks will make a unique path in the environment. Different methods such as the Hidden Markov model [131], conditional random field [180], and dynamic time warping [152], have been used to match the encountered landmark patterns with those in the database, thereby determining the correct landmark.

An additional challenge of using landmarks is dealing with the case that one or more landmarks are missed. In some cases, a landmark may be missed for various reasons. For example, an accelerometer landmark corresponding to a door will be missed if the door is left open, since the user does not stop to open the door (no "Walking–Still–Walking" pattern); also, lamps might be on or off at different times of the day, which will lead to failure in the detection of the corresponding light landmark. In these cases, one can simply ignore the missed landmarks and not correct the user's location until the next landmark is detected. However, this simple strategy may lead to a large error in the location estimation and even result in failure to locate the user. Handling missed landmarks is an open problem for which no appropriate solution currently exists.

5 CONCLUSION AND OPEN CHALLENGES

In this article, we have surveyed the state-of-the-art indoor localization methods and systems. Wireless localization and inertial localization are the most popular methods, which have been applied in many domains. With the advent of smart devices, more sensors have become available in daily-used devices such as smartphones, enabling more localization methods to be explored, such as magnetic localization and light-based localization. Each localization method has its own advantages and limitations. Hybrid localization methods can overcome the limitations of single sensors but will increase the cost of deployment.

Fusing spatial context with indoor localization methods is an effective way to achieve a satisfactory accuracy at no extra cost. The commonly used form of spatial context is map, whereby the localization accuracy can be improved by map matching. Spatial models contain richer information than maps and can better improve the localization performance. However, the construction of spatial models requires significant efforts, and automatic model reconstruction methods are still in their infancy. Also, spatial-model-based indoor localization methods, especially those based on 3D spatial models, are usually computationally expensive and consume battery power quickly.

Landmarks, which can be considered as one type of spatial context, are quite useful in indoor localization. Compared to map-based and spatial-model-based methods, landmark-based methods have lower computational requirement but can achieve similar localization accuracy.

Overall, indoor localization has been studied for decades, and spatial context can improve the localization accuracy without increasing the cost of deployment.

The main challenges in indoor localization that remain open for further research are as follows:

- **Automatic construction of spatial models**. Currently it is feasible to construct a map efficiently using crowdsourcing or SLAM. Spatial models contain richer information than maps and are better suited to enhance indoor localization. However, manual construction of spatial models is labor-intensive and slow, and automatic construction methods are still in their infancy. More work on automated generation, evaluation, and benchmarking of indoor models for localization and navigation purposes is needed [70, 71].
- **Feature learning for sensory landmark detection**. Existing landmark-detection methods require the manual design of features for detecting a landmark. Further research on automatic feature learning methods, e.g., deep learning, will improve the landmark-detection accuracy and lead to more accurate localization methods.
- **Hybrid feature database construction and update for indoor localization**. Despite their promise, hybrid methods typically consider only the integration of a few techniques such as a combination of WiFi fingerprinting and magnetic fingerprinting, a combination of WiFi fingerprinting and maps, or a combination of PDR and landmarks. It is possible to achieve better localization accuracy and robustness by building a hybrid feature database, containing not only WiFi fingerprints, magnetic fingerprints, and sensory landmarks, but also semantic features and other salient parameters. How to efficiently construct and update such a hybrid feature database is a topic deserving further research.
- **Cross-platform generalization of indoor localization.** Most indoor localization systems are implemented on smartphones, which have relatively better computational capability and larger memory than other smart devices such as smart bands, smart watches, and smart glasses. However, existing works usually focus on analyzing the generalization ability of indoor localization approaches on different users. There is a lack of research on how a method, developed for smartphones, works on other platforms such as smart watches. Developing cross-platform indoor localization methods is another possible direction for future research.
- **Battery-friendly lightweight indoor localization methods**. While many researchers seek to improve localization accuracy by integrating a variety of sensors and/or spatial information, the battery power consumption problems are often ignored. Recording data from multiple sensors simultaneously (e.g., WiFi, accelerometer, magnetometer, gyroscope, barometer) can consume the device battery quickly, which may prohibit the developed

systems from being widely used. Also, the fusion of spatial information, especially spatial models, imposes a high computational cost. Developing battery-friendly lightweight indoor localization methods will be crucial to launching a system on a global scale.

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